EXECUTIVE SUMMARY

THE DEVELOPMENT OF A PROCEDURE TO FORECAST TRAFFIC VOLUMES ON URBAN SEGMENTS OF THE STATE AND INTERSTATE HIGHWAY SYSTEMS

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and the
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16. Abstract This study developed a multi-facted procedure to forecast traffic volumes on urban segments of the state and interstate highway systems for the Indiana Department of Transportation. A detailed statistical analysis was conducted to develop alternative models to forecast traffic. The models and the procedures described in this study's Final Report are intended to provide highway planners with a tool for simple, fast and inexpensive estimation of traffic projections. Emphasis was also placed on achieving reliable input information for the forecasts of any background factors (independent variables) used in the models. This study improves on previous efforts to build simple and reliable procedures to forecast traffic. Among the several models examined in this study, elasticity and lag-AADT models were finally selected because of their simplicity and better performance. This study has employed several measures to evaluate the forecasting models. Often, combined forecasts developed in this study were found to perform better than the forecasts from any of the constituent models. Some problems and limitations of the models -- and suggestions to overcome them -- are discussed.			
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The analyses conducted in this study were performed with traffic data gathered from the paper files of INDOT. Other input data were obtained from a variety of sources, for example, the libraries at Purdue University, Census Publications, IU Business Center, and the firm of Woods & Poole Economics. A nationwide survey on "Forecasting Traffic on State Highways" by ITE Technical Council Committee 6F-41 showed the lack of any universally accepted method to address the issue of traffic forecasts in small- to medium-sized urban areas. This study has developed an efficient, inexpensive and easy-to-use method to forecast the traffic on state highways. The greatest strength of this study is the application and description of different statistics, ranging from simple to sophisticated. This report contains a full description of the entire model building process. The major findings of the research are summarized below, with reference to specific chapters and sections of the Final Report.

Data Evaluation and Candidate Elasticity Model

The variables and the data bases used in this study have

been described in Chapter 4. Table 4.7 contains a summary of the quality (cost, availability and reliability) of the variables. The details of the analyses and their results for the evaluation of data and for selection of the candidate regression/elasticity models are presented in Chapter 5. The framework of the analyses for interstate and noninterstate highways are presented in Figures 5.1 and 5.2, respectively. Several variable selection criteria (R_p^2 , R_a^2 , C_p , PC, AIC) have been employed to select the most appropriate model. Despite the merits and demerits of using the R^2 (R_p^2) criterion, it has been adopted by the researchers as the single most useful criterion to gauge the "goodness" of a statistical model. However, analyses in this research were aided by other statistics. The data structure of this study includes the two data bases (segment and county/city average) and the four formats (raw, raw E&L, density, and density E&L). A sensitivity analysis of the "maximum" R^2 value among the competing models that are without any inconsistency in the sign of regression coefficients identifies the combination of county/city average data base and raw format as the best combination from all possible combination of the data structure. A significant improvement in model statistics was found in county/city average data bases over segment data bases. Because all the predictor variables used in this study are totals at either the city, county, or state level, it was not surprising to have traffic data on a county/city average basis perform better than traffic data on a more localized basis.

A similar sensitivity analysis among the data groups revealed the following:

- For Interstate Highways: (1) For separate analysis of rural and urban interstate highways, both statewide and regional (north, central and south regions) models are found to be suitable. (2) A statewide model for the entire interstate network in Indiana was not satisfactory. (3) The improvement of the model statistics is better in case of analysis by geographical region than by the extent of roadway mileage and city group.
- For Urban Principal Arterial: (1) The combination of city group and geographic region performs better than any other possible combination. This second-level stratification by geographical region under each city group has been established as superior to grouping by city group alone. (2) Results improved when the data of city groups A, B and C in the south region were pooled. The alternate was having unstable results with too few observations in each city group.
- For Minor Arterial & Collector: The second-level stratification by geographic region and extent of highway mileage resulted in poor results and groups with too few observations. However, the analysis at this level of stratification identified areas of weakness in the data. After pool-

ing data by city group, the quality of model statistics improved.

The candidate models resulted from narrowing down a list of possible candidate models by comparing the model statistics (R^2 , R_a^2 , PC, RMSE, AIC and C_p) and by applying judgment on the quality (availability, cost and reliability) of the data for the predictor variables in the model. The list of those candidate models are shown in Chapter 5.

Elasticity Based Traffic Model

The final regression equations and the elasticity models developed in this study were shown in Chapter 6. The influential analysis identified the individual outliers and the outlier groups and their effect on model statistics. The diagnostic statistics employed to do influential analysis were shown in Section 6.2.1. Modification of the data (if necessary) or deletion of outliers (if justified) was found to improve the quality of model statistics significantly. For example, it improved the statistics for the normality assumption of errors. Validity of the regression assumptions (linearity, constant variance, and normality of errors) were checked through formal tests and graphical plots -- residual and normal probability plots. Results of significance tests showed that the model parameters are highly significant. A significance of relation also resulted for all the models. The collinearity test found that no significant

relationship existed between the variables of each model. The final regression equations of each group, shown in Tables 6.23-6.25, were produced by comparing the results of the above tests and some model statistics (R^2 , R_a^2 , RMSE, and CV) of the candidate models, and by applying judgment regarding the quality of predictor variables. The R^2 values for the regression models of interstate highways, urban principal arterial, and urban minor arterial & collector have ranges 50.35-88.86, 51.81-94.14 and 62.52-87.18 percent, respectively, with one or two variables in each equation. Each of these models is simple and does not contain more than two predictor variables. The elasticity models developed from the regression models are shown in Tables 6.26-6.28. These models are statistically sound and simple. They require the base year traffic data and base and future year data for the predictor variable(s).

Principal Component Based Traffic Model

The procedure and results for Principal Component Analysis (PCA) were shown in Chapter 7. The PCA was carried out for each group of filtered data which resulted from the influential analysis of Chapter 6. The PCA used 11 predictor variables, but had eliminated the problem of multicollinearity by computing the artificial variables (principal components) which are independent to each other. Some key results of the Principal Component Regression (PSR) model with PCs in the equation are shown in

Tables 7.2-7.4. Appendix Tables D1-D3 show the relationship between the PCs entered in the equation and the original variables. The PCR equations for interstate highways, urban principal arterial and urban minor arterial & collector are shown in Tables 7.5, 7.6 and 7.7, respectively. These tables show a one-to-one comparison of R^2 values between the PCR models and the regression or elasticity models from Chapter 6. The R^2 values for the PCR models had ranges 61.46-90.26, 52.87-97.57 and 66.87-89.31 percent for the three major highway categories in this study. The R^2 ranges for the regression/elasticity models are 50.35-88.86, 51.81-94.14 and 62.52-87.18 percent. This range comparison, plus one-to-one comparisons for each model shown in Tables 7.5-7.7, do not show any significant improvement from the complex PCR model over the simple regression or elasticity model developed in Chapter 6. However, the complex PCR models, which need all variables to compute PCs in the model equation, certified the goodness of the model statistics for the regression or elasticity models that have fewer variables in their equations.

Lagged Traffic (Lag-AADT) Model

The information of traffic data itself and the rate at which traffic had changed were used to develop the inexpensive and simple lagged traffic model. The segment data base of Chapter 4 with a "raw" format (see Chapter 5) was used to build this model. Although Equation (8.2) had used "rate of AADT change", in its

rearranged form, Equation (8.3) needs only one AADT value to forecast traffic on a highway segment. Because the data bases used to build lag-AADT models are different from those used in Chapters 6 and 7, the model statistics of the lag models are not directly compared to those of the other models. However, the traffic forecasting performance of the lag-AADT models were compared with the others in Chapter 10. The lag traffic models for interstate, urban principal arterial and urban minor arterial and collector were presented in Tables 8.1, 8.2 and 8.3, respectively. These tables show, as expected, a very high R^2 values (about 99 percent). The parameters of the models and the regression relationships were found highly significant at very low levels. The nonnormality of the error terms were because of the presence of outliers. The forecasting performance of these models was tested by skipping the last year of AADT values from each segment, reformulating the models, and comparing the resulting forecasts against the skipped values. Very high forecasting quality performance measures and model statistics were found for the models (shown in Appendix E) built with partial data.

Time Series and Ratio Method Forecasts

No forecasts of vehicle registrations and city population are available from outside sources. The structure and results of procedures developed to make these forecasts are shown in Chapter 9 and Appendix F. A ratio method of forecasting city population

was described in Section 9.3.1. Its forecasts for the cities of Indiana were shown in Appendix F. Forecasts of vehicle registration were made through two time series analysis techniques -- the Box-Jenkins ARIMA model and the autoregressive procedure. Parameters of the models were found to be significant at 5 percent level of significance. Both autoregressive and ARIMA procedures produce high quality forecasts in this study. Use of these two different types of models also increased confidence in the forecasts. A combined forecast of vehicle registrations was made by simple averaging of the forecasts from the Box-Jenkins and the autoregressive procedures. The forecast measures of the combined forecasts and the forecasts from the constituent models for the two selected counties were shown in Table 9.7. The values of the performance criteria verified the reliability of the vehicle registration forecasts.

Traffic Model Evaluation

Level of accuracy is a primary concern for the users of traffic forecasts. Inaccurate forecasts can lead to under or over-designed facilities. To determine the tolerable errors in forecast, one needs to know how much error a traffic forecast can have without causing major design changes. However, boundary cases must be examined more carefully. In that case, it will be wise to develop forecasts from several methods to arrive at a "consensus range" of the traffic estimate.

Usually, the error in various travel forecasting methods can be estimated by testing the methods against the actual counts and comparing the results. This study used several forecasting measuring criteria (Section 10.2) to evaluate the performance of the traffic models. The results, shown in Tables 10.1-10.3, show that the mean absolute percentage errors, defined in Section 10.2, are usually less than 10 percent. Regression models developed in Chapter 6 were found to be ineffective in forecasting project site traffic. Despite the difference in model statistics and procedures, both elasticity and lag-AADT models were found to be highly efficient models for forecasting traffic. They were found to work equally well. The combined forecasts, formed by simple averaging of the forecasts from the elasticity and lag-AADT models, did better than either the constituent model in many cases. Combined forecasts are recommended to forecast traffic on the state highway segments. Forecasts from several models provides the opportunity to assess the sensitivity of the forecasts to different model forms. Finally, a procedure, shown in Section 10.4, was developed to monitor the forecasts and to see if there will be any need in the future to recalibrate the models and their parameters.

JOINT HIGHWAY RESEARCH PROJECT

FHWA/IN/JHRP-90/11

Draft Final Report

**THE DEVELOPMENT OF A PROCEDURE
TO FORECAST TRAFFIC VOLUMES ON
URBAN SEGMENTS OF THE STATE
AND INTERSTATE HIGHWAY SYSTEMS**

Sunil K. Saha

Jon D. Fricker

Draft
Final Report

The Development Of A Procedure To Forecast Traffic Volumes On
Urban Segments Of The State And Interstate Highway Systems

TO: H.L. Michael, Director
Joint Highway Research Project
August 22, 1990
Project No. C-36-5400
File No: 3-3-41

FROM: Jon D. Fricker
Associate Professor of Civil Engineering
Purdue University
West Lafayette, Indiana

SUBJ: The Development of a Procedure to Forecast Traffic Volumes on Urban
Segments of the State and Interstate Highway Systems

Attached is the final report of the subject report, which describes the work completed under the expanded project having the title "A Method of Establishing Traffic Growth Factors". The project has been performed by Mr. Sunil Saha, Graduate Research Assistant, under my direction.

After extensive data retrieval and preparation, painstaking statistical analysis and engineering judgement have produced a forecasting procedure that combines explanatory power and ease of use. Using a menu-driven computer program developed to implement the models built during this study, INDOT personnel can now quickly generate a well-documented traffic volume forecast for any urban segment of the state or interstate highway system.

The final report is submitted for review, comment, and acceptance in fulfillment of the referenced study.

Respectfully Submitted

Jon D. Fricker

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Among the most important factors in public investment decisions are the projected demand for an existing or proposed highway facility. The pattern of traffic growth and projected traffic volumes have been recognized as prime factors in most analyses of highway projects. Developing future traffic estimates is not an exact science, dependent as it is on so many hard-to-predict variables. The traffic growth factor has a significant effect on highway investment decisions pertaining to increasing the capacity of existing highways and the construction of new facilities when limited funds are available. Traffic forecasting procedures must be reasonably easy and economical to carry out, be sensitive to a wide range of policy issues and alternatives, and produce information useful to decision-makers in a form that does not require extensive training to understand.

Estimates of future traffic can be arrived at by two very different methods: projections and forecasts. Projections have been used for years and are based on a historical record of the desired data item. Trend lines drawn through prior year data observations are

extrapolated to the target year. In some cases, these extrapolated trends are modified by the analyst based on his experience and knowledge of the route, state or region. Whereas with projections we are dealing only with the traffic data, forecasting techniques are concerned with predicting the future values of economic and other measures or indicators of person and vehicle travel. In forecasting techniques, a relationship between traffic and associated factor(s) is established. The terms prediction and forecasting have been used interchangeably in this dissertation, irrespective of their inherent definitions.

A clear distinction should be made about the nature of traffic forecasting methodologies. They are divided into two separate groups: (1) Those that address the forecasting problem as a network analysis, based on the traditional four-step process that requires large amounts of data and sophisticated computer resources, while not guaranteeing forecasts that are appreciably superior to less detailed methods, and (2) the simple, easy-to-use forecasts on a road-by-road basis that fulfill the particular needs of the local highway departments.

1.2 Background

Traffic data are essential in nearly every step of the planning process. In highway investment (major maintenance, reconstruction or new construction), a reliable estimate of future traffic volume is a key element. The design of roads and analysis of alternative highway projects are dependent on these forecasts.

Traffic forecasts can be prepared with a variety of approaches, depending on whether the forecast refers to an urban or rural area. In urban areas, forecasts are generally based on the four-step (trip generation model, trip distribution model, modal split model and traffic assignment model) travel-simulation process. In these situations, travel on the road network is an output of the assignment process. Most large metropolitan areas have developed and implemented a fairly sophisticated set of computer-based travel simulation models based on the traditional four-step process.

In rural areas, when assignment-based models do not exist or are not practical to apply, traffic estimates are generally made by expanding present traffic into the future based on projections of population, employment, vehicle registration, land-use data, or other parameters [Hazen 1982, Memmott et al. 1981, Neveu 1982]. A family of models for use in forecasting average annual daily traffic (AADT) volumes on the following classes of rural highway segments in the Indiana state and interstate system has been developed [Saha 1986, Fricker & Saha 1987]:

- Rural Interstate
- Rural Principal Arterial
- Rural Minor Arterial
- Rural Major Collector

These models were designed to capture the relationship between AADT and the factors (economic, demographic, etc.) that influence traffic volumes, using input data that are reasonably available and model forms that are flexible and easy to use. While a forecasting

tool can never be validated until the forecast or horizon year becomes the current year, the models that were developed appear to be (a) on a sounder theoretical and statistical basis than those previously found in the literature and (b) in conformity with the goals of the rural study.

It is likely that the rural factors and coefficient values are not applicable to urban segments. Two principal reasons for this probable lack of transferability stand out:

1. Traffic on urban highway segments is more a function of local conditions and factors than the typical rural segment.
2. Traffic on urban segments is much more sensitive to changes in other links in the urban road network.

The urban traffic forecast procedures reviewed to date can be grouped under two general categories: trend forecasting and theoretical forecasting. Trend forecasting can be subdivided into two procedural types: mechanical and analytical. The mechanical methods assume that future travel patterns will be a continuation of past experience, allowing simple projections of past trends forward. The analytical method recognizes the fact that traffic growth is a product, not only of time, but of certain varying internal forces and external stimuli that operate to affect the rate of growth of each contributing factor to the composite growth. Theoretical forecasting procedures can fall into any of the following categories: (a) traditional aggregate 4-step traffic simulation models, (b) disaggregate stochastic behavior models, and (c) econometric models.

Traffic forecasting is the backbone of the transportation planning process. Urban areas approaching the 50,000 population level

face the formidable task of initiating a comprehensive transportation planning process. The following statement in regards to the results of the investigation was made in the executive summary and introduction of the "Framework for the Transferability of Trip Generation Parameters of Small Urban Areas" [Mahmassani & Sinha 1978]:

"Initiating a continuing, comprehensive and coordinated transportation planning process is a considerable task that faces small metropolitan areas as their population reaches 50,000. These areas usually lack the technical know-how as well as the financial capabilities needed to use the battery of computer-oriented planning models more commonly used in large metropolitan areas. In most cases such sophistication is not needed because the problems faced by smaller areas are different in nature and in complexity from those in larger areas."

In early 1987, Purdue University and the Program Development Division of INDOT recognized the need for simplified procedures for small- and medium-sized urban areas, and therefore, organized a research project to develop a procedure to forecast traffic on state highway systems for small- and medium-sized urban areas of Indiana. The planning division of INDOT was aware of the past resources expended in the transportation planning process for many of the urbanized areas in Indiana and therefore realized that the results derived from such a project could be very beneficial.

1.3 Purpose and Scope of the Research

The goal of this research study is to develop a method of establishing a procedure to forecast traffic for the Interstate and small- to mid-size urban state highways that can be used by the Indiana Department of Transportation (INDOT). The research has been carried out by the Joint Highway Research Project (JHRP) at Purdue University

with the sponsorship of the Federal Highway Administration (FHWA) and INDOT.

The primary purpose of this research is to develop model(s) to forecast traffic for use by personnel responsible in planning, design and decision making. A secondary purpose of the proposed research is to advance the body of knowledge regarding traffic forecasts. The model building approach of traffic forecasts has not been confined to the State of Indiana. A related purpose of the proposed research is to establish the groundwork for follow-up studies in other states.

This study has met the ongoing needs of INDOT for a reliable method of estimating future traffic on individual routes, as an aid to the planning process and in implementing the Highway Improvement Program. The proposed method is reliable, with modest data and computational requirements, and is well-documented and flexible. The model developed in this study is simple to apply. A hand calculator is adequate for the application of the model. But, the use of spreadsheet and the interactive programming will improve the efficiency of model application.

Some common criticisms of the models in transportation planning studies are [Richards & Ben-akiva 1975]:

1. The models are too time-consuming, complex and expensive to operate.
2. Too much thought is given to the model building and too little to the elements that are really important in the practical use or implementation.
3. The users (as opposed to the model builders) do not always understand the models.

4. The researchers usually concentrate on building the model, but seldom devote enough effort to model implementation and validation.
5. The models are too data-hungry.

One of the purposes of this study is to develop a model less vulnerable to the above criticisms.

The primary focus of this study is the design and testing of the simple, fast methods to forecast traffic volumes. This study details the development of such a procedure in order to update the method in future years. This study examines previous efforts aimed at forecasting traffic, particularly by using simple and efficient methods, describes the chosen methodology, and evaluates the results of the investigation.

The scope of this study is limited in some important ways. First, although studies from other states and countries have been reviewed and, when appropriate, their findings have been incorporated into the present study, the data bases of this study were created for Indiana. The development of growth factor models for urban state highways in Indiana has remained the primary focus of this research.

1.4 Study Objective

In the overall investigation, the objective will be to make the model(s) as simple as possible. The overall objective of the proposed study is to provide, for the urban highways in Indiana for which INDOT has responsibility, a means of predicting future traffic volumes that are:

- reliable,
- well-documented,
- easy-to-use, and
- based on input factors for which clear relationships and usable forecasts will continue to exist.

The goals leading to the above-mentioned general technical objectives are:

- a. Establish a database of maximum practical accuracy, consistency, and size.
- b. Identify the variables/factors that best describe the response variable. Both judgment and statistical analyses will play a role in this selection process.
- c. Establish causal relationships between traffic volumes on urban highways and input factors of a demographic, economic, and "structural" nature, using statistical analysis techniques.
- d. Test and validate the model(s), and develop guidelines for use of the model(s).

1.5 Study Organization

This study consists of eleven chapters and seven appendices. Chapter 2 reviews the literature on forecasting traffic that uses simple and easy-to-use methods and looks at some of the current procedures practiced by some state highway departments.

Chapter 3 presents the framework of overall analysis for constructing statistical models. This chapter primarily explains only the conceptual ideas behind overall analysis. Chapter 4 describes the variables in the data bases, the data formats and their use in the analyses.

Some statistical analyses of the data gathered in Chapter 4 are provided in Chapter 5. Some useful statistics of the data bases, their formats, and groups are being compared. The candidate models for each group are selected from the best data base and format. Chapter 6 contains all the results of influential analysis, significance, collinearity, and normality statistics of the candidate models identified in Chapter 5. Model statistics are presented as pre and post influence analysis. Sample residual and normality plots are shown for some selected models. Final regression and its variant elasticity model are presented in this chapter.

Chapter 7 contains the results of the analysis done for the principal component based regression model. Some key statistics are compared with models of Chapter 6. Chapter 8 reports another alternative model -- the lagged traffic model. The model statistics and the sample graphical plots are also shown in this chapter, as with the models in Chapters 6 and 7.

Chapter 9 discusses and presents the results of forecasts of input variables for which no forecast is available from outside sources. Two efficient time series analysis techniques to forecast vehicle registration and the "ratio" method to forecast city popula-

tion have been used in this chapter.

Chapter 10 presents the results of some performance measuring criterion to evaluate (a) the traffic models developed in earlier chapters and (b) the forecasts found by combining the efficient models. A monitoring device has been proposed to detect the need for calibration in future. Chapter 11 gives the conclusions of the research as well as guidelines to implement the models developed. This chapter also provides probable problems, limitations and recommendations for further research in areas of traffic forecasting that can use less complicated models.

Some sample data tables developed and analyzed in Chapters 5 to 8 are presented in Appendix A. The complete data bases used in this study are saved on several floppy diskettes for updating the data base with recent information and for future modification of the model, if desired. Appendix B presents the land areas of cities and counties and data for functional class mileage to complete the data bases in Appendix A. A form used for manual retrieval of traffic data is shown in Table B4 of Appendix B.

Appendix C presents the best models without any inconsistency in the regression coefficients for different numbers of variables for each data group, format and data base. The statistics of these models are used to do sensitivity analysis with respect to different data bases and formats. Appendix D shows the eigenvectors of the principal components used in the models, standard deviation and mean of the original variables, and sample graphical plots for principal component

regression. Appendix E contains the results of regression and forecast measures of the lagged model in Chapter 8 with partial data. Sample graphical plots of residual and normality for some selected models are also shown in Appendix E.

Appendix F presents (i) models, forecasts and sample plots of vehicle registration (VR) from the Box-Jenkins and the autoregressive models, (ii) combined VR forecasts and sample plots, (iii) sample plots of residuals and normality, and (iv) city population forecasts. Appendix G presents the 90- and 95-percent confidence limits of the forecast measures for combined traffic forecasts and for the forecasts from each of the constituent models.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

It is the goal of this research to sort through and select the most relevant literature where an abundance presents itself and to add to the store of knowledge where a scarcity exists. The literature of particular interest for this study is that dealing with traffic volume and the background factors that influence it. A review of the literature on traffic forecasting, with particular emphasis on simplified procedures is presented in this chapter. A review of the literature reveals that limited research has been accomplished on the topic of forecasting traffic for small- and medium-sized urban areas. Some ideas from this review study have been incorporated into the present study.

2.2 Transportation Demand Models

The process of relating the demand for transportation to the socioeconomic activities that generate it is known as transportation demand analysis [Kanafani 1983]. The results of this analysis are relationships (often as models) between measures of activity and

measures of transport demand. Such relationships are often referred to as transportation demand models. Although demand analysis is distinct from traffic forecasting, one can use the results of demand analysis to forecast future traffic volumes. The demand models provide major input into the forecasting process. It should be recognized that there are limitations to demand models as forecasting tools. The analyst might well find it reasonable to use models of demand analysis for short-term forecasting to study the impacts of changes in the demand and supply environments of transportation. But as the time frame of forecasting becomes longer, it is unlikely that the same models will continue to be of as much relevance.

2.3 Urban Traffic Simulation Models

The traditional travel simulation model is available in many urban areas. The system was originally developed in the early 1960's and has been widely used in many urban areas ever since. The highly sophisticated simulation procedures are based on a set of procedures to predict urban area trip generation, trip distribution and trip assignment. It is not the purpose of this section to give a detailed description of the procedures, which would be lengthy and time consuming. The principles involved in the system have been described in many urban transportation planning textbooks, such as Hutchinson [1974], Stopher and Meyburg [1975], and Meyer and Miller [1984]. However, this section is intended to introduce an overview of that sophisticated process.

The network-wide travel simulation system requires extensive inputs describing urban area socioeconomic, travel, and highway network characteristics. In general terms, the process consists of developing a trip file describing the rate of trip making in each of the analysis zones of the study area and then distributing those trips between the zones using some form of attraction-production model (for instance, the gravity model or intervening opportunity model). Finally, trip interchanges are assigned to the network based on some preferred iterative technique — for example, minimum path (all-or-nothing), equilibrium or stochastic assignment. Many software packages based on this modeling concept are available on the market.

Prem [1987] had discussed the following travel forecasting tools in terms of their general description, primary task, features and constraints.

1. Urban Transportation Planning Process (UTPS)
2. Manual Quick Response System (QRS)
3. Microcomputer Assignment Models
4. Simplified Project Forecasting (SPF)
5. Traffic Simulation Models

The scope of this study does not allow the researchers to apply these techniques in their forecasts. But, available forecasts from any of the travel simulation model can be easily compared with the forecasts produced by this study.

2.4 ITE Survey Results of State Traffic Forecasting Procedures

A summary of the state of the art of procedures used to forecast traffic by states and provinces was addressed by ITE Technical Committee 6F-41 [ITE, 1990]. The following results are summarized in that report.

- Traffic forecasting remains one of the most important functions of state and provincial planning staffs. Main department offices are primarily responsible for preparing both urban and rural forecasts. Decentralization of the forecasting task to regional groups has not been undertaken, perhaps because such activity requires a specialized set of skills not widely available in regional groups.
- Traffic forecasting remains a combination of art and science requiring the user's judgment and experience. In developing forecasting studies, the following points are stressed [ITE, 1990]:
 - a. Review of Traffic Count History — To develop an understanding of the pattern of growth around the project site.
 - b. Focus on Inputs -- GIGO ("Garbage In Garbage Out"). A model is only as valid as the data used to develop the projections.
 - c. Balance Effort with Project Scale -- A complex and expensive forecasting method may be unnecessary for a project of limited scope and impact.
 - d. Select an Appropriate Level of Accuracy — The purpose of the project will determine the accuracy level desired.

- e. Use Several Methods -- If possible, it may be highly desirable to apply several forecasting methods on the same project. This sensitivity analysis will assist the planner in establishing the range of potential error in a particular forecast.
- Traffic forecasting requires the application of both technical procedures and practical experience. A wide range of procedures have been developed and applied. In general, the methods that have been used are related to the project needs, level of investment, and the range of acceptable error.
- The traditional four-step urban modeling procedure is used in many urban areas. However, a number of states simply extrapolate current trends in traffic counts or use growth factor procedures. In rural areas, simple extrapolation and growth factor procedures are used extensively.
- Certain standard techniques (i.e. extrapolation, time series analysis, elasticity-based, site specific, functional classification based, multivariate statistical analysis, etc.) are likely to predominate. But, very few written documents on these techniques have been published to date. Very few studies are known to the researchers in this study about the quality of the results of the methods practiced by different state highway agencies.
- Many states remain actively engaged in improving forecasting procedures and adopting microcomputer techniques. In addition, improving truck forecasting procedures appears to be a priority for many states.

2.5 Adjustments for Factors not Considered Explicitly in the Model

Many background (socioeconomic) factors may seem to influence travel on roadways. A discussion on (1) how the background factors affect traffic and (2) the role of the background factors can be found in Chapter 2 of Indiana's rural study [Fricker & Saha 1987]. But, most forecasts developed in the past did not include consideration of energy price and supply or improvements in auto fuel economy. Moreover, forecasts do not often recognize the transformations that have occurred in travel-related variables such as household size, auto size, inflation, employment, population age, and settlement patterns. But not all of those factors entered in the model equation because of (a) inadequate information in the past, (b) forecasts into the future are either uncertain or not reliable with a scanty data base, and (c) the factors not significant in the model building process. Additional research is required in this field to develop methods that will adjust traffic for the factors not considered in model. Chapter 9 of the New York State Traffic Forecasting Guide [Trombly & Ouderkirk 1986] presented the tabular values to adjust traffic forecasts. The results are based on some empirical relationships between travel and background factors in the past. So, the results should be applied cautiously. In the absence of any other good source on adjustments or further research, users of the this study may adjust the forecasts if they feel the future conditions are warranted to made such adjustments. Again, a word of caution mentioned in the Guide [Trombly & Ouderkirk 1986] is as follows:

"The adjustment procedures were developed using the best

information available at the time. These data come primarily from the 1970's and earlier. New factors not accounted for in these procedures may influence travel behavior in the future. Two such issues are the economic conditions in the early 1980's, and the decontrol of crude oil prices in early 1981. Finally, the user should be aware of these shortcomings, and is responsible for altering the procedure to more accurately reflect the particular situation."

In general, forecast can not be done without error. Those errors can be attributed to (i) model specification (i.e., wrong or incomplete model terms), (ii) error in the input variables (i.e., a change in the assumptions regarding growth of an input variable), or (iii) calibration errors (i.e., estimation of model parameters). The adjustments presented in the New York State Traffic Forecasting Guide are intended to offset the errors related to model specification and for projection of model input variables.

2.6 Past Research

Traffic forecasting in urban areas has been extensively explored and the forecasting methodologies, mainly based on sophisticated computer modeling programs, are highly advanced. Methods of traffic forecasting were advanced during the mid-sixties when statewide transportation studies were conducted by many states to fulfill the need for developing final statewide transportation plans. Traffic forecasting was a basic input for these studies. However, very little work has been published on developing and testing the simple methods, where sophisticated computer modeling is not possible because of time, cost, technical expertise. Standardized methodologies for nationwide use have not been established for small- to medium-sized urban areas and state authorities develop their own procedures to

accommodate their needs. A main reason for the development of different procedures by different state authorities might be that, since the development of traffic projections is not an exact science, planners base their methods on different conceptual models and thus use different procedures to reduce the uncertainty associated with their projections.

The various state departments of highways developed their own methods to forecast traffic when the 4-step modeling process did not fit the purpose and scope of their study. Very few of these studies are well documented. Some of these studies were summarized in Chapter 1 of Indiana's rural study [Fricker & Saha 1987]. Independent variables used by the model of Indiana's study were population, households, vehicle registrations, employment, and fuel price. Aggregate models represented four categories of rural highways -- Interstates, Principal Arterial, Minor Arterial, and Major Collector -- and resulted in reasonably accurate estimates of future volumes. Disaggregate models were calibrated for specific continuous traffic counting stations and the accuracy of prediction was very good. The R^2 -values for Aggregate and Disaggregate models were 65.8-83.7 percent and 51.5-97.8 percent, respectively. Besides, the variables in the models were statistically significant and no other variables were found to provide additional predictive power to the models. The variables in the models were selected based on statistical analysis as well as on subjective judgment.

2.6.1 Site Traffic Estimate from Volume Ratio Forecast

The Kentucky study [Deacon et al. 1987] to forecast highway traffic volumes involved a two-step modeling process. In the first step, a linear regression relates average travel to personal income, fuel price, and total miles of streets and highways. In the second step, cross-tabulation models relate site-specific traffic growth to statewide ADT. The cross-tabulation refers to highway functional classification, rural/urban location, county population growth, SMSA/non-SMSA designation, and volume level.

The forecast of future traffic volumes at a specific location requires two types of models, one for forecasting average travel (AADT) on all Kentucky highways and the second for forecasting volume ratio (ratio of project site AADT to statewide AADT) and its growth at locations similar to the one under investigation. Forecasts of future year statewide AADT do not vary from project to project. Then, the forecast of site AADT is simply the product of the volume ratio and statewide traffic forecast.

2.6.2 Project-Level Traffic Forecasting

The Simplified Project Forecasting (SPF) [COMSIS 1985, Ismart and Schoener 1987] procedure was developed by COMSIS as a quick-response alternative to the traditional 4-step simulation process. The SPF procedure is designed to produce link-specific traffic forecasts, similar to the 4-step process, with modest data requirements. It produces growth factors to be applied to a base traffic volume

estimate, rather than producing the absolute traffic volume as its primary output. A growth factor is produced for any facility in question by running the SPF model system for the base year and target year and calculating the growth factor as the ratio of the target year to base year traffic volume estimates. This growth factor incorporates the effects of changes both in land use and in the transportation network. This approach parallels the traditional modeling process used by most transportation agencies. While it has the important benefits of familiarity, understandability, and comparability to these existing processes, the data requirements are modest in comparison and most of the operations are transparent to the user.

A typical application of this procedure is when traffic congestion develops on existing urban arterial streets in response to rapid increases in land development. This type of application is becoming prevalent in the fast-growing suburbs of major metropolitan areas. In such an environment, SPF could be used to obtain a quick, yet technically defensible, estimate of traffic for determining the nature of improvement needed to solve the problem. To apply the microcomputer SPF software in this situation, the user supplies as input the population and employment characteristics for the base year and a forecast year for geographical areas surrounding the facility. In addition, coordinates are provided for each geographical area and the facility being evaluated. These coordinates are used by the program to reformat the population and employment data. Default values are also provided in the computer software for link speeds and other factors, some of which may be changed by the user.

2.7 AADT Estimate from Short-Term Counts

The traffic forecasting methods developed in this study need the apply of base year or lag year traffic estimation. Irrespective of these different name (base or lag), one need to obtain or estimate traffic at current or any other chosen year designated as base or lag year. Base or lag year may be different from the current year, but it is the year for which most recent data needed by the model are available. If AADT at base or lag year is not available, then the method described in this section or the one practiced by INDOT can be used to estimate AADT.

INDOT has been developed factors to apply to short-term coverage counts to estimate AADT at a site. The factoring procedure (see Section 2.6 [Fricker & Saha, 1987]) of INDOT follows the recommendation of the Traffic Monitoring Guide of Federal Highway Administration [FHWA 1970]. Those factors are based on the seasonal variation of the traffic, with similar variation patterns grouped according to location (rural/urban) and type of facilities. The data from the continuous count stations located throughout the state are used to develop the factors. These factors can be easily procured by contacting the Division of Program Development, INDOT.

2.8 Traffic Diversion and Reallocation

The traffic models developed in this chapter do not address the issue of increase in capacity or decrease in travel time that resulted from some roadway improvements. There will be a need (1) to

reallocate the traffic in a corridor between the parallel facilities to simulate the actual operating conditions, and (2) to modify traffic flow on a highway segment to reflect the travel time improvements. The above issues are more related to an impact study than a volume forecasting procedure. The scope of this study does not allow the researchers to incorporate such specialized techniques directly. Network-based simulation models would be more appropriate to consider those issues. The simplified techniques found in the literature [NCHRP 187 and 255, Trombly and Ouderkirk 1986] can be applied to the results of this study, if the user decides new improved roads or major development may affect the highway segment for which a forecast is desired.

2.9 Chapter Summary

The objective of this chapter is to provide a brief review of the literature on traffic forecasting, with an emphasis on simplified procedures. Sources to adjust the traffic forecast for the factors not considered explicitly in the models and to refine the forecast for parallel construction and improvement of travel time are presented. Results from a nationwide survey on "Traffic Forecasting on State Highway Segments" by an ITE technical council committee show the status of the procedures practiced by states and provinces. The commonly-cited background factors for traffic forecasting have been identified in this chapter. Some of those factors, for which data are available, are used in this research.

CHAPTER 3

PROBLEM STATEMENT AND EVALUATION FRAMEWORK

3.1 Introduction

Much of the work in forecasting traffic on urban highways was done in the 1960s and 1970s, and was based on the the 4-step sequential modeling process. Few efforts to develop and test simple methods have been found in literature. It is this void that has received the most attention during this research. In this research, an effort has been made to develop models to predict future traffic on Interstate Highways and on state highways in small- to medium-sized urban areas. A previous study [Fricker & Saha 1987] developed a procedure to forecast traffic on rural state highways in Indiana.

The current method at the Indiana Department of Transportation (INDOT) to forecast future traffic on urban state highways is based on 20-year growth factors for each of Indiana's 92 counties. Recognizing that the current set of traffic growth factors are outdated, overly simplistic, and lacking the documentation necessary to update them, the proposed method will provide a means of predicting future traffic volumes that is reliable, well-documented, flexible, and based on

input factors for which clear relationships and usable forecasts will continue to exist.

A clear distinction should be made about the nature of traffic forecasting methodologies. They are divided into two separate groups: (1) Those that address the forecasting problem as a network analysis, based on the traditional four-step process that requires enormous amounts of data and sophisticated computer resources, while not guaranteeing forecasts that are appreciably superior to less detailed methods, and (2) the simple, easy-to-use forecasts on a road-to-road basis that fulfill the particular needs of the local highway departments.

The proposed method seeks a suitable "middle ground" — a method that provides a reliable forecast with modest data and computational requirements. The models developed should be relatively simple to use and be updated without difficulty. This study will meet the continuous needs of INDOT for a reliable method of estimating future traffic on individual routes as an aid to the planning process and in implementing the Highway Improvement Program. In this study, several methods have been examined and developed to determine the sensitivity of the forecasts and to improve the reliability of the forecasts by combining the forecasts.

The study by Morf and Houska [1958] leads to the conclusion that the characteristic "type of service" has a remarkable effect on traffic growth rates. Highways with the greatest percentage of interurban or interregional service generally had the largest

increases in travel. Roads that serve largely urban-to-rural or rural-to-urban travel had the smallest increases. The results of the Morf and Houska study suggest different traffic forecasting models for different functional classes of highway. The functional classification of highway are interstates (representing interurban and interregional service), principal arterials (representing rural-to-urban service), and minor arterials and major collectors (representing rural-to-rural and urban-to-urban service). By using functional class as the determinant, the three major road types -- interstate (rural & urban), urban principal arterial, and urban minor arterial & collector -- were identified in this study.

The principles of the traffic forecasting methods developed in this dissertation can be grouped into the following main phases:

1. Identification and selection of the underlying factors (independent variables) to be taken into account in traffic (dependent variable) forecasting.
2. Determination of the type of functional relationship existing between the dependent variable and the independent variables.
3. Developing and testing the databases, and filtering the data (if necessary).
4. Empirical testing of the mathematical expression for the relationship between the dependent and independent variables, including evaluation of coefficients and validation of model assumptions.
5. Forecast of future values of the independent variables and subsequent derivation of traffic forecast.
6. Comparative evaluation of the level of accuracy between the alternative models and combination of the efficient models.

Statistical analyses in Chapters 5 to 8 suggest different models for each of the three highway categories. Except for the elasticity

model, only conceptual descriptions of the models developed and examined in this study and some key point of analysis are presented in the following sections. A detailed description of the models (other than the elasticity model) and the process by which they were developed can be found in later chapters.

3.2 Data Base and Format

The success of a forecasting method not only depends on the model specification, but also on the reliability of the data and the way the data are used in the model. Availability of past data and projections of future values were also important considerations in selecting data for model development. The traffic volume data will be the dependent variable. The several independent variables will reflect condition at both the local and state level, and the type of highways.

A difference between this study and the rural study [Fricker & Saha 1987] is the primary source of traffic data. The rural study was based on traffic data from continuous count stations. This urban study has used traffic data primarily from coverage count stations, with a few traffic counts from continuous count stations at urban locations. It is expected that 60 telemetering stations, installed in the mid 1980s, will provide adequate data in the future. The large number of traffic volume observations from the coverage count stations are expected to provide better statistical results and more stability in model parameters. In addition, having more data offers the opportunity to test different data structures. One unique aspect of this study is the successful use of coverage count station traffic data and

the evaluation of the alternative data structures.

After some preliminary analysis, the following categorical variables have been chosen to determine the layout of the analysis: (1) city size, (2) geographical region, and (3) extent of roadway mileage. These variables will be used to stratify or group the data base into more homogeneous data groups so that more stable results will be achieved. The way in which the variables are entered in the analysis have depicted in Figures 5.1 (for interstate highways) and 5.2 (for noninterstate highways) in Chapter 5. The two data bases and four data formats will be examined to select the best suitable data base and its format based on the sensitivity of the statistical analysis and engineering judgment.

3.3 Elasticity Based Model

A variety of forecasting models were examined. The simplest one was AADT (Annual Average Daily Traffic) being directly proportional to the socioeconomic factors, such as population or number of households. It was felt that the explanatory power of such a model would be too low to provide reasonably accurate forecasts. This procedure also carries with it a problem inherent in all regression models: the problem of forecasting outside the range of predictor variables in which it was calibrated.

An elasticity-based model [Fricker & Saha 1987] was selected and used to relate future year AADT to present year AADT with a number of background factors. The general form of the model is as follows:

$$AADT_f = AADT_b \left[1.0 + \sum_{j=1}^n e_j (x_{j,f} - x_{j,b}) / x_{j,b} \right] \quad (3.1)$$

or, after rearrangement,

$$\frac{AADT_f - AADT_b}{AADT_b} = \sum_{j=1}^n e_j \left[\frac{x_{j,f} - x_{j,b}}{x_{j,b}} \right] \quad (3.2)$$

where,

$AADT_f$ = AADT in future year,

$AADT_b$ = AADT in base year,

$x_{j,f}$ = value of variable x_j in the future year,

$x_{j,b}$ = value of variable x_j in the base year,

e_j = elasticity of AADT with respect to x_j ,

n = number of associated variables.

The elasticity-based model was preferred for several reasons. The most important reason was that it was believed that the range of volumes over which the model would be applied would be much greater than that used in developing the model, making a simple linear regression model that relates AADT to the background factors directly inappropriate. A proof for this statement can be found during model evaluation in Chapter 10. Second, the use of present year AADT to estimate future year AADT (as a sort of pivot point) would lessen the problem of nonresident (or non-site traffic). Also, the elasticity portion of the model calculates a growth factor directly. (See the right hand side of Equation 3.2)

The elasticities and the appropriate background factors are derived from a linear equation that relates AADT to a variety of the factors in Table 4.3. It can be shown mathematically that, given an equation of the form

$$Y_i = a + \sum_{j=1}^n a_j X_{ij} \quad (3.3)$$

where,

Y_i = value of dependent variable at i th observation;

$i = 1, \dots, n_1,$

X_{ij} = value of j th independent variable at i th observation;

$j = 1, \dots, n,$

a = constant term,

a_j = regression coefficient for j th independent variable,

n_1 = observation number,

n = number of independent variables,

elasticity measures can be estimated by:

$$e_j = a_j \left[\frac{\bar{X}_{1j}}{\bar{Y}_1} \right] \quad (3.4)$$

where,

e_j = elasticity of AADT with respect to independent variable x_j ,

$\bar{X}_{1j}$ = overall mean of the j th independent variable,

$\bar{Y}_1$ = overall mean value of dependent variable,

a_j as defined below Equation (3.3).

Thus, using multiple linear regression, the background factors that best estimate AADT and their respective elasticities can be derived. The data for estimation of the background factors and elasticities came from a variety of sources. Details regarding the data are presented in the next chapter. Both the regression model (Equation 3.3) and the "elasticity model (Equation 3.1) are presented in Chapter 6.

3.4 Principal Component Analysis (PCA) Based Model

Multicollinearity with a large number of independent variables in regression is not unusual. This study has nominated twelve predictor variables to explain variability in traffic because (i) the study did not want to overlook any variables that may be found significant and for which usable data are present for model building, and (ii) the forecasts of those variables are either available or can be generated with reliable methods. Although adequate safeguards have been taken to select the best regression equation in Chapter 6, a complete elimination of collinearity is almost impossible without some advanced techniques. Principal component analysis reduces the dimension of the problem by using some independent factors from the original interrelated independent variables. The PCA-based regression models are presented in Chapter 7. The main purpose of these models is to compare the statistics of these complex models to the regression and elasticity models developed in Chapter 6. The use of PCA models in

forecasting is very limited because forecasts of all independent variables used in the analysis will be required to permit computation of the principal components in the PCA models. The following two reasons justify the use of PCA models in forecasting:

1. A significant improvement in the model statistics in PCA model about the statistics in regression or elasticity model of Chapter 6.
2. The poor performance of the elasticity and regression models.

Otherwise, PCA models will be used to assess the quality of the models in Chapter 6.

3.5 Lag-AADT Model

One of the primary purposes of this research is to develop reliable models for forecasting future traffic volume on state roads and streets of Indiana. Alternative models (for instance, Lag-AADT model) have been developed in this study for use in either urban or rural locations at the project level. The lag-AADT model is simple and inexpensive because only the information on traffic data will be used to build and to use the model. To evaluate the performance of this model, the model will be fitted through a partial data base, which lacks the last year of AADT for each highway segment. The model with this partial data base will be used to forecast the last year of traffic data for each segment. The last year forecasts will then be compared to the observed AADT. The final model will be formed with the complete data base. The lag-AADT models developed in this study are presented in Chapter 8. The performance of the lag-AADT model, regression and elasticity model in Chapter 6, and PCA-based model in

Chapter 7 (if warranted) will be compared in Chapter 10.

3.6 Time Series and Ratio Method Forecasts

The accurate and independent forecasts of input variables in models are important to get reliable estimates and forecasts of traffic. Forecasts from various sources will mainly be used as the input variables for the models in the study. In addition, some efficient and reliable methods have been used to forecast the input variables for which no forecasts are available from any sources. Two time series analysis techniques (Box-Jenkins "ARIMA" and Autoregressive procedures) have been used to forecast vehicle registrations at the county and state levels. In summary, the Autoregressive Integrated Moving Average (ARIMA) procedure fits the model that allows an error term generated by an ARIMA process. The autoregressive process does multiple regression, which allows for a serially correlated error term generated by an autoregressive process.

All time series techniques are based upon the fundamental assumption that a past pattern will be repeated in the future. The methodology suggested by Box and Jenkins represents a systematic approach to modeling and forecasting discrete time series. There are two basic reasons why this methodology can lead to better forecasts than other statistical forecasting methods. First, using traditional approaches requires that the analyst use his or her own experience as a basis of model development. In the past, experienced analysts have developed methods for identifying appropriate mathematical models. They generally relied on plots and indices that aided in identifying the

presence of trends and seasonal patterns. Based upon this analysis, a specific model would be defined. On the other hand, using the Box-Jenkins technique, the analyst does not arbitrarily pick a specific model, but instead eliminates inappropriate models until he or she is left with the most suitable one. Second, the specific form of a given model which is to be used has traditionally been the result of a trial-and-error procedure. Moreover, a good deal of experience and intuitive judgment on the part of the forecaster is often involved. Box-Jenkins [1976] procedure, however, presents a rational structured approach to the determination of a specific model.

A detailed description of modeling with time series analysis will be shown in Chapter 9. Only the input data have been used to forecast the series. Vehicle registration forecasts from the Box-Jenkins and autoregressive procedures will be compared, and then combined based on their performance. A simple but reliable method of population projection, the "ratio" method, will be used to forecast the city population. Section 9.3 presents this technique.

3.7 Evaluation of Traffic Model

In the absence of any universally accepted performance criteria, several measures will be used to compare the different models developed in this study. The description of the performance criterion will be provided in Chapter 10. Forecasts from the efficient models will be combined based on the performance of the models in forecasts. Finally, a monitoring device, also based on performance, will be developed to detect any need for model recalibration in the future.

3.8 Concluding Summary

Travel in urban areas has been increasing due to changing land use, increase in human activity, and growth in vehicle ownership. There are numerous forces that shape the demand for traffic on highways. It is very difficult (to say the least) to accurately represent all interacting forces in a procedure to forecast traffic. The forecasting models and the procedures developed in this study should be used as general guidance. This study restricts its attention to reasonably simple procedures for highway travel demand forecasting.

It is felt that greater sensitivity of forecasts will be obtained by developing alternative models and using variables having a more direct interaction with the variables that create demand for highway traffic. However, there is a great deal of multi-collinearity between many potential decision-related variables. Adequate measures have been taken in this dissertation to avoid any severe multicollinearity problem.

The procedures developed in this study are believed to provide an inexpensive, quick, and transparent technique for forecasting travel in small- and medium-sized urban areas. The model is also suggested for use in cities in less developed and developing countries because of its simplicity and low cost.

CHAPTER 4

DATA BASES

4.1 Introduction

In this chapter, a number of variables that have been used to create tables of input data will be discussed, along with the traffic data for which forecasts are desired. The methodology and quality of forecasts of some demographic and economic variables from our two principal sources will be discussed in this chapter. Advice on how to forecast values of the predictor variables for which forecasts are not available will be offered. The different forms of data tables for the different highway categories will also be discussed. These data tables are the input medium for statistical analysis. The main objective of this chapter is to describe the variables and the evolution of the data tables used in the analysis. These data tables could be modified when new counts and/or new census reports become available, in order to recalibrate and modify the developed traffic forecasting models for use in the future traffic.

4.2 Forecasts of Demographic and Economic Variables

The future-year values for many of the predictor variables used in this study were obtained from

- a. Woods & Poole Economics, Inc. and
- b. the Indiana University Business Research Center.

No demographic and economic data at the city level (except population) have been found that could be usable in model formulation. However, there will be a need to forecast city populations, as well as vehicle registrations at the county and state level. The appropriate forecasting techniques (for example, smoothing and time series analysis) and/or some ad hoc methods (for example, the ratio method) will be used to obtain forecasts of those variables for which there is no forecast available from existing sources.

When comparing the population projections published by the IU Business Research Center and Woods & Poole (W&P), sometimes the W&P values are higher than IU's, and sometimes they are lower. There is no consistent trend. IU used Cohort Analysis [Krueckeberg & Silver 1974, Boyce 1985] only. W&P began with Cohort Analysis, then modified the results with economic adjustment factors [W&P Economics 1988], constrained by national, regional, and state forecasted totals (See Section 4.3 for a brief description). The regional model that produces the forecast component of this database is the product of extensive research by Woods & Poole economists. It is frequently revised and improved to reflect ongoing research by the professional staff, new computational techniques and new sources of regional economic and demographic information. Each year a new forecast is produced with

the most current data available. The sophistication of the W&P economic and demographic forecasting models, and the fact that they rely on a very detailed database, makes the regional model and database one of the most comprehensive county-level forecasting tools available.

4.3 W&P's Forecast Methods

At the most general level, the strengths of the economic and demographic forecasts [W&P Economics, Inc.] stem from the comprehensive nature of the county database and the integrated nature of the model. The forecast for each county in the United States is done simultaneously so that changes in one county will affect growth or decline in other counties. This reflects the flow of economic activity around the county as new industries spring up or relocate in growing areas and as people migrate, in part because of job opportunities. The county forecasts are also developed within the framework of the United States forecast that is determined from Woods & Poole's macro-economic model. This approach of linking the counties together to capture regional flows and constraining the results to a previously determined United States total avoids a common pitfall in regional forecasting. The regional forecasts are sometimes made for a city or county without regard for potential growth in surrounding areas or other areas in the country. Such forecasts may be simple extrapolations of historical trends and may tend to be overly optimistic or pessimistic. If these county forecasts were added together, the total might be considerably different from any conceivable national forecast

scenario, which is the result of the regional forecasts being generated independently without interactive procedures and not being constrained to a consistent national total.

The primary methods used to generate the complete country forecasts proceed in three stages. First, the country is divided into 183 Economic Areas (EAs) as defined by the U.S. Department of Commerce's Bureau of Economic Analysis. The EAs are aggregates of contiguous counties and attempt to measure cohesive economic regions in the United States. For each EA a forecast is made for employment, using an "export-base" approach (explained below), and the employment forecast results are then constrained to a previously determined national forecast. The employment forecast for each EA is then used to estimate earnings in each EA; the earnings forecasts are similarly constrained to the national forecast total. The employment and earnings forecasts then become the principal explanatory variables used to estimate population and number of households in each EA. The population and household forecasts are also constrained to the national totals.

The second stage of the forecast procedure is to make population by age, sex and race forecasts on the basis of net migration rates projected from employment opportunities. The third stage is a replication of the first two stages, except that it is performed at the county level, using the EAs as the control total for the county forecast.

4.3.1 The "Export-Base" Economic Models

The specific economic forecasting models used by Woods & Poole that generate the employment, earnings and income forecasts for each county in the United States generally follow a standard economic "export-base" approach. It is a relatively simple approach to regional employment forecasting. Certain industrial sectors at the regional level are considered "basic". This means that these sectors produce output that is not consumed locally, but is produced for "export" out of the region for national or international consumption. Normally the "basic" sectors are mining, agriculture, manufacturing and the Federal Government. In contrast, "non-basic" sectors are those, such as retail trade, transportation, communication and construction, with output that is usually consumed locally. The growth of the "non-basic" sectors depends largely on the growth of the "basic" sectors that form the basis of the region's economy. Although the theory is appealing, some shortcomings do exist with the "export-base" approach [W&P Economics, Inc.]. For example, some "basic" commodities produced locally are consumed locally. However, despite the shortcomings, the availability of relatively clean data for sub-national geographic areas makes the "export-base" approach very useful, albeit not perfect. The analytical framework for constructing regional models using the "export-base" approach entails estimating demand equations for output by sector. The principal explanatory variable is the national demand for the output of that sector. A modification of the current "export-base" approach of W&P is used in the current W&P forecasting model to account for regional variants to

normal basic/non-basic industry definitions. In addition to following an "export-base" approach, the regional model uses individual EA and county models as forecasting tools.

4.3.2 The Demographic Model

The demographic portion of the regional model follows a traditional cohort-component analysis [Krueckeberg & Silvers 1974] based on net migration rates for the period 1970 to 1982. The migration patterns in the forecast period for population (by age in 5-year cohort groups up to 85 and over), sex, and race (white, black and other) are largely based on employment opportunities. The expected economic growth, or decline, of a city or county therefore has a resulting impact on population growth. This integration of economic and demographic regional analysis is a significant strength of the model.

4.3.3 The Reliability of Forecasts

Unlike other sciences, economics cannot rely on experimentation to test theories and verify hypotheses. Rather, historical data are analyzed and theories are developed that explain the historical data and then are used to make a forecast. The Woods & Poole forecast, like all economic and demographic forecasts, uses this approach. There are, however, some inherent limitations.

One limitation is that the future is not usually known with any reasonable degree of certainty. There is always the possibility of an unprecedented shock to the economy — a shock that could not be fore-

cast based on any analysis of historical data. For instance, a local government may enact a new industrial policy that has an unexpected, beneficial effect on employment growth. Or an abrupt economic change, although anticipated, may occur with much greater intensity or in a shorter time period than expected. Another limitation is a result of doing forecasts for small geographic areas with a small number of observations. Statistically, forecasts become more reliable as the area becomes larger. Error can be reduced, although never eliminated, by constraining the small area forecasts to the forecast totals for a larger area. This is the method used by Woods & Poole. Given these limitations and the inability in economics to experimentally test theories, the most acceptable economic models are those that are modeled on not only known facts, i.e., historical data, but also explain those facts well. One way to evaluate how a forecast explains the historical data is to do "retro-forecasts" and measure how well the model predicts the past. The divergence of the retro-forecast from the actual data measures the accuracy of the model. On the average, all endogenous variables in the Woods & Poole national and regional models have a percent root mean square error of less than three percent.

4.4 Methodology for IU's Population Projections

Indiana University (IU) used demographic models to produce their 1988 population projections at the county and township levels. The demographic approach uses patterns and models of births, deaths, and migration changes to project population. It has been assumed that

general social, environmental, economic and political features of the base year will continue for the life of the projection. The model can be summarized by the following equation:

$$\text{new population} = \text{old population} + \text{births} - \text{deaths} + \text{net migration}$$

The projections were calculated for each of the 92 counties for five-year intervals from 1985-2020. Within each county projection, there are 18 age cohorts (from 0-4 to 85+) for male and for female. The fertility component model was calculated using age-specific birth rates for 1980 and 1984 from the Indiana State Board of Health. The mortality component model was calculated using age-specific deaths for Indiana counties for 1979-81, obtained from Indiana State Board of Health. The age-specific mortality rates used in population projections are assumed to remain constant through the life of the projections.

The Indiana township population projections [Business Research Center, IU] are an extension of the Indiana county population projection. Therefore, the demographic model assumes that population changes within a township are the result of births, deaths, and migration into and out of the township. Similar to the county population projections, township population was divided into cohorts classified by race (white and non-white), sex, and age categories. After the projected population was computed for each township in a county, they were adjusted so that their sum was equal to the projected county population. The assumptions made in computing the township population projections were the same as those for county population projections.

At the township level, the most difficult component of the basic demographic equation was net migration. Knowledge of local conditions provided an important source of information for adjusting and projecting net migration. Although the adjustment factors were based on the extent and number of changing local conditions, the actual assignment of magnitudes was judgmental.

4.5 The Data Tables

This study has been focussed mainly on building traffic forecasting model(s) for urban highway segments in the State of Indiana. The general characteristics of each functional class of urban highway are presented in Table 4.1.

The definition of "urban" highway segments, for purposes of this study, includes Federal Aid Primary, Federal Aid Urban, and other state highways within an urbanized area, as commonly defined. The researcher and advisory committee members agreed to group the urban area into the following three levels:

1. Highest level: Areas with designated Metropolitan Planning Organizations or with population greater than 200,000.
2. Middle-population level: Cities and towns with population greater than 5,000 and not included in level 1.
3. Low population: Cities and towns under 5,000 population.

Since level 2 localities are not likely to have in-house planning capability, the initial research focus was on this level.

The functional classes of all the urban state highway segments for which AADT figures were collected have been identified by examin-

Table 4.1: Urban Functional Classification of Highways

<u>Functional System</u>	<u>General Characteristics</u>
Interstate/ Freeway	<ol style="list-style-type: none"> 1. Provides for expeditious movements of relatively large volumes of traffic between land areas and other freeway with no provisions for direct access to abutting property. 2. By design, interstate/freeway is a multi-lane road or street with grade separations at all cross roads with full control of access.
Principal Arterial	<ol style="list-style-type: none"> 1. Serves the major traffic movements within urbanized areas such as between central business districts and outlying residential areas, between major intercity communities, or between major suburban centers. 2. Serves a major portion of the trips entering and leaving the urban area, as well as the majority of the through traffic desiring to bypass the central city. 3. Provides continuity for all rural arterials that intercept the urban area.
Minor Arterial	<ol style="list-style-type: none"> 1. Serves trips of moderate length at a somewhat lower level of travel mobility than principal arterials. 2. Provides access to geographic areas smaller than those served by the higher system. 3. Provides intracommunity circulation by connecting the existing neighborhoods within the community.
Collector	<ol style="list-style-type: none"> 1. Collects traffic from local routes and channels it into the arterial system. 2. Provides both land access and traffic circulation within residential neighborhoods, commercial and industrial areas.

Sources: 1. AASHTO [1984].
 2. INDOT Road Inventory file.
 3. Meyer and Miller [1984].

ing the Road Inventory file of INDOT (Indiana Department of Transportation). There were only a few urban segments in the "collector" class, and the number of minor arterial segments is much smaller than that of principal arterial. Moreover, the traffic levels of these two class of highways (minor arterial and collector) are almost the same. Therefore, the "collector" segments were pooled with "minor arterial" segments for statistical analysis purposes. The 77 cities in level 2 were further divided into four groups, depending on 1980 city population (see Table 4.2), to determine the effect of city size on traffic. Moreover, to reduce the variation in the data, it was necessary to organize the segments in each population group by common variable characteristics. The variables used to define groups, or "families", of segments are functional classification and city size. The cities for noninterstate highways and the sections for interstate highways are sampled randomly from the available number of cities and roadway sections, respectively. All the segments of the sampled cities are entered in the noninterstate data tables. Table 4.2 shows the number of sampled sections for each group of cities for noninterstate highways and for the two groupings of interstate highways (rural & urban). The growth factor model for rural interstates will be compared with the one developed for urban interstates. Finally, it will be determined if there are advantages to pooling the interstate highway groups into a single group.

The list of items incorporated in data bases is presented in Table 4.3. The description of all the variables is provided in Section 4.6. The column number in the data base for each variable is

Table 4.2: Groupings of Roadway Segments

A. Noninterstate State Highways (Urban):

City Group (*)	Total No. of Cities	No. of Cities Sampled	No. of Road Segments/Sections in Cities Sampled	
			Principal Arterial	Minor Arterial and Collector
A	10	9	142	12
B	9	8	59	14
C	25	19	136	18
D	33	25	98	42
Total:	77	61	435	86

B. Interstate Highways: (Note: 50 out of the 92 counties have interstate highways)

Highway Class	Total No. of Sections	No. of Sections Sampled	Percent of Sections Sampled
Rural Interstate	220	117	53.18
Urban Interstate	79	79	100.00

(*) See Section 4.6 for City Group Classification.

Table 4.3: Description of Items in Data-Bases

Column Number	Variable Symbol	Description of variable	Role/Purpose of Variable	Type of Variable
1	OBS	Observation number	Identification	Demographic
2	CTYN	City number	Identification	
3	CTYNM	City name	Identification	
4	CTYAR	City area in sq. miles	Manipulation	
5	PCTY80	1980 city population	Manipulation, Sorting	
6	CTYGR	City group	Sorting	
7	CNTYN	County number	Identification	
8	CNTYNM	County name	Identification	
9	CNTYAR	County area in sq mi	Manipulation	
10	GREGION	Geographical Region	Sorting	
11	PCNTY80	1980 county population	Informational	Demographic
12	FUNC	Functional class of highway	Identification, Sorting	
13	M88TOT	1988 total mileage	Informational	
14	M88FUNC	1988 total functional mileage	Informational	
15	PM88FUN	Percent of 1988 functional mileage	Informational	
16	FAS	Federal-aid-system class of highway	Identification	
17	HWY	Highway name	Identification	
18	SEC	Section number	Identification, Manipulation	
19	YEAR	Year	Identification, Manipulation	
20	AADT	Annual Average Daily Traffic	Response	
21	CTYPOP	City population	Predictor	Demographic
22	CNTYPOP	County population	Predictor	Demographic
23	CNTYHH	County households	Predictor	Demographic
24	CNTYVR	County vehicle registration	Predictor	Demographic & Economic
25	CNTYEMP	County employment	Predictor	Economic
26	CNTYINC	County per capita income in 1982 \$	Predictor	Economic
27	STPOP	State population	Predictor	Demographic
28	STHH	State households	Predictor	Demographic
29	STVR	State vehicle registration	Predictor	Demographic & Economic
30	STEMP	State employment	Predictor	Economic
31	STINC	State per capita income in 1982 \$	Predictor	Economic
32	STGAS	State hwy gasoline consumption in millions of gallons	Predictor	Economic & Demographic

shown in Table 4.3, along with its corresponding variable name and symbol. The data bases with all the variables of Table 4.3 will be used in statistical analyses to develop the prediction model. There is a separate data base for each noninterstate state highway. Each of these data bases for noninterstate highways is further divided into the four city groups. Similar groupings were done for interstate highway data bases. The following subsections will present the data bases under the two broad headings -- data bases with segment AADT and data bases with county or city average AADT.

4.5.1 Data Tables with Segment AADT

All the data bases began with the AADT of each segment. For these segment AADT data bases, traffic data are taken from all the sampled segments of the selected city or county. In cases where AADT and predictor variable values were not available for the same years, linear interpolations were carried out for the predictor variables to match the year of AADT. The following four forms of data bases were produced from the data bases with segment AADT.

1. Raw form (RAW)
2. Earlier and later years version of the raw form (RAW E&L)
3. Density form (DENSITY)
4. Earlier and later years version of the density form (DENSITY E&L)

A brief description for each of these forms is presented below.

RAW, Raw form and
DENSITY, Density form

The raw form of each data set was developed by direct entry, through a LOTUS 1-2-3 worksheet, of the values of all the variables in Table 4.3. A portion of the data base for urban minor arterial and collector functional class is shown in Appendix Table A1. The item in column 20 is the response variable and items from columns 21 through 32 will be used as predictor variables. All the predictor variables are numerical in nature. The data bases created with the variables described in Table 4.3 will be referred to as "RAW" data bases.

The socioeconomic variables, used as predictor variables in this study, entered in the "RAW" data bases are aggregate over city, county or state. Despite the same level of traffic between two cities or counties, a "scale problem" may arise because of wide variation of the aggregate socioeconomic variables. A schematic representation of the "scale problem" is illustrated in Figure 4.1. In this figure, two cities/counties -- small and large -- with almost identical values of AADT on their roadway sections show the effect of the level of demographic and economic data. In part a of Figure 4.1, large city/county data consistently fall above the data of the small city/county at different years. When these data are employed to predict AADT, they will exhibit the scale effect, as shown in part b of Figure 4.1. In part b of Figure 4.1, large and small city/county data points are separated from each other, in spite of almost identical AADT values. This scale effect will be minimized in the following cases:

1. AADT values are proportional to the level of demographic and economic data of small and large city/county.

Figure 4.1: Schematic Representation of "SCALE" Problem

2. Segregating/subsetting data bases according to levels of demographic and economic data. (See Section 4.5)
3. Normalizing the data bases (for example, the density format described next).

To remove/minimize the scale problem caused by big differences among city/county-level demographic and economic variables in a data base, the RAW data bases have been transformed to a density form. It was expected that a normalized form of the demographic and economic variables would reduce the variation in predictor variables used to explain AADT levels. The DENSITY form of data set was produced by redefining some of the demographic and economic variables in Table 4.3 as follows:

1. CTYPOP: City population per square mile of city area.
2. CNTYPOP: County population per square mile of county area.
3. CNTYHH: County households per square mile of county area.
4. CNTYEMP: County employment per square mile of county area.
5. STPOP: State population per square mile of state area.
6. STHH: State households per square mile of state area.
7. STEMP: State employment per square mile of state area.
8. CNTYVR: County vehicle registrations per 100 county population.
9. STVR: State vehicle registrations per 100 state population.

The variables -- county income, state income and state highway gasoline consumption -- in the DENSITY data set remained unchanged from "RAW" form. A computer program coded in FORTRAN 77 was written to develop the DENSITY data set from the raw data set. A portion of DENSITY data base for urban minor arterial and collector is shown in

Appendix Table A2. (Note: Complete raw data bases for each functional class of highway have been saved on floppy diskettes to permit updating in the future.)

RAW E&L, Earlier & later version of raw form and
DENSITY E&L, Earlier & later version of density form

New data bases, represented as earlier and later year version of raw and density form, were prepared with average values of earlier and later years of traffic and socio-economic variables. Let "a" and "b" be the earliest and latest year of AADT counts for a highway segment. Then, the middle year (m) is the average of a and b, $m = (a + b)/2$. The earlier years (x's) and later years (y's) are defined as follows:

Earlier years: $a < x < m$, and

Later years: $m < y < b$.

The data for the middle year, m, has been included in both earlier and later year data. A computer program, coded in FORTRAN 77, has been written to develop earlier and later year version of raw and density data sets from raw and density data sets. A portion of the earlier and later (E&L) year version of the DENSITY data base for urban minor arterial and collector is shown in Appendix Table A3. The E&L data consist of two data points for each section of highway: the average values of the earlier years' data and of the later years' of data. The E&L transformation will provide a longer interval between observations than that provided by the RAW and DENSITY data bases (See column 19 of Appendix Tables A1 to A6). This longer interval would presumably reduce/eliminate short term fluctuations in data points.

4.5.2 Data Tables with County and City Average AADT

Considerable variability in the data sets was noticed in the segment AADT data base because of wide variation in AADT among the different highway sections within a city or county. Meanwhile, the predictor variables for each section within a city are the same. To remove these variations in segment AADT data bases, the earlier four forms of data (raw, density, raw E&L, and density E&L) were modified by averaging the individual segment AADT values to produce a city or county-wide average AADT for each year under the different functional roadway classes. For rural interstates, averaging within a county was done. For other functional classes of urban highways, averaging over a city was done. Appendix Tables A4 to A6 show the portion of the data tables with county or city average AADT for the three main functional classes, identified in earlier sections.

The statistical quality of the eight different forms of the data bases -- four with segment AADTs and four with county or city average AADTs -- will be evaluated in the next chapter.

4.5.3 Number of Cases

A case is a row or record in a data table. A filter analysis can be performed to remove data points that are obviously wrong (examples: faulty observations, data entry error, etc.). Outlier analysis can be used to remove points that have a high probability of not belonging to the family of data points. Initially, all observations in a data base were used in the analysis. If the data items or amount are found to

be insufficient during the analysis, necessary data will be collected appropriately. Tables 4.4 to 4.6 present the number of cases for each category of highway for all forms of data bases described in earlier sections. These tables also show the number of cases when they are sorted under different variables. All the possibilities will be analyzed in the next chapter to select a particular form of data tables or a combination of forms.

4.6 Description of Variables

In this section, the variables have been grouped into three categories -- Index (categorical) variables, Response variables and Predictor variables -- depending on their roles in the analysis. Table 4.3 has presented the list of all variables with their role, symbol, type and column number of data sets. All these variables are described in this section with respect to their definition, availability, quality and role in analysis.

4.6.1 Index or Categorical Variables

The index or categorical variables are used to perform mainly three kinds of operation -- sorting, identification and manipulation. The sorting of the data sets is performed through the index variable(s) to stratify the data sets. These variables are listed in Table 4.3 with their role as "sorting". Some of the index variables are used to identify the observation during statistical analysis and can be used to modify the data sets in the future for calibration of model. Their roles have been shown as "identification" in Table 4.3.

Table 4.4: Number of Cases for Urban Minor Arterial & Collector

C T Y G R	M F U N C	G R E G I O N	Segment Database		County/City Ave. Database	
			RAW or DENSITY	RAW or DENSITY E&L	RAW or DENSITY	RAW or DENSITY E&L
ALL			392	172	119	54
A			56	24	18	8
B			64	28	13	6
C			78	36	30	14
D			194	84	58	26
A	F1					
A	F2					
A	F3		35	14	10	4
A	F4		21	10	8	4
B	F1					
B	F2					
B	F3					
B	F4		64	28	13	6
C	F1					
C	F2		23	10	14	6
C	F3		20	8	5	2
C	F4		35	18	11	6
D	F1		116	52	30	14
D	F2		14	6	9	4
D	F3		55	22	10	4
D	F4		9	4	9	4
A		n	21	10	8	4
A		c	10	4	5	2
A		s	25	10	5	2
B		n	24	12	8	4
B		c	40	16	5	2
B		s				
C		n	52	24	13	6
C		c	16	8	12	6
C		s	10	4	5	2
D		n	32	16	16	8
D		c	20	10	8	4
D		s	142	58	34	14

Note: See section 4.6.1 for description of CTYGR, MFUNC & GREGION.

Table 4.5: Number of Cases for Urban Principal Arterial

C T Y G R	M F U N C	G R E G I O N	Segment Database		County/City Ave. Database	
			RAW or DENSITY	RAW or DENSITY E&L	RAW or DENSITY	RAW or DENSITY E&L
ALL			2019	870	255	116
A			691	284	43	18
B			265	118	30	14
C			633	272	80	36
D			430	196	102	48
A						
A						
A			295	118	15	6
A			396	166	28	12
B						
B						
B			24	12	4	2
B			241	106	26	12
C						
C			266	112	28	12
C			235	102	26	12
C			132	58	26	12
D			198	94	41	20
D			128	56	27	12
D			60	24	15	6
D			44	22	19	10
A			346	146	23	10
A			280	112	15	6
A			65	26	5	2
B			151	66	13	6
B			94	44	12	6
B			20	8	5	2
C			267	114	30	14
C			326	142	45	20
C			40	16	5	2
D			121	62	34	18
D			109	48	26	12
D			200	86	42	18

Note: See section 4.6.1 for description of CTYGR, MFUNC & GREGION.

Table 4.6: Number of Cases for Interstate Highways

CASE	C T Y G R	M F U N C	G R E G I O N	Segment Database		County/City Ave. Database	
				RAW or DENSITY	RAW or DENSITY E&L	RAW or DENSITY	RAW or DENSITY E&L
RURAL + URBAN	ALL			978	392	313	126
	A+			428	168	76	30
	A			158	68	79	34
	B			94	42	41	18
	C			168	66	61	24
	D			130	48	56	20
	F1			116	44	47	18
	F2			145	62	62	26
	F3			188	66	68	24
	F4			529	220	136	58
	n			259	110	104	44
	c			518	198	132	50
	s			201	84	77	32
RURAL	ALL			595	234	186	74
	A+			260	100	57	22
	A			102	44	51	22
	B			25	12	13	6
	C			107	40	26	10
	D			101	38	39	14
	F1			86	32	37	14
	F2			111	46	44	18
	F3			152	54	44	16
	F4			246	102	61	26
	n			127	54	47	20
	c			321	120	80	30
	s			147	60	59	24

Table 4.6, continued

CASE	C T Y G R	M F U N C	G R E G I O N	Segment Database		County/City Ave. Database	
				RAW or DENSITY	RAW or DENSITY E&L	RAW or DENSITY	RAW or DENSITY E&L
URBAN	ALL			383	158	127	52
	A+			168	68	19	8
	A			56	24	28	12
	B			69	30	28	12
	C			61	26	35	14
	D			29	10	17	6
	F1			30	12	10	4
	F2			34	16	18	8
	F3			36	12	24	8
	F4			283	118	75	32
	n			132	56	57	24
	c			197	78	52	20
	s			54	24	18	8

Note: See section 4.6.1 for description of CTYGR, MFUNC & GREGION.

Also to manipulate the data sets from one form to another, some of the index variables was used. The roles of these index variables are stated as "manipulation" in Table 4.3. Those index variables not used for any of the above three purposes are designated as "informational" in Table 4.3. Sometimes, the informational index variable was used to designate the sorting variable. Some of the variables play more than one role.

OBS, Observation Number

The variable OBS (observation number) is simply the serial number of each observation or record in the data set. The purpose of this variable is to identify the observation during the statistical analyses.

CTYN, City Number and
CTYNM, City Name

The variables CTYN and CTYNM were entered in each record of a data set to identify the observation. They are used in data manipulation and will be helpful modifying the data bases in the future. For each urban highway segment, the CTYN and CTYNM identify the city within which the segment is located. For rural interstates, judgment was applied to identify the city, by size and closeness that is thought to have the largest impact on the highway section. The variables CTYN and CTYNM are shown in Appendix Table B1.

CTYAR, City Area and
CNTYAR, County Area

The 1980 census record was the source of variables CTYAR, City Area in square miles, and CNTYAR, County Area in square miles. The variable CTYAR was used to convert the city population to its density form as city population per square mile. The variable CNTYAR was used to get the density of county population, county household and county employment. The role of CTYAR and CNTYAR is manipulation of data sets from their raw format to density format. Appendix Tables B1 and B2 show the areas in square miles for cities and counties of Indiana.

PCTY80, 1980 City Population
CTYGR, City Group

The variable PCTY80 represents the city population in year 1980. Bureau of Census records (County and City Data Book, Characteristics of the Population) and the STATIS database of Indiana University were used to get the 1980 city population. According to the 1980 census, there were 77 cities in Indiana with a population between 5000 and 50000. For noninterstate highways, the following groupings of the cities were made:

CTYGR	1980 City Population (1000)
A	30 - 50
B	20 - 30
C	10 - 20
D	5 - 10

For interstate highways, an additional group, A+, was designated for cities with more than 50,000 population in 1980. The variable CTYGR was used to sort the data tables by city group based on the

informational variable PCTY80. This subsetting of the data sets will provide an opportunity to observe any improvement in statistical analysis.

CNTYN, County Number

CNTYNM, County Name

Like city number and city name, county number (CNTYN) and county name (CNTYNM) were entered in data sets according to the county in which a highway segment is located. These variables also have a role in identifying an observation and will be useful in modifying the data-base(s) in the future. These variables were used to manipulate the data sets. Appendix Table B2 presents the variable CNTYN and CNTYNM.

GREGION, Geographical Region

As with City Group, the data sets were stratified by geographical region (GREGION) to reduce the variability of the data sets or to improve the quality of results. Figure 4.2 shows the boundaries to demarcate the north, central and south regions of the State of Indiana. A highway section was classified as north, central or south by its location within a city/county. The variable GREGION was recorded as n, c or s in the data sets for north, central and south, respectively.

PCNTY80, 1980 County Population

The county populations were obtained from census records. The

Figure 4.2: Suggested Geographical Boundaries of State of Indiana

variable PCNTY80 represents the county total population in the 1980 census year. PCNTY80 was not used to stratify the data sets, but it was kept in the data sets if any stratification needed to be done based on county population.

FUNC, Functional Class
FAS, Federal-Aid System

Classification is the tool by which a complex network of highways can be allocated into groups or systems of routes having similar characteristics. For transportation planning purposes, as well as for design purposes, highways are most effectively classified by function. Table 4.1 has shown the general definitions of Urban Functional Class (FUNC) -- interstate, principal arterial, minor arterial, collector, and local. Federal-aid system (FAS) classifications -- interstate, primary, secondary, urban, non FAS -- categorize highways based on the distribution and administration of federal-aid highway funds. Both the functional and federal-aid classes of all the state highway segments for which AADT figures have been collected were identified by examining the Road Inventory file of INDOT. The data FUNC and FAS for different highway classes were recorded in data sets as follows:

Functional Class	FUNC	Federal-aid Class	FAS
Urban Interstate	ui	Federal-Aid Interstate	fai
Rural Interstate	ri	Federal-Aid Primary	fap
Urban Principal - Arterial	upa	Federal-Aid Secondary	fas
Urban Minor Arterial	uma	Federal-Aid Urban	fau
Urban Collector	uc		

Initially, all the data sets have been created by functional class on

a LOTUS 1-2-3 worksheet. The variable FUNC has been used for sorting as well as for identification purposes, whereas the variable FAS has been used only for identification.

M88TOT, 1988 Total Mileage
 M88FUNC, 1988 Total Functional Mileage
 MFUNC, Mileage Group
 PM88FUN, Percent of 1988 Functional Mileage

The variable M88TOT represents the total county mileage, both rural and urban, for interstate highways. For noninterstate highways, M88TOT represents the total county urban mileage. For interstates, M88FUNC and PM88FUN represent the miles of interstate highways in a county and the percent of interstate highways in a county with respect to the county's total mileage. For noninterstate highways, M88FUNC represents the miles of state highways within a county other than interstate and PM88FUN is expressed as a percent of M88FUNC with respect to M88TOT for noninterstates.

As with City Group, the data sets were stratified by the extent of miles of road in a city/county based on the values of M88TOT. These groupings were based on quartile ranges. The univariate procedure of SAS [SAS/Basics 1985] was used to find the quartile boundaries. According to the 1988 mileage report of INDOT, there are some counties without any urban mileage. To establish the groupings for non-interstate highways, counties without any urban mileage were dropped from the analysis. The results of the groupings (MFUNC), based on the quartile ranges, are as follows:

(Case A) Non-interstate Urban Highways:

Mileage Group (MFUNC)	County Urban Total Mileage (M88TOT)
F1	33 - 57
F2	57 - 96
F3	96 - 262
F4	262 - 3340

(Case B) Interstate Highways:

Mileage Group (MFUNC)	County Total Mileage (M88TOT)
F1	170 - 820
F2	820 - 940
F3	940 - 1090
F4	1090 - 3340

The variable MFUNC is not recorded in data-sets, but was created during several statistical analyses based on the values of M88TOT. The variable MFUNC has been used to stratify or sort the data-sets. The role of M88TOT, M88FUNC and PM88FUN is informational. The values of M88TOT, M88FUNC and PM88FUN for all 92 counties of Indiana are presented in Appendix Table B3.

HWY, Highway Name
SEC, Section Number

The variable, HWY, represents the jurisdictional name of each section of highway (for example, SR26, US52 and I65). For the RAW data bases, the section number (SEC) was obtained from "Traffic Statistics" book of Indiana Department of Transportation. But in county or city average data bases, the section number (SEC) represents

the number of a section within each county/city used to arrive at the average values. These variables were mainly used for identification of each observation and will be helpful to modify the data-base(s) in future.

YEAR

The variable YEAR represents the year in which all the variables, both dependent and independent, apply for a particular observation. This variable was introduced to reflect the time effect on AADT and the predictor variable(s), and to study patterns of the residuals against time. As a general trend, AADT increases as time passes. It was thought that using YEAR as a predictor variable will lead to high statistical correlation with the other predictor variables. For that reason, YEAR has not used as a predictor variable.

4.6.2 Response variable

The only response variable that needs to be predicted in future years is AADT (Annual Average Daily Traffic). In Indiana, five out of 31 continuous traffic count stations are located in urban areas [INDOT-Traffic Statistics Book, Feb. '87]. The rural study [Fricker and Saha 1987] was based on the continuous count AADT. Because of the limited number of continuous count stations at urban locations, this study was carried out with coverage traffic counts, which are generally done at 3- to 4-year intervals. The coverage count is converted to AADT based on the adjustment factors developed from continuous count stations. Some noise in coverage count traffic data is

expected because of short term counts and the use of adjustment factors developed from continuous count station data. It was felt that averaging over county/city would be useful to filter some of those noises in data.

AADT, Annual Average Daily Traffic (AADT)

AADT is the average 24-hour traffic volume for a given year, for both directions of travel, unless otherwise specified.

There are 77 cities/towns in Indiana with a population between 5,000 and 50,000 (Level 2), and about 850 segments of state, US and interstate routes in these cities. The historical traffic counts were retrieved for most of those segments for certain past years during the period of 1970 to 1987 from INDOT files. The form that was used to record those traffic data over different years is shown in Appendix Table B4. For the raw traffic counts, adjustment factors (prepared by INDOT) were used to convert them to AADT.

4.6.3 Predictor Variables

There are a number of predictor variables that have been identified historically as the primary determinants of highway travel, the major ones being population, income, employment, energy, auto ownership, and household. Twelve predictor variables (see Table 4.3) are used in this study. The main role of these predictor variables is to explain AADT. These predictor variables can be categorized as either demographic or economic. Some fundamental criteria adopted in select-

ing the predictor variables are [Draper & Smith 1981, Freund & Minton 1979]:

1. Are the proposed variables fundamental to the problem?
2. Availability of data (variables)
 - a. Are annual data available?
 - b. Are historical data available?
 - c. What is the most recent year of data?
 - d. Will data be available in the future?
3. Cost to obtain data
4. How reliable are the data?

In this section, each of the predictor variables is discussed with respect to their availability in the past and in the future. Historical data for each of the predictor variables for all the counties or cities are recorded on floppy diskettes using the LOTUS 1-2-3 worksheet. Based on the discussion of the predictor variables in sections 4.3, 4.4 and the current section, a summary table (see Table 4.7) has been prepared regarding fundamental selection criteria. The availability, cost and reliability of the variables is used to identify the "quality" of the variables. An equal weight placed on each of the selection criteria result in the following order of importance (1=most preferable variable):

1. Employment (county and state level)
2. (a). Population, Vehicle Registration and Income
(county and state level)
- (b). State Highway Gasoline consumption

Table 4.7: Availability, Cost and Reliability of the Predictor Variables

Variable Symbol	Variable Description	Past Data (*)	Forecast (**)	Cost of data (***)	Reliability (****)
CTYPOP	City Population	3	3	2	4
CNTYPOP	County Population	2	1	1	2
CNTYHH	County Households	4	1	1	2
CNTYVR	County Veh. Regis.	1	2	2	1
CNTYEMP	County Employment	1	1	1	2
CNTYINC	County Percapita Income in 82 \$	1	1	1	3
STPOP	State Population	2	1	1	2
STHH	State Households	4	1	1	2
STVR	State Veh. Regis.	1	2	2	1
STEMP	State Employment	1	1	1	2
STINC	State Percapita Income in 82 \$	1	1	1	3
STGAS	State Hwy. Gas. Consump. in millions of gallons	1	2	2	1

(*) PAST DATA:

- 1 = available at all years
- 2 = available at census years & intercensus estimation present
- 3 = available at more than census years & estimates done for missing year(s)
- 4 = available at census years & data for missing years are estimated

(***) COST OF DATA:

- 1 = easily available from different sources with negligible cost
- 2 = in-house forecast may make the data comparatively expensive

(****) RELIABILITY:

- 1 = good historical series, so forecasts are expected to be reliable
- 2 = data sources claim their forecasts are reliable
- 3 = despite the reliability claimed by data sources, researchers expect uncertainty in future because of nature of the variable
- 4 = lack of good historical data makes the forecast less reliable

(**) FORECAST:

- 1 = forecasts available from W&P Economics, Inc. and/or IU Business Center
- 2 = Forecast will be generated in this study
- 3 = Forecast available but not complete, missing forecast will be made

3. Households (county and state level)

4. City population

This order of preference in addition to the statistical results will be referred to in later chapter(s) to identify the candidate and final model(s). The literature [McKay 1925, Morf & Houska 1958, Hartgen 1981, Memmott 1983] on traffic forecasting shows that all the predictor variables are relevant to traffic forecasting. The question of relevance will be further examined with respect to the functional class of highway. For example, state level data should have more influence on interstate and principal arterial highways than minor arterial and collector. In addition to the information in Table 4.7, detailed discussions for each of the predictor variables are presented below with respect to their definition, sources, and evolution in data bases.

CTYPOP, City Population

Decennial Bureau of Census [County and City Data Book, Characteristics of the Population] records on population are only done for some major cities. The database STATIS (Statistical Information System), a component of EDIN (Economic Development Information Network) at Indiana University has records of city population for certain past years of all levels of cities. The STATIS database was accessed through the Purdue University Computer Center to obtain the city population data for the years 1970, 1973, 1975, 1978, 1980, 1982, 1984 and 1986. To use in data tables, linear interpolation was done to find

city population for missing years 1971, 1972, 1974, 1976, 1977, 1979, 1981, 1983 and 1985. The city population for 1987 was estimated by adding annual changes between 1984 and 1986 to 1986 population.

An understanding of what is happening to the population is necessary in determining highway travel demands. The variable, City Population (CTYPOP), is taken as a predictor variable on the assumption that the response variable AADT in a particular year at a place is dependent on the number of people living nearby.

Woods and Poole (W&P) Economics Inc. provides the forecast on population of cities, classified as Metropolitan Statistical Areas (MSA). The Indiana Business School also projects the township population for every fifth year over 20-30 future years [Indiana University 1986]. The Indiana township population projections are an extension of the Indiana county population projections. To get the projection for city population other than the MSA population, a "ratio" method -- the proportion of city population to county/township will be used. Based on this proportionality assumption, unknown city populations can be estimated by using equation 4.1.

$$CTYPOP_{Xy} = \left[RCTYPOP_{Ey} + \left[\frac{RCTYPOP_{Ey} - RCTYPOP_{Ry}}{Ry - Ey} \right] \right] \frac{POP(CNTY/TWP)_{Xy}}{(Xy - Ry)} \quad (4.1)$$

where,

$RCTYPOP_{Ry}$ = Ratio of city population to county or township population in a recent known year, Ry ,

$RCTYPOP_{Ey}$ = Ratio of city population to county or township
population in a closest earlier year, Ey ,

$POP(CNTY/TWP)_{Xy}$ = County or Township Population in the year Xy

$CTYPOP_{Xy}$ = City Population in the year Xy .

A small city is generally contained within a township. On the other hand, there are some cities that extend over two or more townships. For the bigger city, ratios can be developed based on multiple townships which enclosed the cities or total county(ies) population projections.

$CNTYPOP$, County Population and
 $STPOP$, State Population

Decennial Bureau of Census [County and City Data Book, Characteristics of the Population] records on population provide state and county values. These variables are taken as predictor variables on the assumption that the response variable AADT in a particular year at a particular place is dependent on the number of people living nearby. Intercensus estimates of $CNTYPOP$ and $STPOP$ from the Indiana School of Business [Indiana University] were used in the data tables for years other than census years.

The Indiana Business School also projects the population for every fifth year over 20-30 future years. Its projections are made at the county level, based on the fertility, mortality, and net migration experiences of the county populations. The state forecasts are the results of the sum of the forecasts of the 92 individual counties. The projections are based on past trends and patterns, but also

involve judgments, because simple historical extrapolation is not always reliable. Wood and Poole Economics, Inc. population projections [W&P, 1987 Indiana State Profile] are also based on cohort-component analysis with consideration of economic growth/decline and constrained by national, regional, and state forecasted totals. Population forecasts from either IU Business School or W&P Economics can be used, but the inclusion of economic factors with the cohort analysis and the consideration of smaller area projections constrained to broader area projections make W&P's forecasts preferable to IU's forecasts.

CNTYHH, County Households, and
STHH, State Households

A household includes all persons who occupy a housing unit. A housing unit is a house, an apartment, a group of rooms, or a single room occupied as separate living quarters or, if vacant, intended for occupancy as separate living quarters. Data for total households include all occupied housing units. The number of occupied housing units is the same as the number of households. The housing statistics presented here for the years 1970 and 1980 are based on the results of the 1970 and 1980 Census of Population and Housing, conducted by the Bureau of Census as of April 1, 1970 and 1980 [Bureau of the Census, County and City Data Book]. Some of the data collected by the Bureau of Census were collected on a 100 percent, or complete-count, housing inventory, while other data were obtained from sample estimates. The samples were 5 percent, 15 percent, and 20 percent, depending on the subject covered. The sample data have been "weighted" or "inflated"

to reflect the entire population or universe. Exact agreement, therefore, is not to be expected between data based on samples and data resulting from complete counts.

A large portion of our society is organized into households. The total number of households in a county in a particular year is CNTYHH for that year. STHH is the statewide value. It was felt that travel demand would very much dependent on this variable. Although the household size and demand are changing, these changes are felt to be somewhat predictable. It was found in a previous study [Neveu 1982] that number of households is a better predictor of AADT than population. The predictor variables — CNTYHH and STHH — are chosen on the assumption that the response variable, AADT, will be adequately explained by using them in models. The Bureau of Census gives the values of CNTYHH and STHH for each census year. Like population, number of households forecasts for county and state can be obtained from Woods and Poole Economics, Inc. The estimates of intercensus households between 1970 and 1987 were accomplished by the interpolation procedure described below [Fricker & Saha 1987].

The slopes of population/household between 1970 and 1980 are less than 0.04 per year [See Figure 4.1 of Fricker & Saha 1987]. With these mild slopes, it has been assumed that the average household size is changing uniformly between the census years. To develop the slope of household size between 1980 and 1990, the 1990 forecasts from W&P forecasts were used with 1980 census data. Based on the above assumptions, households for years 1971 to 1979 are computed by using Equation (4.2).

$$HH_{19XX} = \left[POP/HH_{1970} + \left[\frac{POP/HH_{1980} - POP/HH_{1970}}{10} \right] (19XX - 1970) \right]^{-1} POP_{19XX} \quad \dots(4.2)$$

where,

POP/HH_{1970} = Ratio of population to households in year 1970,

POP/HH_{1980} = Ratio of population to households in year 1980,

POP_{19XX} = Population in year 19XX (1971 < 19XX < 1979),

HH_{19XX} = Households in year 19XX.

Households at years 1981 to 1987 are also computed using Equation (4.2) by replacing (i) POP/HH ratios for 1970 and 1980 by those ratios for 1980 and 1990 respectively, (ii) year 1970 by 1980, and (iii) the range of years 19XX as 1981 < 19XX < 1987.

CNTYVR, County Vehicle Registrations and
STVR, State Vehicle Registrations

The total number of vehicle registrations in the county where a highway segment is located (CNTYVR) and that for the whole state of Indiana (STVR) is published each year by the Indiana Bureau of Motor Vehicles. Historical data for these variables are available for years of 1940, 1941, and 1950 through 1988. Data for vehicle registrations are not available at the city level. The available data are reliable in the sense that they are not estimates, but are counts made at motor vehicle registration offices throughout the state. These variables are proposed to explain AADT on the assumption that AADT in a particular year at a given place is closely related to the number of vehicles registered then and there. The prediction of expected future traffic based on the projection of the trend of motor vehicle registrations is a reasonably accurate indication of future highway traffic. The value

of variables CNTYVR and STVR was used in the data tables for all categories of highways. Because of the good series of historical data, time series analysis and a combination of regression and time series methods will be used to predict the future year values of CNTYVR and STVR. The validity of our forecasts will be assessed through retro-forecasting procedures. The reliability of these forecasts can be assessed by comparing the forecasts with the yearly report on motor vehicle registrations of the Bureau of Motor Vehicles, as they become available from the Bureau's yearly publication.

CNTYEMP, County Employment and
STEMP, State Employment

Employment data [Bureau of Census, Council of Economic Advisers, Indiana Employment Security Division (IESD)] is an economic variable. The County Employment Patterns [IESD] are released each summer and provide "covered employment" data for each month, each county, and each employment category for the previous calendar year. The total "covered employment" [Bureau of Census, IESD], consists of --

1. Mining,
2. Construction,
3. Manufacturing:
 - a. Food,
 - b. Textiles,
 - c. Lumber, Wood Processing,
 - d. Furniture,
 - e. Paper,
 - f. Printing,
 - g. Chemicals,
 - h. Petroleum Products,
 - i. Rubber, Plastics,
 - j. Leather,
 - k. Stone-Clay-Glass,
 - l. Primary Metals,

- m. Fabricated Materials,
 - n. Non-electric Machinery,
 - o. Electric Machinery,
 - p. Transportation Equipment,
 - q. Instruments and
 - r. Misc. Manufacturing,
- 4. Transportation, Communication, Public Utilities,
 - 5. Wholesale Trade,
 - 6. Retail Trade,
 - 7. Finance,
 - 8. Agriculture & Services, and
 - 9. Government.

County Employment Patterns published prior to 1983 do not provide state employment figures. According to the 1976 edition, covered employment represents about 85 percent of nonagricultural wage and salary employment and 78 percent of all employment. Major exceptions to coverage of wage and salary employment are in railroads, small nonprofit institutions, churches, private households, and most government units. State hospitals, schools of higher education, and local government utilities are covered. In addition to these exceptions, self-employed workers (both farm and non-farm) are excluded from coverage.

"County Business Patterns - Indiana", a publication of the US Bureau of Census, furnishes employment data for each year for the week including March 12, and provides such data for the county and state levels. This summary of employment excludes government employees, railroad employees, self-employed persons, etc. This publication also provides Federal Civilian Employment for the mid-March pay period by county and state. The "City and County Data Book" is another publication of the Bureau of Census that presents employment data by county and state in every tenth year. The employment figures in the "City

and County Data Book" are prepared from household surveys, where workers are counted according to their place of residence; whereas for "County Business Patterns", they are counted according to their place of work. There are various reasons for differences in the two series of data:

- a. differences in the reporting systems they use,
- b. differences in the time period to which the reports refer,
- c. sampling variations in the figures based on the sample survey, and
- d. differences in industrial classification.

For the City and County Data Book, the survey information is obtained from respondents in workers' households, while the County Business Patterns industrial classification is based on information either from the employer or administrative sources.

There exists little difference between the numbers in "County Business Patterns" and "County Employment Patterns". The difference is mainly due to the reporting systems and the periods to which the reports refer. The employment numbers from the "County Business Patterns - Indiana" were taken as variable CNTYEMP, County Employment, for the years 1970 to 1987. The state employment totals (STEMP) are found by summing the 92 county employment figures in "County Business Patterns - Indiana".

The forecasts of employment data [W&P,1987] are based on establishment-based employment data, where employment figures are counted according to the place of work. This was one of the main

reasons to choose County Business Patterns historical employment data -- which are also establishment-based data. The employment forecasts from Wood & Poole Economics Inc. will be used in traffic forecasting model(s). Those forecasts are based on "Export-Base" economic models (see Section 4.3.1). The superiority of these forecasts was discussed in some earlier section(s).

CNTYINC, County Per Capita Income ('82 \$)
 STINC, State Per Capita Income ('82 \$)

Income is a economic indicator. Like employment, it is believed that this county and state income influences the traffic on highways. Income was used earlier in New Mexico's [Albright 1985] and Neveu's [1982] study. The City and County Data Book [Bureau of the Census] publishes the per capita personal income and median family income at the state and county level for the year before the census years. The database STATIS (Statistical Information System), a component of EDIN (Economic Development Information Network) of Indiana University has historical records of income along with other information. The STATIS database was accessed through the Purdue University Computer Center to obtain the per capita income in current dollars at county and state for the years 1970 to 1987. For use in the data tables, the county and state per capita incomes were converted to 1982 dollars by applying the consumer price index (CPI) [Bureau of Labor Statistics, Economic Statistics Bureau of Washington] in Equation (4.3).

$$INC_{1982} = \left[\frac{CPI_{1982}}{CPI_{19XX}} \right] INC_{19XX} \quad (4.3)$$

where,

INC_{1982} = County/State Per Capita Income,
in 1982 \$, for the year 19XX,

INC_{19XX} = County/State Per Capita Income,
in current \$, for the year 19XX,

CPI_{1982} = Consumer Price Index for the year 1982,

CPI_{19XX} = Consumer Price Index for the year 19XX.

The converted county and state per capita income in 1982 dollars are represented as variables CNTYINC and STINC in the data tables, respectively. These variables are adopted on the assumption that there exists a significant relationship between income and magnitude of travel. The historical income data are easily available. The forecasts of per capita income at state and county levels are also available from Woods and Poole Economics Inc. Like employment, their income forecasts are also based on their "Export-Base" Economic Models.

STGAS, State Highway Gasoline Consumption in Millions of Gallons

The total amount of yearly gasoline consumption by the vehicles on the roads of Indiana is taken as variable STGAS. The historical data on STGAS are available from Highway Statistics of Federal Highway Administration (FHWA) since 1949. This variable is proposed to explain AADT on the assumption that AADT in a particular year is closely related to amount of highway gasoline used in that year. Because of good historical data, time series analysis and a combination of regression and time series methods will be used to predict the future year values of STGAS. The validity of our forecasts will be

made through retro-forecasting. The reliability of these forecasts can be assessed by comparing the forecasts with data in the yearly publications of FHWA, as they become available.

4.7 Chapter Summary

The central idea of this chapter is to describe the variables and data bases used in model development. The variables have been discussed and the sources of their numerical values are given. The summary regarding availability, cost and reliability of the predictor variables is presented (See Table 4.7). Explanations behind the uses of all the predictor variables (or independent variables, X 's) are given. The role of index or categorical variables is also provided. The methods by which certain data are estimated or interpolated are presented. This chapter is a guide to the data bases created during the study. The chapter also acts as a useful resource for any future modification of the data bases.

CHAPTER 5

SELECTION OF DATA FORMAT AND CANDIDATE MODELS

5.1 Introduction

The statistical quality of the two alternate data bases and their formats/structures (described in Chapter 4) will be evaluated in this chapter. The results of some statistical analyses and judgment will be employed to select the best usable format for each class of highway. The results of these analyses under different groupings will be compared to identify the best grouping of data for further analyses. Some of the frequently used statistical selection criteria will be discussed in this chapter. The candidate models will be identified for the selected group(s) of the data structure.

5.2 Ordinary Least Squares (OLS)

The most common method of fitting a line to a set of data is the method of least squares. The method of least squares chooses a line/plane that makes the sum of the squares of the residuals as small as possible. Consider a dependent variable, Y , and set of independent variables, X 's, which are linearly related in the parameters so that:

$$Y_i = \beta_0 + \sum_{j=1}^n \beta_j X_{ij} + e_i \quad (5.1)$$

where,

Y_i = value of dependent variable at i th observation;

$i=1, \dots, m,$

X_{ij} = value of j th independent variable at i th observation;

$j=1, \dots, n,$

β_0 = constant term,

β_j = regression coefficient for j th independent variable,

e_i = disturbance/error term,

m = observation number,

n = number of independent variables.

The method of ordinary least squares (OLS) assures that, under certain assumptions, the β 's are chosen so that in a given sample, $\sum e_i^2$, the sum of the squared disturbance term, is as small as possible. When these assumptions are satisfied, then β 's have the properties of being the best linear unbiased and efficient estimator among the class of estimators for the given sample observations [Neter et al. 1985].

Some other important properties of OLS are:

1. The estimated regression line/plane will pass through the "point of means", the point $(\bar{Y}, \bar{X}_2, \dots, \bar{X}_n)$.
2. The estimated errors have mean zero, $\sum e_i = 0$, where $i = 1$ to m .
3. The estimated residuals are orthogonal to each

explanatory/predictor variable: the sum of their cross products is zero.

5.2.1 Correlation and the Regression Coefficient

The correlation coefficient measures the strength of the linear association between two quantitative variables. For m observations on two variables x_1 and x_2 , denoted by

$$(x_{11}, x_{21}), \dots, (x_{1i}, x_{2i}), \dots, (x_{1m}, x_{2m}),$$

the correlation coefficient between x_1 and x_2 , r_{12} , can be defined as

$$r_{12} = \frac{1}{n-1} \sum_{i=1}^m \left[\frac{x_{1i} - \bar{x}_1}{s_{x1}} \right] \left[\frac{x_{2i} - \bar{x}_2}{s_{x2}} \right] \quad (5.2)$$

Here $\bar{x}_1$ and s_{x1} are the mean and standard deviation of the x_1 observations alone, and similarly $\bar{x}_2$ and s_{x2} refer to the x_2 observations.

Multicollinearity is said to exist in a regression analysis when the predictor variables or linear combinations of them are highly correlated to each other. It is well known that collinearity need not harm forecasts, even if it has harmed structural estimation, as long as it continues into the forecast period [Draper & Smith 1981, Judge et al. 1980]. In the problem we are confronting with the socioeconomic variables, it is likely that collinearity will continue in future. But, we cannot proceed on that assumption. Consequently, adequate care has been taken by dropping variates thought to be collinear. The dropped variates, which really do belong to the model, may lead to specification errors with their consequent estimation biases. These estimation biases become forecasting biases when

projected into situations where collinearity no longer prevails. An important fact regarding the correlation coefficient is that, when independent variables are highly correlated, the regression coefficient of any independent variable depends on which other independent variables are included in the model. For highly correlated independent variables, a regression coefficient does not reflect any inherent effect of the particular independent variable on the dependent variable, but only a marginal or partial effect, given whatever other correlated independent variables are included in the model. [Draper & Smith 1981, Neter et al. 1985]

In general, when two independent variables are correlated with each other, intercorrelation or multicollinearity among them is said to exist [Neter et al. 1985]. The three important problems that arise when using highly correlated variables are:

1. Adding or deleting an independent variable changes the regression coefficients.
2. The extra sum of squares of regression associated with an independent variable varies depending upon which independent variables are already in the model.
3. The estimated regression coefficients individually may not be statistically significant, even though a definite statistical relationship exists between the dependent variable and a set of independent variables.

The existence of multicollinearity does not invalidate a regression analysis, but neither is the absence of multicollinearity a validation of a particular regression model. Multicollinearity is also not a specification error [Freund & Minton 1979]. However, in this study, the expected signs and the values of the variables in the regression equations will be carefully examined to avoid the problem of multicollinearity in the choice of variables.

5.3 Some Alternative Variable Selection Rules

In this section, some of the most common model selection rules will be discussed. Although most of the criteria can be found in many applied statistical texts, their underlying principles are presented in this section to understand their role in model selection. Moreover, many of these criteria are difficult to understand. Therefore, this section is devoted to a simple presentation. In general, most of these rules rely on discrimination criteria, such as maximizing some modified R^2 , and each one measures how well the models fit the data after some adjustment for number of variables in the equation.

5.3.1 R_p^2 Criterion

The R_p^2 criterion calls for an examination of the coefficient of multiple determination R^2 , to select one or several subsets of X-variables. The subscript "p" of R_p^2 suggests that there are p parameters, or p-1 predictor variables. In this section, R_p^2 will be referred as R^2 -- the coefficient of multiple determination. R^2 measures the proportion of the total variance accounted for regression

relationship through the linear influence of the explanatory variables. The total sum of squares of Y, the dependent variable, about its mean may be partitioned as follows:

$$\begin{array}{rcl} \text{Total sum} & \text{Regression} & \text{Error sum} \\ \text{of squares} & = \text{sum of squares} & + \text{of squares} \\ \text{(SST)} & \text{(SSR)} & \text{(SSE)} \end{array}$$

where,

SSR -- sum of the squares of the deviations of the fitted regression values around mean.

SSE -- sum of the squares of the deviations around the regression line or plane.

SST -- sum of the squares of the total deviations around the mean, SST is fixed for the given Y's.

A graphical description of the partitioning of SST can be found in the literature on applied statistics (for example, Figure 3.5 of Ref. Neter, Wasserman & Kutner [1985]). Given this decomposition of the sample variation of Y about its mean, the coefficient of determination is represented as

$$R_p^2 = \frac{SSR}{SST} = 1 - \frac{SSE}{SST} \quad (5.3)$$

Since R_p^2 is a ratio of the sum of squares and the denominator is constant for all possible regressions, R_p^2 varies inversely with the error sum of squares, SSE_p . But SSE_p can never increase as additional independent variables are included in the model. Thus, R_p^2 will be at a maximum when all $p-1$ potential X-variables are included in the regression model. The reason for using the R_p^2 criterion with the all possible regressions approach therefore cannot be to maximize R_p^2 . The goal is to find the point where adding more variables is not worthwhile because it leads to only a small increase in R_p^2 . Often, this point is reached when only a limited number of X-variables is

included in the regression model. Clearly, the determination of where diminishing returns occurs is a judgmental one.

5.3.2 Adjusted R_a^2 (R_a^2) or MSE_p Criterion

As a basis for model choice, the R^2 measure has an obvious fault — it can be increased by increasing the number of explanatory variables. To take this characteristic of the measure into account, Theil [Judge et al. 1980] proposed a corrected coefficient of multiple determination R_a^2 . The corrected or adjusted R_a^2 is represented as

$$R_a^2 = 1 - \frac{n-1}{n-p}(1 - R^2) = 1 - \frac{MSE}{SST/(n-1)} \quad (5.4)$$

where

$$R^2 = 1 - SSE/SST$$

SSE = Error Sum of Squares

MSE = Mean Square Error [SSE/(n-p)]

SST = Total Sum of Squares

n = number of observations

p = number of parameters including intercept, if any.

Unlike the R_p^2 criterion, the R_a^2 criterion takes the number of parameters in the model into account through the degrees of freedom. It can be seen from equation (5.4) that R_a^2 decreases if and only if MSE decreases, since $SST/(n-1)$ is fixed for the given Y-observations. Thus, R_a^2 or MSE are equivalent criteria. To represent the number of parameters (p) in the equation, MSE_p is used. The MSE_p criterion

seeks to find either the subset of X variables that minimizes MSE_p , or one or several subsets for which MSE_p is so close to the minimum that adding more variables is not worthwhile.

The R_a^2 criterion will lead us to the right model "on the average". However, the expectation property alone is no guarantee of success. Also, the R_p^2 criterion need not be the most powerful of the criteria involving a quadratic form of the residuals that have the property: the expected value is minimized by the true model. A limitation of both the R_p^2 and R_a^2 measures is that they do not include a consideration of the losses associated with choosing an incorrect model. With the goal of eliminating this deficiency, next two criteria based on the mean square error estimate -- C_p and PC -- are presented. [Judge et al. 1980]

5.3.3 Mallows' C_p Criterion

The C_p -criterion is concerned with the total mean squared error (MSE) of the n fitted values for each of the various subset regression models. The C_p statistic is estimated by the following equation

$$C_p = \frac{SSE}{\hat{\sigma}^2} + 2p - n \quad (5.5)$$

where

$\hat{\sigma}^2$ = Estimated error variance fitting the full model

SSE = Error Sum of Squares

n = number of observations

p = number of parameters including intercept, if any.

When the C_p values for all possible regression models are plotted against P , those models with little bias — measured numerically as the difference between the center of the sampling distribution and the true parameter value — will tend to fall near the line $C_p = P$ [Draper & Smith 1981]. Models with substantial bias will tend to fall considerably above this line.

In using the C_p -criterion, the subsets of X variables for which (1) C_p value is small and (2) the C_p value is near P , are considered for the model. Sets of X variables with small C_p values have a small total mean squared error and, when the C_p value is also near P , the bias of the regression model is small. It may sometimes occur that the regression model based on the subset of X variables with the smallest C_p value involves substantial bias. In that case, one may at times prefer a regression model on a somewhat larger subset of X variables for which the C_p value is slightly larger and that does not involve a substantial bias component. Thus, one should look for a regression with a low C_p value about equal to P . When the choice is not clear-cut, then it is a matter of personal judgment whether one prefers a biased equation or an equation with more parameters.

5.3.4 Amemiya's Prediction Criterion (PC)

To include a consideration of the losses associated with choosing an incorrect model, Amemiya [1980] developed a criterion based on the

unconditional mean squared prediction error as the risk function. This results in a modification of R^2 that corrects the degrees of freedom to a greater extent than Theil's R_a^2 . Amemiya's criterion is known as the Prediction Criterion (PC), which can also be used as a selection criterion in a nonlinear regression model. In terms of R^2 , PC can be represented as [Amemiya 1980]:

$$PC = \frac{n+p}{n-p}(1 - R^2) \quad (5.6)$$

where the definitions of n , p and R^2 are same as under equations 5.4 and 5.5. The PC has a higher penalty for adding variables than Theil's adjusted R^2 . In using the PC criterion, one seeks to identify subsets of X variables for which the PC value is small.

5.3.5 Akaike's Information Criterion (AIC)

The information measure or criterion seeks to incorporate in the model selection the divergent considerations of accuracy of estimation and the "best" approximation to reality. Thus use of this criterion involves a statistic that incorporates a measure of the precision of the estimate and a measure of the rule of parsimony, to be defined in Section 5.6, in the parameterization of a statistical model.

The classical method of maximum likelihood could be represented to identify a statistical model by maximizing an estimate of the generalized entropy, or the expected log likelihood, of the model being fitted [Akaike 1981]. The log maximum-likelihood is a biased estimate of the expected log likelihood of the model with parameters determined

by the method of maximum-likelihood. The correction of this bias leads to an information criterion, AIC -- the Akaike Information Criterion [Akaike 1981] -- defined by

$$\begin{aligned} \text{AIC} = & (-2) \ln (\text{maximum likelihood}) \\ & + 2 (\text{number of free parameters within the model}) \end{aligned} \quad (5.7)$$

Therefore, many important statistical problems could be solved simply by specifying a set of models and estimating the parameters within each model by the method of maximum likelihood and then selecting a model with the minimum value of AIC. This procedure, called the minimum AIC estimation procedure, produces a new approach to statistical model identification that could provide a unifying view of the problems. AIC has an important advantage, in that it can be used not only in regression analysis, but also to choose among various linear constraints in the general parametric model. The AIC can be used in any model where the likelihood function is specified. For the OLS (see equation 5.1), equation 5.7 reduces to

$$\text{AIC} = (n) \ln(\text{SSE}/n) + 2p \quad (5.8)$$

where the definitions of n and p remain the same as equation 5.4. The above equation shows explicitly the penalty for increasing the number of parameters. In using the AIC criterion, the user needs to identify subsets of X variables for which AIC value is small.

5.4 Multiple Linear Regression Analysis

In this section, the results of some analyses are presented. Each analysis is discussed briefly, together with some interpretations and criteria for selection. The RSQUARE procedure [SAS/Statistics 1985] was used to select the optimal subsets of predictor variables in a multiple regression analysis. The procedure finds the subsets of predictor variables that best predict a response variable by linear regression in the given sample. The R^2 statistic is the criterion for selecting subsets. PROC RSQUARE can also efficiently evaluate all possible subset regressions and print the models in decreasing order of R^2 magnitude within each subset size. Other statistics (for example, R_a^2 , PC, RMSE, AIC and C_p) are also available for comparing subsets of different sizes. The definitions of R_p^2 , R_a^2 , PC, AIC and C_p have been provided in earlier sections. RMSE is the square root of Mean Square Error (MSE) and is calculate by the following equation

$$RMSE = \sqrt{\frac{SSE}{n-p}} \quad (5.9)$$

These statistics, as well as estimated regression coefficients, were computed through RSQUARE procedure of SAS [SAS/Statistics 1985]. While RSQUARE is a useful tool for exploratory model building, no statistical method can be relied on to identify the "true" model. Effective model building requires background theory to suggest relevant predictors and plausible functional forms for the model.

5.4.1 Interstate Highways

All four formats of data bases — Raw, Raw E&L, Density and Density E&L (for definitions, see Section 4.5.1) — are analyzed using segment AADT and county & city average AADT. The layout of analysis is shown in Figure 5.1. This layout is formulated under the following assumptions: (i) traffic growth is primarily associated with the functional class of highway and (ii) CTYGR, MFUNC and GREGION have a secondary effect on traffic growth. These effects are shown as Phases 1 and 2 in Figure 5.1. In Phase 1, the data bases are grouped and analyzed by rural, urban location and both together. Phase 1 will compare the results of analysis for the three groupings of highways. In Phase 2, the data bases are grouped and analyzed by the categorical variables CTYGR, MFUNC and GREGION (for definitions, see Section 4.6.1) under each combination of Phase 1. CTYGR, MFUNC and GREGION have 5, 4 and 3 levels, respectively. Phase 2 will compare the results within the groupings of each of the three categorical variables and between the groups. Moreover, a comparison between the two main forms of data bases by their four formats will be done at each phase. Also, a comparison among the four formats within each of the main data forms can be made. The results of Phase 2 will also identify any misclassified observations.

The best models without any inconsistency in the sign of regression coefficient of all possible combinations are identified for different number of variables in the equation. For example, a positive sign is expected for population on the assumption of increase of AADT because of population increase. Appendix Tables C1 and C3 present the

Data Structure

Figure 5.1: Layout of Analysis for Interstate Highways

results of raw and density format data bases for county or city average AADT. The results of earlier and later year versions of raw and density data bases for the same are shown in Tables C2 and C4. These results are based on a linear functional form of predictor variables. The first column in these tables presents the combination/case and the number of observations, N. The second and the ninth columns present the number of variables (p-1) and the corresponding variable names in the equation. The second through eighth columns show criterion measures and statistics. The last (tenth) column contains the values of regression coefficients corresponding to the variables in the ninth column. Similar data tables result from using segment AADT, but these tables are not shown.

5.4.2 Noninterstate Urban State Highways

The layout of analysis for noninterstate urban state highways is shown in Figure 5.2. This layout is formulated under the following assumptions: (i) the functional class of highway is the most important determinant of traffic growth, (ii) CTYGR, based on city population, has the next greatest impact on traffic growth and (iii) MFUNC or GREGION has a tertiary effect on traffic growth. With the data bases, these three levels of influences are represented as Phases 1, 2 and 3. In Phase 1, the data bases are grouped and analyzed by the following functional classes:

- a. Urban Principal Arterial, and
- b. Urban Minor Arterial and Collector

In Phase 2, the data bases are grouped and analyzed by the categorical

Data Structure

Figure 5.2: Layout of Analysis for Non-Interstate Urban State Highways

variable CTYGR, with four levels under each level of Phase 1. In Phase 3, the variables MFUNC and GREGION, with 4 and 3 levels, respectively, are grouped and analyzed with each combination of Phases 1 and 2. For interstate highways, CTYGR, MFUNC and GREGION are all addressed in Phase 2. As for interstate highways, the results at different phases will be used to compare the different format of data bases and to identify the misclassified observations in the data bases.

The best models without any inconsistency in regression coefficient are identified for all possible combinations of variables in the equation for the two main functional classes of highways. Appendix Tables C5 and C7 present the results of raw and density format data bases for county or city average AADT on urban principal arterials. The results of the earlier and later year version of raw and density data bases for the same highway class are shown in Tables C6 and C8. An analysis by GREGION is done for city and county average raw data bases. The results of north(n), central(c) and south(s) are presented in Appendix Table C5.1. The statistical quality of results by GREGION and CTYGR (see Tables C5 and C5.1) does not provide an edge for one over the other. Table C5.1 also shows the results of pooled CTYGR A, B and C for the south region. One main reason for this pooling is that only five observations resulted in county and city average data base for each of the three city groups in the south region. This pooling has improved some statistics of the models — for example, C_p value in Table C5.1 with respect to that in Table C5. Some other considerations in this pooling will be addressed in Section 5.6.2.

Tables C9 to C12 (Tables C9 & C11 for raw and density format; Tables C10 and C12 for raw E&L and density E&L format) present the results of urban minor arterial and collector for county and city average AADT. All these results are based on linear functional form. The column descriptions of the tables follow the descriptions, provided in the latter part of Section 5.4.1.

5.5 Data Format and Group Selection

Several alternative selection rules and the values of the relevant statistics have been presented in Sections 5.3 and 5.4.1. It is not the intention of this study to use any single criterion as the sole basis for selecting a model. It can be argued from this study's results that, in general, most of the selection rules supplement each other in the selection of the regressor variable(s). If one reviews the procedures on variable selection of statistical model building, there appears to have been a strong desire by many to designate some single statistic or index to gauge the "goodness" of a statistical model. One natural candidate for this honor would be the coefficient of multiple determination, R^2 .

In the following subsections, the values of R^2 for the different data formats will be compared to each other to select the most promising and practical data format(s). The values of R^2 will play a major role in this selection process. In the final selection of data format, the criteria of establishing high R^2 will not be considered exclusively. Because R^2 is a relative quantity, it shows how large the Regression Sum of Squares (SSR) is relative to the Total Sum of

Squares (SST). In some situations, data may be scattered and a large R^2 may not show a good fit. In more controlled situations, a small R^2 may show a good fit [Freund & Minton 1979]. A high R^2 value does not necessarily mean a good fit. In that respect, the selection process will occasionally be aided by the other statistics — R_a^2 , PC, RMSE, AIC & C_p . In addition to data format selection, subsets or groups of data will be identified to do further analysis from the selected data format.

5.5.1 Interstate Highways

The maximum values of R^2 for the "all data" formats and their subsets are identified in Tables C1 to C4 for county and city average AADT data tables. Similar identification was carried out for segment AADT data tables. Table 5.1 shows the maximum R^2 value, in percent, for all possible combinations of Interstate highways. These results have evolved without any inconsistency in the regression coefficients. The number of variables that corresponds to each of the R^2 values in Table 5.1 is shown in Table 5.2. By observing the results of Table 5.1 with an almost equal number of variables in the equation (see Table 5.2), one can observe the superiority of the county/city average data bases over the segment data bases. The marginal improvement in the maximum R^2 value for all four formats of data tables is shown in Table 5.3. This table shows that there is a significant improvement in most of the cases.

For the "raw" format, there is 12.03 percent increase in R^2 value, when all data for interstate have been analyzed together. An

Table 5.1: Maximum R^2 value for Interstate Highways

CASE	C T Y GR	M F U NC	G R E GION	Segment Data base				County/City Average Data base			
				Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
RURAL + URBAN	ALL			40.26	41.00	50.14	51.95	52.29	51.70	49.42	49.56
	A+			26.30	27.58	49.56	55.25	40.28	41.59	33.16	35.46
	A			28.70	23.89	39.19	32.17	29.98	20.72	32.74	25.78
	B			60.31	55.02	61.32	63.09	64.15	63.32	53.13	49.05
	C			35.60	34.05	37.16	36.39	67.45	65.84	63.16	63.04
	D			9.28	X	9.35	X	12.90	X	21.32	12.69
	F1			53.53	54.79	59.72	60.96	52.98	54.53	63.53	65.40
	F2			72.55	72.47	70.83	72.54	75.59	74.63	71.76	73.26
	F3			28.62	28.42	28.60	28.54	52.55	52.14	52.59	52.13
	F4			23.69	26.49	40.59	45.72	44.66	46.48	40.45	43.06
	n			37.87	35.83	37.17	32.53	47.31	45.32	48.98	47.19
	c			54.58	55.65	55.86	55.84	73.08	75.91	73.47	76.30
	s			63.42	66.12	57.68	58.51	61.77	64.68	56.67	57.67
	RURAL	ALL			47.59	48.95	46.54	48.08	40.60	37.14	40.19
A+			49.62	52.38	44.88	47.99	66.09	68.62	51.92	53.19	
A			51.25	44.91	47.12	41.75	47.06	38.31	42.54	37.65	
B			30.87	36.14	44.88	57.82	30.79	52.51	70.61	65.86	
C			24.77	30.28	15.30	18.63	75.06	81.76	91.69	94.81	
D			7.49	X	7.49	X	9.67	X	16.37	X	
F1			40.38	41.42	46.12	48.91	37.26	37.81	48.42	50.85	
F2			66.45	64.89	64.28	65.36	76.77	75.27	72.20	73.27	
F3			27.06	28.40	27.04	28.40	50.41	54.03	54.07	53.97	
F4			43.18	45.78	43.61	45.84	37.75	35.41	39.00	35.36	
n			29.75	25.58	27.51	25.58	30.64	27.32	30.60	27.31	
c			40.73	44.76	40.79	44.49	51.12	56.21	51.49	51.21	
s			42.61	44.78	48.98	49.66	41.76	44.69	55.11	52.46	

Table 5.1, continued

CASE	C T Y G R	M F U N C	G R E G I O N	Segment Data base				County/City Average Data base			
				Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
URBAN	ALL			32.05	32.37	51.58	54.97	55.57	53.63	50.75	50.86
	A+			2.80	X	68.91	71.12	7.48	6.52	38.41	11.36
	A			15.26	X	22.43	16.84	20.13	X	19.93	12.66
	B			75.20	80.00	74.72	80.77	80.83	89.46	80.26	90.74
	C			36.68	32.30	35.37	33.38	67.27	65.48	60.72	60.06
	D			35.60	38.84	58.64	60.72	34.63	31.18	60.64	58.57
	F1			49.86	47.56	49.65	47.55	91.57	(**)	93.28	(**)
	F2			70.08	70.54	70.40	71.38	79.47	79.65	78.14	78.07
	F3			63.76	62.91	65.21	70.15	67.77	72.48	67.74	76.94
	F4			14.09	17.51	46.69	52.95	45.26	47.07	39.09	41.78
	n			36.05	32.10	44.09	38.11	50.03	46.73	51.63	48.63
	c			61.43	61.01	66.46	64.11	84.52	88.34	86.81	88.52
	s			62.78	66.48	58.60	63.93	81.34	85.23	77.05	82.94

Note: X=Not Available; (**)=N<5

Table 5.2: Number of Variables for Maximum R^2 value for Interstate Highways

CASE	C T Y GR	M F U NC	G R E GION	Segment Data base				County/City Average Data base			
				Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
RURAL + URBAN	ALL			2	2	4	3	2	2	2	2
	A+			2	2	4	3	2	2	1	1
	A			2	2	3	2	2	2	2	2
	B			3	2	3	3	4	3	3	2
	C			2	2	2	2	3	2	2	2
	D			1	X	1	X	1	X	2	1
	F1			2	2	2	2	2	2	2	2
	F2			4	2	3	2	4	2	3	2
	F3			2	2	2	2	2	2	2	2
	F4			2	2	3	2	2	2	2	2
	n			2	2	3	2	2	2	2	2
	c			3	3	3	2	3	3	3	3
	s			2	2	2	2	2	1	2	2
RURAL	ALL			4	4	3	3	3	3	3	3
	A+			4	4	2	2	4	3	2	2
	A			2	2	3	2	2	2	2	2
	B			2	1	2	2	2	2	3	2
	C			3	3	3	2	2	2	4	3
	D			1	X	1	X	1	X	2	X
	F1			2	2	2	2	2	2	2	2
	F2			4	2	2	2	4	3	2	2
	F3			2	2	2	2	2	2	2	2
	F4			3	4	3	3	3	3	3	2
	n			3	2	2	2	2	2	2	2
	c			3	4	3	3	3	3	3	2
	s			2	2	2	2	2	1	2	1

Table 5.2, continued

CASE	C T Y G R	M F U N C	G R E G I O N	Segment Data base				County/City Average Data base			
				Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
URBAN	ALL			2	2	4	3	2	2	2	2
	A+			1	X	4	3	1	1	2	1
	A			1	X	2	1	1	X	1	1
	B			3	3	3	4	3	3	3	4
	C			2	2	2	2	3	2	2	2
	D			1	1	2	1	2	1	2	1
	F1			2	1	2	1	2	X	2	X
	F2			2	2	2	2	2	2	2	2
	F3			2	2	2	2	2	2	2	2
	F4			2	2	3	2	2	2	2	2
	n			2	2	2	2	2	2	2	2
	c			2	2	3	3	3	2	3	2
s			2	2	2	2	2	2	2	2	

Note: X=Not Available

Table 5.3: Marginal Improvement in Maximum R^2 value of County/City
Average AADT over Segment AADT for Interstate Highways

CASE	C T Y G R	M F U N C	G R E I O N	Segment Data base				County/City Average Data base			
				Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
RURAL + URBAN	ALL							12.03	10.70	-0.72	-2.39
	A+							13.98	14.01	-16.40	-19.79
	A							1.28	-3.17	-6.45	-6.39
	B							3.84	8.30	-8.19	-14.04
	C							31.85	31.79	26.00	26.65
	D							3.62	N/P	11.97	N/P
	F1							-0.55	-0.26	3.81	4.44
	F2							3.04	2.16	0.93	0.72
	F3							23.93	23.72	23.99	23.59
	F4							20.97	19.99	-0.14	-2.66
	n							9.44	9.49	11.81	14.66
	c							18.50	20.26	17.61	20.46
	s							-1.65	-1.44	-1.01	-0.84
RURAL	ALL							-6.99	-11.81	-6.35	-11.47
	A+							16.47	16.24	7.04	5.20
	A							-4.19	-6.60	-4.58	-4.10
	B							-0.08	16.37	25.73	8.04
	C							50.29	51.48	76.39	76.18
	D							2.18	N/P	8.88	N/P
	F1							-3.12	-3.61	2.30	1.94
	F2							10.32	10.38	7.92	7.91
	F3							23.35	25.63	27.03	25.57
	F4							-5.43	-10.37	-4.61	-10.48
	n							0.89	1.74	3.09	1.73
	c							10.39	11.45	10.70	6.72
	s							-0.85	-0.09	6.13	2.80

Table 5.3, continued

CASE	C T Y GR	M F U NC	G R E GION	Segment Data base				County/City Average Data base			
				Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
URBAN	ALL					23.52	21.26	-0.83	-4.11		
	A+					4.68	N/P	N/P	N/P		
	A					4.87	N/P	-2.50	-4.18		
	B					5.63	9.46	5.54	9.97		
	C					30.59	33.18	25.35	26.68		
	D					-0.97	-7.66	2.00	-2.15		
	F1					41.71	N/P	43.63	N/P		
	F2					9.39	9.11	7.74	6.69		
	F3					4.01	9.57	2.53	6.79		
	F4					31.17	29.56	-7.60	-11.17		
	n					13.98	14.63	7.54	10.52		
	c					23.09	27.33	20.35	24.41		
	s					18.56	18.75	18.45	19.01		

Note: N/P=Not Possible

increase of 23.52 percent R^2 value is observed for the "urban-all" case, but a decrease of 6.99 percent R^2 value is found for the "rural-all" case. The values of PC, RMSE, AIC and C_p for the "rural-all" case with R^2 of 40.60 percent ($R_a^2 = 39.62$ percent) and 3 variables in the equation are 0.6201, 7344, 3315.4 and 24.73 respectively for county/city average data table (see Appendix Table C1). On the other hand, the values of PC, RMSE, AIC and C_p for the same with R^2 of 47.59 percent ($R_a^2 = 47.23$ percent) and 4 variables in the equation are 0.5330, 9300, 10879 and 33.90 for segment AADT data table. All these statistics except PC establish that the results from county and city average AADT data table are better for rural interstates in spite of a small decrease in R^2 value.

A further examination of Table 5.1 reveals that the results have usually been improved when the data tables have been grouped by CTYGR, MFUNC and GREGION. Table 4.6 has shown the number of observations for different groupings according to the layout analysis presented in Figure 5.1. The analysis by CTYGR shows that data for 'CTYGR D' are not good for the "rural" and "rural+urban" cases (see Table 5.1). The data for 'CTYGR A+' are also not successful in producing statistically good results. By observing the results of Table 5.1 and its "parent" (Appendix Tables C.1 to C.4), in general, the results by GREGION are better than those by CTYGR and MFUNC.

Tables 5.4, 5.5 and 5.6 are produced from Table 5.1 to answer the following questions:

1. Are the improvements in raw E&L, density and density E&L formats about raw format enough to justify their selection? (Table 5.4)

Table 5.4: Marginal Improvement in Maximum R^2 value of Raw E&L, Density and Density E&L Formats over Raw Format for Interstate Highways

CASE	C T Y G R	M F U N C	G R E G I O N	Segment Data base				County/City Average Data base			
				Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
RURAL + URBAN	ALL				0.74	9.88	11.69		-0.59	-2.87	-2.73
	A+				1.28	23.26	28.95		1.31	-7.12	-4.82
	A				-4.81	10.49	3.47		-9.26	2.76	-4.20
	B				-5.29	1.01	2.78		-0.83	-11.02	-15.10
	C				-1.55	1.56	0.79		-1.61	-4.29	-4.41
	D				N/P	0.07	N/P		N/P	8.42	-0.21
	F1				1.26	6.19	7.43		1.55	10.55	12.42
	F2				-0.08	-1.72	-0.01		-0.96	-3.83	-2.33
	F3				-0.20	-0.02	-0.08		-0.41	0.04	-0.42
	F4				2.80	16.90	22.03		1.82	-4.21	-1.60
	n				-2.04	-0.70	-5.34		-1.99	1.67	-0.12
	c				1.07	1.28	1.26		2.83	0.39	3.22
	s				2.70	-5.74	-4.91		2.91	-5.10	-4.10
RURAL	ALL				1.36	-1.05	0.49		-3.46	-0.41	-3.99
	A+				2.76	-4.74	-1.63		2.53	-14.17	-12.90
	A				-6.34	-4.13	-9.50		-8.75	-4.52	-9.41
	B				5.27	14.01	26.95		21.72	39.82	35.07
	C				5.51	-9.47	-6.14		6.70	16.63	19.75
	D				N/P	0.00	N/P		N/P	6.70	N/P
	F1				1.04	5.74	8.53		0.55	11.16	13.59
	F2				-1.56	-2.17	-1.09		-1.50	-4.57	-3.50
	F3				1.34	-0.02	1.34		3.62	3.66	3.56
	F4				2.60	0.43	2.66		-2.34	1.25	-2.39
	n				-4.17	-2.24	-4.17		-3.32	-0.04	-3.33
	c				4.03	0.06	3.76		5.09	0.37	0.09
	s				2.17	6.37	7.05		2.93	13.35	10.70

Table 5.4, continued

CASE	C T Y GR	M F U NC	G R E GION	Segment Data base				County/City Average Data base			
				Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
URBAN	ALL			0.32	19.53	22.92	-1.94	-4.82	-4.71		
	A+			N/P	N/P	N/P	-0.96	30.93	3.88		
	A			N/P	7.17	1.58	N/P	-0.20	-7.47		
	B			4.80	-0.48	5.57	8.63	-0.57	9.91		
	C			-4.38	-1.31	-3.30	-1.79	-6.55	-7.21		
	D			3.24	23.04	25.12	-3.45	26.01	23.94		
	F1			-2.30	-0.21	-2.31	N/P	1.71	N/P		
	F2			0.46	0.32	1.30	0.18	-1.33	-1.40		
	F3			-0.85	1.45	6.39	4.71	-0.03	9.17		
	F4			3.42	32.60	38.86	1.81	-6.17	-3.48		
	n			-3.95	8.04	2.06	-3.30	1.60	-1.40		
	c			-0.42	5.03	2.68	3.82	2.29	4.00		
	s			3.70	-4.18	1.15	3.89	-4.29	1.60		

Note: N/P=Not Possible

Table 5.5: Marginal Improvement in Maximum R^2 value of Earlier & Later (E&L) Year Data Format for Interstate Highways

CASE	C T Y G R	M F U N C	G R I O N	Segment Data base				County/City Average Data base			
				Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
RURAL + URBAN	ALL				0.74		1.81		-0.59		0.14
	A+				1.28		5.69		1.31		2.30
	A				-4.81		-7.02		-9.26		-6.96
	B				-5.29		1.77		-0.83		-4.08
	C				-1.55		-0.77		-1.61		-0.12
	D				N/P		N/P		N/P		-8.63
	F1				1.26		1.24		1.55		1.87
	F2				-0.08		1.71		-0.96		1.50
	F3				-0.20		-0.06		-0.41		-0.46
	F4				2.80		5.13		1.82		2.61
	n				-2.04		-4.64		-1.99		-1.79
	c				1.07		-0.02		2.83		2.83
	s				2.70		0.83		2.91		1.00
RURAL	ALL				1.36		1.54		-3.46		-3.58
	A+				2.76		3.11		2.53		1.27
	A				-6.34		-5.37		-8.75		-4.89
	B				5.27		12.94		21.72		-4.75
	C				5.51		3.33		6.70		3.12
	D				N/P		N/P		N/P		N/P
	F1				1.04		2.79		0.55		2.43
	F2				-1.56		1.08		-1.50		1.07
	F3				1.34		1.36		3.62		-0.10
	F4				2.60		2.23		-2.34		-3.64
	n				-4.17		-1.93		-3.32		-3.29
	c				4.03		3.70		5.09		-0.28
	s				2.17		0.68		2.93		-2.65

Table 5.5, continued

CASE	C	M	G	Segment Data base				County/City Average Data base			
	T	F	R	Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
	Y	U	E								
	ALL			0.32		3.39		-1.94		0.11	
	A+			N/P		2.21		-0.96		-27.05	
	A			N/P		-5.59		N/P		-7.27	
	B			4.80		6.05		8.63		10.48	
	C			-4.38		-1.99		-1.79		-0.66	
	D			3.24		2.08		-3.45		-2.07	
	F1			-2.30		-2.10		N/P		N/P	
	F2			0.46		0.98		0.18		-0.07	
	F3			-0.85		4.94		4.71		9.20	
	F4			3.42		6.26		1.81		2.69	
URBAN	n			-3.95		-5.98		-3.30		-3.00	
	c			-0.42		-2.35		3.82		1.71	
	s			3.70		5.33		3.89		5.89	

Note: N/P=Not Possible

Table 5.6: Marginal Improvement in Maximum R^2 value of
Density Format over Raw Format for Interstate Highways

CASE	C T Y G R	M F U N C	G R E I O N	Segment Data base				County/City Average Data base			
				Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
RURAL + URBAN	ALL			9.88	10.95			-2.87	-2.14		
	A+			23.26	27.67			-7.12	-6.13		
	A			10.49	8.28			2.76	5.06		
	B			1.01	8.07			-11.02	-14.27		
	C			1.56	2.34			-4.29	-2.80		
	D			0.07	N/P			8.42	N/P		
	F1			6.19	6.17			10.55	10.87		
	F2			-1.72	0.07			-3.83	-1.37		
	F3			-0.02	0.12			0.04	-0.01		
	F4			16.90	19.23			-4.21	-3.42		
	n			-0.70	-3.30			1.67	1.87		
	c			1.28	0.19			0.39	0.39		
	s			-5.74	-7.61			-5.10	-7.01		
RURAL	ALL			-1.05	-0.87			-0.41	-0.53		
	A+			-4.74	-4.39			-14.17	-15.43		
	A			-4.13	-3.16			-4.52	-0.66		
	B			14.01	21.68			39.82	13.35		
	C			-9.47	-11.65			16.63	13.05		
	D			0.00	N/P			6.70	N/P		
	F1			5.74	7.49			11.16	13.04		
	F2			-2.17	0.47			-4.57	-2.00		
	F3			-0.02	0.00			3.66	-0.06		
	F4			0.43	0.06			1.25	-0.05		
	n			-2.24	0.00			-0.04	-0.01		
	c			0.06	-0.27			0.37	-5.00		
	s			6.37	4.88			13.35	7.77		

Table 5.6, continued

CASE	C T Y GR	M F U NC	G R E GION	Segment Data base				County/City Average Data base			
				Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
URBAN	ALL					19.53	22.60			-4.82	-2.77
	A+					N/P	N/P			30.93	4.84
	A					7.17	N/P			-0.20	N/P
	B					-0.48	0.77			-0.57	1.28
	C					-1.31	1.08			-6.55	-5.42
	D					23.04	21.88			26.01	27.39
	F1					-0.21	-0.01			1.71	N/P
	F2					0.32	0.84			-1.33	-1.58
	F3					1.45	7.24			-0.03	4.46
	F4					32.60	35.44			-6.17	-5.29
	n					8.04	6.01			1.60	1.90
	c					5.03	3.10			2.29	0.18
	s					-4.18	-2.55			-4.29	-2.29

Note: N/P=Not Possible

2. Does the Earlier and Later (E&L) year data format improve the results significantly? (Table 5.5)
3. Is the density data format better than the raw format? (Table 5.6)

The results of Table 5.4 and the other related statistics of Appendix Tables C1 to C4 do not show any significant change in the quality of the results except the AIC values, which are more directly related to the number of observations (see equation 5.7). Tables C2 and C4 show that AIC values for the "Earlier & Later" format are much lower than the AIC values of the non-E&L format. Thus statistics like AIC will be more appropriate to compare the different models under a data format that keeps their observations the same. For "GREGION c" of rural highways under the county/city average data base, there is a 5.09 percent increase in R^2 value for the "raw E&L" format (see Table 5.4). The associated statistics from Tables C1 and C2 for this case of "raw" and "raw E&L" formats are as follows:

Format	R^2	R_a^2	PC	AIC	C_p	No of Variables
Raw	51.12	49.19	0.5402(*)	1411.9	10.01	3
Raw E&L	56.21(*)	51.16(*)	0.5726	528.1(*)	3.83(*)	3

(*) = the better values.

Despite this small improvement of "raw E&L" format over "raw" format, the "raw E&L" format will not be considered because of the simplicity of "raw" format when compared with the "raw E&L" format. Similar arguments could be made from the results of Tables C1 to C4 and Tables 5.5 and 5.6 to justify the raw data format over the others.

By considering the results of Table 5.1 and Table C.1, the interstate highways will be further analyzed with the "raw" format of the

county/city average data base. The analysis will be carried out by Phase 1 (rural interstate, urban interstate and their combined form) and by Phase 2 with GREGION.

5.5.2 Urban Principal Arterial

The analysis for urban principal arterials follows Figure 5.2 (see Section 5.4.2). Table 5.7 presents the maximum R^2 value, in percent, corresponding to the layout of Figure 5.2. The results of county/city average data base are obtained from Appendix Tables C.5 to C.8. The number of variables for each value of R^2 in Table 5.7 is shown in Table 5.8. In most of the cases, the number of variables entered in equations for each combination under the different data formats of the segment and county/city average data bases are almost equal. Thus the number of variables do not pose a problem in comparing different data bases. Table 5.7 shows a clear margin of improvement for county/city average data base over its counterpart -- the segment data base. One reason behind this improvement is the elimination of variation in AADT within the sections of urban principal arterials in a city or county for county/city average data base.

Tables 5.9, 5.10, 5.11 and 5.12 result from Table 5.7 and show the extent of improvement in maximum R^2 value for

1. County/city average data bases over segment data bases (Table 5.9),
2. Raw E&L, density and density E&L formats over raw format (Table 5.10),
3. Earlier and Later (E&L) formats over non-E&L formats (Table 5.11), and

Table 5.7: Maximum R^2 value for Urban Principal Arterial

C T Y GR	M F U NC	G R E GN	Segment Data base				County/City Average Data base			
			Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
ALL			14.39	16.57	14.33	16.55	37.11	39.15	34.98	35.79
A			6.11	7.46	7.08	8.04	34.48	42.85	33.43	41.09
B			18.28	24.60	23.96	29.24	36.84	50.75	50.50	60.49
C			19.23	19.31	15.99	14.76	49.89	46.73	40.63	36.27
D			10.54	10.67	10.01	9.96	39.67	41.25	35.70	38.83
A	F3		17.26	21.58	17.26	21.15	70.37	88.76	70.37	85.91
A	F4		8.95	11.13	4.46	3.76	53.67	70.31	24.40	26.59
B	F3		X	0.03	0.06	0.03	(**)	(**)	(**)	(**)
B	F4		18.75	25.20	26.30	31.52	35.31	48.92	57.85	66.35
C	F2		4.83	4.20	4.72	4.55	45.79	51.32	48.75	51.73
C	F3		30.59	36.60	22.44	28.99	81.14	85.27	59.71	67.31
C	F4		42.25	41.00	40.03	39.72	66.27	56.07	64.64	56.80
D	F1		3.16	X	3.16	2.39	9.06	X	9.06	X
D	F2		28.52	29.37	12.58	20.07	86.29	92.36	42.12	57.08
D	F3		31.45	31.92	21.72	21.81	89.71	95.34	61.96	66.20
D	F4		45.24	45.32	41.26	44.53	68.01	66.01	62.08	60.53
A		n	9.40	11.76	4.57	4.04	53.03	X	26.20	36.00
A		c	16.66	20.40	14.50	20.43	82.30	96.38	71.31	97.83
A		s	1.26	1.13	1.26	1.13	89.09	(**)	89.11	(**)
B		n	7.63	8.44	9.03	8.87	83.95	88.73	92.90	99.34
B		c	41.93	45.16	42.18	45.55	95.30	99.43	95.85	99.99
B		s	41.07	42.68	41.60	42.68	99.30	(**)	99.30	(**)
C		n	23.00	21.97	21.12	18.35	40.16	20.53	36.66	24.04
C		c	24.24	27.21	18.39	17.83	62.04	69.85	49.24	48.05
C		s	11.82	6.34	11.90	6.34	81.68	(**)	82.25	(**)
D		n	18.11	19.81	29.27	32.52	49.28	50.37	66.90	70.10
D		c	15.20	17.90	7.23	6.64	65.50	79.61	20.53	22.92
D		s	12.58	14.50	12.51	14.33	45.20	51.38	42.99	50.48

Note: X=Not Available; (**) = N<5

Table 5.8: Number of Variables for Maximum R^2 value
for Urban Principal Arterial

C T Y GR	M F U NC	G R E GN	Segment Data base				County/City Average Data base			
			Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
ALL			4	4	4	4	4	4	4	3
A			2	2	3	3	3	3	3	3
B			2	2	3	3	2	2	3	3
C			3	3	3	2	3	3	2	2
D			3	3	3	2	4	3	3	2
A	F3		1	2	1	1	1	2	1	1
A	F4		2	2	3	3	3	3	3	3
B	F3		X	1	1	1	(**)	(**)	(**)	(**)
B	F4		2	2	3	3	2	2	3	3
C	F2		2	2	2	2	2	2	3	2
C	F3		4	3	4	4	4	3	4	4
C	F4		2	2	2	2	2	2	2	2
D	F1		1	X	1	1	1	X	1	X
D	F2		3	2	2	3	3	3	3	3
D	F3		3	3	2	3	3	3	2	2
D	F4		3	3	3	3	3	3	3	2
A		n	2	2	2	2	3	X	2	2
A		c	2	2	2	3	2	2	2	3
A		s	1	1	1	1	1	(**)	1	(**)
B		n	2	2	4	3	3	2	4	3
B		c	2	2	2	3	2	2	2	3
B		s	2	1	2	1	2	(**)	2	(**)
C		n	2	2	2	2	2	2	2	2
C		c	2	2	3	2	3	3	2	3
C		s	2	1	2	1	2	(**)	2	(**)
D		n	2	2	4	3	3	2	4	3
D		c	3	3	3	2	3	4	2	2
D		s	3	2	2	2	3	2	2	1

Note: X=Not Available; (**)=N<5

Table 5.9: Marginal Improvement in Maximum R^2 value of
County/City Average AADT over Segment AADT for
Urban Principal Arterial

C T Y GR	M F U NC	G R E GN	Segment Data base				County/City Average Data base			
			Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
ALL							22.72	22.58	20.65	19.24
A							28.37	35.39	26.35	33.05
B							18.56	26.15	26.54	31.25
C							30.66	27.42	24.64	21.51
D							29.13	30.58	25.69	28.87
A	F3						53.11	67.18	53.11	64.76
A	F4						44.72	59.18	19.94	22.83
B	F3						N/P	N/P	N/P	N/P
B	F4						16.56	23.72	31.55	34.83
C	F2						40.96	47.12	44.03	47.18
C	F3						50.55	48.67	37.27	38.32
C	F4						24.02	15.07	24.61	17.08
D	F1						5.90	N/P	5.90	N/P
D	F2						57.77	62.99	29.54	37.01
D	F3						58.26	63.42	40.24	44.39
D	F4						22.77	20.69	20.82	16.00
A		n					43.63	N/P	21.63	31.96
A		c					65.64	75.98	56.81	77.40
A		s					87.83	N/P	87.85	N/P
B		n					76.32	80.29	83.87	90.47
B		c					53.37	54.27	53.67	54.44
B		s					58.23	N/P	57.70	N/P
C		n					17.16	-1.44	15.54	5.69
C		c					37.80	42.64	30.85	30.22
C		s					69.86	N/P	70.35	N/P
D		n					31.17	30.56	37.63	37.58
D		c					50.30	61.71	13.30	16.28
D		s					32.62	36.88	30.48	36.15

Note: N/P=Not Possible

Table 5.10: Marginal Improvement in Maximum R^2 value of Raw E&L, Density and Density E&L Formats over Raw Format for Urban Principal Arterial

C T Y GR	M F U NC	G R E GN	Segment Data base				County/City Average Data base			
			Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
ALL				10.46	8.22	10.44		2.04	-2.13	-1.32
A				1.35	0.97	1.93		8.37	-1.05	6.61
B				6.32	5.68	10.96		13.91	13.66	23.65
C				0.08	-3.24	-4.47		-3.16	-9.26	-13.62
D				0.13	-0.53	-0.58		1.58	-3.97	-0.84
A	F3			4.32	0.00	3.89		18.39	0.00	15.54
A	F4			2.18	-4.49	-5.19		16.64	-29.27	-27.08
B	F3			N/P	N/P	N/P		N/P	N/P	N/P
B	F4			6.45	7.55	12.77		13.61	22.54	31.04
C	F2			-0.63	-0.11	-0.28		5.53	2.96	5.94
C	F3			6.01	-8.15	-1.60		4.13	-21.43	-13.83
C	F4			-1.25	-2.22	-2.53		-10.20	-1.63	-9.47
D	F1			N/P	0.00	-0.77		N/P	0.00	N/P
D	F2			0.85	-15.94	-8.45		6.07	-44.17	-29.21
D	F3			0.47	-9.73	-9.64		5.63	-27.75	-23.51
D	F4			0.08	-3.98	-0.71		-2.00	-5.93	-7.48
A		n		2.36	-4.83	-5.36		N/P	-26.83	-17.03
A		c		3.74	-2.16	3.77		14.08	-10.99	15.53
A		s		-0.13	0.00	-0.13		N/P	0.02	N/P
B		n		0.81	1.40	1.24		4.78	8.95	15.39
B		c		3.23	0.25	3.62		4.13	0.55	4.69
B		s		1.61	0.53	1.61		N/P	0.00	N/P
C		n		-1.03	-1.88	-4.65		-19.63	-3.50	-16.12
C		c		2.97	-5.85	-6.41		7.81	-12.80	-13.99
C		s		-5.48	0.08	-5.48		N/P	0.57	N/P
D		n		1.70	11.16	14.41		1.09	17.62	20.82
D		c		2.70	-7.97	-8.56		14.11	-44.97	-42.58
D		s		1.92	-0.07	1.75		6.18	-2.21	5.28

Note: N/P=Not Possible

Table 5.11: Marginal Improvement in Maximum R^2 value of Earlier
& Later (E&L) Year Data Format for Urban Principal Arterial

C T Y GR	M F U NC	G R E GN	Segment Data base				County/City Average Data base			
			Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
ALL			2.18		2.22		2.04		0.81	
A			1.35		0.96		8.37		7.66	
B			6.32		5.28		13.91		9.99	
C			0.08		-1.23		-3.16		-4.36	
D			0.13		-0.05		1.58		3.13	
A F3			4.32		3.89		18.39		15.54	
A F4			2.18		-0.70		16.64		2.19	
B F3			N/P		-0.03		N/P		N/P	
B F4			6.45		5.22		13.61		8.50	
C F2			-0.63		-0.17		5.53		2.98	
C F3			6.01		6.55		4.13		7.60	
C F4			-1.25		-0.31		-10.20		-7.84	
D F1			N/P		-0.77		N/P		N/P	
D F2			0.85		7.49		6.07		14.96	
D F3			0.47		0.09		5.63		4.24	
D F4			0.08		3.27		-2.00		-1.55	
A n			2.36		-0.53		N/P		9.80	
A c			3.74		5.93		14.08		26.52	
A s			-0.13		-0.13		N/P		N/P	
B n			0.81		-0.16		4.78		6.44	
B c			3.23		3.37		4.13		4.14	
B s			1.61		1.08		N/P		N/P	
C n			-1.03		-2.77		-19.63		-12.62	
C c			2.97		-0.56		7.81		-1.19	
C s			-5.48		-5.56		N/P		N/P	
D n			1.70		3.25		1.09		3.20	
D c			2.70		-0.59		14.11		2.39	
D s			1.92		1.82		6.18		7.49	

Note: N/P=Not Possible

Table 5.12: Marginal Improvement in Maximum R^2 value of Density
Format over Raw Format for Urban Principal Arterial

C T Y GR	M F U NC	G R E GN	Segment Data base				County/City Average Data base			
			Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
ALL					-0.06	-0.02			-2.13	-3.36
A					0.97	0.58			-1.05	-1.76
B					5.68	4.64			13.66	9.74
C					-3.24	-4.55			-9.26	-10.46
D					-0.53	-0.71			-3.97	-2.42
A	F3				0.00	-0.43			0.00	-2.85
A	F4				-4.49	-7.37			-29.27	-43.72
B	F3				N/P	0.00			N/P	N/P
B	F4				7.55	6.32			22.54	17.43
C	F2				-0.11	0.35			2.96	0.41
C	F3				-8.15	-7.61			-21.43	-17.96
C	F4				-2.22	-1.28			-1.63	0.73
D	F1				0.00	N/P			0.00	N/P
D	F2				-15.94	-9.30			-44.17	-35.28
D	F3				-9.73	-10.11			-27.75	-29.14
D	F4				-3.98	-0.79			-5.93	-5.48
A		n			-4.83	-7.72			-26.83	N/P
A		c			-2.16	0.03			-10.99	1.45
A		s			0.00	0.00			0.02	N/P
B		n			1.40	0.43			8.95	10.61
B		c			0.25	0.39			0.55	0.56
B		s			0.53	0.00			.000	N/P
C		n			-1.88	-3.62			-3.50	3.51
C		c			-5.85	-9.38			-12.80	-21.80
C		s			0.08	0.00			0.57	N/P
D		n			11.16	12.71			17.62	19.73
D		c			-7.97	-11.26			-44.97	-56.69
D		s			-0.07	-0.17			-2.21	-0.90

Note: N/P=Not Possible

4. Density formats over raw formats (Table 5.12).

Table 5.10 does not show any significant improvement of raw E&L, density and density E&L formats over raw format. For example, the different statistics for "CTYGR D" and "GREGION C" of raw E&L format over raw format with a 14.11 percent increase in R^2 , for county/city average data base are:

Format	R^2	R_a^2	PC	AIC	C_p	No of Variables
Raw	65.50	60.79	0.4705(*)	362.7	2.15(*)	3
Raw E&L	79.61(*)	67.96(*)	0.4951	164.4(*)	N/A	4

(*) = the better values, N/A = Not Available.

In spite of a 14.11 percent increase of R^2 for the "raw E&L" format, there is only a 7.17 percent increase in R_a^2 , which is R^2 with adjustment for the number of variables in the model equation. It has been mentioned in Section 5.5.1 that AIC is suitable for comparing models that use the same data sets and equal observations. Therefore, AIC values will not be considered in the above tables, because of the unequal numbers of observations in the two different data sets (see Table 4.5). The value of PC supports the raw format over the raw E&L format. The data structure of the raw format is also much simpler than that of raw E&L format. A similar argument can be made from Tables 5.11 and 5.12 to establish the superiority of the raw format over its counterparts — raw E&L, density and density E&L formats.

The following points are derived from careful examination of the values in Table 5.7 and its parent Table C5:

1. No significant change in R^2 value at Phase 2 (analysis by CTYGR) versus Phase 1 ("all" case). The definitions of Phase 1, 2 and 3 analysis are provided in Figure 5.2.
2. The data structure of Phase 3 analysis by the CTYGR and MFUNC combination is incomplete. For example, CTYGR "A" and MFUNC "F1" combination are absent in the data sets.
3. At Phase 3, the results for CTYGR & GREGION combination have improved in CTYGR A and B than those for CTYGR & MFUNC combination.
4. Some of the C_p values are not available at Phase 3 for the CTYGR-GREGION combination, because of error variances too small to compute C_p .
5. The R^2 values at Phase 3 for the CTYGR-GREGION combination ranges 53-89, 83-99, 40-82 and 49-66 percent for CTYGR A, B, C and D, respectively.
6. The PC values at Phase 3 with CTYGR-GREGION combination ranges 0.25-0.66, 0.03-0.30, 0.45-0.73 and 0.47-0.66 for CTYGR A, B, C and D, respectively. The PC values at Phase 2 by CTYGR are 0.79, 0.77, 0.53 and 0.67 for CTYGR A, B, C and D, respectively.

As for R^2 and PC values, the improvement in RMSE and AIC is noticed at the Phase 3 analysis with the CTYGR-GREGION combination, when compared to the Phase 2 analysis. Thus, further analyses for urban principal arterials will be carried out with the raw format of county/city average data base at Phase 3 with the CTYGR-GREGION combination.

5.5.3 Urban Minor Arterial and Collector

The layout of analysis for urban minor arterials and collectors was kept the same as for urban principal arterials (see Figure 5.2). The maximum R^2 values for urban minor arterials and collectors are shown in Table 5.13. The corresponding numbers of variables in the equations are presented in Table 5.14. The parent tables of Table 5.13 are Appendix Tables C9 to C12. Table 5.13 shows the improvement in R^2 value with county/city average data bases over segment data bases. The data structure for Phase 3 analysis in both of the CTYGR-MFUNC and CTYGR-GREGION combinations is incomplete. Many cells in Phase 3 also have few (for example, fewer than five) observations in Earlier and Later (E&L) data format (see Table 4.4). As with urban principal arterial and interstate highway, Tables 5.15, 5.16, 5.17 and 5.18 are constructed from Table 5.13 to show the marginal improvement in the maximum R^2 value for

1. County/city average data bases over segment data bases (Table 5.15),
2. Raw E&L, density and density E&L formats over raw format (Table 5.16),
3. Earlier and Later (E&L) formats over non-E&L formats (Table 5.17), and
4. Density formats over raw formats (Table 5.18).

Despite the gaps in the data structure, Table 5.16 shows the superiority of county/city average data bases over its counterpart, the segment data bases. As for interstate highways and urban principal arterials, Table 5.16 does not show any consistent or significant gain for the raw E&L, density and density E&L formats over raw format. For example, the CTYGR A at Phase 2 analysis shows a 17.54 percent

Table 5.13: Maximum R^2 value for Urban Minor Arterial & Collector

C T Y GR	M F U NC	G R E GN	Segment Data base				County/City Average Data base			
			Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
ALL			14.14	18.36	11.24	14.34	33.83	40.75	21.33	25.24
A			30.47	40.67	36.96	41.23	65.94	83.48	78.29	87.35
B			36.13	42.96	36.06	44.04	69.50	78.06	72.55	83.12
C			7.06	10.69	10.07	9.99	9.40	12.56	9.30	11.52
D			11.18	X	8.58	5.58	21.40	17.11	15.69	9.78
A	F3		16.42	36.44	44.93	50.92	27.90	(**)	88.49	(**)
A	F4		3.98	6.57	6.78	6.57	42.74	(**)	75.39	(**)
B	F4		36.13	42.96	36.06	44.04	69.50	78.06	72.55	83.12
C	F2		16.27	33.36	16.05	33.37	17.45	46.10	17.16	41.59
C	F3		0.23	0.09	0.23	0.10	16.34	(**)	16.35	(**)
C	F4		46.62	47.59	46.64	47.30	83.63	84.17	81.09	83.59
D	F1		X	43.60	47.77	43.60	X	X	50.18	42.94
D	F2		85.99	91.84	72.00	91.84	96.78	(**)	84.78	(**)
D	F3		21.53	22.20	21.53	22.20	81.71	(**)	81.68	(**)
D	F4		98.30	(**)	98.62	(**)	98.40	(**)	98.62	(**)
A		n	3.98	6.57	6.78	6.57	42.74	(**)	75.39	(**)
A		c	14.42	(**)	14.65	(**)	51.65	(**)	51.03	(**)
A		s	27.17	25.36	27.17	25.36	79.65	(**)	79.66	(**)
B		n	X	X	50.84	56.26	33.89	(**)	89.72	(**)
B		c	0.35	0.42	0.35	0.42	20.99	(**)	21.03	(**)
B		s								
C		n	24.58	28.80	29.12	31.82	78.69	85.97	93.25	94.97
C		c	X	26.99	10.25	26.96	X	35.48	14.25	35.44
C		s	79.88	(**)	79.76	(**)	99.40	(**)	99.26	(**)
D		n	9.67	14.90	14.79	14.90	35.88	35.81	54.92	55.14
D		c	X	26.19	25.62	26.19	88.06	(**)	88.06	(**)
D		s	9.11	7.19	9.82	7.19	18.97	19.06	20.52	20.11

Note: X=Not Available; (**) = N<5

Table 5.14: Number of Variables for Maximum R^2 value for
Urban & Minor Arterial Collector

C T Y GR	M F U NC	G R E GN	Segment Data base				County/City Average Data base			
			Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
ALL			4	3	2	2	4	3	3	2
A			2	2	2	2	2	2	2	2
B			2	2	2	2	2	2	2	2
C			1	1	2	1	1	1	1	1
D			2	X	1	1	3	2	2	1
A	F3		1	1	2	2	1	(**)	2	(**)
A	F4		2	2	2	2	2	(**)	2	(**)
B	F4		2	2	2	2	2	2	2	2
C	F2		1	1	1	1	1	1	1	1
C	F3		1	1	1	1	1	(**)	1	(**)
C	F4		3	2	3	2	3	2	2	2
D	F1		X	2	2	2	X	X	2	2
D	F2		2	2	1	2	2	(**)	1	(**)
D	F3		2	1	2	1	2	(**)	2	(**)
D	F4		2	(**)	3	(**)	3	(**)	3	(**)
A		n	2	2	1	1	2	(**)	2	(**)
A		c	1	(**)	1	(**)	1	(**)	1	(**)
A		s	1	1	1	1	1	(**)	1	(**)
B		n	X	X	2	2	1	(**)	2	(**)
B		c	1	1	1	1	1	(**)	1	(**)
B		s								
C		n	2	1	3	2	2	1	3	2
C		c	X	1	1	1	X	1	1	1
C		s	2	(**)	2	(**)	2	(**)	2	(**)
D		n	1	2	2	2	2	2	2	2
D		c	X	1	2	1	1	(**)	1	(**)
D		s	1	1	2	1	1	1	2	2

Note: X=Not Available; (**) = N<5

Table 5.15: Marginal Improvement in Maximum R^2 value of
County/City Average AADT over Segment AADT for
Urban Minor Arterial & Collector

C T Y GR	M F U NC	G R E GN	Segment Data base				County/City Average Data base			
			Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
ALL							19.69	22.39	10.09	10.90
A							35.47	42.81	41.33	46.12
B							33.37	35.10	36.49	39.08
C							2.34	1.87	-0.77	1.53
D							10.22	N/P	7.11	4.20
A	F3						11.48	N/P	43.56	N/P
A	F4						38.76	N/P	68.61	N/P
B	F4						33.37	35.10	36.49	39.08
C	F2						1.18	12.74	1.11	8.22
C	F3						16.11	N/P	16.12	N/P
C	F4						37.01	36.58	34.45	36.29
D	F1						N/P	N/P	2.41	-0.66
D	F2						10.79	N/P	12.78	N/P
D	F3						60.18	N/P	60.15	N/P
D	F4						0.10	N/P	0.00	N/P
A		n					38.76	N/P	68.61	N/P
A		c					37.23	N/P	36.38	N/P
A		s					52.48	N/P	52.49	N/P
B		n					N/P	N/P	38.88	N/P
B		c					20.64	N/P	20.68	N/P
B		s								
C		n					54.11	57.17	64.13	63.15
C		c					N/P	8.49	4.00	8.48
C		s					19.52	N/P	19.50	N/P
D		n					26.21	20.91	40.13	40.24
D		c					N/P	N/P	62.44	N/P
D		s					9.86	11.87	10.70	12.92

Note: N/P=Not Possible

Table 5.16: Marginal Improvement in Maximum R^2 value of Raw E&L, Density and Density E&L Formats over Raw Format for Urban Minor Arterial & Collector

C T Y GR	M F U NC	G R E GN	Segment Data base				County/City Average Data base			
			Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
ALL			-12.11	-19.23	-16.13		6.92	-12.50	-8.59	
A			10.20	6.49	10.76		17.54	12.35	21.41	
B			6.83	-0.07	7.91		8.56	3.05	13.62	
C			3.63	3.01	2.93		3.16	-0.10	2.12	
D			N/P	-2.60	-5.60		-4.29	-5.71	-11.62	
A	F3		20.02	28.51	34.50		N/P	60.59	N/P	
A	F4		2.59	2.80	2.59		N/P	32.65	N/P	
B	F4		6.83	-0.07	7.91		8.56	3.05	13.62	
C	F2		17.09	-0.22	17.10		28.65	-0.29	24.14	
C	F3		-0.14	0.00	-0.13		N/P	0.01	N/P	
C	F4		0.97	0.02	0.68		0.54	-2.54	-0.04	
D	F1		N/P	N/P	N/P		N/P	N/P	N/P	
D	F2		5.85	-13.99	5.85		N/P	-12.00	N/P	
D	F3		0.67	0.00	0.67		N/P	-0.03	N/P	
D	F4		N/P	0.32	N/P		N/P	0.22	N/P	
A		n	2.59	2.80	2.59		N/P	32.65	N/P	
A		c	N/P	0.23	N/P		N/P	-0.62	N/P	
A		s	-1.81	0.00	-1.81		N/P	0.01	N/P	
B		n	N/P	N/P	N/P		N/P	55.83	N/P	
B		c	0.07	0.00	0.07		N/P	0.04	N/P	
B		s								
C		n	4.22	4.54	7.24		7.28	14.56	16.28	
C		c	N/P	N/P	N/P		35.48	14.25	35.44	
C		s	N/P	-0.12	N/P		N/P	-0.14	N/P	
D		n	5.23	5.12	5.23		-0.07	19.04	19.26	
D		c	N/P	N/P	N/P		N/P	0.00	N/P	
D		s	-1.92	0.71	-1.92		0.09	1.55	1.14	

Note: N/P=Not Possible

Table 5.17: Marginal Improvement in Maximum R^2 value of Earlier & Later (E&L) Year Data Format for Urban Minor Arterial & Collector

C T Y GR	M F U NC	G R E GN	Segment Data base				County/City Average Data base			
			Raw	Raw	Density	Density	Raw	Raw	Density	Density
				E&L		E&L		E&L		E&L
ALL			4.22		3.10		6.92		3.91	
A			10.20		4.27		17.54		9.06	
B			6.83		7.98		8.56		10.57	
C			3.63		-0.08		3.16		2.22	
D			N/P		-3.00		-4.29		-5.91	
A	F3		20.02		5.99		N/P		N/P	
A	F4		2.59		-0.21		N/P		N/P	
B	F4		6.83		7.98		8.56		10.57	
C	F2		17.09		17.32		28.65		24.43	
C	F3		-0.14		-0.13		N/P		N/P	
C	F4		0.97		0.66		0.54		2.50	
D	F1		N/P		-4.17		N/P		-7.24	
D	F2		5.85		19.84		N/P		N/P	
D	F3		0.67		0.67		N/P		N/P	
D	F4		N/P		N/P		N/P		N/P	
A		n	2.59		-0.21		N/P		N/P	
A		c	N/P		N/P		N/P		N/P	
A		s	-1.81		-1.81		N/P		N/P	
B		n	N/P		5.42		N/P		N/P	
B		c	0.07		0.07		N/P		N/P	
B		s								
C		n	4.22		2.70		7.28		1.72	
C		c	N/P		16.71		N/P		21.19	
C		s	N/P		N/P		N/P		N/P	
D		n	5.23		0.11		-0.07		0.22	
D		c	N/P		0.57		N/P		N/P	
D		s	-1.92		-2.63		0.09		-0.41	

Note: N/P=Not Possible

Table 5.18: Marginal Improvement in Maximum R^2 value of Density
Format over Raw Format for Urban Minor Arterial & Collector

C T Y GR	M F U NC	G R E GN	Segment Data base				County/City Average Data base			
			Raw	Raw E&L	Density	Density E&L	Raw	Raw E&L	Density	Density E&L
ALL					-2.90	-4.02			-12.50	-15.51
A					6.49	0.56			12.35	3.87
B					-0.07	1.08			3.05	5.06
C					3.01	-0.70			-0.10	-1.04
D					-2.60	N/P			-5.71	-7.33
A	F3				28.51	14.48			60.59	N/P
A	F4				2.80	0.00			32.65	N/P
B	F4				-0.07	1.08			3.05	5.06
C	F2				-0.22	0.01			-0.29	-4.51
C	F3				0.00	0.01			0.01	N/P
C	F4				0.02	-0.29			-2.54	-0.58
D	F1				N/P	0.00			N/P	N/P
D	F2				-13.99	0.00			-12.00	N/P
D	F3				0.00	0.00			-0.03	N/P
D	F4				0.32	N/P			0.22	N/P
A		n			2.80	0.00			32.65	N/P
A		c			0.23	N/P			-0.62	N/P
A		s			0.00	0.00			0.01	N/P
B		n			N/P	N/P			55.83	N/P
B		c			0.00	0.00			0.04	N/P
B		s								
C		n			4.54	3.02			14.56	9.00
C		c			10.25	-0.03			14.25	-0.04
C		s			-0.12	N/P			-0.14	N/P
D		n			5.12	0.00			19.04	19.33
D		c			25.62	0.00			0.00	N/P
D		s			0.71	0.00			1.55	1.05

Note: N/P=Not Possible

increase in R^2 value for raw E&L format over raw format for county/city average data base. The statistics for this case are (see Tables C9 and C10):

Format	R^2	R_a^2	PC	AIC	C_p	No of Variables
Raw	65.94	61.39	0.4769	280.6	62.54(*)	2
Raw E&L	83.48(*)	76.87(*)	0.3638(*)	121.9(*)	N/A	2

(*) = the better values, N/A = Not Available.

In spite of the minor improvement in some of these statistics for the E&L format over the raw format; one will prefer raw format because of its simplicity in data structure. The "raw" data is simple, that is only averaged values over county/city for each highway class. But additional work is involved to build the "raw E&L" data structure (See Chapter 4). Usually, the improvement in R^2 value is not enough (see Table 5.16). The rest of this section's discussion will be concerned with the raw format of the county/city average data base.

Because of incompleteness of data structure and the fewer observations at Phase 3, the quality of Phase 3 analysis will not be judged against phase 2 or 1. But the results of Phase 3 will be used to identify the way to improve the Phase 2 results. The Phase 2 results show the clear margin of improvement for CTYGR A and B by comparing results with Phase 1 ("all" case). The rest of the analysis for urban minor arterials and collectors for CTYGR A and B will be done at the Phase 2 level. For CTYGR C, the value of R^2 is only 9.40 percent (see Table 5.13), with PC of 1.0355 (A PC value greater than unity suggests a poor result). Some statistics for possible R^2 cases after phase 3 analysis with both MFUNC and GREGION are (from Table C5):

MFUNC	GREGION	R^2	R_a^2	PC	No of Variables	No of Observations
F2		17.45	10.57	1.1007	1	14
F3		16.34	11.55	1.9521	1	5
F4(*)		83.63	76.62	0.3507	3	11
	c	N/A	N/A	N/A	N/A	12
	n(*)	78.69	74.43	0.3409	2	13
	s(*)	99.40	98.80	0.0239	2	5

(*) = the case shows better statistical results, N/A = Not Available.

The results for the combination MFUNC "F2", "F3" and GREGION "c" are not promising. For example, MFUNC "F2" and "F3" have PC values more than unity — unacceptable PC values — and low R^2 values. Regression analysis with the RSQUARE procedure of SAS [SAS/Statistics 1985] was performed on the modified data set of "CTYGR C" — deleting the GREGION "c" observations and then combining the rest of the observations at phase 3. The analysis on this modified data set shows only one variable in the equation without inconsistency in the regression coefficients. The maximum R^2 values for this one-variable case are as follows:

$$\bullet R^2 = 0.2692, R_a^2 = 0.2235, \text{RMSE} = 2269,$$

$$\bullet \text{PC} = 0.9136, \text{AIC} = 281.6 \text{ and } C_p = 11.03.$$

These statistics show the significant change in R^2 value for analysis of GREGION "n" and "s" separately. The GREGION "s" has few observations in the current data set. Considering all these facts, the rest of the analysis of "CTYGR C" will be followed with the following groups of raw format of county/city average data base:

● MFUNC = F4

● GREGION = n

Later, the deleted observations could be used to evaluate the performance of the final model(s).

The value 21.40 percent for R^2 and PC equal to 0.9025 for CTYGR D at Phase 2 are not good enough to pursue the rest of its analysis. The maximum R^2 values for CTYGR "D" at the Phase 3 analysis with MFUNC and GREGION are (from Table C5):

MFUNC	GREGION	R^2	R_a^2	PC	No of Variable	No of Observation
F1		N/A	N/A	N/A	N/A	30
F2		96.78	95.70	0.0645	2	9
F3		81.71	76.49	0.3395	2	10
F4		98.40	97.44	0.4160	3	9
	c	88.06	86.06	0.1991	1	8
	n	35.88	26.01	0.9372	2	16
	s	18.97	16.44	0.9115	1	34

This table suggests the following alternatives:

1. Delete MFUNC "F1" observations and experiment with Phase 2 analysis by combining other groups of MFUNC.
2. Delete GREGION "n or s" observations and do Phase 2 analysis by combining "c and s or n" groups of GREGION.

Regression analysis with the RSQUARE procedure is conducted for these cases. The resulting maximum R^2 values without any inconsistency in the regression coefficients are as follows:

Case	Variable in model	R^2	R_a^2	PC	AIC	C_p
MFUNC= F2+F3+F4	CNTYINC	.3998	.3767	.6925	444.1	146.74
	CNTYINC CTYPOP	.5437	.5072	.5658	438.4	107.82
GREGION= c+n	CNTYINC	.5398	.5189	.5439	340.9	-2.34
	CNTYINC STEMP	.5426	.4991	.5881	342.7	-0.35
GREGION= c+s	CNTYINC	.1712	.1505	.9117	681.4	16.94
	CNTYINC STEMP	.1944	.1531	.9295	682.2	17.40

This table shows that "MFUNC=F2+F3+F4" and "GREGION=c+n" will be two good choices to do further analyses for CTYGR D under the raw format of the county/city average data base. The deleted observations may be used to evaluate the performance of the final model(s).

5.6 Candidate Regression Model Selection

Sections 5.5.1 to 5.5.3 have identified the most promising data group and data format for the three classes of highways, primarily to achieve high R^2 values. The "raw" format under the city/county average data base has been chosen in all cases. In this section, candidate models from those identified groups will be selected from a pool of possible candidate models. The possible candidate models will be those models that have good statistics and are free from any inconsistency in regression coefficients. The statistics — R^2 , R_a^2 , PC, RMSE, AIC and C_p — have been used to compare the possible candidate models and narrow down the number of candidate regression models. In addition, the quality of the predictor variables (i.e., availability, cost and reliability) has been considered to identify the candidate regression models. Based on these considerations, the following order of importance (1 = most preferable) of the predictor variables was

determined (See Chapter 4):

1. Employment (county and state level)
2. (a) Population, Vehicle Registration and Income
(county & state level)
(b) State Highway Gasoline consumption
3. Households (county and state level)
4. City population.

The choices will lead to parsimony — a decrease in the number of variables in the equation with a minor loss in statistical quality. In addition, the variables will be judged by whether they are fundamental to the problem. For example, a state-level variable is preferable to a local-level variable for interstate highways and vice versa for local highways. Thus, both statistical results and judgment will be employed to select the candidate regression models.

The final selection of the model variables will be aided by residual analyses. Information gained by these analyses, together with the investigator's knowledge about the phenomenon under study, will be helpful in choosing the final regression model to be employed [Neter et al. 1985].

5.6.1 Interstate Highways

The analysis of Section 5.5.1 determined the following twelve groups, comprising Phase 1 and GREGION combination of Phase 2, to select candidate models from each of these groups for interstate high-

ways:

- i. Interstate Highways (rural and urban)
- ii. Rural Interstate Highways
- iii. Urban Interstate Highways
- iv. Region 'c' of Interstate Highways
- v. Region 'n' of Interstate Highways
- vi. Region 's' of Interstate Highways
- vii. Region 'c' of Rural Interstate Highways
- viii. Region 'n' of Rural Interstate Highways
- ix. Region 's' of Rural Interstate Highways
- x. Region 'c' of Urban Interstate Highways
- xi. Region 'n' of Urban Interstate Highways
- xii. Region 's' of Urban Interstate Highways

These groups are not mutually exclusive. For example, groups (iv) through (vi) are subsets of group (i). But the groups (iv) to (vi) are mutually exclusive. Thus four alternate models are possible from the above twelve groups. For example, the models from groups (i), (ii), (iv) and (vii) are applicable for a rural interstate section in REGION 'c'. Table 5.19 shows all the possible candidate models under each group, without any inconsistency in the sign of regression coefficients. From this table, the following remarks can be drawn about the associated statistics for the models of each group:

- Group i: No significant changes in the statistics among the 13 possible candidate models. UR4 and UR13 are the two best models for the 1 variable and 2 variable equations.

Table 5.19: Possible Candidate Models for Interstate Highways

i. Interstate Highways [DATA = "ALL"]

Model	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
UR1	41.90	41.72	0.5884	14827.2	6014.24	124.25	CNTYEMP	0.12650
UR2	48.94	48.78	0.5172	13900.2	5973.82	71.77	CNTYVR	0.08801
UR3	49.39	49.22	0.5126	13839.2	5971.06	68.43	CNTYHH	0.17075
UR4	50.30	50.14	0.5034	13714.0	5965.38	61.64	CNTYPOP	0.06291
UR5	51.02	50.70	0.4993	13636.0	5962.80	58.25	CNTYHH STMP	0.17067 0.02192
UR6	51.23	50.91	0.4972	13607.0	5961.47	56.70	CNTYHH STINC	0.16966 4.64730
UR7	51.24	50.93	0.4970	13605.2	5961.38	56.61	CNTYHH CNTYINC	0.15836 2.03630
UR8	51.28	50.97	0.4966	13599.3	5961.11	56.29	CNTYPOP STPOP	0.06261 0.02499
UR9	51.38	51.07	0.4956	13585.9	5960.49	55.57	CNTYPOP STVR	0.06231 0.00633
UR10	51.45	51.14	0.4948	13575.4	5960.01	55.02	CNTYPOP STHH	0.06254 0.02041
UR11	52.12	51.81	0.4881	13482.3	5955.70	50.07	CNTYPOP CNTYINC	0.05845 2.01590
UR12	52.27	51.96	0.4866	13461.3	5954.73	48.95	CNTYPOP STINC	0.06259 4.80470
UR13	52.29	51.99	0.4863	13457.5	5954.55	48.75	CNTYPOP STMP	0.06311 0.02423

ii. Rural Interstate Highways [DATA = "RURAL-ALL"]

R1	31.01	30.64	0.7049	7871.8	3339.22	53.45	CNTYINC	3.54721
R2	35.68	34.98	0.6642	7621.3	3328.17	39.50	CNTYINC CTYPOP	2.95107 0.00916
R3	36.28	35.58	0.6581	7586.0	3326.44	37.47	CNTYINC CNTYEMP	3.09435 0.03361
R4	37.49	36.81	0.6456	7513.6	3322.88	33.34	CNTYINC CNTYPOP	3.01986 0.01746
R5	37.63	36.95	0.6441	7505.1	3322.46	32.86	CNTYINC CNTYHH	3.02135 0.04812
R6	37.82	37.14	0.6422	7493.6	3321.89	32.21	CNTYINC CNTYVR	2.94719 0.02519
R7	38.31	37.29	0.6440	7484.6	3322.42	32.54	CNTYINC CNTYVR STINC	2.72424 0.02598 1.28150
R8	38.32	37.31	0.6439	7483.7	3322.38	32.49	CNTYINC CNTYHH STHH	2.92675 0.04831 0.00772
R9	38.48	37.47	0.6422	7474.0	3321.89	31.95	CNTYINC CNTYVR STHH	2.85593 0.02523 0.00754
R10	38.66	37.65	0.6404	7463.3	3321.36	31.34	CNTYINC CNTYPOP STMP	2.77225 0.01825 0.00940
R11	38.73	37.72	0.6396	7459.2	3321.15	31.11	CNTYINC CNTYHH STMP	2.78521 0.04992 0.00909
R12	38.90	37.90	0.6378	7448.4	3320.62	30.51	CNTYINC CNTYVR STMP	2.71129 0.02607 0.00903
R13	39.38	38.38	0.6328	7419.3	3319.16	28.88	CNTYINC CNTYEMP CTYPOP	2.66636 0.02867 0.00760
R14	40.47	39.49	0.6214	7352.3	3315.79	25.16	CNTYINC CNTYPOP CTYPOP	2.60183 0.01527 0.00744
R15	40.49	39.50	0.6213	7351.4	3315.74	25.12	CNTYINC CNTYHH CTYPOP	2.61528 0.04179 0.00730
R16	40.60	39.62	0.6201	7344.5	3315.39	24.73	CNTYINC CNTYVR CTYPOP	2.55744 0.02185 0.00721

Table 5.19, continued

iii. Urban Interstate Highways [DATA = "URBAN-ALL"]

Model	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
U1	43.25	42.80	0.5856	18430.7	2496.71	45.12	CNTYEMP	0.13161
U2	51.20	50.81	0.5036	17091.9	2477.56	21.58	CNTYVR	0.09331
U3	52.28	51.90	0.4924	16900.6	2474.70	18.37	CNTYHH	0.18115
U4	53.38	53.01	0.4811	16704.4	2471.73	15.10	CNTYPOP	0.06708
U5	53.88	53.13	0.4836	16683.0	2472.39	15.65	CNTYHH STMP	0.18069 0.02769
U6	54.07	53.33	0.4815	16647.4	2471.85	15.06	CNTYHH STINC	0.17935 5.77150
U7	54.82	54.09	0.4737	16511.8	2469.77	12.86	CNTYPOP STPOP	0.06628 0.03756
U8	55.13	54.41	0.4704	16453.9	2468.88	11.92	CNTYPOP STHH	0.06613 0.03200
U9	55.25	54.53	0.4691	16432.3	2468.54	11.57	CNTYPOP STVR	0.06577 0.01081
U10	55.37	54.65	0.4679	16411.0	2468.21	11.23	CNTYPOP STINC	0.06651 6.07240
U11	55.57	54.85	0.4658	16373.8	2467.64	10.63	CNTYPOP STMP	0.06728 0.03243

iv. Region 'c' of Interstate Highways [DATA = "ALL & GREGION-c"]

URc1	64.83	64.56	0.3625	9560.0	2421.63	47.15	CNTYPOP	0.04996
URc2	65.41	65.14	0.3566	9481.2	2419.45	44.27	CNTYEMP	0.09792
URc3	65.72	65.45	0.3534	9438.8	2418.27	42.74	CNTYHH	0.13260
URc4	66.29	66.03	0.3475	9359.3	2416.03	39.87	CNTYVR	0.06850
URc5	68.91	68.43	0.3254	9023.4	2407.37	28.84	CNTYHH STINC	0.13135 4.98860
URc6	69.04	68.56	0.3240	9003.6	2406.79	28.16	CNTYVR STHH	0.06642 0.02454
URc7	69.11	68.63	0.3232	8993.8	2406.50	27.82	CNTYEMP STMP	0.09640 0.02599
URc8	69.12	68.64	0.3232	8992.8	2406.47	27.79	CNTYPOP STMP	0.04936 0.02794
URc9	69.26	68.79	0.3216	8971.5	2405.84	27.06	CNTYVR STINC	0.06777 4.81640
URc10	69.71	69.24	0.3170	8906.6	2403.93	24.86	CNTYHH STMP	0.13078 0.02697
URc11	70.00	69.53	0.3140	8863.8	2402.65	23.41	CNTYVR STMP	0.06746 0.02600
URc12	71.32	70.87	0.3002	8666.5	2396.71	16.83	CNTYPOP CNTYINC	0.04418 3.26150
URc13	71.66	71.22	0.2966	8614.4	2395.12	15.12	CNTYEMP CNTYINC	0.08668 3.20780
URc14	71.98	71.55	0.2932	8565.8	2393.62	13.53	CNTYVR CNTYINC	0.06075 3.07490
URc15	72.02	71.59	0.2928	8559.8	2393.44	13.34	CNTYHH CNTYINC	0.11747 3.21770
URc16	72.43	71.78	0.2929	8529.9	2393.49	13.29	CNTYHH CNTYINC STVR	0.11729 2.89590 0.00318
URc17	72.50	71.86	0.2922	8519.1	2393.15	12.94	CNTYPOP CNTYINC STMP	0.04500 2.60420 0.01622
URc18	72.50	71.86	0.2921	8518.5	2393.14	12.93	CNTYEMP CNTYINC STHH	0.08655 2.76990 0.01446
URc19	72.58	71.93	0.2914	8507.6	2392.80	12.57	CNTYVR CNTYINC STPOP	0.06061 2.68320 0.01637
URc20	72.59	71.94	0.2913	8506.0	2392.75	12.52	CNTYEMP CNTYINC STMP	0.08785 2.63570 0.01430
URc21	72.67	72.03	0.2904	8493.3	2392.35	12.12	CNTYHH CNTYINC STPOP	0.11727 2.80680 0.01709
URc22	72.77	72.13	0.2893	8476.9	2391.85	11.59	CNTYVR CNTYINC STHH	0.06063 2.65250 0.01401
URc23	72.86	72.23	0.2883	8462.5	2391.40	11.13	CNTYHH CNTYINC STHH	0.11729 2.77910 0.01448
URc24	73.01	72.37	0.2868	8440.5	2390.71	10.43	CNTYVR CNTYINC STMP	0.06168 2.46660 0.01508
URc25	73.08	72.45	0.2860	8428.6	2390.34	10.05	CNTYHH CNTYINC STMP	0.11934 2.59940 0.01535

Table 5.19, continued

v. Region 'n' of Interstate Highways [DATA = "ALL & GREGION-n"]

Model	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
URn1	37.64	37.03	0.6481	19365.8	2055.20	35.79	CNTYEMP	0.20807
URn2	43.77	43.22	0.5844	18389.0	2044.44	22.44	CNTYVR	0.11874
URn3	45.08	44.54	0.5707	18173.2	2041.98	19.58	CNTYPOP	0.07776
URn4	45.33	44.79	0.5681	18132.0	2041.51	19.04	CNTYHH	0.22742
URn5	46.16	45.09	0.5704	18082.6	2041.92	19.23	CNTYPOP STHH	0.07833 0.02566
URn6	46.20	45.13	0.5700	18076.0	2041.84	19.15	CNTYPOP STVR	0.07762 0.00859
URn7	46.30	45.24	0.5689	18058.8	2041.64	18.93	CNTYPOP STPOP	0.07899 0.03740
URn8	46.33	45.27	0.5685	18053.5	2041.58	18.86	CNTYHH CNTYINC	0.21994 2.21680
URn9	46.63	45.57	0.5654	18003.8	2041.01	18.21	CNTYHH STEMP	0.22956 0.02588
URn10	47.02	45.97	0.5613	17938.0	2040.25	17.37	CNTYPOP STEMP	0.07926 0.03170
URn11	47.24	46.19	0.5590	17900.8	2039.82	16.89	CNTYHH STINC	0.22531 6.25960
URn12	47.31	46.26	0.5582	17889.0	2039.68	16.74	CNTYPOP STINC	0.07726 6.75860

vi. Region 's' of Interstate Highways [DATA = "ALL & GREGION-s"]

URs1	58.60	58.05	0.4361	8117.5	1388.25	47.19	CNTYEMP	1.14760
URs2	59.82	59.28	0.4232	7997.2	1385.95	43.66	CNTYPOP	0.38398
URs3	60.19	59.66	0.4193	7959.9	1385.23	42.57	CNTYVR	0.49214
URs4	61.42	60.90	0.4064	7836.7	1382.83	39.02	CNTYHH	1.10194
URs5	61.77	60.74	0.4133	7853.2	1384.12	39.99	CNTYHH STEMP	1.09169 0.00676

vii. Region 'c' of Rural Interstate Highways [DATA = "RURAL-ALL & GREGION-c"]

Rc1	38.38	37.59	0.6478	7351.6	1426.40	27.40	CNTYINC	3.89030
Rc2	44.29	42.84	0.6005	7035.2	1420.33	19.48	CNTYINC CTYPOP	3.29554 0.00781
Rc3	47.51	46.14	0.5658	6829.2	1415.58	14.08	CNTYINC CNTYEMP	3.43086 0.03198
Rc4	48.45	47.11	0.5557	6767.7	1414.13	12.50	CNTYINC CNTYPOP	3.37292 0.01724
Rc5	48.49	47.16	0.5552	6764.6	1414.06	12.43	CNTYINC CNTYHH	3.37863 0.04462
Rc6	48.73	47.40	0.5527	6749.4	1413.70	12.04	CNTYINC CNTYVR	3.30847 0.02388
Rc7	50.56	48.60	0.5465	6671.4	1412.79	10.97	CNTYINC CNTYEMP CTYPOP	3.05733 0.02732 0.00578
Rc8	50.63	48.68	0.5457	6666.6	1412.68	10.85	CNTYINC CNTYHH STHH	3.03607 0.04534 0.01286
Rc9	50.67	48.72	0.5452	6663.6	1412.60	10.78	CNTYINC CNTYPOP STHH	3.02088 0.01722 0.01313
Rc10	50.78	48.83	0.5440	6656.4	1412.43	10.60	CNTYINC CNTYHH STEMP	2.95025 0.04675 0.01237
Rc11	50.79	48.85	0.5439	6655.4	1412.40	10.57	CNTYINC CNTYPOP STEMP	2.93680 0.01773 0.01254
Rc12	50.79	48.85	0.5438	6655.2	1412.40	10.57	CNTYINC CNTYVR STHH	2.97314 0.02367 0.01267
Rc13	50.97	49.04	0.5419	6643.2	1412.11	10.27	CNTYINC CNTYVR STEMP	2.88330 0.02442 0.01226
Rc14	50.99	49.06	0.5417	6641.9	1412.08	10.24	CNTYINC CNTYPOP CTYPOP	3.04313 0.01467 0.00534
Rc15	51.05	49.11	0.5411	6638.1	1411.99	10.14	CNTYINC CNTYHH CTYPOP	3.04697 0.03886 0.00535
Rc16	51.12	49.19	0.5402	6632.9	1411.86	10.01	CNTYINC CNTYVR CTYPOP	2.99880 0.02032 0.00521

Table 5.19, continued

viii. Region 'n' of Rural Interstate Highways [DATA = "RURAL-ALL & GREGION-n"]

Model	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
Rn1	27.90	26.19	0.7863	7504.4	840.74	67.66	CNTYINC	3.62066
Rn2	29.96	26.77	0.7959	7474.4	841.31	66.34	CNTYINC STVR	3.47581 0.00390
Rn3	30.24	27.07	0.7927	7459.4	841.12	65.91	CNTYINC STINC	2.91200 2.96540
Rn4	30.34	27.17	0.7916	7454.1	841.05	65.75	CNTYINC STPOP	3.45135 0.01861
Rn5	30.37	27.20	0.7913	7452.7	841.03	65.71	CNTYINC STEMP	3.12513 0.01362
Rn6	30.64	27.49	0.7882	7437.9	840.85	65.29	CNTYINC STHH	3.47227 0.01405

ix. Region 's' of Rural Interstate Highways [DATA = "RURAL-ALL & GREGION-s"]

Rs1	40.46	39.42	0.6371	4999.4	1006.98	43.62	CNTYPOP	0.20608
Rs2	40.88	39.84	0.6327	4981.8	1006.56	42.93	CNTYHH	0.58700
Rs3	41.73	39.65	0.6451	4989.7	1007.71	43.51	CNTYPOP STEMP	0.20333 0.00698
Rs4	41.76	39.68	0.6448	4988.7	1007.68	43.47	CNTYHH STEMP	0.57794 0.00582

x. Region 'c' of Urban Interstate Highways [DATA = "URBAN-ALL & GREGION-c"]

Uc1	82.09	81.73	0.1935	9214.0	951.32	18.78	CNTYPOP	0.05996
Uc2	83.40	83.06	0.1793	8870.8	947.38	13.90	CNTYVR	0.08177
Uc3	83.57	83.24	0.1774	8823.4	946.82	13.24	CNTYHH	0.15923
Uc4	84.52	84.21	0.1672	8566.6	943.75	9.73	CNTYEMP	0.11876
Uc5	85.46	84.87	0.1632	8384.8	942.46	8.20	CNTYEMP STVR	0.11624 0.00648
Uc6	85.47	84.88	0.1631	8381.6	942.42	8.16	CNTYHH CNTYINC	0.14521 3.25150
Uc7	85.56	84.97	0.1621	8357.6	942.13	7.85	CNTYEMP STINC	0.11789 3.93370
Uc8	85.73	85.15	0.1602	8307.1	941.50	7.20	CNTYEMP STPOP	0.11577 0.03026
Uc9	85.76	85.17	0.1599	8299.7	941.40	7.10	CNTYVR STEMP	0.08082 0.02962
Uc10	85.83	85.25	0.1591	8279.3	941.15	6.84	CNTYEMP CNTYINC	0.10963 2.73990
Uc11	85.99	85.42	0.1573	8231.7	940.55	6.24	CNTYEMP STHH	0.11564 0.02520
Uc12	86.05	85.49	0.1565	8212.2	940.30	5.99	CNTYHH STEMP	0.15746 0.03037
Uc13	86.52	85.97	0.1513	8074.4	938.54	4.26	CNTYEMP STEMP	0.11725 0.02732
Uc14	86.77	85.94	0.1543	8081.3	939.56	5.32	CNTYEMP STEMP CNTYINC	0.11293 0.02170 1.39080

Table 5.19, continued

xi. Region "n" of Urban Interstate Highways [DATA = "URBAN-ALL & GREGION-n"]

Model	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
Un1	41.37	40.30	0.6289	21756.0	1140.56	10.19	CNTYEMP	0.25065
Un2	47.56	46.61	0.5625	20575.3	1134.19	3.52	CNTYVR	0.14156
Un3	48.39	47.45	0.5536	20412.0	1133.29	2.62	CNTYPOP	0.09061
Un4	48.79	47.85	0.5494	20333.8	1132.85	2.20	CNTYHH	0.26560
Un5	49.28	47.40	0.5635	20421.8	1134.30	3.67	CNTYHH STVR	0.26471 0.00726
Un6	49.52	47.65	0.5609	20374.2	1134.03	3.41	CNTYPOP STHH	0.09190 0.03200
Un7	49.53	47.67	0.5607	20370.6	1134.01	3.39	CNTYHH STMP	0.26773 0.02347
Un8	49.68	47.81	0.5592	20342.1	1133.85	3.24	CNTYHH CNTYINC	0.26215 2.69850
Un9	49.70	47.84	0.5589	20337.0	1133.82	3.21	CNTYPOP STPOP	0.09280 0.04641
Un10	49.75	47.89	0.5583	20326.6	1133.76	3.16	CNTYPOP STVR	0.09111 0.01205
Un11	49.95	48.10	0.5561	20285.9	1133.53	2.94	CNTYPOP STMP	0.09256 0.03407
Un12	50.03	48.18	0.5552	20270.3	1133.45	2.86	CNTYHH STINC	0.26356 5.90690
Un13	50.03	48.18	0.5552	20270.0	1133.44	2.86	CNTYPOP STINC	0.09020 6.77590

xii. Region "s" of Urban Interstate Highways [DATA = "URBAN-ALL & GREGION-s"]

Us1	62.88	60.56	0.4640	9070.2	329.94	110.62	CNTYPOP	0.39544
Us2	64.42	62.19	0.4448	8880.3	329.18	105.45	CNTYEMP	1.10581
Us3	68.73	66.77	0.3909	8324.8	326.85	90.98	CNTYHH	1.16050
Us4	73.11	71.43	0.3361	7719.7	324.13	76.27	CNTYVR	0.52365
Us5	76.01	72.81	0.3359	7530.8	324.08	68.54	CNTYVR STMP	0.48955 0.01921
Us6	76.23	73.06	0.3328	7496.7	323.92	67.81	CNTYHH STVR	1.00753 0.01153
Us7	76.90	73.82	0.3234	7389.2	323.40	65.54	CNTYEMP STPOP	1.02348 0.05393
Us8	77.68	74.70	0.3125	7263.5	322.78	62.92	CNTYVR STPOP	0.47823 0.03405
Us9	77.98	75.04	0.3083	7214.7	322.54	61.92	CNTYHH STHH	1.03188 0.04050
Us10	78.52	75.66	0.3007	7125.3	322.09	60.10	CNTYEMP STVR	0.97439 0.01515
Us11	78.78	75.95	0.2971	7083.1	321.88	59.25	CNTYVR STVR	0.45967 0.01017
Us12	80.48	77.88	0.2732	6792.0	320.36	53.51	CNTYVR STHH	0.46748 0.03654
Us13	81.34	78.86	0.2612	6640.8	319.55	50.63	CNTYEMP STHH	1.01685 0.05309

- Groups ii and vii: The improvement in the statistics of R6 (Group ii) and Rc6 (Group vii), the best model with 2 variables in equation in the respective groups, establishes their superiority over R1 (Group ii) and Rc1 (Group vii), the best models with 1 variable in equation, respectively.
- Groups iii and v: Among the 1-variable cases, U1 of Group iii and Urn1 of Group v are inferior to others in their respective groups. Only a slight difference in statistics is noticed among the 2-variable cases.
- Group iv: Virtually no difference in statistics is noticed among the candidate models with either 1 or 2 or 3 variables in the equation.
- Groups vi and x: For Group vi, all the statistics show the superiority of URs4, the best model with 1 variable in the equation, over Urs5 -- the only possible model with 2 variables in the equation. For Group x, Ucl3, the best model with 2 variables in the equation, supercedes the choice Ucl4, the only possible model with 3 variables. There is almost no change in the statistics among the choices with 1 or 2 variables in the equation of Group x.
- Groups viii and ix: Despite low values in R^2 and R_a^2 , the PC and AIC statistics suggest that Rn1 (the only possible model with 1 variable in equation of Group viii) and Rs1 of Group ix are better choices than others in their respective groups.

- Group xi: The models Un12 and Un13 have almost identical statistics. But the preference of population over household cancels the choice Un12 in favor of Un13. For the 1-variable case, Un1 is inferior to others. The results of the 2-variable cases show that the choices are almost identical.

- Group xii: The latter choices of either 1 or 2 variables in the equation are better than the former of those, respectively.

The foregoing comparative evaluations among the models of each group with respect to their statistics, parsimony, and the preferences of variables concerning their quality (see Chapter 4) have been used to identify the following candidate models for each group of Interstate highways.

Group	Model Number					
i	UR2	UR4	UR12	UR13		
ii	R3	R4	R6	R16		
iii	U2	U4	U9	U11		
iv	URc3	URc4	URc14	URc15	URc24	URc25
v	URn2	URn3	URn4	URn10	URn12	
vi	URs1	URs2	URs3	URs4		
vii	Rc4	Rc5	Rc6	Rc14	Rc15	Rc16
viii	Rn1	Rn4	Rn5	Rn6		
ix	Rs1	Rs2	Rs3	Rs4		
x	Uc1	Uc2	Uc3	Uc4	Uc12	Uc13
xi	Un2	Un3	Un4	Un11	Un13	
xii	Us3	Us4	Us10	Us11	Us12	Us13

Further analyses in later chapter(s) will determine the final model from these candidate models in each group.

5.6.2 Urban Principal Arterial

Based on the analysis of Section 5.5.2, the following twelve groups, which are mutually exclusive, are determined to find the model(s) from each of these groups:

- i. City Group = A and Region = c
- ii. City Group = A and Region = n
- iii. City Group = A and Region = s
- iv. City Group = B and Region = c
- v. City Group = B and Region = n
- vi. City Group = B and Region = s
- vii. City Group = C and Region = c
- viii. City Group = C and Region = n
- ix. City Group = C and Region = s
- x. City Group = D and Region = c
- xi. City Group = D and Region = n
- xii. City Group = D and Region = s

As the groups are mutually exclusive, model(s) from a particular group is(are) applicable for each highway section. The applicable group will be determined through the definition of CTYGR and GREGION from the location of the highway section. Table 5.20 shows all the possible candidate models under each group that have no inconsistency in their regression coefficients. From this table, the following remarks could be made about the statistics associated with the models of each group:

- Group i: The possible candidate models show a clear margin of improvement in 2-variable cases over 1-variable cases.

Table 5.20: Possible Candidate Models for Urban Principal Arterial

i. City Group = A & Region = c [DATA = CTYGR(A) & GREGION(c)]

Model	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
Ac1	45.71	41.53	0.7099	1993.6	229.78	317.28	CNTYVR	0.12476
Ac2	57.71	54.46	0.5530	1759.5	226.04	244.72	CNTYEMP	0.37527
Ac3	64.52	58.61	0.5322	1677.4	225.40	205.52	CNTYEMP STHH	0.33280 0.00520
Ac4	76.19	72.22	0.3571	1374.1	219.42	134.96	CNTYHH CNTYINC	0.29043 2.00873
Ac5	77.13	73.32	0.3430	1346.7	218.81	129.28	CNTYVR CNTYINC	0.14354 1.40742
Ac6	78.18	74.54	0.3274	1315.6	218.12	122.97	CNTYEMP CNTYINC	0.38159 1.11802
Ac7	82.30	79.35	0.2655	1184.8	214.97	98.03	CNTYPOP CNTYINC	0.09702 2.26556

ii. City Group = A & Region = n [DATA = CTYGR(A) & GREGION(n)]

An1	46.40	43.85	0.6381	2445.4	360.80	18.72	CTYPOP	0.44957
An2	46.45	41.09	0.6962	2504.8	362.78	20.69	CTYPOP CNTYVR	0.45138 0.00069
An3	46.52	41.17	0.6953	2503.2	362.75	20.64	CTYPOP CNTYPOP	0.45262 0.00068
An4	46.53	41.18	0.6952	2503.0	362.75	20.64	CTYPOP CNTYHH	0.45322 0.00212
An5	46.69	41.36	0.6930	2499.1	362.68	20.52	CTYPOP CNTYINC	0.42135 0.20971
An6	49.32	44.25	0.6588	2436.6	361.51	18.67	CTYPOP STVR	0.48797 0.00184
An7	49.44	44.38	0.6573	2433.9	361.46	18.59	CTYPOP STMP	0.46735 0.00557
An8	51.45	46.60	0.6311	2384.8	360.52	17.17	CTYPOP STPOP	0.50113 0.00996
An9	52.84	48.13	0.6131	2350.5	359.86	16.19	CTYPOP STHH	0.51206 0.00803
An10	52.94	45.52	0.6687	2408.9	361.81	18.12	CTYPOP STHH CNTYHH	0.51531 0.00802 0.00194
An11	53.03	45.61	0.6675	2406.8	361.76	18.06	CTYPOP STHH CNTYPOP	0.51634 0.00808 0.00086

iii. City Group = A & Region = s [DATA = CTYGR(A) & GREGION(s)]

As1	73.56	64.75	0.6169	231.7	55.90	(*)	STVR	0.00059
As2	75.79	67.73	0.5648	221.7	55.46	(*)	STPOP	0.00251
As3	82.32	76.43	0.4125	189.5	53.89	(*)	CNTYVR	0.04496
As4	83.14	77.52	0.3934	185.0	53.65	(*)	STHH	0.00226
As5	88.43	84.58	0.2699	153.3	51.77	(*)	CNTYHH	0.17139
As6	89.09	85.45	0.2546	148.9	51.48	(*)	CNTYPOP	0.11112

Table 5.20, continued

iv. City Group = B & Region = c [DATA = CTYGR(B) & GREGION(c)]

Model	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
Bc1	80.93	79.02	0.2670	2808.4	192.38	(*)	CTYPOP	2.10017
Bc2	93.56	92.92	0.0901	1631.3	179.34	(*)	CNTYPOP	0.01908
Bc3	93.83	93.21	0.0864	1597.2	178.84	(*)	CNTYHH	0.05081
Bc4	94.14	93.56	0.0820	1556.3	178.21	(*)	CNTYEMP	0.03779
Bc5	94.36	93.79	0.0790	1527.4	177.76	(*)	CNTYVR	0.02604
Bc6	94.58	93.38	0.0903	1577.7	179.28	(*)	CNTYVR STEMP	0.02592 0.00257
Bc7	94.78	93.62	0.0870	1548.5	178.83	(*)	CNTYEMP STINC	0.03745 0.84460
Bc8	94.82	93.67	0.0864	1543.1	178.74	(*)	CNTYPOP CNTYINC	0.01621 1.02811
Bc9	94.92	93.79	0.0847	1528.1	178.51	(*)	CNTYHH CNTYINC	0.04359 0.96643
Bc10	94.94	93.81	0.0844	1525.2	178.47	(*)	CNTYVR STINC	0.02582 0.80430
Bc11	95.11	94.02	0.0815	1499.2	178.05	(*)	CNTYEMP CNTYINC	0.03268 0.91644
Bc12	95.30	94.26	0.0783	1468.8	177.56	(*)	CNTYVR CNTYINC	0.02257 0.90649

v. City Group = B & Region = n [DATA = CTYGR(B) & GREGION(n)]

Bn1	41.61	36.30	0.7963	1450.9	191.11	15.25	STPOP	0.01581
Bn2	48.08	43.36	0.7080	1368.1	189.58	12.57	STINC	2.08902
Bn3	49.38	44.78	0.6902	1350.8	189.25	12.02	STVR	0.00365
Bn4	56.55	52.61	0.5924	1251.5	187.26	9.05	STEMP	0.01250
Bn5	59.08	55.36	0.5580	1214.6	186.49	8.00	CNTYVR	0.11499
Bn6	67.08	60.50	0.5267	1142.5	185.66	6.67	STEMP CNTYINC	0.00992 0.58040
Bn7	70.91	65.10	0.4654	1074.0	184.05	5.08	CNTYVR STGAS	0.12776 3.26653
Bn8	71.19	65.43	0.4610	1068.9	183.92	4.97	CNTYINC CNTYPOP	1.04606 0.10919
Bn9	73.24	67.89	0.4281	1030.1	182.96	4.11	CNTYVR STEMP	0.07498 0.00768
Bn10	75.16	70.19	0.3975	992.5	182.00	3.31	CNTYVR STINC	0.08630 1.33923
Bn11	76.16	71.39	0.3814	972.3	181.46	2.90	STPOP CNTYINC	0.01513 0.94934
Bn12	76.74	72.09	0.3721	960.4	181.14	2.66	STVR CNTYINC	0.00326 0.85245
Bn13	76.75	72.10	0.3720	960.2	181.13	2.66	CNTYINC CNTYHH	1.22230 0.27179
Bn14	78.67	74.40	0.3413	919.8	180.02	1.86	CNTYVR CNTYINC	0.09824 0.73647
Bn15	78.80	74.55	0.3393	917.0	179.94	1.81	CNTYINC STHH	1.05470 0.01052
Bn16	81.21	74.95	0.3549	909.8	180.36	2.80	CNTYVR CNTYINC STPOP	0.06187 0.81100 0.00698
Bn17	81.89	75.85	0.3422	893.4	179.89	2.52	CNTYVR CNTYINC STHH	0.05244 0.88939 0.00572
Bn18	82.12	76.17	0.3376	887.5	179.72	2.42	CNTYVR CNTYINC STINC	0.08694 0.52885 0.74792
Bn19	82.13	76.18	0.3375	887.3	179.71	2.42	CNTYINC STHH CNTYPOP	1.06051 0.00760 0.04831
Bn20	82.68	76.90	0.3272	873.6	179.31	2.20	STEMP CNTYINC CNTYPOP	0.00680 0.74845 0.08160
Bn21	83.95	78.61	0.3031	840.8	178.31	1.66	CNTYVR CNTYINC STEMP	0.07539 0.58548 0.00504

Table 5.20, continued

vi. City Group = B & Region = s [DATA = CTYGR(B) & GREGION(s)]

Model	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
Bs1	95.76	94.34	0.0990	758.8	67.76	(*)	STHH	0.01985
Bs2	96.08	94.77	0.0916	729.7	67.37	(*)	STVR	0.00549
Bs3	97.09	96.12	0.0679	628.3	65.88	(*)	CNTYVR	0.25577
Bs4	97.53	96.71	0.0575	578.5	65.05	(*)	CNTYHH	0.84968
Bs5	98.00	97.34	0.0466	520.3	63.99	(*)	CNTYPOP	0.54790
Bs6	98.97	98.63	0.0241	374.1	60.69	(*)	STPOP	0.02344
Bs7	99.30	98.61	0.0279	376.7	60.73	(*)	CNTYPOP CNTYEMP	0.57032 0.22379

vii. City Group = C & Region = c [DATA = CTYGR(C) & GREGION(c)]

Cc1	31.48	29.89	0.7489	3762.9	742.92	99.81	CTYPOP	0.73585
Cc2	43.95	42.64	0.6127	3403.5	733.88	74.19	CNTYINC	1.87331
Cc3	44.49	41.85	0.6344	3426.9	735.44	75.07	CNTYINC CNTYHH	1.82311 0.03172
Cc4	45.05	42.43	0.6280	3409.7	734.99	73.93	CNTYINC CNTYVR	1.75708 0.01953
Cc5	45.17	42.56	0.6267	3406.0	734.89	73.68	CNTYINC CNTYPOP	1.79287 0.01645
Cc6	61.65	59.82	0.4383	2848.5	718.80	39.81	CNTYINC CTYPOP	1.59431 0.56681
Cc7	61.96	59.18	0.4546	2871.2	720.43	41.16	CNTYINC CTYPOP CNTYVR	1.53609 0.55790 0.01052
Cc8	62.04	59.27	0.4536	2868.2	720.34	41.00	CNTYINC CTYPOP CNTYPOP	1.55306 0.55707 0.00942

viii. City Group = C & Region = n [DATA = CTYGR(C) & GREGION(n)]

Cn1	31.79	29.36	0.7795	2259.7	465.31	7.56	CNTYINC	1.38579
Cn2	32.93	27.96	0.8198	2281.9	466.81	9.00	CNTYINC STHH	1.28106 0.00254
Cn3	33.11	28.16	0.8175	2278.8	466.72	8.90	CNTYINC CNTYPOP	1.30983 0.00160
Cn4	33.26	28.32	0.8157	2276.2	466.66	8.83	CNTYINC CNTYHH	1.30868 0.00498
Cn5	33.55	28.63	0.8122	2271.4	466.53	8.69	CNTYINC CNTYVR	1.28313 0.00290
Cn6	34.57	29.73	0.7997	2253.8	466.06	8.19	CNTYINC CNTYEMP	1.22026 0.00713
Cn7	40.16	35.72	0.7314	2155.5	463.38	5.44	CNTYINC CTYPOP	1.18695 0.25756

ix. City Group = C & Region = s [DATA = CTYGR(C) & GREGION(s)]

Cs1	59.83	46.44	0.9372	1254.4	72.79	(*)	STINC	1.53076
Cs2	64.87	53.17	0.8196	1173.1	72.12	(*)	STEMP	0.01047
Cs3	67.17	56.22	0.7661	1134.1	71.78	(*)	CNTYHH	1.51091
Cs4	71.19	61.58	0.6723	1062.4	71.13	(*)	CNTYPOP	1.11370
Cs5	79.16	58.32	0.8335	1106.6	71.51	(*)	CNTYPOP STINC	0.77945 0.75064
Cs6	80.66	61.31	0.7737	1066.1	71.14	(*)	STINC CNTYEMP	1.54549 1.83761
Cs7	81.68	63.37	0.7326	1037.4	70.86	(*)	CNTYPOP CNTYINC	1.45225 1.31074

Table 5.20, continued

x. City Group = D & Region = c [DATA = CTYGR(D) & GREGION(c)]

Model	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
Dc1	36.76	34.12	0.7378	1293.2	374.49	14.93	CTYPOP	0.67290
Dc2	39.59	34.34	0.7616	1291.0	375.30	15.27	CTYPOP CNTYPOP	0.69688 0.00644
Dc3	39.70	34.45	0.7603	1290.0	375.25	15.21	CTYPOP CNTYEMP	0.70634 0.01910
Dc4	39.95	34.73	0.7571	1287.2	375.14	15.06	CTYPOP CNTYHH	0.70246 0.01944
Dc5	40.96	35.82	0.7443	1276.4	374.70	14.47	CTYPOP CNTYVR	0.70908 0.00989
Dc6	53.38	49.33	0.5878	1134.2	368.56	7.22	CTYPOP CNTYINC	0.98844 0.66616
Dc7	53.97	49.97	0.5804	1127.0	368.23	6.88	CTYPOP STPOP	0.71713 0.00741
Dc8	54.40	50.43	0.5750	1121.8	367.99	6.63	CTYPOP STINC	0.76541 1.10903
Dc9	56.10	52.29	0.5535	1100.6	367.00	5.63	CTYPOP STHH	0.70696 0.00581
Dc10	56.98	53.24	0.5424	1089.5	366.47	5.12	CTYPOP STVR	0.73143 0.00175
Dc11	58.88	55.30	0.5185	1065.2	365.30	4.01	CTYPOP STEMP	0.73274 0.00725
Dc12	59.99	54.54	0.5456	1074.3	366.59	5.36	CTYPOP STVR STINC	0.76234 0.00120 0.59380
Dc13	60.06	54.62	0.5446	1073.3	366.54	5.32	CTYPOP STEMP CNTYHH	0.74883 0.00699 0.01197
Dc14	60.24	54.82	0.5421	1070.9	366.42	5.21	CTYPOP STEMP CNTYVR	0.75085 0.00690 0.00574
Dc15	61.07	55.76	0.5308	1059.7	365.88	4.73	CTYPOP STHH STINC	0.75398 0.00400 0.69059
Dc16	62.45	57.33	0.5121	1040.8	364.94	3.93	CTYPOP STPOP CNTYINC	0.94436 0.00567 0.50163
Dc17	64.23	59.35	0.4878	1015.9	363.68	2.89	CTYPOP STVR CNTYINC	0.94046 0.00137 0.46847
Dc18	64.32	59.46	0.4865	1014.5	363.61	2.83	CTYPOP STEMP CNTYINC	0.91773 0.00561 0.41917
Dc19	65.50	60.79	0.4705	997.7	362.74	2.15	CTYPOP STHH CNTYINC	0.94592 0.00475 0.51758

xi. City Group = D & Region = n [DATA = CTYGR(D) & GREGION(n)]

Dn1	42.03	40.22	0.6522	2447.8	532.54	0.30	CNTYEMP	0.03529
Dn2	42.19	40.38	0.6504	2444.5	532.45	0.21	CNTYPOP	0.01324
Dn3	42.78	40.99	0.6438	2432.0	532.10	-0.09	CNTYHH	0.03866
Dn4	43.82	42.06	0.6321	2409.8	531.48	-0.64	CNTYVR	0.01941
Dn5	45.90	42.41	0.6457	2402.5	532.19	0.27	CNTYVR STEMP	0.01857 0.00455
Dn6	45.94	42.45	0.6453	2401.7	532.17	0.25	CNTYEMP STPOP	0.03310 0.00754
Dn7	46.01	42.53	0.6444	2400.1	532.12	0.22	CNTYHH STPOP	0.03620 0.00690
Dn8	46.08	42.60	0.6436	2398.6	532.08	0.18	CNTYPOP STHH	0.01246 0.00548
Dn9	46.15	42.68	0.6427	2397.0	532.03	0.14	CNTYHH STHH	0.03634 0.00512
Dn10	46.28	42.81	0.6412	2394.2	531.95	0.08	CNTYEMP STHH	0.03329 0.00571
Dn11	46.33	42.86	0.6406	2393.0	531.92	0.05	CNTYVR STVR	0.01832 0.00134
Dn12	46.57	43.12	0.6377	2387.6	531.77	-0.07	CNTYPOP CNTYINC	0.00964 1.00114
Dn13	46.90	43.47	0.6338	2380.3	531.56	-0.25	CNTYVR CNTYINC	0.01464 0.87511
Dn14	46.90	43.47	0.6338	2380.2	531.56	-0.25	CNTYVR STPOP	0.01820 0.00674
Dn15	47.11	43.70	0.6312	2375.4	531.42	-0.36	CNTYVR STHH	0.01827 0.00507
Dn16	47.25	43.85	0.6296	2372.3	531.33	-0.43	CNTYHH CNTYINC	0.02839 1.00117
Dn17	48.86	43.75	0.6477	2374.4	532.27	0.73	CNTYVR STPOP CNTYINC	0.01451 0.00552 0.71667
Dn18	48.94	43.83	0.6468	2372.7	532.23	0.69	CNTYPOP CNTYINC STHH	0.00963 0.83035 0.00439
Dn19	49.08	43.99	0.6449	2369.3	532.13	0.61	CNTYHH CNTYINC STPOP	0.02801 0.85218 0.00533
Dn20	49.10	44.01	0.6447	2368.9	532.12	0.60	CNTYVR STHH CNTYINC	0.01455 0.00423 0.71812
Dn21	49.28	44.21	0.6425	2364.7	532.00	0.51	CNTYHH CNTYINC STHH	0.02803 0.85643 0.00406

Table 5.20, continued

xii. City Group = D & Region = s [DATA = CTYGR(D) & GREGION(s)]

Model	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
De1	35.40	33.78	0.7106	1790.2	631.12	2.28	STVR	0.00352
De2	37.43	35.87	0.6882	1761.8	629.77	1.01	STEMP	0.01286
De3	37.48	35.91	0.6878	1761.2	629.75	0.99	STHH	0.01153
De4	39.85	38.34	0.6617	1727.5	628.12	-0.49	STPOP	0.01546
De5	40.46	37.41	0.6870	1740.5	629.69	1.13	STEMP CTYPOP	0.01228 0.22443
De6	40.48	37.43	0.6868	1740.2	629.68	1.11	STEMP STVR	0.00793 0.00173
De7	40.59	37.54	0.6855	1738.7	629.60	1.05	STPOP STGAS	0.01574 1.17000
De8	41.03	38.01	0.6804	1732.1	629.28	0.77	STPOP CNTYINC	0.01450 0.19043
De9	42.21	39.25	0.6668	1714.7	628.43	0.03	STHH STEMP	0.00651 0.00723
De10	42.34	39.38	0.6653	1712.8	628.34	-0.05	STPOP CTYPOP	0.01477 0.20442
De11	42.16	39.46	0.6644	1711.7	628.29	-0.09	STPOP STEMP	0.00971 0.00598
De12	42.84	39.91	0.6595	1705.3	627.97	-0.36	STHH STINC	0.00842 1.08856
De13	43.03	40.10	0.6574	1702.6	627.84	-0.47	STPOP STINC	0.01177 0.89367
De14	44.67	40.30	0.6698	1699.8	628.61	0.50	STHH STEMP CTYPOP	0.00613 0.00704 0.20273
De15	44.82	40.47	0.6679	1697.5	628.50	0.41	STPOP STEMP CTYPOP	0.00912 0.00588 0.20086
De16	45.02	40.68	0.6655	1694.4	628.34	0.28	STHH STINC CTYPOP	0.00809 1.03582 0.19128
De17	45.20	40.87	0.6634	1691.7	628.21	0.17	STPOP STINC CTYPOP	0.01130 0.84841 0.19102

(*) Error-Variance too small to compute C_p

- Group ii: Despite large R^2 values, the R_a^2 , PC, RMSE, AIC and C_p statistics make An10 and An11 -- models with 3 variables in their equations -- inferior to the best model with 2 variables in its equation (An9). There is practically no difference in associated statistics among models An2 to An5. For 2-variable cases, a slight improvement in statistics of An6 to An 9 is noticed in comparison to the statistics of An2 to An9.
- Group iii: The associated statistics of As3 to As6 make them preferable to As1 and As2.
- Group iv: The improvement in the statistics of Bc2 to Bc12, when compared to the statistics of Bc1, makes Bc1 inferior to other choices with 1 variable. Only slight improvement in statistics is noticed for the best models with 2 variables over those with 1 variable. PC and AIC criteria invalidate the choices Bc6-Bc11 versus Bc5.
- Group v: The statistics of 2-variable cases make them preferable to 1-variable cases. Despite a higher R^2 for Bn16 than for Bn15, the PC and AIC criteria reject Bn16 in favor of Bn15.
- Group vi: Despite a small improvement in R^2 value for Bs7 over Bs6, the associated statistics make Bs6 more worthwhile to pursue than Bs7.
- Group vii: The statistics show a significant improvement in Cc2 over Cc1. Despite high values in R^2 , the other associated statistics suggest that Cc7 and Cc8 are inferior to Cc6.

- Groups viii and ix: Each of these groups shows some improvement in statistics of latter choices (Cn5-Cn7, Cs4-Cs7) in comparison to earlier choices (Cn1-Cn4, Cs1-Cs3) in the lists.
- Group x: For 2-variable cases, the latter models (Dc6-D11) are better than the earlier choices (Dc2-Dc5). There is only slight improvement in statistics of the better models (Dc18-Dc19) with 3 variables over those with 2 variables.
- Groups xi and xii: An increase in the number of variables has not changed the associated statistics significantly. For group xi, the PC and AIC criteria make Dn5-Dn14 inferior to Dn4. For group xii, the PC and AIC criterion establish the superiority of Ds4 and Ds12-Ds13 over Ds5-Ds11 and Ds14-Ds17, respectively.

These comparative evaluations, parsimony, and the quality of the variables have been used to identify the following candidate models for each group of urban principal arterials.

Group	Model Number			
i	Ac4	Ac5	Ac6	Ac7
ii	An6	An7	An8	An9
iii	As3	As4	As5	As6
iv	Bc3	Bc4	Bc5	Bc12
v	Bn12	Bn14	Bn15	Bn21
vi	Bs3	Bs4	Bs5	Bs6
vii	Cc5	Cc6		
viii	Cn5	Cn6	Cn7	
ix	Cs4	Cs5	Cs6	Cs7
x	Dc10	Dc11	Dc18	Dc19
xi	Dn3	Dn4	Dn15	Dn16
xii	Ds3	Ds4	Ds12	Ds13

In Section 5.4.2, an analysis of pooled data for CTYGR A, B and C has been undertaken because of the low number of observations for each of the city groups. This pooling has given the opportunity to produce statistically more significant results by incorporating a larger data set (n=15) than the data set (n=5) for each group separately. Table C5.1 has some of the statistical measures for the best models with 1 or 2 variables in the equation for this pooled data set. The separation of the city group 'D' from the pooled data set has resulted in good statistical measures. Moreover, the resulting observations (n=42) can be considered large enough to do the further statistical analyses and to produce significant statistical results. Thus, a common final model for the south region of CTYGR A, B and C will be selected from the pooled data set -- Group xiii. And the models for the groups iii, vi and ix -- the individual groups of CTYGR A, B and C in the south region -- will not be evaluated. The nine possible candidate models for the pooled group are shown in Table 5.20.1. Of those, the five models (ABCs3-ABCs4 and ABCs7-ABCs9) have been selected as the candidate models based on their associated statistics and quality of variables in the models. Further analyses in later chapter(s) will determine the final model from these candidate models under each of the selected groups.

Table 5.20.1: Possible Candidate Models for South Region of
CTYGR A, B and C of Urban Principal Arterial

xiii. City Group = A+B+C & Region = s [DATA = CTYGR(A+B+C) & GREGION(s)]

Model	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
ABCs1	67.38	64.87	0.4266	3889.2	249.83	158.50	CNTYPOP	0.12476
ABCs2	69.03	66.65	0.4049	3789.0	249.05	149.88	CNTYHH	0.37527
ABCs3	72.43	70.31	0.3605	3575.2	247.31	132.23	CNTYVR	0.33280 0.00520
ABCs4	81.08	79.63	0.2474	2961.5	241.66	87.28	CNTYEMP	0.29043 2.00873
ABCs5	83.50	80.74	0.2476	2879.2	241.61	76.75	CNTYEMP STEMP	0.14354 1.40742
ABCs6	84.19	81.55	0.2372	2818.2	240.97	73.15	CNTYEMP STINC	0.38159 1.11802
ABCs7	85.14	82.66	0.2229	2732.1	240.04	68.21	CNTYEMP STVR	0.09702 2.26556
ABCs8	85.44	83.01	0.2184	2704.2	239.73	66.64	CNTYEMP STHH	0.38159 1.11802
ABCs9	85.53	83.12	0.2170	2695.6	239.63	66.16	CNTYEMP STPOP	0.09702 2.26556

5.6.3 Urban Minor Arterial and Collector

The data groups determined in Section 5.5.3 for minor arterials and collectors are as follows:

- i. City Group = A
- ii. City Group = B
- iii. City Group = C (with GREGION 'n' group data)
- iv. City Group = C (with MFUNC 'F4' group data)
- v. City Group = D (with MFUNC 'F2+F3+F4' group data)
- vi. City Group = D (with GREGION 'c+n' group data)

This grouping offers two alternative models for City Groups 'C' and 'D'; and one choice of model for each of City Group 'A' and 'B'. The all possible candidate models under each group, without any inconsistency in regression coefficients, are presented in Table 5.21. The following remarks apply to the associated statistics for the models in each group:

- Group i: The possible candidate models show a clear margin of improvement for A4-A7 with 2 variables versus A2 with 1 variable. For the two 1-variable cases, A2 is preferable to A1.
- Group ii: For 1-variable cases, the statistics of B2 invalidate the choice of B1. Despite a minor improvement in the R^2 value of 2-variable cases over B2 with 1 variable, the associated statistics make 2-variable choices inferior to B2.
- Group iii: A significant improvement is noticed in the statistics of C2, C3 and C4 over C1, all with 1 variable in their equations. The associated statistics make the choices with 2 variables

Table 5.21: Possible Candidate Models for Urban Minor Arterial and Collector

i. City Group = A [DATA = CTYGR(A)]

Model	R^2	R_a^2	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
A1	43.40	39.86	0.7075	2805.5	287.70	109.86	CNTYEMP	0.04083
A2	53.57	50.67	0.5804	2540.9	284.13	87.60	CNTYINC	2.09310
A3	56.02	50.16	0.6157	2554.0	285.15	84.23	CNTYINC STHH	1.87679 0.00497
A4	62.07	57.01	0.5310	2372.0	282.49	71.00	CNTYINC CNTYHH	1.84437 0.01934
A5	62.07	57.02	0.5310	2371.8	282.49	70.99	CNTYINC CNTYPOP	1.83370 0.00668
A6	64.04	59.25	0.5034	2309.5	281.53	66.69	CNTYINC CNTYVR	1.73620 0.01145
A7	65.94	61.39	0.4769	2247.8	280.56	62.54	CNTYINC CNTYEMP	1.54569 0.02481

ii. City Group = B [DATA = CTYGR(B)]

B1	40.76	35.40	0.8079	3096.8	210.82	(*)	CTYPOP	1.91741
B2	66.94	63.94	0.4507	2313.1	203.23	(*)	CNTYINC	2.40789
B3	66.96	60.35	0.5287	2425.6	205.23	(*)	CNTYINC CNTYVR	2.40330 0.00034
B4	66.97	60.37	0.5284	2425.1	205.22	(*)	CNTYINC CNTYHH	2.40411 0.00094
B5	67.00	60.41	0.5279	2423.9	205.21	(*)	CNTYINC STVR	2.38507 0.00025
B6	67.15	60.68	0.5243	2415.5	205.12	(*)	CNTYINC STPOP	2.36248 0.00240
B7	67.23	61.17	0.5177	2400.4	204.96	(*)	CNTYINC STHH	2.36762 0.00284
B8	67.58	63.40	0.4880	2330.4	204.19	(*)	CNTYINC CTYPOP	2.02801 0.61712

iii. City Group = C [DATA = CTYGR(C) & GREGION(n)]

Model	R^2	R_a^2	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
C1	61.45	57.95	0.5257	1229.4	186.80	(*)	CNTYEMP	0.02291
C2	71.58	68.99	0.3876	1055.7	182.84	(*)	CNTYVR	0.01283
C3	73.88	71.50	0.3562	1012.0	181.74	(*)	CNTYPOP	0.00849
C4	75.74	73.53	0.3309	975.4	180.78	(*)	CNTYHH	0.02504
C5	77.04	72.44	0.3674	995.2	182.06	(*)	CNTYHH STPOP	0.02399 0.00226
C6	77.79	73.35	0.3554	978.7	181.63	(*)	CNTYPOP STHH	0.00797 0.00310
C7	77.94	73.52	0.3530	975.5	181.54	(*)	CNTYHH STMP	0.02430 0.00234
C8	78.69	74.43	0.3409	958.7	181.09	(*)	CNTYHH STHH	0.02358 0.00271

Table 5.21, continued

iv. City Group = C [DATA = CTYGR(C) & MFUNC(F4)]

Model	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients in order
C9	74.85	72.05	0.3633	1267.9	158.99	(*)	CNTYEMP	0.03364
C10	76.60	74.00	0.3381	1223.0	158.19	(*)	CNTYPOP	0.01123
C11	78.08	75.64	0.3166	1183.6	157.47	(*)	CNTYVR	0.01828
C12	78.30	75.88	0.3135	1177.8	157.36	(*)	CNTYHH	0.03289
C13	80.39	75.49	0.3431	1187.3	158.24	(*)	CNTYPOP STHH	0.01093 0.00532
C14	80.69	75.86	0.3379	1178.3	158.08	(*)	CNTYVR STMP	0.01830 0.00548
C15	80.74	75.93	0.3370	1176.7	158.05	(*)	CNTYEMP STHH	0.03303 0.00660
C16	80.76	75.95	0.3367	1176.2	158.04	(*)	CNTYEMP STVR	0.03305 0.00245
C17	80.92	76.15	0.3339	1171.3	157.94	(*)	CNTYVR STHH	0.01775 0.00462
C18	80.94	76.17	0.3335	1170.6	157.93	(*)	CNTYHH STHH	0.03193 0.00447
C19	81.06	76.32	0.3315	1167.0	157.87	(*)	CNTYHH STMP	0.03297 0.00564
C20	81.09	76.37	0.3309	1166.0	157.85	(*)	CNTYPOP STPOP	0.01091 0.00901
C21	81.55	76.94	0.3229	1151.8	157.58	(*)	CNTYVR STPOP	0.01772 0.00795
C22	81.71	77.13	0.3201	1146.8	157.48	(*)	CNTYHH STPOP	0.03187 0.00788
C23	81.80	77.25	0.3185	1143.9	157.43	(*)	CNTYEMP STPOP	0.03306 0.01115
C24	83.14	75.92	0.3612	1176.8	158.58	(*)	CNTYPOP STPOP CNTYEMP	0.00501 0.01865 0.01012
C25	83.63	76.62	0.3507	1159.7	158.26	(*)	CNTYHH STPOP CNTYEMP	0.01616 0.00944 0.01716

v. City Group = D [DATA = CTYGR(D) & MFUNC(F2+F3+F4)]

D1	39.98	37.67	0.6925	2686.4	446.10	146.74	CNTYINC	2.04400
D2	39.98	35.18	0.7442	2739.6	446.10	148.74	CNTYINC STGAS	2.03917 0.09900
D3	39.98	35.18	0.7442	2739.5	446.09	148.73	CNTYINC STHH	2.03185 0.00021
D4	39.99	35.19	0.7441	2739.3	445.53	148.71	CNTYINC STINC	2.01787 0.07403
D5	41.18	36.48	0.7293	2712.1	438.43	145.33	CNTYINC STMP	1.84212 0.00424
D6	54.37	50.72	0.5658	2388.8	181.63	107.82	CNTYINC CTYPOP	1.68745 0.88901

vi. City Group = D [DATA = CTYGR(D) & GREGION(c+n)]

D7	53.98	51.89	0.5439	1167.0	340.89	146.74	CNTYINC	1.16659
D8	54.12	49.75	0.5898	1192.5	342.82	148.74	CNTYINC STHH	1.15432 0.00060
D9	54.13	49.76	0.5898	1192.5	342.82	148.73	CNTYINC STPOP	1.15390 0.00087
D10	54.22	49.86	0.5887	1191.3	342.77	148.71	CNTYINC STVR	1.15009 0.00024
D11	54.26	49.91	0.5881	1190.7	342.75	145.33	CNTYINC STMP	1.14898 0.00103

(*) Error-Variance is too small to compute C_p

inferior to C4, which is the best model with one variable.

- Group iv: A minor amount of change in the statistics is noticed among the possible candidate models. The PC and AIC criteria establish that C12 with 1 variable is slightly better than the choices with 2 and 3 variables.
- Group v: The statistics of D6 establish that it is the best selection among all choices.
- Group vi: Despite a small improvement in R^2 value for D8-D11 with 2 variables over D7 with 1 variable, the associated statistics qualify D7 over D8-D11.

These comparative evaluations, parsimony and the quality of variables have been used to identify the following candidate model(s) for each group of urban minor arterials and collectors.

Group	Model Number			
i	A2	A5	A6	A7
ii	B2			
iii	C2	C3	C4	
iv	C9	C10	C11	C12
v	D6			
vi	D7			

Further analyses in the next chapter(s) will determine the final model from these candidate models under each group.

5.7 Chapter Summary

This chapter has described all the statistics that were employed to compare the data bases, data formats and groups. A summary of all important results has been provided. Among the four alternative data formats, the "RAW" data format of county/city average data base is found to be the best. The evaluation of alternative data structures has avoided the risk of working with a weak data structure and thus avoided accepting poor statistical results. In addition to data format and structure selection, groupings of data have been made to produce statistically sound results. Finally, the combination of statistical evaluation and judgment based on quality of the predictor variables is employed to identify candidate regression models for further analysis in the following chapter and in earlier in chapter.

CHAPTER 6

DIAGNOSIS AND FINAL SELECTION OF MODEL

6.1 Introduction

The aim of regression diagnostics is to exhibit the degree of appropriateness of the assumptions made in fitting a regression model to a specific set of data. Answers are sought to such questions as

- i. Are there outliers?
- ii. Should the response variable be transformed?
- iii. Is the variance constant?
- iv. Are all the explanatory variables in the model necessary?
- v. Is the systematic part of the model adequate? If not, should variables be added or should the form of the model be altered?
- vi. How do the answers to these questions depend on individual observations?

In this chapter, influential analysis will be carried out to identify the outliers and influential observations (if present) for all the candidate models selected in Chapter 5. The statistical background and mechanism for doing this influential analysis will be

described in this chapter. The statistical results of pre and post influence analysis have shown significant improvements in some of the statistics in later. Thus, the influence analysis has avoided many unexpected transformation to satisfy some assumptions of regression analysis. All important assumptions regarding regression analysis and model aptness are examined for the candidate models. Significance and collinearity of regression coefficients will be evaluated to find the most useful variables and to avoid the problem of selection with multicollinearity. The selection of the final model, both regression and elasticity-based, for each group of different highways under consideration will be based primarily on the quality of statistical results of the candidate model.

6.2 Detecting Outliers and Influential Observations

Outliers are extreme observations. In general, an observation is considered influential if removing it would markedly change the position of the regression line. But, not all influential observations are outliers. After the multiple regression has been performed, most detection procedures focus on the residuals, the fitted(predicted) values, and the explanatory variables.

Outliers can create great difficulty. A major reason for discarding outlier(s) is that, under the least squares method, a fitted line may be pulled disproportionately toward an outlier because the sum of the squared deviations is minimized. The three main problems with an outlier are as follows:

1. An outlier can pull down the value of regression coefficient(s) toward zero so that the value of the t-statistic for testing $H_0: \beta_j = 0$ is also going to be smaller. Thus, it would cause the null hypothesis to be unnecessarily accepted even though the dependent and the independent variables do have a significant regression relation.
2. Outliers could also pull up the value of the slope of the fitted line and also the t-statistic for testing for significance of regression. Thus, a significant regression relation may be concluded when there is no such relationship.
3. The outliers are unlikely to affect the analysis if regarded one at a time. But a cluster of outliers can affect the analysis as a group. Thus, studying the effect of influential observations, it is not enough to consider them one at a time, but it is also necessary to study them as a group.

In this study, some techniques [SAS/STATISTICS 1985; Belsley, Kuh & Welsch 1980] are used for diagnosing influential data points that avoid some of the problems described in above paragraphs. Two representative candidate models, Cn5 and Un4 (see Chapter 5), are selected to show the individual and group effect of outliers, respectively.

6.2.1 Diagnostic Techniques of Detecting Outliers

A brief description from SAS/STATISTICS [1985] and Belsley, Kuh, and Welsch [1980] regarding the technical background for diagnosing

influential data points is provided in this section. In interpreting the results of each of the diagnostic techniques, judgment and intuition, guided by statistical theory, are used to determine the reasonable cutoffs beyond which a particular measure of leverage or influence is large enough to be worthy of further examination. An outlier or a group of outliers are considered influential when several of the diagnostic techniques mentioned in the next sections determine the fact.

6.2.1.1 Partial Regression Residual Plots

Simple 2-variable regression scatterplots contain much diagnostic information about residuals and provide much guidance about influential subsets of data that might escape detection with the formal diagnostic techniques. The partial "regression leverage/residual plot" is the plot of the response variable and the regressor after they have been made orthogonal to the other regressors in the model. These plots (see Figures 6.1-6.3) are generated by plotting the residuals of the response variable omitting the selected regressor against the residuals of the selected regressor on all the other regressor(s). A line fit to the points has a slope equal to the parameter estimate in the full model.

The partial regression residual plots are an important part of regression diagnostics. They supplant the traditional plots of residuals against explanatory/independent variables. However, partial-regression leverage plots cannot tell us everything. Certain types of influential data can be overlooked and the influence of the leverage

points detected in the plot will sometimes be difficult to quantify.
[Belsley, Kuh and Welsch 1980]

The partial regression plots of model Cn5 are shown in Figures 6.1 and 6.2. Both of these plots show that one observation (id=35, where 35 represents the variable CTYN) is a possible candidate for an outlier. The "*"s in these plots are representation of overlapping of observations. The mild slope of the plot in Figure 6.2 suggests that the variable CNTYVR is not useful in the presence of variable CNTYINC in the model. Figure 6.3 presents the partial regression plot of model Un4. Although the outlier(s) is(are) not clear in this plot, some other diagnostic measures of the following subsections have proved that a group of observations, with id=6 in the plot, is a potential candidate as a group of outliers. The mild slope and more scattered observation indicate a lower value of R^2 .

6.2.1.2 Studentized Residual (RSTUDENT)

One way to try to detect outliers is to produce the standardized residual at the i th observation (d_i) as follows:

$$d_i = \frac{e_i}{\sqrt{\text{MSE}}} \quad (6.1)$$

where, e_i is the residual corresponding to i -th observation and MSE stands for the Mean Square Error, taken as an estimate of standard deviation. A rough rule-of-thumb — if the true errors are iid and $N(0, \sigma^2)$, then 95 percent and 99.7 percent of standardized residuals

Figure 6.1: Partial Regression Residual Plot for Regressor CNTYINC of Model Cn5 [Individual case of Pre-Influence Analysis]

Figure 6.2: Partial Regression Residual Plot for Regressor CNTYVR of Model Cn5 [Individual case of Pre-Influence Analysis]

Figure 6.3: Partial Regression Residual Plot for Regressor CNTYHH
of Model Un4 [Group case of Pre-Influence Analysis]

should fall between ± 2 and ± 3 , respectively. Thus, if a standardized residual is bigger than 3, then it is a potential outlier with much skewness and/or kurtosis.

The studentized residual (RSTUDENT) differs slightly from the d_i because RSTUDENT is calculated with the current observation deleted. The cutoff value for RSTUDENT is usually taken as 2.0. This absolute cutoff value is independent on the sample size.

The third column of Tables 6.1 and 6.2 shows the values of RSTUDENT in models Cn5 and Un4, respectively. The observations with (*) beside the statistics have exceeded the suggested cutoff values. The group effect of City Number (CTYN) 6 is evident from the results of Table 6.2.

6.2.1.3 Change in the Fitted Values (DFFITS)

A way to summarize coefficient changes and, at the same time, to gain insight into the forecasting effects when an observation is deleted, is by the change in fit. The DFFITS statistic is a scaled measure of the change in the predicted value for the i th observation and is calculated by deleting the i th observation. The observation i is considered to be influential if

$$|DFFITS_i| > 2\sqrt{\frac{q+1}{n}} \quad (6.2)$$

where q and n are the number of predictor variables and total number of observations, respectively. The right hand side of Equation (6.2)

Table 6.1: Some Major Influential Diagnostics of Model Cn5
 [An illustration of individual effect before
 deleting any observation]

OBS	ID (City #)	RSTUDENT	HAT DIAG H	DFFITS	INTERCEP DFBETAS	CNTYINC DFBETAS	CNTYVR DFBETAS
1	30	0.2908	0.1061	0.1002	-0.0758	0.0826	-0.0325
2	30	0.5997	0.0768	0.1729	-0.1170	0.1298	-0.0474
3	30	1.1604	0.0507	0.2680	0.1766	-0.1566	0.0414
4	30	2.3459(*)	0.0429	0.4967	-0.1915	0.2342	-0.0578
5	30	1.8285	0.2995(*)	1.1956(*)	-1.0810(*)	1.1269(*)	-0.3171
6	33	0.4459	0.1041	0.1520	0.1213	-0.1084	-0.0274
7	33	0.0277	0.0497	0.0063	0.0011	-0.0003	-0.0034
8	33	-0.3251	0.0677	-0.0876	0.0368	-0.0469	0.0534
9	33	0.6679	0.0737	0.1884	0.1290	-0.1101	-0.0486
10	33	-0.1163	0.0697	-0.0318	0.0139	-0.0175	0.0195
11	35	-4.3482(*)	0.1849	-2.0712(*)	0.9574(*)	-0.9006(*)	-1.2981(*)
12	35	-0.6100	0.1661	-0.2723	-0.0989	0.1079	-0.2406
13	35	-0.8647	0.1445	-0.3554	-0.1143	0.1249	-0.3099
14	36	-1.0096	0.0722	-0.2817	-0.1787	0.1487	0.0923
15	36	-1.0029	0.0514	-0.2336	-0.0063	-0.0242	0.1374
16	36	-0.6248	0.0591	-0.1566	-0.0790	0.0607	0.0617
17	36	-0.7057	0.0578	-0.1747	0.0432	-0.0649	0.1085
18	41	1.3302	0.1364	0.5287	0.1534	-0.1685	0.4584(*)
19	41	-0.0104	0.1849	-0.0050	0.0023	-0.0022	-0.0031
20	41	1.0379	0.1661	0.4633	0.1682	-0.1835	0.4093(*)
21	41	0.8621	0.1445	0.3543	0.1140	-0.1245	0.3090
22	45	0.2272	0.1927	0.1110	0.1014	-0.0946	-0.0053
23	45	-0.1565	0.0748	-0.0445	-0.0295	0.0249	0.0133
24	45	-1.0733	0.0516	-0.2505	0.0142	-0.0467	0.1491
25	45	-0.0988	0.0804	-0.0292	-0.0208	0.0179	0.0073
26	45	-0.4946	0.0506	-0.1142	0.0018	-0.0166	0.0666
27	54	-0.2471	0.0468	-0.0547	-0.0143	0.0074	0.0248
28	54	-0.4545	0.0577	-0.1124	0.0430	-0.0559	0.0617
29	54	0.3494	0.0475	0.0780	0.0337	-0.0246	-0.0258
30	54	0.3881	0.0891	0.1214	-0.0777	0.0888	-0.0615

(*) Exceeds cutoff values: RSTUDENT=2.0; HAT DIAG=0.20; DFFITS=0.6325; DFBETAS=0.3651.

Table 6.2: Some Major Influential Diagnostics of Model Un4
 [An illustration of group effect before deleting
 any observation]

OBS	ID (City #)	RSTUDENT	HAT DIAG H	DFFITS	INTERCEP DFBETAS	CNTYHH DFBETAS
1	14	-0.8512	0.0283	-0.1451	-0.1387	0.0894
2	14	-0.8372	0.0274	-0.1405	-0.1335	0.0843
3	14	-0.6898	0.0267	-0.1142	-0.1077	0.0668
4	18	-0.3077	0.0346	-0.0582	-0.0572	0.0409
5	18	0.3161	0.0325	0.0580	0.0566	-0.0393
6	18	0.3132	0.0324	0.0573	0.0559	-0.0388
7	18	0.3239	0.0324	0.0593	0.0579	-0.0401
8	18	0.4544	0.0323	0.0830	0.0810	-0.0561
9	21	0.7507	0.0366	0.1464	0.1447	-0.1057
10	21	1.1309	0.0334	0.2104	0.2061	-0.1451
11	21	0.9255	0.0312	0.1660	0.1612	-0.1097
12	21	1.0885	0.0310	0.1947	0.1890	-0.1283
13	21	1.2589	0.0302	0.2223	0.2150	-0.1440
14	23	-0.5242	0.0316	-0.0946	0.0114	-0.0631
15	23	-0.1971	0.0326	-0.0362	0.0050	-0.0246
16	23	-0.0489	0.0346	-0.0093	0.0016	-0.0065
17	23	0.0320	0.0358	0.0062	-0.0011	0.0044
18	23	0.5443	0.0360	0.1052	-0.0198	0.0754
19	41	-1.9009	0.0346	-0.3599	0.0607	-0.2527
20	41	-1.8815	0.0358	-0.3623	0.0669	-0.2586
21	41	-1.5769	0.0360	-0.3049	0.0574	-0.2184
22	62	-0.2082	0.0466	-0.0461	-0.0460	0.0364
23	62	-0.2644	0.0462	-0.0582	-0.0581	0.0458
24	62	-0.2267	0.0463	-0.0499	-0.0499	0.0393
25	62	-0.2657	0.0463	-0.0585	-0.0585	0.0461
26	62	-0.0215	0.0463	-0.0047	-0.0047	0.0037
27	62	-0.0192	0.0462	-0.0042	-0.0042	0.0033
28	62	0.3514	0.0461	0.0773	0.0772	-0.0608
29	79	-0.2066	0.0490	-0.0469	-0.0469	0.0376

Table 6.2, continued

OBS	ID (City #)	RSTUDENT	HAT DIAG H	DFFITS	INTERCEP DFBETAS	CNTYHH DFBETAS
30	79	-0.3525	0.0479	-0.0790	-0.0790	0.0629
31	79	-0.4232	0.0479	-0.0949	-0.0948	0.0755
32	79	-0.2386	0.0477	-0.0534	-0.0534	0.0425
33	79	0.0264	0.0475	0.0059	0.0059	-0.0047
34	2	-0.9912	0.0180	-0.1341	-0.0928	0.0208
35	2	-1.1132	0.0175	-0.1488	-0.0863	0.0015
36	2	-0.8797	0.0175	-0.1176	-0.0671	-0.0001
37	2	-0.2671	0.0176	-0.0357	-0.0198	-0.0008
38	23	-0.6433	0.0316	-0.1161	0.0140	-0.0774
39	23	-0.4059	0.0326	-0.0745	0.0103	-0.0506
40	23	-0.5878	0.0346	-0.1113	0.0188	-0.0781
41	23	-0.6092	0.0353	-0.1166	0.0209	-0.0828
42	23	-0.4113	0.0358	-0.0792	0.0146	-0.0565
43	3	-1.2241	0.0316	-0.2210	0.0266	-0.1473
44	3	-0.7281	0.0326	-0.1337	0.0184	-0.0908
45	3	-0.7914	0.0346	-0.1498	0.0253	-0.1052
46	3	-0.6854	0.0353	-0.1312	0.0235	-0.0931
47	3	-0.5720	0.0358	-0.1102	0.0203	-0.0786
48	6	1.2954	0.0316	0.2339	-0.0281	0.1558
49	6	2.3499(*)	0.0326	0.4314(*)	-0.0594	0.2931(*)
50	6	2.7940(*)	0.0346	0.5289(*)	-0.0892	0.3714(*)
51	6	2.8883(*)	0.0353	0.5529(*)	-0.0990	0.3923(*)
52	6	3.0217(*)	0.0358	0.5819(*)	-0.1075	0.4153(*)
53	41	-0.3867	0.0316	-0.0698	0.0084	-0.0465
54	41	0.4664	0.0326	0.0856	-0.0118	0.0582
55	41	0.6321	0.0346	0.1197	-0.0202	0.0840
56	41	0.5102	0.0353	0.0977	-0.0175	0.0693
57	41	0.4485	0.0358	0.0864	-0.0160	0.0616

(*) Exceeds cutoff values: RSTUDENT=2.0; HAT DIAG=0.0702;
DFFITS=0.3746; DFBETAS=0.2649.

represents the cutoff value for DFFITS. The values of DFFITS statistics (column 5) and their cutoff values for models Cn5 and Un4 are shown in Table 6.1 and Table 6.2, respectively.

6.2.1.4 Change in the Regression Coefficients (DFBETAS)

The estimated regression coefficients are primarily of interest to the users of regression models. DFBETAS are the scaled measures of the change in each parameter/coefficient estimate and are calculated by deleting the i th observation. The cutoff for DFBETAS is calculated as $\frac{2}{\sqrt{n}}$, where n is the total number of observations. If the absolute value of DFBETAS is at least equal to this cutoff value, then the observation is a potential candidate to be an outlier. The last columns of Tables 6.1 and 6.2 show the values of DFBETAS of the parameter of the model.

6.2.1.5 Diagonal Element of Hat Matrix (HAT DIAG)

HAT DIAG (h_i) is the i th diagonal element of the hat matrix [SAS/STATISTICS 1985; Belsley, Kuh and Welsch 1980]. The h_i can be viewed as the coefficient of dependent variable (y_i) in its predicted value ($\hat{y}_i$). Thus, if one h_i 's is larger compared to the rest, then that element has more influence on the analysis than the rest. The observation i is considered to be influential if

$$h_i > 2 \frac{q+1}{n} \quad (6.3)$$

where the definitions of q and n remain the same as in Equation 6.2.

The fourth column of Tables 6.1 and 6.2 show the values of h_1 ("HAT DIAG").

6.2.1.6 Residual and Normal Probability Plots

Oftentimes, the residual plots convey more information about outliers and are generally used to detect them. The normal probability plot is not generally taken as a suggestive measure to detect the outlier(s). However, the effect of an outlier is often evident in the normal probability plot. A detailed discussion of the use of these plots is presented in Section 6.3 and its subsections. In using the residual plots, the observations with more than 2-3 times the standard deviation of the residuals are taken as possible candidates for the outlier. The residual plots and RSTUDENT measure in Section 6.2.1.2 are very close to each other. The residual plots of Figures 6.4 to 6.6 against predicted value and the regressor variables suggest that one observation (represented by the right hand bottom point of these plots) is a potential candidate to be an influential observation. Despite a higher P-value for normality, the normal probability plot of model Cn5 in Figure 6.7 also concludes that the observation corresponding to the lower left hand corner of Figure 6.7 is a suspected outlier — the same suspected point as in Figures 6.4 to 6.6.

The residual plots against the predicted values, regressor in the model, and the normal probability plot model Un4 are shown in Figures 6.8, 6.9, and 6.10, respectively. The four observations (represented by four right hand upper points in these plots) are suspected as a

Figure 6.4: Residual Plot against Predicted value of Model Cn5
[Individual case of Pre-Influence Analysis]

Figure 6.5: Residual Plot against Regressor CNTYINC of Model Cn5
[Individual case of Pre-Influence Analysis]

Figure 6.6: Residual Plot against Regressor CNTYVR of Model Cn5
[Individual case of Pre-Influence Analysis]

Figure 6.7: Normal Probability Plot of Model Cn5
[Individual case of Pre-Influence Analysis]

Figure 6.8: Residual Plot against Predicted value of Model Un4
[Group case of Pre-Influence Analysis]

Figure 6.9: Residual Plot against Regressor CNTYHH of Model Un4
[Group case of Pre-Influence Analysis]

Figure 6.10: Normal Probability Plot of Model Un4
[Group case of Pre-Influence Analysis]

possible group to be considered influential.

6.2.2 Pre and Post Analysis of Outliers

Outlier observations, if present, have an unusually high influence on parameter estimates, the ANOVA table, etc. A safe rule frequently suggested is to discard an outlier only if there is direct evidence that it represents an error in recording, processing, or a similar type of circumstance. Once an influential unit has been identified, efforts should be made to find out if any error was made in data collection or data manipulation associated with that unit. In the absence of such errors, the units that exceed at least three of the diagnostic cutoff values referred to Section 6.2.1 can be deleted from the data set. For example, the influential observations identified by the diagnostic measures -- RSTUDENT, DFFITS, HAT DIAG and DFBETAS -- have been examined in terms of partial regression plots, the normality plot, and residual plots against the predicted values and regressors to see whether they are posing any problem in getting statistically good results. Once an outlier or group of outliers has been identified, the observation(s) corresponding to the outlier(s) is(are) carefully examined to see if any of the following is the cause of being influential.

- i. Is there any error in data entry?
- ii. Is there any error in processing the data sets? (For example, computing county & city average data from the segment data.)

- iii. Did the county & city average AADT data get influenced by one or more segment's data? In that case, the influential segment(s) is(are) dropped from the segment data base and the county & city average data are recomputed from the remaining segments in the segment data base.
- iv. If some years of AADT values in any data base are thought to be due to faulty recording and/or an abnormal increase/decrease in AADT for some reasons (for example, construction, parallel/alternate road closure/opening, etc.), then those years of data were omitted in further analysis.
- v. Finally, if the outliers are not errors or mistakes, they are legitimate data values that just don't fit our simple linear model. Our theoretical model is not good enough to classify those outliers, or the prescribed model may not be correct.

After deletion of any influential observations, all the influential diagnostic measures and plots of residual and normal probability plots are reevaluated on the modified data sets. Such analysis after deletion of outliers is referred to as "Post-Influence Analysis", whereas the analysis before deletion of observations has been referred to as "Pre-Influence Analysis". The diagnostics and plots of Pre-Influence analysis confirmed that one observation (OBS 11 of Table 6.1) at year 1978 of city number 35 (Crown Point) is an outlier for model Cn5. A very low county or city average AADT for observation 11 causes it to be an outlier. For model Un4, the group of observations (OBS 49-52 of Table 6.2) with "city number = 6" (Hammond) appeared to be influen-

tial. Although observations 49-52 (see 6's in the partial regression plot of Figure 6.3) have predictor variable values within the range of values associated with the other observations, these four observations have AADT values outside the range of the other observations. Perhaps factors other than those included in our analysis could explain this anomaly. However, our only recourse here is to remove the outlying observations from the otherwise consistent data set.

At this stage, the model parameters are recalculated by deleting the outlier(s) confirmed through the influence analysis. The diagnostic statistics and the associated plots of this post-influence analysis for model Cn5 are shown in Table 6.3 and Figures 6.11 to 6.16. At least three of the four tests have been required as evidence of an outlier. Some judgment was used to verify outliers by reviewing the diagnostic measures and plots. The post-analysis results for model Un4 are shown in Table 6.4 and Figures 6.17 to 6.20. The results of the post-influence analysis are examined carefully to detect any additional possible outliers in the data set. If necessary, post-influence analysis is carried out further until the data set appears to be reasonably good about any apparent outlier.

Comparing the results of pre- and post-influence analysis (see table below), one can easily see the improvement in the model statistics. For example, the results of the P-value for normality, ST. DEV. of residuals, R^2 , R_a^2 , RMSE and Coefficient of Variation (C.V.) for the models Cn5 and Un4 are as follows:

Table 6.3: Some Major Influential Diagnostics of Model Cn5
[After deleting observation 11 of Table 6.1]

OBS	ID (City #)	RSTUDENT	HAT DIAG H	DFBETAS	INTERCEP DFBETAS	CNTYINC DFBETAS	CNTYVR DFBETAS
1	30	0.0013	0.1129	0.0005	-0.0004	0.0004	-0.0001
2	30	0.4392	0.0823	0.1316	-0.0913	0.1003	-0.0236
3	30	1.4855	0.0507	0.3433	0.2182	-0.1939	0.0542
4	30	2.8758(*)	0.0464	0.6344	-0.2671	0.3170	-0.0182
5	30	1.5598	0.3213(*)	1.0732(*)	-0.9751(*)	1.0130(*)	-0.1833
6	33	0.8626	0.1078	0.2998	0.2417	-0.2170	-0.0669
7	33	0.0948	0.0499	0.0217	0.0041	-0.0013	-0.0114
8	33	-0.5068	0.0680	-0.1369	0.0583	-0.0736	0.0768
9	33	1.0667	0.0755	0.3049	0.2115	-0.1819	-0.0879
10	33	-0.2398	0.0701	-0.0658	0.0291	-0.0364	0.0370
11	35	-1.4441	0.1823	-0.6818(*)	-0.1872	0.2113	-0.6091(*)
12	35	-1.7951	0.1601	-0.7836(*)	-0.1813	0.2066	-0.6921(*)
13	36	-1.1076	0.0742	-0.3135	-0.2026	0.1702	0.1117
14	36	-1.2709	0.0515	-0.2962	-0.0102	-0.0278	0.1700
15	36	-0.6655	0.0601	-0.1684	-0.0869	0.0678	0.0692
16	36	-0.9477	0.0578	-0.2347	0.0581	-0.0867	0.1377
17	41	1.1199	0.1522	0.4744	0.0945	-0.1093	0.4169(*)
18	41	-1.0283	0.2269(*)	-0.5571	0.2785	-0.2627	-0.3705
19	41	0.7322	0.1823	0.3457	0.0949	-0.1072	0.3088
20	41	0.5278	0.1601	0.2304	0.0533	-0.0608	0.2035
21	45	0.7479	0.2014	0.3756	0.3444	-0.3224	-0.0391
22	45	0.0003	0.0768	0.0001	0.0000	-0.0000	-0.0000
23	45	-1.3917	0.0517	-0.3248	0.0171	-0.0584	0.1865
24	45	0.0870	0.0828	0.0261	0.0188	-0.0164	-0.0075
25	45	-0.6197	0.0506	-0.1431	0.0015	-0.0198	0.0807
26	54	-0.2681	0.0469	-0.0595	-0.0158	0.0085	0.0267
27	54	-0.6940	0.0582	-0.1726	0.0677	-0.0870	0.0854
28	54	0.5134	0.0477	0.1149	0.0500	-0.0368	-0.0385
29	54	0.2841	0.0914	0.0901	-0.0587	0.0667	-0.0391

(*) Exceeds cutoff values: RSTUDENT=2.0; HAT DIAG=0.2069;
DFBETAS=0.6433; DFBETAS=0.3714.

Figure 6.11: Partial Regression Residual Plot for Regressor CNTYINC of Model Cn5 [Individual case of Post-Influence Analysis]

Figure 6.12: Partial Regression Residual Plot for Regressor CNTYVR of Model Cn5 [Individual case of Post-Influence Analysis]

LEGEND: A = 1 OBS, B = 2 OBS, ETC.

Figure 6.13: Residual Plot against Predicted value of Model Cn5
[Individual case of Post-Influence Analysis]

Figure 6.14: Residual Plot against Regressor CNTYINC of Model Cn5
[Individual case of Post-Influence Analysis]

Figure 6.15: Residual Plot against Regressor CNTYVR of Model Cn5
[Individual case of Post-Influence Analysis]

Figure 6.16: Normal Probability Plot of Model Cn5
[Individual case of Post-Influence Analysis]

Table 6.4: Some Major Influential Diagnostics of Model Un4
 [After deleting OBS 48-52 with ID (City #) 6 of Table 6.2]

OBS	ID (City #)	RSTUDENT	HAT DIAG H	DFFITS	INTERCEP DFBETAS	CNTYHH DFBETAS
1	14	-1.2175	0.0284	-0.2080	-0.1970	0.1181
2	14	-1.1837	0.0276	-0.1992	-0.1872	0.1095
3	14	-0.9443	0.0268	-0.1568	-0.1462	0.0835
4	18	-0.4547	0.0346	-0.0861	-0.0843	0.0573
5	18	0.5193	0.0326	0.0953	0.0926	-0.0609
6	18	0.5166	0.0324	0.0945	0.0918	-0.0602
7	18	0.5326	0.0324	0.0975	0.0947	-0.0622
8	18	0.7342	0.0323	0.1342	0.1303	-0.0854
9	21	1.1460	0.0367	0.2235	0.2203	-0.1541
10	21	1.7845	0.0335	0.3321	0.3240(*)	-0.2166
11	21	1.4835	0.0312	0.2662	0.2571	-0.1649
12	21	1.7466	0.0310	0.3126	0.3016(*)	-0.1929
13	21	2.0347(*)	0.0303	0.3596	0.3454(*)	-0.2173
14	23	-0.0977	0.0380	-0.0194	0.0027	-0.0137
15	23	0.4133	0.0393	0.0836	-0.0129	0.0597
16	23	0.6647	0.0417	0.1386	-0.0253	0.1017
17	23	0.8033	0.0431	0.1704	-0.0337	0.1268
18	23	1.6240	0.0434	0.3459	-0.0694	0.2581
19	41	-2.1752(*)	0.0417	-0.4536(*)	0.0829	-0.3329(*)
20	41	-2.1303(*)	0.0431	-0.4519(*)	0.0892	-0.3362(*)
21	41	-1.6497	0.0434	-0.3513	0.0705	-0.2622
22	62	-0.4143	0.0468	-0.0917	-0.0916	0.0704
23	62	-0.4967	0.0463	-0.1094	-0.1093	0.0837
24	62	-0.4395	0.0464	-0.0969	-0.0968	0.0742
25	62	-0.4994	0.0464	-0.1102	-0.1100	0.0843
26	62	-0.1262	0.0464	-0.0278	-0.0278	0.0213
27	62	-0.1221	0.0463	-0.0269	-0.0269	0.0206
28	62	0.4434	0.0462	0.0976	0.0974	-0.0746

Table 6.4, continued

OBS	ID (City #)	RSTUDENT	HAT DIAG H	DFFITS	INTERCEP DFBETAS	CNTYHH DFBETAS
29	79	-0.4313	0.0492	-0.0981	-0.0981	0.0766
30	79	-0.6456	0.0480	-0.1450	-0.1448	0.1122
31	79	-0.7545	0.0480	-0.1694	-0.1693	0.1312
32	79	-0.4697	0.0479	-0.1053	-0.1052	0.0815
33	79	-0.0634	0.0477	-0.0142	-0.0142	0.0110
34	2	-1.2004	0.0193	-0.1684	-0.1090	0.0108
35	2	-1.3342	0.0194	-0.1875	-0.0991	-0.0156
36	2	-0.9695	0.0194	-0.1364	-0.0708	-0.0128
37	2	-0.0279	0.0195	-0.0039	-0.0020	-0.0004
38	23	-0.2784	0.0380	-0.0553	0.0077	-0.0389
39	23	0.0943	0.0393	0.0191	-0.0029	0.0136
40	23	-0.1595	0.0417	-0.0333	0.0061	-0.0244
41	23	-0.1837	0.0426	-0.0387	0.0075	-0.0287
42	23	0.1212	0.0431	0.0257	-0.0051	0.0191
43	3	-1.1597	0.0380	-0.2305	0.0320	-0.1620
44	3	-0.3945	0.0393	-0.0797	0.0123	-0.0570
45	3	-0.4676	0.0417	-0.0975	0.0178	-0.0716
46	3	-0.2991	0.0426	-0.0631	0.0121	-0.0467
47	3	-0.1230	0.0431	-0.0261	0.0052	-0.0194
48	41	0.1113	0.0380	0.0221	-0.0031	0.0155
49	41	1.4557	0.0393	0.2943	-0.0456	0.2102
50	41	1.7517	0.0417	0.3653	-0.0668	0.2681
51	41	1.5603	0.0426	0.3290	-0.0633	0.2436
52	41	1.4646	0.0431	0.3107	-0.0614	0.2311

(*) Exceeds cutoff values: RSTUDENT=2.0; HAT DIAG=0.0769;
DFFITS=0.3992; DFBETAS=0.2774.

Figure 6.18: Residual Plot against Predicted value of Model Un4
[Group case of Post-Influence Analysis]

Figure 6.19: Residual Plot against Regressor CNTYHH of Model Un4
[Group case of Post-Influence Analysis]

Figure 6.20: Normal Probability Plot of Model Un.
[Group case of Post-Influence Analysis]

Model (***)	Ana- lysis	ST DEV (*)	P-value of W-test (*)	R^2 (**)	R_a^2 (**)	RMSE (**)	C.V. (**)
Cn5	Pre	2192	0.347	33.55	28.63	2271	20.57
	Post	1697	0.672	58.04	54.81	1761	15.74
Un4	Pre	20152	<0.01	48.79	47.85	20333	46.04
	Post	13205	0.137	55.64	54.76	13336	35.24

(*) See Tables 6.17, 6.18, 6.20, 6.21.

(**) See Figures 6.4-6.10, 6.13-6.16, 6.18-6.20.

(***) Model Cn5: 1 of 30 original observations deleted as outlier.
Model Un4: 4 of 56 original observations deleted as outliers.

Tables in Section 6.3 and 6.4 show the improvement in statistics for all the candidate models owing to this influence analysis.

6.3 Validity of Regression Assumptions and Model Aptness

Due to the fact that the estimation of model regression parameters depends on assumptions concerning the statistical characteristics of the error components in the model, these assumptions are crucial in determining the specific estimation procedure. Three most important assumptions regarding regression are

1. Linearity of the model,
2. Homoscedasticity of variance, and
3. Normality of the errors.

In this section, some formal tests and a commonly used graphic residual analysis are used to verify the above assumptions and to check the aptness of the models. The validity of some of the tests (for example, the significance test of the parameter — see Section 6.4.2) depends on one or some of these assumptions (for example, normality assumption is crucial for significance test).

The residual plots shown in this section are generated by the SAS package [SAS/Basics 1985]. The plots were done to check the aptness of each model. The i th residual, denoted by e_i , is the difference between the observed value Y_i and the corresponding fitted value $\hat{Y}_i$ (i.e., $e_i = Y_i - \hat{Y}_i$).

6.3.1 Scatterplots: Linear Pattern of the Model

Scatterplots display the relationships between two quantitative variables graphically. It is a good plot if the general pattern shows the direction, form, and strength of the relationship between the variables. The strength of a scatterplot is that it provides a complete picture of the relationship between two variables — at least as far as that relationship is reflected in the available data. A complete picture is often too detailed for easy interpretation. But one can easily see a general pattern by smoothing a scatterplot. The smoothing is done by averaging the y values separately for each x value. Figures 6.21-6.23 show the three representative plots, one from each highway category. A linear pattern is plausible in each of these plots.

6.3.2 Residual Plots: Independence and Linearity of the Model

The independence assumption is all but impossible to check (or correct) after the experiment is over. The plot of residuals against the time in which data were collected, help to detect correlations or dependence in the residuals. But runs of positive and negative residuals is usually an expected result from the cross-classified (data

Figure 6.21: A Scatterplot for Region "s" of Urban Interstate Highways

Figure 6.22: A Scatterplot for City Group "C" and Region "n" of Urban Principal Arterial

Figure 6.23: A Scatterplot for City Group "D" and Region "c+n" of Urban Minor Arterial and Collector

from different counties/cities) data we have. If the residuals tend to spread more or less over time, then there is a problem of non-constant error variance. For a linear model, the scatter plots of Y against X 's should depict no nonlinear trend. Also, a parallel horizontal band of the plots of residuals against each predictor variable suggests linearity of the model.

The plots of residuals against the fitted response variable and predictor variables (see the representative Figures 6.13-6.15, 6.18 and 6.19) suggest no grounds for questioning the appropriateness of the linearity of the regression function or the constancy of the error variance. There are no suggestions in any of these plots that systematic deviation from the fitted response plane (for more than one variable in the equation) or line (for one variable in the equation) is present. The error variance varies in some of these plots with the level of $\hat{Y}$ and X 's, but this variation does not exhibit any gross departure. After correction through influence analysis, the residual plots against the $\hat{Y}$ (predicted values) and the X 's (regressors in the model) do not suggest the presence of any outlier. In a residual plot, outliers are the points that lie far beyond the scatter of the remaining residuals, perhaps 3 or more standard deviations from zero [Neter et al. 1985].

Residual plots were also generated against variables not included in the model, to check whether some key independent or predictor variables could provide important additional descriptive and predictive power to the model. Three representative plots (Figures 6.24-6.26) of residuals against CNTYINC for models Rsl (Gr-ix), Ds4 (Gr-xii) and C4

(Gr-iii) (one from each highway category) do not show any correlation between the error terms and the variable, CNTYINC, which is not included in the models. This is because the residuals are random around the zero line. Thus, it is confirmed that the appropriate variables are included in the model and no additional variable will provide significant additional power to the model.

6.3.3 Residuals Plots: Homoscedasticity of Variance

If the model is correct, and three assumptions -- normality, independence and linearity -- hold, the residuals should be without pattern or structure. To see if there is a pattern or structure, we plot the residuals against: (1) the dependent variable, (2) the predicted values and (3) independent variables. This type of test to see the non-constant variance is an informal, but most widely accepted, procedure for testing the homogeneity of residuals. A horizontal random parallel band of these plots (see the representative plots 6.13-6.15, 6.18-6.19, 6.24-6.26) suggests the homoscedasticity of variances. In other words, absence of heteroscedasticity is visually indicated by a scatter of points uniformly distributed across the graph. As with the normality assumption (see Section 6.3.4), the assumption of constant variance is important for consistent and efficient estimates of the regression coefficients.

6.3.4 Normality Tests and Plots: Normality of Errors

The assumption of normality is often made that data come from a suitable normal distribution. Since the validity of many results

Figure 6.24: Residual Plot against CNTYINC of Model Rsl
[Region "s" of Rural Interstate Highways]

Figure 6.25: Residual Plot against CNTYINC of Model Ds4
[City Group "D" & Region "s" of Urban Principal Arterial]

Figure 6.26: Residual Plot against CNTYINC of Model C4
[City Group "C" of Urban Minor Arterial & Collector]

often depend on the validity of the normal assumption, it is important to test for normality. If the true errors are iid and $N(0, \sigma^2)$, then the normal probability plot should be (close to) a straight line. In general, the greater the amount of non-normality, the lower the power of the ANOVA F-test to detect the significance of the variable(s).

A heuristic test of normality is to draw the histogram to see if the distribution is reasonably symmetric. Two informal tests of normality are also done through the coefficient of skewness and the coefficient of kurtosis. The coefficient of skewness indicates whether the distribution is symmetric or not. For a normal distribution, the expected value of this coefficient is zero. Since normal distributions are not the only symmetric distributions, a skewness test is not by itself a sufficient check for normality. The coefficient of kurtosis measures the peakedness of the data set. For a normal distribution, the expected value of this coefficient is 3.

The standard and widely used tests for normality are the Wilk-Shapiro W test and normal probability plots. SAS procedure UNIVARIATE [SAS/BASICS 1985] was used to test normality. For fewer than 51 observations, the W statistic is calculated, whereas for 51 or more observations, the Kolmogorov D statistic is computed by the SAS UNIVARIATE procedure. Small values of W leads to the rejection of the null hypothesis of normality. Probabilities, $PROB>W$ (for $N < 51$) and $PROB<D$ (for $N \geq 51$) are used for testing that the data come from a normal distribution. Values of these probabilities higher than the specified α -level (usually, 5 percent) show that data are drawn from a normal distribution. In pre-influence analysis, the results of these

normality tests along with standard deviation, skewness and kurtosis of residuals of all the model data models are shown in Table 6.5 to 6.7 for different groups of highway classes, identified in Chapter 5. Tables 6.8 to 6.10 show normality test results in post-influence analysis. Comparing the results of normality tests in pre- and post-influence analysis, one can see the improvement in results in post-influence analysis. In all data groups in Tables 6.8 to 6.10 except Group i of Interstate Highways, the P-value ($\text{PROB} < D$ or $\text{PROB} > W$) of the normality test is greater than 0.05. With these general improvements in the results of normality tests in post-influence analysis (compared to pre-influence analysis), a significant improvement — from non-normal distributions to normal distributions — is noticed in Groups iii, v, vi, ix, xi of Interstate Highways (see Tables 6.5 and 6.8). These results also prove the usefulness of the influence analysis.

Normal quantile plots (often called normal probability plots) are recommended for assessing normality. There are several variations on the normal quantile plot. Approximately normal data will produce plotted points that lie close to a line. Real data will almost always show some departure from the theoretical normal model, so it is important to confine the examination of a normal quantile plot to searching for shapes that show clear departures from normality. In other words, minor wiggles are not a major concern. [Moore & McCabe 1989]. Three representative normal probability plots after the influence analysis, one from each highway category, are presented in Figures 6.27 to 6.29. Figures 6.7, 6.10, 6.16 and 6.20 also have illustrated the normal probability plots. All these normal probability plots fall reasonably

Table 6.5: Normality Statistics of Residuals in Pre-Influence Analysis
[Interstate Highways]

Model Gr.	Model No.	N	Std. Dev.	Skewness	Kurtosis	Shapiro-Wilk, Prob>W (W)	Kolmogorov, Prob<D (D)
i. Inter- state High- ways	UR2	313	13878	1.655	6.759		0.0999 <0.01
	UR4	313	13692	1.534	6.198		0.0894 <0.01
	UR12	313	13418	1.565	6.771		0.0915 <0.01
	UR13	313	13414	1.564	6.640		0.0837 <0.01
ii. Rural Inter- state Hwys.	R3	186	7545	0.197	-0.181		0.0382 >0.15
	R4	186	7473	0.215	-0.252		0.0356 >0.15
	R6	186	7453	0.216	-0.242		0.0358 >0.15
	R16	186	7285	0.426	0.046		0.0657 0.048
iii. Urban Inter- state Hwys.	U2	127	17024	1.635	4.139		0.1392 <0.01
	U4	127	16638	1.564	3.867		0.1230 <0.01
	U9	127	16301	1.524	3.931		0.1305 <0.01
	U11	127	16243	1.622	4.284		0.1303 <0.01
iv. Region 'c' of Inter- state High- ways	URc3	132	9403	0.266	0.995		0.0425 >0.15
	URc4	132	9324	0.251	1.131		0.0442 >0.15
	URc14	132	8500	0.089	1.503		0.0514 >0.15
	URc15	132	8494	0.068	1.395		0.0523 >0.15
	URc24	132	8343	-0.005	1.398		0.0664 >0.15
	URc25	132	8332	-0.034	1.293		0.0751 0.068

Table 6.5, continued

Model Gr.	Model No.	N	Std. Dev.	Skewness	Kurtosis	Shapiro-Wilk, Prob>W (W)	Kolmogorov, Prob<D (D)
v. Region 'n' of	URn2	104	18300	1.108	2.985		0.1189 <0.01
	URn3	104	18085	1.123	3.146		0.1170 <0.01
	URn4	104	18044	1.080	2.921		0.1187 <0.01
	URn10	104	17763	1.124	3.318		0.1309 <0.01
	URn12	104	17715	1.175	3.616		0.1368 <0.01
vi. Region 's' of	URs1	77	8064	0.799	0.948		0.1253 <0.01
	URs2	77	7944	1.049	2.156		0.1141 0.014
	URs3	77	7907	0.848	1.214		0.1108 0.020
	URs4	77	7785	0.979	1.748		0.1180 <0.01
vii. Region 'c' of	Rc4	80	6681	0.060	-0.149		0.0528 >0.15
	Rc5	80	6678	0.061	-0.128		0.0555 >0.15
	Rc6	80	6663	0.064	-0.159		0.0536 >0.15
	Rc14	80	6515	0.312	0.068		0.0763 >0.15
	Rc15	80	6511	0.320	0.086		0.0821 >0.15
	Rc16	80	6506	0.311	0.047		0.0840 >0.15
viii. Region 'n' of Rural Int. Hwys.	Rn1	47	7422	0.419	0.658	0.9814 0.769	
	Rn4	47	7290	0.273	0.671	0.9815 0.774	
	Rn5	47	7289	0.310	0.522	0.9801 0.722	
	Rn6	47	7274	0.249	0.703	0.9808 0.746	

Table 6.5, continued

Model Gr.	Model No.	N	Std. Dev.	Sk ne	Kur-tosis	Shapiro-Wilk, Prob>W (W)	Kolmo-grov, Prob<D (D)
ix. Region 's' of Rural Int. Hwys.	Rs1	59	4956	0.019	1.007		0.1457 <0.01
	Rs2	59	4939	0.	1.080		0.1623 <0.01
	Rs3	59	4903		1.316		0.1548 <0.01
	Rs4	59	4902		1.351		0.1290 0.016
x. Region 'c' of Urban Interstate Highways	Uc1	52	9123	0.571	0.395		0.0821 >0.15
	Uc2	52	8783	0.518	0.207		0.0754 >0.15
	Uc3	52	8736	0.490	0.114		0.0862 >0.15
	Uc4	52	8482	0.405	-0.352		0.0904 >0.15
	Uc12	52	8050	0.330	-0.270		0.1038 >0.15
	Uc13	52	7915	0.312	-0.461		0.0942 >0.15
xi. Region 'n' of Urban Int. Hwys.	Un2	57	20391	1.013	1.451		0.1170 0.050
	Un3	57	20229	1.073	1.582		0.1291 0.019
	Un4	57	20152	1.004	1.423		0.1396 <0.01
	Un11	57	19920	1.055	1.668		0.1251 0.025
	Un13	57	19905	1.124	1.836		0.1223 0.033
xii. Region 's' of Urban Interstate Highways	Us3	18	8076	0.948	1.374	0.9373 0.322	
	Us4	18	7489	0.873	1.179	0.9450 0.395	
	Us10	18	6693	0.876	1.232	0.9491 0.434	
	Us11	18	6653	1.087	1.736	0.9184 0.142	
	Us12	18	6380	1.262	2.016	0.8974 0.051	
	Us13	18	6238	1.117	1.613	0.9221 0.177	

Table 6.6: Normality Statistics of Residuals in Pre-Influence Analysis
[Urban Principal Arterial]

Model Gr.	Model No.	N	Std. Dev.	Skew- ness	Ku- rtosis	Shapiro Wilk, Prob>W (W)	Kolmo- grov, Prob<D (D)
i. City Gr.=A & Region =c	Ac4	15	1272	-1.042	1.000	0.9143 0.208	
	Ac5	15	1247	-0.894		0.9319 0.352	
	Ac6	15	1218	-0.975		0.8831 0.055	
	Ac7	15	1097	-1.125	1.000	0.9295 0.333	
ii. City Gr.=A & Region =s	An6	23	2323	0.494	0.530	0.9447 0.296	
	An7	23	2321	0.565	0.522	0.9495 0.352	
	An8	23	2274	0.489	0.403	0.9505 0.365	
	An9	23	2241	0.504	0.514	0.9572 0.444	
xiii. City Gr.=A+ B+C & Region =s	ABCs3	15	3445	-0.858	-0.874	0.8324 <0.01	
	ABCs4	15	2854	-0.190	-1.185	0.9495 0.496	
	ABCs7	15	2529	-0.646	-0.782	0.9179 0.238	
	ABCs8	15	2504	-0.730	-0.698	0.8922 0.078	
	ABCs9	15	2496	-0.711	-0.847	0.8900 0.073	
iv. City Gr.=B & Region =c	Bc3	12	1523	-0.791	-0.986	0.8519 0.043	
	Bc4	12	1484	-0.778	-0.903	0.8689 0.071	
	Bc5	12	1456	-0.839	-0.784	0.8612 0.055	
	Bc12	12	1329	-0.499	-1.534	0.8664 0.065	
v. City Gr.=B & Region =n	Bn12	13	877	-0.268	-1.060	0.9560 0.651	
	Bn14	13	840	0.540	-0.167	0.9477 0.537	
	Bn15	13	837	-0.179	-1.238	0.9493 0.559	
	Bn21	13	728	0.074	-0.416	0.9792 0.951	

Table 6.6, continued

Model Gr.	Model No.	N	Std. Dev.	Skew- ness	Kur- tosis	Shapiro -Wilk, Prob>W (W)	Kolmo- grov, Prob<D (D)
vii. City Gr.=C & Region =c	Cc5	45	3328	0.797	1.433	0.9433 0.045	
	Cc6	45	2783	0.088	0.255	0.9923 1.000	
viii. City Gr.=C & Region =n	Cn5	30	2192	-0.604	2.547	0.9563 0.347	
	Cn6	30	2175	-0.743	2.988	0.9474 0.221	
	Cn7	30	2080	-0.524	1.138	0.9688 0.547	
x. City Gr.=D & Region =c	Dc10	26	1045	0.085	-0.252	0.9803 0.860	
	Dc11	26	1022	0.165	0.269	0.9779 0.804	
	Dc18	26	952	0.046	-0.337	0.9635 0.481	
	Dc19	26	936	0.183	-0.599	0.9350 0.125	
xi. City Gr.=D & Region =n	Dn3	34	2395	0.375	-0.271	0.9541 0.270	
	Dn4	34	2373	0.421	-0.175	0.9496 0.201	
	Dn15	34	2302	0.470	-0.443	0.9384 0.077	
	Dn16	34	2299	0.365	-0.569	0.9645 0.430	
xii. City Gr.=D & Region =s	Ds3	42	1740	0.504	1.599	0.9691 0.444	
	Ds4	42	1706	0.530	2.279	0.9574 0.221	
	Ds12	42	1663	0.402	1.755	0.9651 0.368	
	Ds13	42	1661	0.482	2.192	0.9559 0.193	

Table 6.7: Normality Statistics of Residuals in Pre-Influence Analysis
[Urban Minor Arterial & Collector]

Model Gr.	Model No.	N	Std. Dev.	Skew- ness	Kur- tosis	Shapiro -Wilk, Prob>W (W)	Kolmo- grov, Prob<D (D)
i. City Gr.=A	A2	18	2465	0.592	-0.201	0.9341 0.291	
	A5	18	2228	0.815	0.365	0.9356 0.306	
	A6	18	2169	0.748	0.214	0.9393 0.341	
	A7	18	2111	0.651	0.989	0.9449 0.394	
ii. City Gr.=B	B2	13	2215	-0.066	-0.887	0.9714 0.864	
iii. City Gr.=C	C2	13	1011	-0.923	-0.542	0.8452 0.028	
	C3	13	969	-0.818	-0.591	0.8752 0.070	
	C4	13	934	-0.844	-0.465	0.8544 0.038	
iv. City Gr.=C	C9	11	1203	-0.052	-1.762	0.9034 0.271	
	C10	11	1160	-0.183	0.052	0.9739 0.907	
	C11	11	1123	0.304	-0.049	0.9533 0.661	
	C12	11	1117	-0.198	0.338	0.9741 0.909	
v. City Gr.=D	D6	28	2299	0.878	-0.055	0.9062 0.018	
vi. City Gr.=D	D7	24	1141	-0.311	-0.185	0.9788 0.851	

Table 6.8: Normality Statistics of Residuals in Post-Influence Analysis
[Interstate Highways]

Model Gr.	Model No.	N	Std. Dev.	Skewness	Kurtosis	Shapiro-Wilk, Prob>W (W)	Kolmogorov, Prob<D (D)
i. Interstate Highways	UR2	225	5899	0.214	-1.037		0.0782 <0.01
	UR4	225	6109	0.241	-1.025		0.0733 <0.01
	UR12	225	5989	0.195	-0.962		0.0674 <0.01
	UR13	225	5981	0.196	-1.007		0.0720 <0.01
ii. Rural Interstate Hwys.	R3	121	3983	0.258	-0.899		0.0632 >0.15
	R4	121	3809	0.403	-0.753		0.0854 0.029
	R6	121	3767	0.454	-0.738		0.0823 0.043
	R16	121	3766	0.441	-0.748		0.0844 0.034
iii. Urban Interstate Hwys.	U2	103	8774	0.119	-0.698		0.0693 >0.15
	U4	103	8585	0.207	-0.687		0.0800 0.102
	U9	103	8251	0.034	-0.667		0.0716 >0.15
	U11	103	8105	0.133	-0.488		0.0528 >0.15
iv. Region 'c' of Interstate Highways	URc3	116	6831	0.080	-0.730		0.0468 >0.15
	URc4	116	6745	0.090	-0.737		0.0490 >0.15
	URc14	116	6124	-0.083	-0.620		0.0559 >0.15
	URc15	116	6131	-0.111	-0.577		0.0470 >0.15
	URc24	116	6035	-0.190	-0.662		0.0683 >0.15
	URc25	116	6035	-0.230	-0.607		0.0593 >0.15

Table 6.8, continued

Model Gr.	Model No.	N	Std. Dev.	Skewness	Kurtosis	Shapiro-Wilk, Prob>W (W)	Kolmogorov, Prob<D (D)
v. Region 'n' of Interstate Highways	URn2	77	8830	0.142	0.326		0.0860 >0.15
	URn3	77	8585	0.396	0.225		0.0863 >0.15
	URn4	77	8380	0.327	-0.004		0.0876 0.149
	URn10	77	7936	0.094	-0.107		0.0816 >0.15
	URn12	77	7922	0.203	0.036		0.1158 0.012
vi. Region 's' of Interstate Hwys.	URs1	57	4136	-0.018	-0.589		0.0619 >0.15
	URs2	57	4094	-0.133	-0.426		0.0748 >0.15
	URs3	57	4243	-0.186	-0.373		0.0612 >0.15
	URs4	57	4079	-0.089	-0.567		0.0729 >0.15
vii. Region 'c' of Rural Interstate Highways	Rc4	71	5200	0.031	-1.027		0.0811 >0.15
	Rc5	71	5178	0.037	-1.043		0.0841 >0.15
	Rc6	71	5183	0.037	-1.054		0.0800 >0.15
	Rc14	71	5132	0.107	-0.979		0.0774 >0.15
	Rc15	71	5112	0.117	-1.001		0.0818 >0.15
	Rc16	71	5123	0.112	-1.010		0.0780 >0.15
viii. Region 'n' of Rural Int. Hwys.	Rn1	35	4313	0.174	-0.266	0.9805 0.807	
	Rn4	35	4100	-0.050	-0.088	0.9796 0.783	
	Rn5	35	4079	0.132	-0.303	0.9695 0.513	
	Rn6	35	4057	-0.145	0.050	0.9780 0.739	

Table 6.8, continued

Model Gr.	Model No.	N	Std. Dev.	Skewness	Kurtosis	Shapiro-Wilk, Prob>W (W)		Kolmogorov, Prob<D (D)	
ix. Region 's' of Rural Int. Hwys.	Rs1	43	2225	-0.129	-0.673	0.9675	0.401		
	Rs2	43	2285	-0.344	-0.506	0.9569	0.207		
	Rs3	43	2198	-0.194	-0.585	0.9620	0.300		
	Rs4	43	2272	-0.398	-0.426	0.9498	0.092		
x. Region 'c' of Urban Inter- state High- ways	Uc1	50	7716	0.262	-0.740	0.9613	0.233		
	Uc2	50	7461	0.187	-0.842	0.9597	0.200		
	Uc3	50	7473	0.175	-0.858	0.9597	0.199		
	Uc4	50	7396	0.130	-0.925	0.9586	0.175		
	Uc12	50	6941	-0.038	-0.974	0.9577	0.157		
	Uc13	50	6943	-0.005	-0.815	0.9633	0.275		
xi. Region 'n' of Urban Int. Hwys.	Un2	52	13391	0.152	-0.554			0.1064	0.146
	Un3	52	13260	0.262	-0.545			0.1142	0.089
	Un4	52	13205	0.173	-0.463			0.1074	0.137
	Un11	52	12762	0.073	-0.442			0.1167	0.077
	Un13	52	12688	0.204	-0.449			0.1259	0.039
xii. Region 's' of Urban Inter- state High- ways	Us3	16	4679	-0.020	-1.104	0.9547	0.544		
	Us4	16	4402	0.086	-1.101	0.9618	0.664		
	Us10	16	3986	0.249	-1.197	0.9408	0.403		
	Us11	16	3534	-0.014	-0.763	0.9724	0.840		
	Us12	16	3161	-0.075	-1.044	0.9691	0.785		
	Us13	16	3423	0.171	-1.370	0.9388	0.386		

Table 6.9: Normality Statistics of Residuals in Post-Influence Analysis
[Urban Principal Arterial]

Model Gr.	Model No.	N	Std. Dev.	Skew- ness	Kur- tosis	Shapiro -Wilk, Prob>W (W)	Kolmo- grov, Prob<D (D)
i. City Gr.=A & Region =c	Ac4	14	945	-0.122	-1.292	0.9173 0.271	
	Ac5	14	932	0.175	-0.829	0.9555 0.621	
	Ac6	14	1004	-0.850	-0.479	0.8907 0.090	
	Ac7	14	808	-0.316	-1.007	0.9461 0.493	
ii. City Gr.=A & Region =s	An1	21	1631	-0.009	-0.544	0.9845 0.961	
	An6	21	1437	0.038	-0.747	0.9619 0.539	
	An7	21	1537	0.365	-0.205	0.9722 0.744	
	An8	21	1447	0.169	-0.724	0.9465 0.354	
	An9	21	1402	0.106	-0.749	0.9625 0.551	
xiii. City Gr.=A+ B+C & Region =s	ABCs3	15	3458	-0.764	-0.972	0.8563 0.021	
	ABCs4	15	2688	-0.057	-1.419	0.9354 0.381	
	ABCs7	15	2389	-0.564	-0.902	0.9288 0.327	
	ABCs8	15	2357	-0.657	-0.835	0.9066 0.145	
	ABCs9	15	2353	-0.645	-0.932	0.9035 0.121	
iv. City Gr.=B & Region =c	Bc3	12	1523	-0.791	-0.986	0.8519 0.043	
	Bc4	12	1484	-0.778	-0.903	0.8689 0.071	
	Bc5	12	1456	-0.839	-0.784	0.8612 0.055	
	Bc12	12	1329	-0.499	-1.534	0.8664 0.065	
v. City Gr.=B & Region =n	Bn12	13	877	-0.268	-1.060	0.9560 0.651	
	Bn14	13	840	0.540	-0.167	0.9477 0.537	
	Bn15	13	837	-0.179	-1.238	0.9493 0.559	
	Bn21	13	728	0.074	-0.416	0.9792 0.951	

Table 6.9, continued

Model Gr.	Model No.	N	Std. Dev.	Skewness	Kurtosis	Shapiro-Wilk, Prob>W (W)	Kolmogorov, Prob<D (D)
vii. City Gr.=C & Region =c	Cc5	42	2755	0.161	0.672	0.9616 0.303	
	Cc6	42	2282	-0.009	-0.619	0.9786 0.704	
viii. City Gr.=C & Region =n	Cn1	29	1860	0.546	-0.365	0.9597 0.413	
	Cn5	29	1697	0.422	-0.003	0.9729 0.672	
	Cn6	29	1641	0.305	-0.057	0.9768 0.771	
	Cn7	29	1732	0.309	-0.647	0.9602 0.421	
x. City Gr.=D & Region =c	Dc10	25	876	0.055	-0.874	0.9752 0.765	
	Dc11	25	805	-0.181	-1.071	0.9549 0.390	
	Dc18	25	774	0.031	-1.170	0.9426 0.241	
	Dc19	25	820	0.445	-1.021	0.9212 0.062	
xi. City Gr.=D & Region =n	Dn3	33	2169	0.099	-1.043	0.9402 0.092	
	Dn4	33	2141	0.137	-0.990	0.9371 0.078	
	Dn15	33	2107	0.273	-0.936	0.9269 0.041	
	Dn16	33	2129	0.226	-0.851	0.9509 0.237	
xii. City Gr.=D & Region =s	Ds3	39	1273	0.115	-0.407	0.9749 0.621	
	Ds4	39	1185	0.223	-0.205	0.9825 0.853	
	Ds12	39	1210	-0.036	0.308	0.9922 1.000	
	Ds13	39	1160	0.120	0.270	0.9896 0.990	

Table 6.10: Normality Statistics of Residuals in Post-Influence Analysis
[Urban Minor Arterial & Collector]

Model Gr.	Model No.	N	Std. Dev.	Skewness	Kurtosis	Shapiro-Wilk, Prob>W (W)	Kolmogorov, Prob<D (D)
i. City Gr.=A	A2	16	1959	0.515	0.819	0.9605 0.642	
	A5	16	1543	0.020	-0.959	0.9761 0.901	
	A6	16	1533	-0.001	-0.960	0.9777 0.917	
	A7	16	1551	0.095	-0.766	0.9768 0.908	
ii. City Gr.=B	B2	12	1905	0.218	-1.412	0.9362 0.455	
iii. City Gr.=C	C2	13	625	-0.285	-1.157	0.9383 0.452	
	C3	13	598	-0.111	-1.073	0.9601 0.709	
	C4	13	555	-0.056	-0.810	0.9583 0.684	
iv. City Gr.=C	C9	11	1203	-0.052	-1.762	0.9034 0.271	
	C10	11	1160	-0.183	0.052	0.9739 0.907	
	C11	11	1123	0.304	-0.049	0.9533 0.661	
	C12	11	1117	-0.198	0.338	0.9741 0.909	
v. City Gr.=D	D6	25	1649	0.614	-0.703	0.9132 0.041	
vi. City Gr.=D	D7	23	1018	-0.019	-0.659	0.9713 0.696

Figure 6.27: Normal Probability Plot of Model Rsl
[Region "s" of Rural Interstate Highways]

Figure 6.28: Normal Probability Plot of Model Ds4
[City Group "D" & Region "s" of Urban Principal Arterial]

Figure 6.29: Normal Probability Plot of Model C4
[City Group "C" of Urban Minor Arterial & Collector]

close to straight lines, suggesting that the error terms are approximately normally distributed. A slight departure is noticed for the normal probability plot of some cases. It is believed [Neter et al. 1985] that this small departure from normality will not create any serious problems.

6.4 Significance and Collinearity of Regression Coefficients

During the process of selecting the possible candidate models in Chapter 5, the models with consistency in sign of their regression coefficients were chosen. The correspondence between the regression coefficients and collinearity problem does not guarantee that our selections are free of collinearity problem. In subsection 6.4.1, some formal tests of collinearity are performed on the selected candidate models.

The test for significance of the parameters in the model and overall significance test for regression relation are carried out in Subsection 6.4.2. The presence of multicollinearity affects the significance of these tests. But the absence of multicollinearity does not guarantee that all the variables in the model are significant.

6.4.1 Collinearity Diagnostics of Regression Coefficients

When a regressor is a nearly linear combination of other regressors in the model, the affected estimates are unstable and have high standard errors. Examining the correlation matrix of the explanatory variables is a commonly employed procedure since this matrix is a

standard output of most regression packages. A high correlation coefficient between the two explanatory variates can indeed point to a possible collinearity problem. The diagonal elements of the inverse of the correlation matrix are called the Variance Inflation Factors (VIF). The diagnostic value of VIF of the k -th independent variable (X_k) is calculated as follows:

$$VIF_k = \frac{1}{1-R_k^2} \quad (6.4)$$

where, R_k^2 is the multiple correlation coefficient of X_k regressed on the remaining explanatory variables. Thus, VIF_k is equal to 1 when $R_k^2=0$, i.e., when X_k is not linearly related to the other X variables. On the other hand, a high VIF indicates an R_k^2 near unity, and hence points to collinearity. A maximum VIF_k above 10 is often taken as an indication that multicollinearity may be unduly influencing the least squares estimates.

A limitation of the correlation matrix and VIF for detecting multicollinearities is that they cannot distinguish between several simultaneous multicollinearities. It is clearly possible for three or more variates to be collinear while no two of the variates taken alone are highly correlated. The correlation matrix and the VIF are wholly incapable of diagnosing such a situation. Condition numbers/indices and the variance-decomposition proportion [Belsley, Kuh and Welsch 1980] have been used to identify this collinearity problem. The condition numbers are defined as the square roots of the ratio of the largest eigenvalue to each individual eigenvalue. When this number is

large, the problem is said to be ill-conditioned. Weak dependencies are associated with condition indexes around 5 or 10, whereas moderate to strong relations are associated with condition indices of 30 to 100. A high condition index causes substantial variance inflation and great potential harm to the regression estimates. For each predictor variable, the SAS regression procedure prints the proportion of the variance of the estimate accounted for by each principal component. The diagnostic procedure: A collinearity problem occurs when a component associated with a high condition index contributes strongly to the variance of two or more variables. Thus high condition index (greater than 30) and the large variance-decomposition proportions (say, greater than .60) associated with each high condition index identifies the involving variates have the problem of multicollinearity. [Belsley, Kuh and Welsch 1980; SAS/Statistics 1985]

The above interpretation of VIF, condition number and variance-decomposition presumes at least two variates in the equation. The results of these collinearity statistics in pre- and post-influence analyses of models with at least 2 variables are shown in Tables 6.11-6.13 and 6.14-6.16, respectively. In general, there is no problem of collinearity statistics for most of the candidate models. The results of the collinearity diagnostics are useful for comparative evaluation of models within a selected group and then for selecting the best model.

Table 6.11: Collinearity Statistics for > 2 variables in the Model
in Pre-Influence Analysis [Interstate Highways]

Model Gr.	Model No.	Variance Influence Factor (VIF)		Number	Condition Index	Variance Proportion by		
		Var. (*)	Value			Var1 (*)	Var2 (*)	Var3 (*)
i. Inter- state High- ways	UR12	CNTYPOP	1.0007	1	1.000	0.4869	0.4869	
		STINC	1.0007	2	1.026	0.5131	0.5131	
	UR13	CNTYPOP	1.0003	1	1.000	0.4919	0.4919	
		STEMP	1.0003	2	1.016	0.5081	0.5081	
ii. Rural Inter- state High- ways	R3	CNTYINC	1.0959	1	1.000	0.3521	0.3521	
		CNTYEMP	1.0959	2	1.357	0.6479	0.6479	
	R4	CNTYINC	1.1058	1	1.000	0.3453	0.3453	
		CNTYPOP	1.1058	2	1.377	0.6547	0.6547	
	R6	CNTYINC	1.1303	1	1.000	0.3302	0.3302	
		CNTYVR	1.1303	2	1.424	0.6698	0.6698	
	R16	CNTYINC	1.2652	1	1.000	0.1664	0.1506	0.1618
		CNTYVR	1.1790	2	1.557	0.0771	0.8176	0.2945
		CTYPOP	1.2386	3	1.684	0.7564	0.0318	0.5437
iii. Urban	U9	CNTYPOP	1.0109	1	1.000	0.4481	0.4481	
		STVR	1.0109	2	1.110	0.5519	0.5519	
Int. Hwys.	U11	CNTYPOP	1.0002	1	1.000	0.4925	0.4925	
		STEMP	1.0002	2	1.015	0.5075	0.5075	
iv. Region 'c' of Inter- state High- ways	URc14	CNTYVR	1.1492	1	1.000	0.3199	0.3199	
		CNTYINC	1.1492	2	1.458	0.6801	0.6801	
	URc15	CNTYHH	1.1357	1	1.000	0.3371	0.3371	
		CNTYINC	1.1357	2	1.434	0.6729	0.6729	
	URc24	CNTYVR	1.1610	1	1.000	0.1272	0.2126	0.1524
		CNTYINC	1.3991	2	1.301	0.5280	0.0002	0.3719
		STEMP	1.2225	3	1.816	0.3448	0.7872	0.4756
	URc25	CNTYHH	1.1481	1	1.000	0.1236	0.2184	0.1576
		CNTYINC	1.3849	2	1.289	0.5472	0.0003	0.3508
		STEMP	1.2232	3	1.799	0.3292	0.7813	0.4912

Table 6.11, continued

Model Gr.	Model No.	Variance Influence Factor (VIF)		Number	Condition Index	Variance Proportion by		
		Var. (*)	Value			Var1 (*)	Var2 (*)	Var3 (*)
v. Region 'n' of Int. Hwys.	URn10	CNTYPOP	1.0086	1	1.000	0.4538	0.4538	
		STEMP	1.0086	2	1.097	0.5462	0.5462	
	URn12	CNTYPOP	1.0008	1	1.000	0.4856	0.4856	
		STINC	1.0008	2	1.029	0.5144	0.5144	
vii. Region 'c' of Rural Interstate Highways	Rc4	CNTYINC	1.0674	1	1.000	0.3743	0.3743	
		CNTYPOP	1.0674	2	1.293	0.6257	0.6257	
	Rc5	CNTYINC	1.0656	1	1.000	0.3759	0.3759	
		CNTYHH	1.0656	2	1.288	0.6241	0.6241	
	Rc6	CNTYINC	1.0830	1	1.000	0.3616	0.3616	
		CNTYVR	1.0830	2	1.329	0.6384	0.6384	
	Rc14	CNTYINC	1.1760	1	1.000	0.1637	0.1597	0.1839
		CNTYPOP	1.1610	2	1.481	0.5182	0.6226	0.0019
		CTYPOP	1.2530	3	1.645	0.3181	0.2177	0.8142
	Rc15	CNTYINC	1.1749	1	1.000	0.1645	0.1597	0.1850
		CNTYHH	1.1582	2	1.476	0.5091	0.6283	0.0025
		CTYPOP	1.2582	3	1.643	0.3264	0.2120	0.8125
	Rc16	CNTYINC	1.1844	1	1.000	0.1585	0.1591	0.1754
		CNTYVR	1.1871	2	1.520	0.5939	0.5721	0.0001
		CTYPOP	1.2625	3	1.663	0.2476	0.2688	0.8245
viii. Region 'n' of Rural Int. Highways	Rn4	CNTYINC	1.0238	1	1.000	0.4237	0.4237	
		STPOP	1.0238	2	1.166	0.5763	0.5763	
	Rn5	CNTYINC	1.2021	1	1.000	0.2950	0.2950	
		STEMP	1.2021	2	1.546	0.7050	0.7050	
	Rn6	CNTYINC	1.0164	1	1.000	0.4365	0.4365	
		STHH	1.0164	2	1.136	0.5635	0.5635	

Table 6.11, continued

Model Gr.	Model No.	Variance Influence Factor (VIF)		Number	Condition Index	Variance Proportion by		
		Var.(*)	Value			Var1 (*)	Var2 (*)	Var3 (*)
ix. Region 's' of Rural Int. Hwys.	Rs3	CNTYPOP	1.0057	1	1.000	0.4625	0.4625	
		STEMP	1.0057	2	1.078	0.5375	0.5375	
	Rs4	CNTYHH	1.0111	1	1.000	0.4476	0.4476	
		STEMP	1.0111	2	1.111	0.5524	0.5524	
x. Region 'c' of Urban Int. Hwys.	Uc12	CNTYHH	1.0042	1	1.000	0.4676	0.4676	
		STEMP	1.0042	2	1.067	0.5324	0.5324	
	Uc13	CNTYEMP	1.0068	1	1.000	0.4591	0.4591	
		STEMP	1.0068	2	1.086	0.5409	0.5409	
xi. Region 'n' of Urban Int. Hwys.	Un11	CNTYPOP	1.0144	1	1.000	0.4405	0.4405	
		STEMP	1.0144	2	1.127	0.5595	0.5595	
	Un13	CNTYPOP	1.0006	1	1.000	0.4879	0.4879	
		STINC	1.0006	2	1.025	0.5121	0.5121	
xii. Region 's' of Urban Inter- state High- ways	Us10	CNTYEMP	1.0645	1	1.000	0.3769	0.3769	
		STVR	1.0645	2	1.286	0.6231	0.6231	
	Us11	CNTYVR	1.1926	1	1.000	0.2991	0.2991	
		STVR	1.1926	2	1.531	0.7009	0.7009	
	Us12	CNTYVR	1.1141	1	1.000	0.3400	0.3400	
		STHH	1.1141	2	1.393	0.6600	0.6600	
	Us13	CNTYEMP	1.0246	1	1.000	0.4225	0.4225	
		STHH	1.0246	2	1.169	0.5775	0.5775	

(*) Var1, Var2 and Var3 represent the variables in the order that shown under column 3 (Var.) for each model.

Table 6.12: Collinearity Statistics for > 2 variables in the Model
in Pre-Influence Analysis [Urban Principal Arterial]

Model Gr.	Model No.	Variance Influe- nce Factor (VIF)		Num- ber	Condi- tion Index	Variance Proportion by		
		Var.(*)	Value			Var1 (*)	Var2 (*)	Var3 (*)
i. City Gr.=A & Region =c	Ac4	CNTYHH	1.2537	1	1.000	0.2751	0.2751	
		CNTYINC	1.2537	2	1.623	0.7249	0.7249	
	Ac5	CNTYVR	1.0330	1	1.000	0.4107	0.4107	
		CNTYINC	1.0330	2	1.197	0.5893	0.5893	
	Ac6	CNTYEMP	1.0010	1	1.000	0.4859	0.4859	
		CNTYINC	1.0010	2	1.029	0.5141	0.5141	
	Ac7	CNTYPOP	1.3710	1	1.000	0.2399	0.2399	
		CNTYINC	1.3710	2	1.780	0.7601	0.7601	
ii. City Gr.=A & Region =s	An6	CTYPOP	1.1159	1	1.000	0.3388	0.3388	
		STVR	1.1159	2	1.397	0.6612	0.6612	
	An7	CTYPOP	1.0239	1	1.000	0.4236	0.4236	
		STEMP	1.0239	2	1.167	0.5764	0.5764	
	An8	CTYPOP	1.2080	1	1.000	0.3359	0.3359	
		STPOP	1.2080	2	1.406	0.6641	0.6641	
	An9	CTYPOP	1.1392	1	1.000	0.3252	0.3252	
		STHH	1.1392	2	1.440	0.6748	0.6748	
xiii. City Gr.=A+ B+C & Region =s	ABCs7	CNTYEMP	1.0002	1	1.000	0.4932	0.4932	
		STVR	1.0002	2	1.014	0.5068	0.5068	
	ABCs8	CNTYEMP	1.0017	1	1.000	0.4797	0.4797	
		STHH	1.0017	2	1.042	0.5203	0.5203	
	ABCs9	CNTYEMP	1.0024	1	1.000	0.4755	0.4755	
		STPOP	1.0024	2	1.050	0.5245	0.5245	

Table 6.12, continued

Model Gr.	Model No.	Variance Influence Factor (VIF)		Number	Condition Index	Variance Proportion by		
		Var.(*)	Value			Var1 (*)	Var2 (*)	Var3 (*)
iv. City Gr.=B & Region =c	Bc12	CNTYVR	2.7745	1	1.000	0.1001	0.1001	
		CNTYINC	2.7745	2	2.998	0.8999	0.8999	
v. City Gr.=B & Region =n	Bn12	STVR	1.0206	1	1.000	0.4290	0.4290	
		CNTYINC	1.0206	2	1.154	0.5710	0.5710	
	Bn14	CNTYVR	1.0640	1	1.000	0.3774	0.3774	
		CNTYINC	1.0640	2	1.284	0.6226	0.6226	
	Bn15	CNTYINC	1.0032	1	1.000	0.4716	0.4716	
		STHH	1.0032	2	1.058	0.5284	0.5284	
	Bn21	CNTYVR	1.5051	1	1.000	0.1212	0.1075	0.1295
		CNTYINC	1.2296	2	1.155	0.2732	0.7094	0.0110
		STEMP	1.7393	3	2.208	0.6056	0.1831	0.8595
vii. City Gr.=C & Region =c	Cc5	CNTYINC	1.0664	1	1.000	0.3753	0.3753	
		CNTYPOP	1.0664	2	1.290	0.6247	0.6247	
	Cc6	CNTYINC	1.0551	1	1.000	0.3858	0.3858	
		CTYPOP	0.0551	2	1.262	0.6142	0.6142	
viii. City Gr.=C & Region =n	Cn5	CNTYINC	1.0993	1	1.000	0.3497	0.3497	
		CNTYVR	1.0993	2	1.364	0.6503	0.6503	
	Cn6	CNTYINC	1.1631	1	1.000	0.3128	0.3128	
		CNTYEMP	1.1631	2	1.482	0.6872	0.6872	
	Cn7	CNTYINC	1.0782	1	1.000	0.3653	0.3653	
		CTYPOP	1.0782	2	1.318	0.6347	0.6347	

Table 6.12, continued

Model Gr.	Model No.	Variance Inflation Factor (VIF)		Number	Condition Index	Variance Proportion by		
		Var.(*)	Value			Var1 (*)	Var2 (*)	Var3 (*)
x. City Gr.=D & Region =c	Dc10	CTYPOP	1.0137	1	1.000	0.4418	0.4418	
		STVR	1.0137	2	1.124	0.5582	0.5582	
	Dc11	CTYPOP	1.0131	1	1.000	0.4431	0.4431	
		STEMP	1.0131	2	1.121	0.5569	0.5569	
	Dc18	CTYPOP	1.5233	1	1.000	0.1260	0.0940	0.1460
		STEMP	1.2247	2	1.403	0.2378	0.6156	0.0020
		CNTYINC	1.7966	3	2.240	0.6362	0.2904	0.8520
	Dc19	CTYPOP	1.4983	1	1.000	0.1672	0.0618	0.1821
		STHH	1.0735	2	1.318	0.1064	0.8265	0.0040
		CNTYINC	1.5876	3	2.031	0.7265	0.1117	0.8139
xi. City Gr.=D & Region =n	Dn15	CNTYVR	1.0460	1	1.000	0.3952	0.3952	
		STHH	1.0460	2	1.237	0.6048	0.6048	
	Dn16	CNTYHH	1.6755	1	1.000	0.1825	0.1825	
		CNTYINC	1.6755	2	2.116	0.8175	0.8175	
xii. City Gr.=D & Region =s	Ds12	STHH	1.5069	1	1.000	0.2100	0.2100	
		STINC	1.5069	2	1.940	0.7900	0.7900	
	Ds13	STPOP	1.7158	1	1.000	0.1770	0.1770	
		STINC	1.7158	2	2.156	0.8230	0.8230	

(*) Var1, Var2 and Var3 represent the variables in the order that shown under column 3 (Var.) for each model.

Table 6.13: Collinearity Statistics for ≥ 2 variables in the Model
in Pre-Influence Analysis [Urban Minor Arterial & Collector

Model Gr.	Model No.	Variance Influen- ce Factor (VIF)		Num- ber	Condi- tion Index	Vari. Prop. by	
		Var. (*)	Value			Var1 (*)	Var2 (*)
i. City Gr.=A	A5	CNTYINC	1.0968	1	1.000	0.3515	0.3515
		CNTYPOP	1.0968	2	1.358	0.6485	0.6485
	A6	CNTYINC	1.1488	1	1.000	0.3201	0.3201
		CNTYVR	1.1488	2	1.458	0.6799	0.6799
	A7	CNTYINC	1.2963	1	1.000	0.2609	0.2609
		CNTYEMP	1.2963	2	1.683	0.7391	0.7391
v. City Gr.=D	D6	CNTYINC	1.0845	1	1.000	0.3604	0.3604
		CTYPOP	1.0845	2	1.332	0.6396	0.6396

(*) Var1 and Var2 represent the variables in the order
that shown under column 3 (Var.) for each model.

Table 6.14: Collinearity Statistics for > 2 variables in the Model
in Post-Influence Analysis [Interstate Highways]

Model Gr.	Model No.	Variance Influence Factor (VIF)		Number	Condition Index	Variance Proportion by		
		Var.(*)	Value			Var1 (*)	Var2 (*)	Var3 (*)
i. Interstate Highways	UR12	CNTYPOP	1.0017	1	1.000	0.4797	0.4797	
		STINC	1.0017	2	1.042	0.5203	0.5203	
	UR13	CNTYPOP	1.0001	1	1.000	0.4963	0.4963	
		STEMP	1.0001	2	1.007	0.5037	0.5037	
ii. Rural Interstate Highways	R3	CNTYINC	1.1140	1	1.000	0.3401	0.3401	
		CNTYEMP	1.1140	2	1.393	0.6599	0.6599	
	R4	CNTYINC	1.2161	1	1.000	0.2892	0.2892	
		CNTYPOP	1.2161	2	1.568	0.7108	0.7108	
	R6	CNTYINC	1.3717	1	1.000	0.2397	0.2397	
		CNTYVR	1.3717	2	1.781	0.7603	0.7603	
	R16	CNTYINC	1.5814	1	1.000	0.1341	0.1260	0.1203
		CNTYVR	1.3819	2	1.625	0.0081	0.3986	0.6768
		CTYPOP	1.2679	3	2.053	0.8578	0.4754	0.2029
iii. Urban Int. Hwys.	U9	CNTYPOP	1.0088	1	1.000	0.4532	0.4532	
		STVR	1.0088	2	1.098	0.5468	0.5468	
	U11	CNTYPOP	1.0011	1	1.000	0.4832	0.4832	
		STEMP	1.0011	2	1.034	0.5168	0.5168	
iv. Region 'c' of Interstate Highways	URc14	CNTYVR	1.0926	1	1.000	0.3545	0.3545	
		CNTYINC	1.0926	2	1.349	0.6455	0.6455	
	URc15	CNTYHH	1.0805	1	1.000	0.3635	0.3635	
		CNTYINC	1.0805	2	1.323	0.6365	0.6365	
	URc24	CNTYVR	1.1016	1	1.000	0.1177	0.2486	0.1806
		CNTYINC	1.2953	2	1.245	0.6010	0.0003	0.3122
		STEMP	1.1869	3	1.682	0.2813	0.7511	0.5071
	URc25	CNTYHH	1.0903	1	1.000	0.1089	0.2567	0.1897
		CNTYINC	1.2830	2	1.231	0.6267	0.0002	0.2840
		STEMP	1.1879	3	1.665	0.2644	0.7431	0.5262

Table 6.14, continued

Model Gr.	Model No.	Variance Influence Factor (VIF)		Number	Condition Index	Variance Proportion by		
		Var.(*)	Value			Var1 (*)	Var2 (*)	Var3 (*)
v. Region 'n' of Int. Hwys.	URn10	CNTYPOP	1.0043	1	1.000	0.4672	0.4672	
		STEMP	1.0043	2	1.068	0.5328	0.5328	
	URn12	CNTYPOP	1.0024	1	1.000	0.4754	0.4754	
		STINC	1.0024	2	1.051	0.5246	0.5246	
vii. Region 'c' of Rural Inter- state High- ways	Rc4	CNTYINC	1.0726	1	1.000	0.3699	0.3699	
		CNTYPOP	1.0726	2	1.305	0.6301	0.6301	
	Rc5	CNTYINC	1.0707	1	1.000	0.3715	0.3715	
		CNTYHH	1.0707	2	1.301	0.6285	0.6285	
	Rc6	CNTYINC	1.0886	1	1.000	0.3574	0.3574	
		CNTYVR	1.0886	2	1.341	0.6426	0.6426	
	Rc14	CNTYINC	1.2001	1	1.000	0.1598	0.1528	0.1772
		CNTYPOP	1.1701	2	1.502	0.4740	0.6601	0.0059
		CTYPOP	1.2830	3	1.690	0.3662	0.1871	0.8170
	Rc15	CNTYINC	1.1991	1	1.000	0.1603	0.1528	0.1781
		CNTYHH	1.1674	2	1.497	0.4687	0.6620	0.0062
		CTYPOP	1.2824	3	1.688	0.3711	0.1852	0.8156
	Rc16	CNTYINC	1.2084	1	1.000	0.1545	0.1523	0.1692
		CNTYVR	1.1971	2	1.542	0.5420	0.6200	0.0012
		CTYPOP	1.2933	3	1.707	0.3035	0.2277	0.8296
viii. Region 'n' of Rural Int. High- ways	Rn4	CNTYINC	1.0339	1	1.000	0.4094	0.4094	
		STPOP	1.0339	2	1.201	0.5906	0.5906	
	Rn5	CNTYINC	1.2835	1	1.000	0.2650	0.2650	
		STEMP	1.2835	2	1.665	0.7350	0.7350	
	Rn6	CNTYINC	1.0310	1	1.000	0.4133	0.4133	
		STHH	1.0310	2	1.192	0.5867	0.5867	

Table 6.14, continued

Model Gr.	Model No.	Variance Influence Factor (VIF)		Number	Condition Index	Variance Proportion by		
		Var.(*)	Value			Var1 (*)	Var2 (*)	Var3 (*)
ix. Region 's' of Rural Int. Hwys.	Rs3	CNTYPOP STEMP	1.0184	1	1.000	0.4329	0.4329	
			1.0184	2	1.145	0.5671	0.5671	
	Rs4	CNTYHH STEMP	1.0123	1	1.000	0.4448	0.4448	
			1.0123	2	1.117	0.5552	0.5552	
x. Region 'c' of Urban Int. Hwys.	Uc12	CNTYHH STEMP	1.0003	1	1.000	0.4918	0.4918	
			1.0003	2	1.016	0.5082	0.5082	
	Uc13	CNTYEMP STEMP	1.0009	1	1.000	0.4854	0.4854	
			1.0009	2	1.030	0.5146	0.5146	
xi. Region 'n' of Urban Int. Hwys.	Un11	CNTYPOP STEMP	1.0103	1	1.000	0.4496	0.4496	
			1.0103	2	1.106	0.5504	0.5504	
	Un13	CNTYPOP STINC	1.0010	1	1.000	0.4842	0.4842	
			1.0010	2	1.032	0.5158	0.5158	
xii. Region 's' of Urban Inter- state High- ways	Us10	CNTYEMP STVR	1.0199	1	1.000	0.4301	0.3769	
			1.0199	2	1.151	0.5699	0.6231	
	Us11	CNTYVR STVR	1.1126	1	1.000	0.3409	0.2991	
			1.1126	2	1.390	0.6591	0.7009	
	Us12	CNTYVR STHH	1.0562	1	1.000	0.3847	0.3400	
			1.0562	2	1.265	0.6153	0.6600	
	Us13	CNTYEMP STHH	1.0018	1	1.000	0.4786	0.4786	
			1.0018	2	1.044	0.5214	0.5214	

(*) Var1, Var2 and Var3 represent the variables in the order that shown under column 3 (Var.) for each model.

Table 6.15: Collinearity Statistics for > 2 variables in the Model
in Post-Influence Analysis [Urban Principal arterial]

Model Gr.	Model No.	Variance Influen- ence Factor (VIF)		Num- ber	Condi- tion Index	Variance Proportion by		
		Var.(*)	Value			Var1 (*)	Var2 (*)	Var3 (*)
i. City Gr.=A & Region =c	Ac4	CNTYHH	1.2518	1	1.000	0.2758	0.2758	
		CNTYINC	1.2518	2	1.621	0.7242	0.7242	
	Ac5	CNTYVR	1.0322	1	1.000	0.4117	0.4117	
		CNTYINC	1.0322	2	1.195	0.5883	0.5883	
	Ac6	CNTYEMP	1.0005	1	1.000	0.4884	0.4884	
		CNTYINC	1.0005	2	1.024	0.5116	0.5116	
	Ac7	CNTYPOP	1.3685	1	1.000	0.2406	0.2406	
		CNTYINC	1.3685	2	1.777	0.7594	0.7594	
ii. City Gr.=A & Region =s	An6	CTYPOP	1.3052	1	1.000	0.2582	0.2582	
		STVR	1.3052	2	1.695	0.7418	0.7418	
	An7	CTYPOP	1.1030	1	1.000	0.3472	0.3472	
		STEMP	1.1030	2	1.371	0.6528	0.6528	
	An8	CTYPOP	1.2917	1	1.000	0.2624	0.2624	
		STPOP	1.2917	2	1.677	0.7376	0.7376	
	An9	CTYPOP	1.3271	1	1.000	0.2518	0.2518	
		STHH	1.3271	2	1.724	0.7482	0.7482	
xiii. City Gr.=A+ B+C & Region =s	ABCs7	CNTYEMP	1.0002	1	1.000	0.4932	0.4932	
		STVR	1.0002	2	1.014	0.5068	0.5068	
	ABCs8	CNTYEMP	1.0017	1	1.000	0.4797	0.4797	
		STHH	1.0017	2	1.042	0.5203	0.5203	
	ABCs9	CNTYEMP	1.0024	1	1.000	0.4755	0.4755	
		STPOP	1.0024	2	1.050	0.5245	0.5245	

Table 6.15, continued

Model Gr.	Model No.	Variance Influence Factor (VIF)		Number	Condition Index	Variance Proportion by		
		Var.(*)	Value			Var1 (*)	Var2 (*)	Var3 (*)
iv. City Gr.=B & Region =c	Bc12	CNTYVR	2.7745	1	1.000	0.1001	0.1001	
		CNTYINC	2.7745	2	2.998	0.8999	0.8999	
v. City Gr.=B & Region =n	Bn12	STVR	1.0206	1	1.000	0.4290	0.4290	
		CNTYINC	1.0206	2	1.154	0.5710	0.5710	
	Bn14	CNTYVR	1.0640	1	1.000	0.3774	0.3774	
		CNTYINC	1.0640	2	1.284	0.6226	0.6226	
	Bn15	CNTYINC	1.0032	1	1.000	0.4716	0.4716	
		STHH	1.0032	2	1.058	0.5284	0.5284	
	Bn21	CNTYVR	1.5051	1	1.000	0.1212	0.1075	0.1295
		CNTYINC	1.2296	2	1.155	0.2732	0.7094	0.0110
		STEMP	1.7393	3	2.208	0.6056	0.1831	0.8595
vii. City Gr.=C & Region =c	Cc5	CNTYINC	1.1243	1	1.000	0.3337	0.3337	
		CNTYPOP	1.1243	2	1.413	0.6663	0.6663	
	Cc6	CNTYINC	1.1080	1	1.000	0.3439	0.3439	
		CTYPOP	1.1080	2	1.381	0.6561	0.6561	
viii. City Gr.=C & Region =n	Cn5	CNTYINC	1.0528	1	1.000	0.3880	0.3880	
		CNTYVR	1.0528	2	1.256	0.6120	0.6120	
	Cn6	CNTYINC	1.1002	1	1.000	0.3491	0.3491	
		CNTYEMP	1.1002	2	1.365	0.6509	0.6509	
	Cn7	CNTYINC	1.0870	1	1.000	0.3585	0.3585	
		CTYPOP	1.0870	2	1.338	0.6415	0.6415	

Table 6.15, continued

Model Gr.	Model No.	Variance Influen- ence Factor (VIF)		Num- ber	Condi- tion Index	Variance Proportion by		
		Var.(*)	Value			Var1 (*)	Var2 (*)	Var3 (*)
x. City Gr.=D & Region =c	Dc10	CTYPOP	1.0075	1	1.000	0.4569	0.4569	
		STVR	1.0075	2	1.090	0.5431	0.5431	
	Dc11	CTYPOP	1.0103	1	1.000	0.4496	0.4496	
		STEMP	1.0103	2	1.106	0.5504	0.5504	
	Dc18	CTYPOP	1.4406	1	1.000	0.1296	0.1007	0.1567
		STEMP	1.2312	2	1.383	0.2777	0.5731	0.0011
		CNTYINC	1.7134	3	2.158	0.5927	0.3262	0.8422
	Dc19	CTYPOP	1.4180	1	1.000	0.1957	0.0422	0.2115
		STHH	1.0475	2	1.268	0.0813	0.8601	0.0009
		CNTYINC	1.4717	3	1.901	0.7231	0.0977	0.7876
xi. City Gr.=D & Region =n	Dn15	CNTYVR	1.0554	1	1.000	0.3855	0.3855	
		STHH	1.0554	2	1.263	0.6145	0.6145	
	Dn16	CNTYHH	1.7547	1	1.000	0.1721	0.1721	
		CNTYINC	1.7547	2	2.193	0.8279	0.8279	
xii. City Gr.=D & Region =s	Ds12	STHH	1.4693	1	1.000	0.2174	0.2174	
		STINC	1.4693	2	1.897	0.7826	0.7826	
	Ds13	STPOP	1.6820	1	1.000	0.1816	0.1816	
		STINC	1.6820	2	2.123	0.8184	0.8184	

(*) Var1, Var2 and Var3 represent the variables in the order that shown under column 3 (Var.) for each model.

Table 6.16: Collinearity Statistics for > 2 variables in the Model in Post-Influence Analysis [Urban Minor Arterial & Collector]

Model Gr.	Model No.	Variance Influence Factor (VIF)		Number	Condition Index	Vari. Prop. by	
		Var.(*)	Value			Var1 (*)	Var2 (*)
i. City Gr.=A	A5	CNTYINC	1.0995	1	1.000	0.3596	0.3596
		CNTYPOP	1.0995	2	1.364	0.6504	0.6504
	A6	CNTYINC	1.1524	1	1.000	0.3182	0.3182
		CNTYVR	1.1524	2	1.464	0.6818	0.6818
	A7	CNTYINC	1.2970	1	1.000	0.2607	0.2607
		CNTYEMP	1.2970	2	1.684	0.7393	0.7393
v. City Gr.=D	D6	CNTYINC	1.0358	1	1.000	0.4071	0.4071
		CTYPOP	1.0577	2	1.207	0.5929	0.5929

(*) Var1 and Var2 represent the variables in the order that shown under column 3 (Var.) for each model.

6.4.2 Testing Hypothesis Concerning Regression Coefficients

The F-test for the regression relation explains whether the variables in the model have any statistical relation to the dependent variable. The hypotheses are

$$H_0 : \beta_1 = \beta_2 = \dots = \beta_{P-1} = 0 \quad (6.5)$$

$$H_a : \text{all } \beta_k \text{ (} k = 1, \dots, P-1 \text{)} \neq 0 \quad (6.6)$$

The test statistic is given by F-value, the ratio of Mean Square Regression (MSR) to Mean Square Error (MSE).

If the calculated F-value $< F(1-\alpha, P-1, n-P)$ or the P-value (PROB>F) is greater than the specified α -level, then H_0 holds and proves that the variables in the model do not have any statistical relation to the dependent variable. Larger values of F or smaller P-values lead to the conclusion H_a . The results of this F-test on candidate models of Interstate, Urban Principal Arterial and Urban Minor Arterial & Collector for the pre-influence case have been presented in Tables 6.17, 6.18 and 6.19, respectively. The test results conclude that hypothesis H_a (i.e., the relationships among the variables in the models exist) cannot be rejected at an α level of 0.01. A p-value (PROB>F) of 0.0001 in the tables indicates that there is less than one chance in 10,000 of obtaining an F this large or larger by chance alone if H_0 holds.

Table 6.17: Significance of Variable(s) in Model in Pre-Influence Analysis [Interstate Highways]

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2	RMSE	df_r	F-Value	Variable	t-value	Prob>t	Standardized Est.
		R_a^2	C.V.	df_e	Prob>F				
i. Inter- state High- ways	UR2	48.94	13900.	1	298.089	CNTYVR	17.265	0.0001	0.6996
		48.78	50.513	311	0.0001				
	UR4	50.30	13713.	1	314.741	CNTYPOP	17.741	0.0001	0.7092
		50.14	49.837	311	0.0001				
	UR12	52.27	13461.	2	169.727	CNTYPOP STINC	17.974	0.0001	0.7055
		51.96	48.918	310	0.0001				
	UR13	52.29	13457.	2	169.912	CNTYPOP STEMP	18.135	0.0001	0.7115
		51.99	48.904	310	0.0001				
ii. Rural Inter- state High- ways	R3	36.28	7585.9	2	52.095	CNTYINC CNTYEMP	7.864	0.0001	0.4858
		35.58	38.047	183	0.0001				
	R4	37.49	7513.5	2	54.875	CNTYINC CNTYPOP	7.714	0.0001	0.4741
		36.81	37.684	183	0.0001				
	R6	37.82	7493.5	2	55.658	CNTYINC CNTYVR	7.466	0.0001	0.4627
		37.14	37.583	183	0.0001				
	R16	40.60	7344.4	3	41.462	CNTYINC CNTYVR CTYPOP	6.248	0.0001	0.4015
		39.62	36.836	182	0.0001				
iii. Urban Inter- state High- ways	U2	51.20	17091.	1	131.132	CNTYVR	11.451	0.0001	0.7155
		50.81	44.258	125	0.0001				
	U4	53.38	16704.	1	143.153	CNTYPOP	11.965	0.0001	0.7306
		53.10	43.255	125	0.0001				
	U9	55.25	16432.	2	76.553	CNTYPOP STVR	11.861	0.0001	0.7164
		54.53	42.550	124	0.0001				
	U11	55.57	16373.	2	77.546	CNTYPOP STEMP	12.242	0.0001	0.7329
		54.85	42.399	124	0.0001				

Table 6.17, continued

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R ²	RMSE	df _r	F-Value	Variable	t-value	Prob>t	Standard-ized Est.
		R ² _a	C.V.	df _e	Prob>F				
iv. Region 'c' of Inter-state High-ways	URc3	65.72	9438.8	1	249.175	CNTYHH	15.785	0.0001	0.8106
		65.45	33.865	130	0.0001				
	URc4	66.29	9359.2	1	255.647	CNTYVR	15.989	0.0001	0.8142
		66.03	33.579	130	0.0001				
	URc14	71.98	8565.7	2	165.705	CNTYVR	14.453	0.0001	0.7221
		71.45	30.732	129	0.0001				
	URc15	72.02	8559.7	2	166.026	CNTYHH	14.469	0.0001	0.7181
		71.59	30.711	129	0.0001				
	URc24	73.01	8440.5	3	115.392	CNTYVR	14.815	0.0001	0.7331
		72.37	30.283	128	0.0001	CNTYINC	3.777	0.0002	0.2051
						STEMP	2.204	0.0293	0.1119
	URc25	73.08	8428.6	3	115.838	CNTYHH	14.848	0.0001	0.7296
		72.45	30.240	128	0.0001	CNTYINC	4.006	0.0001	0.2162
						STEMP	2.246	0.0264	0.1139
v. Region 'n' of Inter-state High-ways	URn2	43.77	18388.	1	79.397	CNTYVR	8.911	0.0001	0.6616
		43.22	54.335	102	0.0001				
	URn3	45.08	18173.	1	83.729	CNTYPOP	9.150	0.0001	0.6714
		44.54	53.698	102	0.0001				
	URn4	45.33	18131.	1	84.576	CNTYHH	9.197	0.0001	0.6733
		44.79	53.576	102	0.0001				
	URn10	47.02	17937.	2	44.816	CNTYPOP	9.408	0.0001	0.6843
		45.97	53.002	101	0.0001				
	URn12	47.31	17889.	2	45.339	CNTYPOP	9.232	0.0001	0.6671
		46.26	52.858	101	0.0001				

Table 6.17, continued

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2	RMSE	df_r	F-Value	Variable	t-value	Prob>t	Standardized Est.
		R_a^2	C.V.	df_e	Prob>F				
vi. Region 's' of Inter- state High- ways	URs1	58.60	8117.4	1	106.167	CNTYEMP	10.304	0.0001	0.7655
		58.05	44.196	75	0.0001				
	URs2	59.82	7997.1	1	111.661	CNTYPOP	10.567	0.0001	0.7734
		59.28	43.541	75	0.0001				
	URs3	60.19	7959.9	1	113.411	CNTYVR	10.649	0.0001	0.7758
		59.66	43.338	75	0.0001				
	URs4	61.42	7836.7	1	119.381	CNTYHH	10.926	0.0001	0.7837
		60.90	42.668	75	0.0001				
vii. Region 'c' of Rural Inter- state High- ways	Rc4	48.45	6767.7	2	36.182	CNTYINC	6.354	0.0001	0.5371
		47.11	28.345	77	0.0001	CNTYPOP	3.878	0.0002	0.3278
	Rc5	48.49	6764.6	2	36.251	CNTYINC	6.373	0.0001	0.5380
		47.16	28.333	77	0.0001	CNTYHH	3.889	0.0002	0.3283
	Rc6	48.73	6749.3	2	36.588	CNTYINC	6.204	0.0001	0.5269
		47.40	28.269	77	0.0001	CNTYVR	3.942	0.0002	0.3348
	Rc14	50.99	6641.8	3	26.359	CNTYINC	5.565	0.0001	0.4846
		49.06	27.818	76	0.0001	CNTYPOP	3.223	0.0019	0.2790
						CTYPOP	1.986	0.0506	0.1785
	Rc15	51.05	6638.1	3	26.417	CNTYINC	5.578	0.0001	0.4852
		49.11	27.803	76	0.0001	CNTYHH	3.239	0.0018	0.2797
						CTYPOP	1.991	0.0501	0.1787
	Rc16	51.12	6632.9	3	26.499	CNTYINC	5.472	0.0001	0.4775
		49.19	27.781	76	0.0001	CNTYVR	3.259	0.0017	0.2848
						CTYPOP	1.931	0.0573	0.1740

Table 6.17, continued

Model	Model	Model Statistics				Variables in Model			
Gr.	No.	R ²	RMSE	df _r	F-Value	Variable	t-value	Prob>t	Standard- ized Est.
		R ² _a	C.V.	df _e	Prob>F				

viii. Region 'n' of	Rn1	27.90	7504.4	1	17.318	CNTYINC	4.162	0.0001	0.5272
		26.19	35.182	45	0.0001				
Rural	Rn4	30.34	7454.0	2	9.581	CNTYINC	3.947	0.0003	0.5025
		27.17	34.946	44	0.0004	STPOP	1.269	0.2112	0.1615
Inter- state	Rn5	30.37	7452.6	2	9.593	CNTYINC	3.299	0.0019	0.4550
		27.20	34.942	44	0.0003	STEMP	1.276	0.2088	0.1759
High- ways	Rn6	30.64	7437.8	2	9.719	CNTYINC	3.994	0.0002	0.5056
		27.49	34.871	44	0.0003	STHH	1.345	0.0186	0.1702

ix. Region 's' of	Rs1	40.46	4999.3	1	38.742	CNTYPOP	6.224	0.0001	0.6361
		39.42	37.055	57	0.0001				
Rural	Rs2	40.88	4981.8	1	39.416	CNTYHH	6.278	0.0001	0.6394
		39.84	36.926	57	0.0001				
Inter- state	Rs3	41.73	4989.7	2	20.056	CNTYPOP	6.136	0.0001	0.6276
		39.65	36.984	56	0.0001	STEMP	1.105	0.2740	0.1130
High- ways	Rs4	41.76	4988.6	2	20.076	CNTYHH	6.139	0.0001	0.6295
		39.68	36.976	56	0.0001	STEMP	0.918	0.3623	0.0942

x. Region 'c' of	Uc1	82.09	9213.9	1	229.126	CNTYPOP	15.137	0.0001	0.9060
		81.73	27.083	50	0.0001				
	Uc2	83.40	8870.8	1	251.137	CNTYVR	15.847	0.0001	0.9132
		83.06	26.075	50	0.0001				
	Uc3	83.57	8823.3	1	254.386	CNTYHH	15.949	0.0001	0.9142
		83.24	25.935	50	0.0001				
	Uc4	84.52	8566.6	1	272.901	CNTYEMP	16.520	0.0001	0.9193
		84.21	25.181	50	0.0001				
	Uc12	86.05	8212.1	2	151.188	CNTYHH	16.909	0.0001	0.9040
		85.49	24.139	49	0.0001	STEMP	2.953	0.0048	0.1579
High- ways	Uc13	86.52	8074.4	2	157.235	CNTYEMP	17.247	0.0001	0.9077
		85.97	23.734	49	0.0001	STEMP	2.699	0.0095	0.1420

Table 6.17, continued

Model Statistics and Variables in Model										
Model Gr.	Model No.	Model Statistics				Variables in Model				
		R^2 R_a^2	RMSE C.V.	df_r df_e	F-Value Prob>F	Variable	t-value	Prob>t	Standard- ized Est.	
xi. Region 'n' of	Un2	47.56	20575.	1	49.886	CNTYVR	7.063	0.0001	0.6897	
		46.61	46.590	55	0.0001					
	Un3	48.39	20412.	1	51.571	CNTYPOP	7.181	0.0001	0.6956	
		47.45	46.221	55	0.0001					
	Urban	Un4	48.79	20333.	1	52.392	CNTYHH	7.238	0.0001	0.6985
			47.85	46.044	55	0.0001				
Inter- state	Un11	49.95	20285.	2	26.951	CNTYPOP STEMP	7.329	0.0001 0.1996	0.7106 0.1259	
		48.10	45.935	54	0.0001					
High- ways	Un13	50.03	20269.	2	27.035	CNTYPOP STINC	7.197	0.0001 0.1885	0.6925 0.1281	
		48.18	45.899	54	0.0001					
xii. Region 's' of	Us3	68.73	8324.8	1	35.163	CNTYHH	5.930	0.0001	0.8290	
		66.77	24.237	16	0.0001					
	Us4	73.11	7719.6	1	43.499	CNTYVR	6.595	0.0001	0.8550	
		71.43	22.475	16	0.0001					
	Us10	78.52	7125.3	2	27.421	CNTYEMP STVR	5.728	0.0001 0.0068	0.7072 0.3875	
		75.66	20.745	15	0.0001					
	Inter- state	Us11	78.78	7083.0	2	27.837	CNTYVR STVR	5.778	0.0001 0.0638	0.7506 0.2600
			75.95	20.622	15	0.0001				
	High- ways	Us12	80.48	6791.9	2	30.931	CNTYVR STHH	6.340	0.0001 0.0310	0.7633 0.2867
			77.88	19.774	15	0.0001				
		Us13	81.34	6640.8	2	32.701	CNTYEMP STHH	6.538	0.0001 0.0022	0.7380 0.4165
			78.86	19.334	15	0.0001				

Table 6.18: Significance of Variable(s) in Model in Pre-Influence Analysis [Urban Principal Arterial]

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R ²	RMSE	df _r	F-Value	Variable	t-value	Prob>t	Standard-ized Est.
		R ² _a	C.V.	df _e	Prob>F				
i. City Gr.=A & Region =c	Ac4	76.19	1374.0	2	19.202	CNTYHH	5.390	0.0002	0.8501
		72.22	10.310	12	0.0002	CNTYINC	5.156	0.0002	0.8131
	Ac5	77.13	1346.7	2	20.237	CNTYVR	5.544	0.0001	0.7778
		73.32	10.105	12	0.0001	CNTYINC	4.061	0.0016	0.5697
	Ac6	78.18	1315.6	2	21.492	CNTYEMP	5.726	0.0001	0.7725
		74.54	9.871	12	0.0001	CNTYINC	3.035	0.0057	0.4526
	Ac7	82.30	1184.7	2	27.899	CNTYPOP	6.574	0.0001	0.9349
		79.35	8.889	12	0.0001	CNTYINC	6.449	0.0001	0.9171
ii. City Gr.=A & Region =s	An6	49.32	2436.6	2	9.732	CTYPOP	4.397	0.0003	0.7394
		44.25	17.864	20	0.0011	STVR	1.073	0.2959	0.1805
	An7	49.44	2433.8	2	9.777	CTYPOP	4.401	0.0003	0.7081
		44.38	17.843	20	0.0011	STEMP	1.095	0.2863	0.1762
	An8	51.45	2384.8	2	10.599	CTYPOP	4.604	0.0002	0.7593
		46.60	17.484	20	0.0007	STPOP	1.443	0.1646	0.2379
	An9	52.84	2350.5	2	11.205	CTYPOP	4.734	0.0001	0.7759
		48.13	17.232	20	0.0005	STHH	1.652	0.1141	0.2708
xiii. City Gr.=A+ B+C & Region =s	ABCs3	72.43	3575.1	1	34.156	CNTYVR	5.844	0.0001	0.8511
		70.31	24.422	13	0.0001				
	ABCs4	81.08	2961.4	1	55.725	CNTYEMP	7.465	0.0001	0.9005
		79.63	20.230	13	0.0001				
	ABCs7	85.14	2732.1	2	34.374	CNTYEMP	8.115	0.0001	0.9032
		82.66	18.663	12	0.0001	STVR	1.809	0.0955	0.2014
	ABCs8	85.44	2704.1	2	35.212	CNTYEMP	8.245	0.0001	0.9090
		83.01	18.472	12	0.0001	STHH	1.895	0.0824	0.2089
	ABCs9	85.53	2695.5	2	35.475	CNTYEMP	8.286	0.0001	0.9108
		83.12	18.414	12	0.0001	STPOP	1.921	0.0788	0.2112

Table 6.18, continued

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2 R_a^2	RMSE C.V.	df_r df_e	F-Value Prob>F	Variable	t- value	Prob>t	Standard- ized Est.
iv. City Gr.=B & Region =c	Bc3	93.83	1597.1	1	152.108	CNTYHH	12.333	0.0001	0.9687
		93.21	10.576	10	0.0001				
	Bc4	94.14	1556.2	1	160.736	CNTYEMP	12.678	0.0001	0.9703
		93.56	10.306	10	0.0001				
	Bc5	94.36	1527.3	1	167.261	CNTYVR	12.933	0.0001	0.9714
		93.79	10.114	10	0.0001				
	Bc12	95.30	1468.8	2	91.336	CNTYVR	6.997	0.0001	0.8418
		94.26	9.727	9	0.0001	CNTYINC	1.346	0.2111	0.1620
v. City Gr.=B & Region =n	Bn12	76.74	960.4	2	16.498	STVR	4.074	0.0022	0.6277
		72.09	7.794	10	0.0007	CNTYINC	3.430	0.0064	0.5284
	Bn14	78.67	919.8	2	18.436	CNTYVR	4.359	0.0014	0.6567
		74.40	7.465	10	0.0004	CNTYINC	3.030	0.0127	0.4565
	Bn15	78.80	916.9	2	18.579	CNTYINC	4.482	0.0012	0.6538
		74.55	7.442	10	0.0004	STHH	4.379	0.0014	0.6387
	Bn21	83.95	840.8	3	15.697	CNTYVR	3.076	0.0132	0.5039
		78.61	6.824	9	0.0006	CNTYINC	2.451	0.0367	0.3629
vii. City Gr.=C & Region =c	Cc5	45.17	3406.0	2	17.298	CNTYINC	5.377	0.0001	0.6344
		42.56	26.870	42	0.0001	CNTYPOP	0.967	0.3390	0.1141
	Cc6	61.65	2848.5	2	33.757	CNTYINC	5.748	0.0001	0.5642
		59.82	22.472	42	0.0001	CTYPOP	4.403	0.0001	0.4322
viii. City Gr.=C & Region =n	Cn5	33.55	2271.3	2	6.815	CNTYINC	3.174	0.0037	0.5221
		28.63	20.565	27	0.004	CNTYVR	0.845	0.4056	0.1390
	Cn6	34.57	2253.7	2	7.133	CNTYINC	2.957	0.0064	0.4965
		29.73	20.406	27	0.0033	CNTYEMP	1.071	0.2936	0.1798
	Cn7	40.16	2155.4	2	9.059	CNTYINC	3.124	0.0042	0.4829
		35.72	19.515	27	0.0001	CTYPOP	1.943	0.0625	0.3003

Table 6.18, continued

Model Statistics										Variables in Model			
Model Gr.	Model No.	R^2	RMSE	df_r	F-Value	Variable	t-		Prob>t	Standard-ized Est.			
		R_a^2	C.V.	df_e	Prob>F		value						
x. City Gr.=D & Region =c	Dc10	56.98	1089.4	2	15.234	CTYPOP	4.786	0.0001		0.6590			
		53.24	13.174	23	0.0001	STVR	3.288	0.0032		0.4528			
	Dc11	58.88	1065.2	2	16.467	CTYPOP	4.905	0.0001		0.6602			
		55.30	12.881	23	0.0001	STEMP	3.518	0.0019		0.4734			
	Dc18	64.32	1014.4	3	13.222	CTYPOP	5.261	0.0001		0.8269			
		59.46	12.267	22	0.0001	STEMP	2.598	0.0164		0.3661			
						CNTYINC	1.832	0.0805		0.3128			
	Dc19	65.50	997.67	3	13.921	CTYPOP	5.560	0.0001		0.8523			
		60.79	12.064	22	0.0001	STHH	2.779	0.0109		0.3606			
						CNTYINC	2.447	0.0228		0.3862			
	xi. City Gr.=D & Region =n	Dn3	42.78	2431.9	1	23.922	CNTYHH	4.891	0.0001		0.6540		
			40.99	23.452	32	0.0001							
Dn4		43.82	2409.7	1	24.956	CNTYVR	4.996	0.0001		0.6619			
		42.06	23.237	32	0.0001								
Dn15		47.11	2375.4	2	13.808	CNTYVR	4.664	0.0001		0.6230			
		43.70	22.906	31	0.0001	STHH	1.390	0.1743		0.1857			
Dn16		47.25	2372.3	2	13.884	CNTYHH	2.844	0.0078		0.4802			
		43.85	22.876	31	0.0001	CNTYINC	1.621	0.1151		0.2738			
xii. City Gr.=D & Region =s	Ds3	37.48	1761.1	1	23.975	STHH	4.896	0.0001		0.6122			
		35.91	16.939	40	0.0001								
	Ds4	39.85	1727.4	1	26.497	STPOP	5.148	0.0001		0.6312			
		38.34	16.614	40	0.0001								
	Ds12	42.84	1705.3	2	14.618	STHH	3.009	0.0046		0.4472			
		39.91	16.401	39	0.0001	STINC	1.914	0.0630		0.2845			
	Ds13	43.03	1702.6	2	14.726	STPOP	3.034	0.0043		0.4804			
		40.10	16.375	39	0.0001	STINC	1.475	0.1482		0.2335			

Table 6.19: Significance of Variable(s) in Model in Pre-Influence Analysis [Urban Minor Arterial & Collector]

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2	RMSE	df_r	F-Value	Variable	t-value	Prob>t	Standardized Est.
		R_a^2	C.V.	df_e	Prob>F				
i. City Gr.=A	A2	53.57	2540.9	1	18.461	CNTYINC	4.297	0.0006	0.7319
		50.67	23.074	16	0.0006				
	A5	62.07	2371.8	2	12.275	CNTYINC	3.850	0.0016	0.6412
		57.02	21.539	15	0.0007	CNTYPOP	1.834	0.0866	0.3054
	A6	64.04	2309.5	2	13.357	CNTYINC	3.658	0.0023	0.6071
		59.25	20.973	15	0.0005	CNTYVR	2.090	0.0541	0.3468
	A7	65.94	2247.8	2	14.517	CNTYINC	3.150	0.0066	0.5405
		61.39	20.412	15	0.0003	CNTYEMP	2.333	0.0340	0.4004
ii. City Gr.=B	B2	66.95	2313.1	1	22.278	CNTYINC	4.720	0.0006	0.8182
		63.94	27.638	11	0.0006				
iii. City Gr.=C	C2	71.58	1055.6	1	27.701	CNTYVR	5.263	0.0003	0.8460
		68.99	12.641	11	0.0003				
	C3	73.88	1012.0	1	31.111	CNTYPOP	5.578	0.0002	0.8595
		71.50	12.118	11	0.0002				
	C4	75.74	975.4	1	34.334	CNTYHH	5.860	0.0001	0.8703
		73.53	11.679	11	0.0001				
iv. City Gr.=C	C9	74.85	1267.8	1	26.781	CNTYEMP	5.175	0.0006	0.8651
		72.05	12.371	9	0.0006				
	C10	76.60	1223.0	1	29.456	CNTYPOP	5.427	0.0004	0.8752
		74.00	15.052	9	0.0004				
	C11	78.08	1183.6	1	32.058	CNTYVR	5.662	0.0003	0.8836
		75.64	14.567	9	0.0003				
	C12	78.30	1177.7	1	32.467	CNTYHH	5.698	0.0003	0.8849
		75.88	14.495	9	0.0003				

Table 6.19, continued

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2	RMSE	df_r	F-Value	Variable	t- value	Prob>t	Standard- ized Est.
		R^2_a	C.V.	df_e	Prob>F				
v. City Gr.=D	D6	54.37 50.72	2388.8 38.123	2 25	14.893 0.0001	CNTYINC CTYPOP	3.710 2.807	0.0011 0.0095	0.5220 0.3950
vi. City Gr.=D	D7	53.98 51.89	1166.9 26.347	1 22	25.804 0.0001	CNTYINC	5.080	0.0001	0.7347

In addition to the F-value and the corresponding P-value (PROB>F), the associated degrees of freedom for the residual (df_r) and the error (df_e) are shown in Tables 6.17-6.19. The values of R^2 , R_a^2 , RMSE (see Chapter 5 for definition) and coefficient of variation (C.V.) for each of the candidate models are also shown in these tables. The coefficient of variation (C.V.) is expressed as a percentage; it is a measure of the relative variation of the ratio of RMSE to the mean of the dependent variable. The C.V. is sometimes used as a standard to gauge the relative magnitude of error variation. The results of the F-test and other associated model statistics from post-influence analysis for all the candidate models of three highway classes are shown in Tables 6.20-6.22. By comparing the results of pre- and post-influence cases, one can see the significant improvements in model statistics in post-influence analysis. In general, higher values of R^2 , R_a^2 and F-ratio, and lower values of RMSE and C.V., result from influence analysis.

To test the significance of each variable ($H_0 : \beta_k = 0$; $H_a : \beta_k \neq 0$ for $1 < k < P-1$), the usual t-test is employed. A high value of t or a small P-value (PROB>t) concludes that the parameter involved is significant. The results of this t-test and the associated P-value (PROB>t) are presented in Tables 6.17-6.19 (pre-influence case) and in Tables 6.20-6.22 (post-influence case). For a 1-variable model, the t test is equivalent to the F-test because $F=t^2$. A P-value greater than 0.05 has been taken as an indication that the parameter involved is not significant, where 0.05 represents the user-specified risk or α level. The t-value (P-value) for CNTYVR in model Cn5 in pre

Table 6.20: Significance of Variable(s) in Model in Post-Influence Analysis [Interstate Highways]

Model Gr.	Model No.	Model Statistics				Variables in Model				
		R ²	RMSE	df _r	F-Value	Variable	t-value	Prob>t	Standard-ized Est.	
		R ² _a	C.V.	df _e	Prob>F					
i. Inter- state High- ways	UR2	71.36	5912.4	1	555.515	CNTYVR	23.569	0.0001	0.8447	
		71.23	28.541	223	0.0001					
	UR4	69.28	6122.9	1	502.890	CNTYPOP	22.425	0.0001	0.8323	
		69.14	29.558	223	0.0001					
	UR12	70.48	6015.9	2	264.977	CNTYPOP STINC	22.683 3.001	0.0001 0.0030	0.8279 0.1095	
		70.21	29.041	222	0.0001					
	UR13	70.56	6007.7	2	265.998	CNTYPOP STEMP	22.878 3.104	0.0001 0.0022	0.8332 0.1130	
		70.29	29.001	222	0.0001					
ii. Rural Inter- state High- ways	R3	71.27	4016.5	2	146.332	CNTYINC CNTYEMP	11.947 7.780	0.0001 0.0001	0.6222 0.4052	
		70.78	21.218	118	0.0001					
	R4	73.72	3841.4	2	165.484	CNTYINC CNTYPOP	10.743 8.785	0.0001 0.0001	0.5591 0.4572	
		73.27	20.293	118	0.0001					
	R6	74.29	3799.0	2	170.524	CNTYINC CNTYVR	9.053 9.031	0.0001 0.0001	0.4949 0.4937	
		73.86	20.069	118	0.0001					
	R16	74.31	3813.7	3	112.836	CNTYINC CNTYVR CTYPOP	8.289 8.938 0.300	0.0001 0.0001 0.7644	0.4884 0.4923 0.0159	
		73.66	20.147	117	0.0001					
	iii. Urban Inter- state High- ways	U2	74.00	8816.9	1	287.500	CNTYVR	16.956	0.0001	0.8602
			73.75	27.859	101	0.0001				
		U4	75.11	8627.6	1	304.733	CNTYPOP	17.457	0.0001	0.8666
			74.86	27.261	101	0.0001				
U9		77.01	8333.1	2	167.462	CNTYPOP STVR	17.725 2.875	0.0001 0.0049	0.8537 0.1385	
		76.55	26.330	100	0.0001					
U11		77.81	8185.9	2	175.349	CNTYPOP STEMP	18.506 3.492	0.0001 0.0007	0.8722 0.1646	
		77.37	25.865	100	0.0001					

Table 6.20, continued

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2	RMSE	df_r	F-Value	Variable	t-value	Prob>t	Standardized Est.
		R_a^2	C.V.	df_e	Prob>F				
iv. Region 'c' of	URc3	67.45	6861.2	1	236.203	CNTYHH	15.369	0.0001	0.8213
		67.16	28.114	114	0.0001				
	URc4	68.27	6774.0	1	245.280	CNTYVR	15.661	0.0001	0.8263
		67.99	27.756	114	0.0001				
	URc14	73.84	6177.6	2	159.499	CNTYVR CNTYINC	15.002	0.0001	0.7544
		73.38	25.313	113	0.0001				
	Inter- state	73.78	6184.8	2	158.998	CNTYHH CNTYINC	14.976	0.0001	0.7498
		73.32	25.342	113	0.0001				
	High- ways	74.60	6114.9	3	109.631	CNTYVR CNTYINC STEMP	15.258	0.0001	0.7627
		73.92	25.056	112	0.0001				
	URc25	74.59	6115.3	3	109.612	CNTYHH CNTYINC STEMP	15.257	0.0001	0.7576
		73.91	25.058	112	0.0001				
v. Region 'n' of	URn2	69.22	8888.5	1	168.662	CNTYVR	12.987	0.0001	0.8320
		68.81	32.625	75	0.0001				
	URn3	70.90	8642.2	1	182.747	CNTYPOP	13.518	0.0001	0.8420
		70.51	31.721	75	0.0001				
	Inter- state	72.28	8435.8	1	195.515	CNTYHH	13.983	0.0001	0.8501
		71.91	30.963	75	0.0001				
	High- ways	75.14	8042.2	2	111.823	CNTYPOP STEMP	14.718	0.0001	0.8555
		74.47	29.518	74	0.0001				
	URn12	75.22	8028.4	2	112.333	CNTYPOP STINC	14.357	0.0001	0.8318
		74.55	29.468	74	0.0001				

Table 6.20, continued

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2	RMSE	df_r	F-Value	Variable	t-value	Prob>t	Standardized Est.
		R^2_a	C.V.	df_e	Prob>F				
vi. Region 's' of Inter-state Highways	URs1	74.07	4173.8	1	157.087	CNTYEMP	12.533	0.0001	0.8606
		73.60	29.677	55	0.0001				
	URs2	74.60	4130.8	1	161.535	CNTYPOP	12.710	0.0001	0.8637
		74.14	29.370	55	0.0001				
	URs3	72.72	4281.3	1	146.578	CNTYVR	12.107	0.0001	0.8527
		72.22	30.441	55	0.0001				
	URs4	74.78	4116.0	1	163.094	CNTYHH	12.771	0.0001	0.8648
		74.32	29.265	55	0.0001				
vii. Region 'c' of Rural Inter-state Highways	Rc4	61.62	5275.6	2	54.594	CNTYINC	7.788	0.0001	0.6059
		60.49	21.946	68	0.0001	CNTYPOP	4.701	0.0001	0.3658
	Rc5	61.95	5253.2	2	55.354	CNTYINC	7.829	0.0001	0.6060
		60.83	21.852	68	0.0001	CNTYHH	4.783	0.0001	0.3702
	Rc6	61.87	5258.7	2	55.167	CNTYINC	7.614	0.0001	0.5949
		60.75	21.875	68	0.0001	CNTYVR	4.763	0.0001	0.3721
	Rc14	62.61	5246.1	3	37.397	CNTYINC	6.970	0.0001	0.5704
		60.94	21.823	67	0.0001	CNTYPOP	4.143	0.0001	0.3348
						CTYPOP	1.330	0.1880	0.1125
	Rc15	62.91	5224.7	3	37.888	CNTYINC	7.006	0.0001	0.5707
		61.25	21.734	67	0.0001	CNTYHH	4.225	0.0001	0.3396
						CTYPOP	1.321	0.1911	0.1113
	Rc16	62.75	5235.9	3	37.628	CNTYINC	6.861	0.0001	0.5624
		61.09	21.781	67	0.0001	CNTYVR	4.182	0.0001	0.3411
						CTYPOP	1.262	0.2115	0.1070

Table 6.20, continued

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2	RMSE	df_r	F-Value	Variable	t-value	Prob>t	Standardized Est.
		R_a^2	C.V.	df_e	Prob>F				
viii. Region 'n' of	Rn1	43.89	4377.7	1	25.810	CNTYINC	5.080	0.0001	0.6625
		42.19	24.444	33	0.0001				
	Rn4	49.28	4226.5	2	15.547	CNTYINC	4.841	0.0001	0.6197
		46.11	23.599	32	0.0001	STPOP	1.845	0.0743	0.2362
	Inter-state	49.81	4204.5	2	15.878	CNTYINC	3.756	0.0007	0.5329
		46.67	23.476	32	0.0001	STEMP	1.943	0.0609	0.2768
High-ways	Rn6	50.35	4181.9	2	16.224	CNTYINC	4.884	0.0001	0.6177
		47.24	23.350	32	0.0001	STHH	2.040	0.0496	0.2581
ix. Region 's' of	Rs1	76.47	2251.5	1	133.238	CNTYPOP	11.543	0.0001	0.8745
		75.90	19.292	41	0.0001				
	Rs2	75.17	2312.7	1	124.131	CNTYHH	11.141	0.0001	0.8670
		74.57	19.817	41	0.0001				
	Inter-state	77.02	2252.5	2	67.043	CNTYPOP	11.565	0.0001	0.8846
		75.87	19.300	40	0.0001	STEMP	0.982	0.3321	0.0751
	High-ways	75.44	2328.6	2	61.448	CNTYHH	11.072	0.0001	0.8728
		74.22	19.952	40	0.0001	STEMP	0.667	0.5085	0.0526
x. Region 'c' of	Uc1	83.41	7795.7	1	241.261	CNTYPOP	15.533	0.0001	0.9133
		83.06	24.472	48	0.0001				
	Uc2	84.48	7538.5	1	261.339	CNTYVR	16.166	0.0001	0.9191
		84.16	23.664	48	0.0001				
	Uc3	84.43	7550.9	1	260.323	CNTYHH	16.135	0.0001	0.9189
		84.11	23.703	48	0.0001				
	Uc4	84.75	7472.2	1	266.848	CNTYEMP	16.335	0.0001	0.9206
		84.44	23.456	48	0.0001				
	Uc12	86.57	7086.9	2	151.507	CNTYHH	17.144	0.0001	0.9165
		86.00	22.024	47	0.0001	STEMP	2.737	0.0087	0.1463
High-ways	Uc13	86.56	7089.2	2	151.394	CNTYEMP	17.137	0.0001	0.9167
		85.99	22.254	47	0.0001	STEMP	2.515	0.0154	0.1345

Table 6.21: Significance of Variable(s) in Model in Post-Influence Analysis [Urban Principal Arterial]

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2	RMSE	df_r	F-Value	Variable	t-value	Prob>t	Standardized Est.
		R^2_a	C.V.	df_e	Prob>F				
i. City Gr.=A & Region =c	Ac4	86.09	1027.3	2	34.038	CNTYHH	7.076	0.0001	0.8903
		83.59	7.574	11	0.0001	CNTYINC	6.966	0.0001	0.8765
	Ac5	86.48	1012.8	2	35.175	CNTYVR	7.199	0.0001	0.8109
		84.02	7.468	11	0.0001	CNTYINC	5.507	0.0002	0.6203
	Ac6	84.30	1091.3	2	29.533	CNTYEMP	6.566	0.0001	0.7846
		81.45	8.047	11	0.0001	CNTYINC	4.146	0.0016	0.4954
	Ac7	89.84	878.2	2	48.609	CNTYPOP	8.519	0.0001	0.9580
		87.99	6.475	11	0.0001	CNTYINC	8.664	0.0001	0.9743
ii. City Gr.=A & Region =s	An1	64.32	1672.8	1	34.247	CTYPOP	5.852	0.0001	0.8020
		62.44	12.666	19	0.0001				
	An6	72.30	1514.2	2	23.494	CTYPOP	6.761	0.0001	0.9581
		69.22	11.465	18	0.0001	STVR	2.278	0.0352	0.3228
	An7	68.31	1619.7	2	19.400	CTYPOP	6.215	0.0001	0.8661
		64.79	12.263	18	0.0001	STEMP	1.506	0.1494	0.2099
	An8	71.88	1525.7	2	23.006	CTYPOP	6.691	0.0001	0.9505
		68.76	11.552	18	0.0001	STPOP	2.200	0.0411	0.3126
xiii. City Gr.=A+B+C & Region =s	ABCs3	72.45	3588.1	1	34.187	CNTYVR	5.847	0.0001	0.8512
		70.33	24.344	13	0.0001				
	ABCs4	83.35	2789.8	1	65.057	CNTYEMP	8.066	0.0001	0.9129
		82.06	18.928	13	0.0001				
	ABCs7	86.85	2580.5	2	39.613	CNTYEMP	8.743	0.0001	0.9155
		84.65	17.508	12	0.0001	STVR	1.787	0.0992	0.1871
	ABCs8	87.19	2546.1	2	40.855	CNTYEMP	8.907	0.0001	0.9209
		85.06	17.275	12	0.0001	STHH	1.899	0.0818	0.1964
	ABCs9	87.24	2541.8	2	41.013	CNTYEMP	8.936	0.0001	0.9226
		85.11	17.246	12	0.0001	STPOP	1.913	0.0799	0.1975

Table 6.21, continued

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2	RMSE	df_r	F-Value	Variable	t- value	Prob>t	Standard- ized Est.
		R_a^2	C.V.	df_e	Prob>F				
iv. City Gr.=B & Region =c	Bc3	93.83	1597.1	1	152.108	CNTYHH	12.333	0.0001	0.9687
		93.21	10.576	10	0.0001				
	Bc4	94.14	1556.2	1	160.736	CNTYEMP	12.678	0.0001	0.9703
		93.56	10.306	10	0.0001				
	Bc5	94.36	1527.3	1	167.261	CNTYVR	12.933	0.0001	0.9714
		93.79	10.114	10	0.0001				
	Bc12	95.30	1468.8	2	91.336	CNTYVR	6.997	0.0001	0.8418
		94.26	9.727	9	0.0001	CNTYINC	1.346	0.2111	0.1620
v. City Gr.=B & Region =n	Bn12	76.74	960.4	2	16.498	STVR	4.074	0.0022	0.6277
		72.09	7.794	10	0.0007	CNTYINC	3.430	0.0064	0.5284
	Bn14	78.67	919.8	2	18.436	CNTYVR	4.359	0.0014	0.6567
		74.40	7.465	10	0.0004	CNTYINC	3.030	0.0127	0.4565
	Bn15	78.80	916.9	2	18.579	CNTYINC	4.482	0.0012	0.6538
		74.55	7.442	10	0.0004	STHH	4.379	0.0014	0.6387
	Bn21	83.95	840.8	3	15.697	CNTYVR	3.076	0.0132	0.5039
		78.61	6.824	9	0.0006	CNTYINC	2.451	0.0367	0.3629
					STEMP	1.722	0.1191	0.3033	
vii. City Gr.=C Region =c	Cc5	56.10	2824.9	2	24.916	CNTYINC	6.237	0.0001	0.7017
		53.85	22.789	39	0.0001	CNTYPOP	1.044	0.3030	0.1174
	Cc6	69.88	2339.9	2	45.234	CNTYINC	6.631	0.0001	0.6134
		68.33	18.876	39	0.0001	CTYPOP	4.408	0.0001	0.4078
viii. City Gr.=C & Region =n	Cn1	49.59	1894.2	1	26.565	CNTYINC	5.154	0.0001	0.7042
		47.73	16.934	27	0.0001				
	Cn5	58.04	1761.2	2	17.982	CNTYINC	4.890	0.0001	0.6374
		54.81	15.744	26	0.0001	CNTYVR	2.288	0.0305	0.2982
	Cn6	60.77	1702.9	2	20.138	CNTYINC	4.644	0.0001	0.5984
		57.75	15.223	26	0.0001	CNTYEMP	2.722	0.0114	0.3507
	Cn7	56.30	1797.3	2	16.750	CNTYINC	4.645	0.0001	0.6278
		52.94	16.067	26	0.0001	CTYPOP	1.998	0.0563	0.2700

Table 6.21, continued

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2	RMSE	df_r	F-Value	Variable	t-value	Prob>t	Standardized Est.
		R_a^2	C.V.	df_e	Prob>F				
x. City Gr.=D & Region =c	Dc10	70.44	915.4	2	26.218	CTYPOP	6.486	0.0001	0.7546
		67.76	11.093	22	0.0001	STVR	3.767	0.0011	0.4382
	Dc11	75.05	841.1	2	33.085	CTYPOP	7.157	0.0001	0.7661
		72.78	10.193	22	0.0001	STEMP	4.568	0.0001	0.4890
	Dc18	76.96	827.2	3	23.384	CTYPOP	6.816	0.0001	0.8568
		73.67	10.024	21	0.0001	STEMP	3.648	0.0015	0.4240
						CNTYINC	1.321	0.2008	0.1811
	Dc19	74.16	876.2	3	20.086	CTYPOP	6.739	0.0001	0.8902
		70.46	10.617	21	0.0001	STHH	3.096	0.0055	0.3515
						CNTYINC	2.265	0.0342	0.3049
xi. City Gr.=D & Region =n	Dn3	50.52	2204.0	1	31.650	CNTYHH	5.626	0.0001	0.7108
		48.92	21.573	31	0.0001				
	Dn4	51.81	2175.0	1	33.332	CNTYVR	5.773	0.0001	0.7198
		50.26	21.289	31	0.0001				
	Dn15	53.32	2176.1	2	17.133	CNTYVR	5.392	0.0001	0.6909
		50.21	21.300	30	0.0001	STHH	0.984	0.3331	0.1261
	Dn16	52.35	2198.6	2	16.481	CNTYHH	3.553	0.0013	0.5932
		49.17	21.519	30	0.0001	CNTYINC	1.074	0.2913	0.1793
xii. City Gr.=D & Region =s	Ds3	45.61	1290.0	1	31.023	STHH	5.570	0.0001	0.6753
		44.14	12.653	37	0.0001				
	Ds4	52.85	1201.0	1	41.481	STPOP	6.441	0.0001	0.7270
		51.58	11.781	37	0.0001				
	Ds12	50.88	1242.9	2	18.641	STHH	3.659	0.0008	0.5181
		48.15	12.190	36	0.0001	STINC	1.965	0.0572	0.2782
	Ds13	54.82	1191.9	2	21.840	STPOP	4.207	0.0002	0.6112
		52.31	11.690	36	0.0001	STINC	1.251	0.2189	0.1818

Table 6.22: Significance of Variable(s) in Model in Post-Influence Analysis [Urban Minor Arterial & Collector]

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2 R_a^2	RMSE C.V.	df_r df_e	F-Value Prob>F	Variable	t-value	Prob>t	Standardized Est.
i. City Gr.=A	A2	67.06	2028.2	1	28.497	CNTYINC	5.338	0.0001	0.8189
		64.70	19.405	14	0.0001				
	A5	79.58	1657.0	2	25.337	CNTYINC	5.382	0.0001	0.7072
		76.44	15.853	13	0.0001	CNTYPOP	2.824	0.0143	0.3711
	A6	79.85	1646.2	2	25.754	CNTYINC	5.082	0.0002	0.6793
		76.75	15.750	13	0.0001	CNTYVR	2.872	0.0131	0.3839
	A7	79.36	1665.9	2	24.997	CNTYINC	4.374	0.0008	0.6277
		76.19	15.938	13	0.0001	CNTYEMP	2.784	0.0155	0.3995
ii. City Gr.=B	B2	77.58	1998.0	1	34.602	CNTYINC	5.882	0.0002	0.8808
		75.34	23.854	10	0.0002				
iii. City Gr.=C	C2	86.00	652.9	1	67.574	CNTYVR	8.220	0.0001	0.9274
		84.73	7.609	11	0.0001				
	C3	87.18	624.8	1	74.809	CNTYPOP	8.649	0.0001	0.9337
		86.02	7.281	11	0.0001				
	C4	88.98	579.3	1	88.839	CNTYHH	9.425	0.0001	0.9433
		87.98	6.749	11	0.0001				
iv. City Gr.=C	C9	74.85	1267.8	1	26.781	CNTYEMP	5.175	0.0006	0.8651
		72.05	12.371	9	0.0006				
	C10	76.60	1223.0	1	29.456	CNTYPOP	5.427	0.0004	0.8752
		74.00	15.052	9	0.0004				
	C11	78.08	1183.6	1	32.058	CNTYVR	5.662	0.0003	0.8836
		75.64	14.567	9	0.0003				
	C12	78.30	1177.7	1	32.467	CNTYHH	5.698	0.0003	0.8849
		75.88	14.495	9	0.0003				

Table 6.22, continued

Model Gr.	Model No.	Model Statistics				Variables in Model			
		R^2 R_a^2	RMSE C.V.	df_r df_e	F-Value Prob>F	Variable	t- value	Prob>t	Standard- ized Est.
v. City Gr.=D	D6	71.79 69.23	1722.3 29.792	2 22	27.995 0.0001	CNTYINC CTYPOP	5.241 4.273	0.0001 0.0003	0.6040 0.4924
vi. City Gr.=D	D7	62.52 60.73	1042.3 23.078	1 21	35.027 0.0001	CNTYINC	5.918	0.0001	0.7907

and post influence cases is 0.845 (0.4056) and 2.288 (0.0305), respectively. The partial regression residual plot in Figure 6.2 is also an indication of nonsignificance of the predictor variable in the pre-influence case, because the plot is scattered and because the presence of an outlier causes a mild slope. Removing the outlier resulted in an increased slope and less scatter (see Figure 6.12). Thus, the results for model Cn5 prove that a variable that was found to be nonsignificant in the pre-influence case may become significant in the post-influence case. A decreased slope could also happen, if the outlier(s) had caused the particular predictor variable to be less significant. Additional candidate models are evaluated (if necessary) in the post-influence case by dropping the nonsignificant variable in the pre-influence case. For example, model Cn1 (see Table 6.21) is considered in the post-influence case by dropping variable CNTYVR from Cn5 of the pre-influence case. In section 6.5, only the models with significant variables in their equations will be considered to find the final selection.

To test the significance of each subset with more than one variable ($H_0 : \beta_1 = \dots = \beta_j = 0$; $H_a : \text{all } \beta_j \neq 0 \text{ for } 1 < j < P-1$), a general linear test [Neter et al. 1985] was employed. The applicable F-statistic is shown in equation 6.7.

$$F^* = \frac{\frac{SSE(R) - SSE(F)}{df_R - df_F}}{\frac{SSE(F)}{df_F}} \quad (6.7)$$

where,

F^* = F statistic,

SSE(R) = Error Sum of Squares for the Reduced model,

SSE(F) = Error Sum of Squares for the Full model,

df_R = degrees of freedom of the Reduced model, and

df_F = degrees of freedom of the Full model.

The reduced model was obtained by dropping the element(s) to be tested from the full model under H_0 . The test results (not presented) show that when variables are dropped from the model, there still exist regression relationships. The hypothesis H_a cannot be rejected at an α level of 0.01.

6.4.3 Standardized Regression Coefficients

Ordinarily, it is difficult to compare regression coefficients because of differences in the units involved (for example, income in dollars and population in number of persons). Standardized regression coefficients help to compare the regression coefficients. The standardized regression coefficients (B_j 's) are defined as follows:

$$B_j = b_j \left[\frac{s_j}{s_Y} \right] \quad (6.8)$$

where s_j and s_Y are the standard deviation of X_j and Y observations, respectively, and b_j is the parameter estimate of x_j (i.e., β_j of Equation 5.1). The term in brackets makes B_j dimensionless. The coefficient of B_j reflects the change in the independent variable x_j (in units of standard deviation of Y) per unit change in the indepen-

dent variable x_j (in units of standard deviation of x_j) when all other independent variables are held constant. [Neter et. al. 1985]

The standardized estimate for each variable of the model is shown in the last column of Tables 6.19-6.24. Interpretation regarding the importance of independent variables in regression coefficients can be affected by the problem of multicollinearity. So, interpretation is not wise if multicollinearity exists. But, tests in Section 6.4.1 have shown that in most of the selections, the problem of multicollinearity is either absent or not significant. Thus, the values of standardized estimates provide information about the importance of variables in the models and for comparison of different candidate models.

6.5 Final Model Selection

The preceding sections have demonstrated the usefulness of influence analysis through improvement in statistical results. For example, influence analysis has satisfied the normality assumption of regression analysis. It has also avoided the awkward transformations often needed to satisfy the normality assumptions. All the final model selections are based on the results of post-influence analysis. The results (see Tables 6.8 - 6.10) of normality statistics of residuals in "post-influence" indicate that all the selected groups except Group 1 (Interstate Highways) have models that satisfy the normality assumptions of residuals. Because of the information described above and the high number of influential observations for overall/combined analysis of Interstate Highways, Group 1 of interstate highways has

not been considered further to select any model from this group. Instead, regional analysis (Groups iv-vi in Section 5.6.1) of the combined urban-rural model, separate rural and urban analysis (Groups ii and iii) and combined regional analysis (Groups vii-xii) of Interstate Highways have been used to select one final model from each of these groups. Thus, three alternate elasticity models for Interstate Highways are possible. One such model has finally selected from the candidate model(s) for each group of non-interstate highways.

Both statistical results and judgment are employed to decide the final selections. The following criteria are employed to draw the final selection from the candidate models for each group under consideration.

1. Elimination of candidate models having nonsignificant predictor variables. (Tables 6.20-6.22)
2. Comparison of the results of the standard regression assumptions (for example, normality and homogeneity) for the candidate models. (Tables 6.8-6.10)
3. Overall significance of the candidate models. In other words, how useful is the candidate model. (Tables 6.20-6.22)
4. Comparative evaluation of the collinearity statistics of the candidate models. (Tables 6.14-6.16)
5. Comparison of some model statistics (R^2 , R_a^2 , RMSE, C.V., standardized regression coefficients etc.) for the candidate models. Elimination of candidate model(s) having more predictor variables

without having a significant change in the quality of results in comparison to the models with fewer predictor variable(s). In other words, the final selection should lead to parsimony -- a decrease in number of variables with minor cost in statistical quality.

6. Consideration of the quality (availability, cost and reliability -- See Chapter 4) of the predictor variables in the model. For almost identical statistical results for candidate models, the order of importance of predictor variables (See Section 5.6) has been considered to evaluate the candidate models and to make the final model selection.

The first four criteria are primarily considered to select the final model. Criteria 5 and 6 have been taken into account in candidate model selection (Chapter 5). In final model selection, the last two criteria are used to break any ties that result from the first four criteria.

The final regression equations, along with the R^2 values and elasticities, are presented in Tables 6.23, 6.24 and 6.25 for Interstates, Urban Principal Arterial, and Urban Minor Arterial & Collector, respectively. The elasticities shown in these tables were obtained from the output of Multiple Linear Regression on final selected variables computed according to Equation (3.4) of Chapter 3. The equations that resulted from the specified criteria are the best possible, considering all the limitations. The equations in the final selections use variables that are easily available from a variety of sources for both historical and future trends, or else future values

Table 6.23: Final Regression Equations for Interstate Highways

A. Interstate Highways (Rural & Urban): Regional Model				
A1. <u>North Region</u> :	AADT = 15547.16 + 0.21125 CNTYHH			
[Model URn4]	$R^2=72.28$	e=0.42934		
A2. <u>Central Region</u> :	AADT = -7966.25 + 0.06329 CNTYVR + 2.42706 CNTYINC			
[Model URc14]	$R^2=73.84$	e=0.22043	e=1.10598	
A3. <u>South Region</u> :	AADT = 2740.56 + 0.30750 CNTYPOP			
[Model URs2]	$R^2=74.60$	e=0.80514		
B. Rural Interstate Highways: Statewide Model				
B. <u>All Region</u> :	AADT = -17827.83 + 3.22885 CNTYINC + 0.31447 CNTYEMP			
[Model R3]	$R^2=71.27$	e=1.76217	e=0.17962	
C. Rural Interstate Highways: Regional Model				
C1. <u>North Region</u> :	AADT = -41867.50 + 3.12508 CNTYINC + 0.01406 STHH			
[Model Rn6]	$R^2=50.35$	e=1.83854	e=1.49922	
C2. <u>Central Region</u> :	AADT = -14090.09 + 3.26066 CNTYINC + 0.01643 CNTYPOP			
[Model Rc4]	$R^2=61.62$	e=1.51360	e=0.07252	
C3. <u>South Region</u> :	AADT = 5323.00 + 0.20373 CNTYPOP			
[Model Rs1]	$R^2=76.47$	e=0.54390		

Table 6.23, continued

D. Urban Interstate Highways: Statewide Model			
D. <u>All Region:</u>	AADT = -25675.04 + 0.05678 CNTYPOP + 0.02507 STEMP		
[Model U11]	R ² =77.81	e=0.39991	e=1.41132

E. Urban Interstate Highways: Regional Model			
E1. <u>North Region:</u>	AADT = 18252.32 + 0.06837 CNTYPOP		
[Model Un3]	R ² =55.27	e=0.51775	
E2. <u>Central Region:</u>	AADT = 19636.66 + 0.10909 CNTYEMP		
[Model Uc4]	R ² =84.75	e=0.38358	
E3. <u>South Region:</u>	AADT = -59503.65 + 0.80685 CNTYEMP + 0.04124 STHH		
[Model Us13]	R ² =88.86	e=0.39837	e=2.54131

Note: See Table 4.3 for description of variables.

Table 6.24: Final Regression Equations for Urban Principal Arterial

City Group "A" [City Population: 30,000 to 50,000]			
<u>North Region:</u>	AADT = -26421.85 + 0.52378 CTYPOP + 0.00937 STHH		
[Model An9]	R ² =73.62	e=1.66514	e=1.33545
<u>Central Region:</u>	AADT = -18289.30 + 0.09361 CNTYPOP + 2.25619 CNTYINC		
[Model Ac7]	R ² =89.84	e=0.59626	e=1.75219
<u>South Region:</u>	AADT = 5610.51 + 0.61280 CNTYEMP		
[Model ABCs4]	R ² =83.35	e=0.61934	

City Group "B" [City Population: 20,000 to 30,000]			
<u>North Region:</u>	AADT = -19774.52 + 1.05470 CNTYINC + 0.01052 STHH		
[Model Bn15]	R ² =78.80	e=1.00064	e=1.60420
<u>Central Region:</u>	AADT = 10898.88 + 0.03779 CNTYEMP		
[Model Bc4]	R ² =94.14	e=0.27825	
<u>South Region:</u>	AADT = 5610.51 + 0.61280 CNTYEMP		
[Model ABCs4]	R ² =83.35	e=0.61934	

Table 6.24, continued

City Group "C" [City Population: 10,000 to 20,000]			
<u>North Region:</u>	AADT = -5610.46 + 1.46963 CNTYINC + 0.01433 CNTYEMP		
[Model Cn6]	$R^2=60.77$	e=1.42975	e=0.07181
<u>Central Region:</u>	AADT = -13752.45 + 1.57494 CNTYINC + 0.55774 CTYPOP		
[Model Cc6]	$R^2=69.88$	e=1.50307	e=0.60636
<u>South Region:</u>	AADT = 5610.51 + 0.61280 CNTYEMP		
[Model ABCs4]	$R^2=83.35$	e=0.61934	

City Group "D" [City Population: 5,000 to 10,000]			
<u>North Region:</u>	AADT = 8600.77 + 0.02033 CNTYVR		
[Model Dn4]	$R^2=51.81$	e=0.15817	
<u>Central Region:</u>	AADT = -10386.38 + 0.86685 CTYPOP + 0.00744 STEMP		
[Model Dc11]	$R^2=75.05$	e=0.67228	e=1.58639
<u>South Region:</u>	AADT = -64757.26 + 0.01379 STPOP		
[Model Ds4]	$R^2=52.85$	e=7.35150	

Note: See Table 4.3 for description of variables.

Table 6.25: Final Regression Equations for Urban Minor Arterial & Collector

City Group "A" [City Population: 30,000 to 50,000]			
[Model A5]:	AADT = -10509.44 + 1.82159 CNTYINC + 0.00720 CNTYPOP		
	$R^2=79.58$	$e=1.89210$	$e=0.11339$
City Group "B" [City Population: 20,000 to 30,000]			
[Model B2]:	AADT = -21894.69 + 2.78261 CNTYINC		
	$R^2=77.58$	$e=3.61401$	
City Group "C" [City Population: 10,000 to 20,000]			
[Model C3]:	AADT = 7057.95 + 0.00813 CNTYPOP		
	$R^2=87.18$	$e=0.17757$	
City Group "D" [City Population: 5,000 to 10,000]			
[Model D7]:	AADT = -8374.10 + 1.22039 CNTYINC		
	$R^2=62.52$	$e=2.85405$	

Note: See Table 4.3 for description of variables.

can be generated from the available information. Each of the variables is significant at the 95 percent confidence level.

Using the elasticities obtained from the regression analysis, a forecasting model was developed for each selected group under different highway categories by substituting those elasticities into Equation (3.1) of Chapter 3. The elasticity models are presented in Tables 6.26, 6.27 and 6.28 for Interstates, Urban Principal Arterial, and Urban Minor Arterial & Collector, respectively. These models generally satisfy all the criteria specified earlier. Each of the models is relatively simple, containing not more than two variables. The use of these models is also straightforward. The input values are the base year AADT and the base and future year value (the year for which the traffic forecast is needed) of the predictor variables.

The elasticity of urban interstate AADT in the north region is 0.51775 (See Table 6.26) with respect to county population, meaning that a 1 percent change in the number of county population results in 0.52 percent increase in urban interstate traffic in the north region. The larger the elasticity of a given model, the greater the variable's effect on AADT. Because of this and the linear relationship of the model, an error of 10 percent in the predicted value of county population will change projected traffic by 5.18 percent in the urban interstate north region model. Thus, accurate forecasts for the input variables is a requirement for the success of the elasticity model in traffic forecasting.

Table 6.26: Elasticity-based Traffic Models for Interstate Highways

A. Interstate Highways (Rural & Urban): Regional Model	
A1. <u>North Region</u> :	$AADT_f = AADT_b [1 + 0.42934 (\Delta CNTYHH)]$
A2. <u>Central Region</u> :	$AADT_f = AADT_b [1 + 0.22043 (\Delta CNTYVR) + 1.10598 (\Delta CNTYINC)]$
A3. <u>South Region</u> :	$AADT_f = AADT_b [1 + 0.80514 (\Delta CNTYPOP)]$
B. Rural Interstate Highways: Statewide Model	
B. <u>All Region</u> :	$AADT_f = AADT_b [1 + 1.76217 (\Delta CNTYINC) + 0.17962 (\Delta CNTYEMP)]$
C. Rural Interstate Highways: Regional Model	
C1. <u>North Region</u> :	$AADT_f = AADT_b [1 + 1.83854 (\Delta CNTYINC) + 1.49922 (\Delta STHH)]$
C2. <u>Central Region</u> :	$AADT_f = AADT_b [1 + 1.51360 (\Delta CNTYINC) + 0.07252 (\Delta CNTYPOP)]$
C3. <u>South Region</u> :	$AADT_f = AADT_b [1 + 0.54390 (\Delta CNTYPOP)]$

Table 6.26, continued

D. Urban Interstate Highways: Statewide Model	
D. <u>All Region</u> :	
	$AADT_f = AADT_b [1 + 0.39991 (\Delta \text{ CNTYPOP}) + 1.41132 (\Delta \text{ STEMP})]$
E. Urban Interstate Highways: Regional Model	
E1. <u>North Region</u> :	$AADT_f = AADT_b [1 + 0.51775 (\Delta \text{ CNTYPOP})]$
E2. <u>Central Region</u> :	$AADT_f = AADT_b [1 + 0.38358 (\Delta \text{ CNTYEMP})]$
E3. <u>South Region</u> :	$AADT_f = AADT_b [1 + 0.39837 (\Delta \text{ CNTYEMP}) + 2.54131 (\Delta \text{ STHH})]$

Note: (i) See Table 4.3 for description of variables.

(ii) Δ represents change in predictor variable with respect to its

base value in fraction. For example, $\Delta X = \frac{X_f - X_b}{X_b}$, where X_b and X_f denote base and future values of X .

Table 6.27: Elasticity-based Traffic Models for Urban Principal Arterial

City Group "A" [City Population: 30,000 to 50,000]	
<u>North Region:</u>	$AADT_f = AADT_b [1 + 1.66514 (\Delta CTYPOP) + 1.33545 (\Delta STHH)]$
<u>Central Region:</u>	$AADT_f = AADT_b [1 + 0.59626 (\Delta CNTYPOP) + 1.75219 (\Delta CNTYINC)]$
<u>South Region:</u>	$AADT_f = AADT_b [1 + 0.61934 (\Delta CNTYEMP)]$

City Group "B" [City Population: 20,000 to 30,000]	
<u>North Region:</u>	$AADT_f = AADT_b [1 + 1.00064 (\Delta CNTYINC) + 1.60420 (\Delta STHH)]$
<u>Central Region:</u>	$AADT_f = AADT_b [1 + 0.27825 (\Delta CNTYEMP)]$
<u>South Region:</u>	$AADT_f = AADT_b [1 + 0.61934 (\Delta CNTYEMP)]$

Table 6.27, continued

City Group "C" [City Population: 10,000 to 20,000]	
<u>North Region:</u>	
	$AADT_f = AADT_b [1 + 1.42975 (\Delta CNTYINC) + 0.07181 (\Delta CNTYEMP)]$
<u>Central Region:</u>	
	$AADT_f = AADT_b [1 + 1.50307 (\Delta CNTYINC) + 0.60636 (\Delta CTYPOP)]$
<u>South Region:</u>	
	$AADT_f = AADT_b [1 + 0.61934 (\Delta CNTYEMP)]$

City Group "D" [City Population: 5,000 to 10,000]	
<u>North Region:</u>	
	$AADT_f = AADT_b [1 + 0.15817 (\Delta CNTYVR)]$
<u>Central Region:</u>	
	$AADT_f = AADT_b [1 + 0.67228 (\Delta CTYPOP) + 1.58639 (\Delta STEMP)]$
<u>South Region:</u>	
	$AADT_f = AADT_b [1 + 7.35150 (\Delta STPOP)]$

Note: (i) See Table 4.3 for description of variables.

(ii) Δ represents change in predictor variable with respect to its

base value in fraction. For example, $\Delta X = \frac{X_f - X_b}{X_b}$, where X_b and X_f denote base and future values of X .

Table 6.28: Elasticity-based Traffic Models for Urban Minor Arterial & Collector

City Group "A" [City Population: 30,000 to 50,000]
$AADT_f = AADT_b [1 + 1.89210 (\Delta \text{ CNTYINC}) + 0.11339 (\Delta \text{ CNTYPOP})]$
City Group "B" [City Population: 20,000 to 30,000]
$AADT_f = AADT_b [1 + 3.61401 (\Delta \text{ CNTYINC})]$
City Group "C" [City Population: 10,000 to 20,000]
$AADT_f = AADT_b [1 + 0.17757 (\Delta \text{ CNTYPOP})]$
City Group "D" [City Population: 5,000 to 10,000]
$AADT_f = AADT_b [1 + 2.85405 (\Delta \text{ CNTYINC})]$

Note: (i) See Table 4.3 for description of variables.

(ii) Δ represents change in predictor variable with respect to its

base value in fraction. For example, $\Delta X = \frac{X_f - X_b}{X_b}$, where X_b and X_f denote base and future values of X .

6.6 Chapter Summary

All the statistics employed in influential analysis, testing regression assumptions, and significance and collinearity of the regression assumptions have been described in this chapter. A summary of results of all statistical analyses has been provided. Results of pre and post influence analysis have been compared to show the usefulness of detecting outliers and influential observations. Significance tests on variables in the candidate models have found useful predictor variables, whereas the overall significance test has found that strong relationships exist between the response and the selected predictor variables. Collinearity statistics on regression coefficients are used to detect the degree of multicollinearity (if any exists). The collinearity statistics and significance tests have identified useful models with minimized multicollinearity and fewer variables (≤ 2) in each final model selected. The statistical results of post-influence analysis are used to draw a final selection from the group of candidate models. Finally, elasticity models (See Tables 6.26-6.28) are formed for different groups under each highway class. Performance of this model form, in addition to some alternative model structures, will be evaluated in a later chapter.

CHAPTER 7

PRINCIPAL COMPONENT ANALYSIS BASED MODEL

7.1 Introduction

The forecasting of traffic volumes is a complex task. Besides the many measurable variables that influence traffic, there are others that cannot be measured. This study has been based on a large number of variables (twelve) that may explain traffic volumes. In Chapter 6, it has been noted that at most two variables out of twelve useful variates are retained in our final regression equations. The main reason for this is that we are primarily working with socioeconomic variables, and it is more likely that these variates are collinear. In Chapters 5 and 6, variates thought to be collinear were dropped and diagnostic tests for collinearity were carried out. Another strategy that can be applied is replacing subsets of the collinear variates by specific linear combinations (such as principal components). Principal Component Analysis (PCA) is a multivariate technique for examining relationships among several quantitative variables, and it can be used to reduce the number of variables in regression.

7.2 Principal Component Analysis

The statistical technique of Principal Component Analysis (PCA) can be related in many aspects to the "principal stress analysis" of structural analysis. For example, the equivalents of the direction cosine vectors in structural analysis are eigenvectors in this statistical technique [Harr 1987]. PCA is a multivariate analysis technique that attempts to describe interrelationships among a set of variables. PCA can be thought as a dimension reduction technique and is useful because problems with many variables are hard to model, to parametrize, to analyze, to interpret. Also, it is difficult to keep track of the correlation structure with a large number of variables. The description of principal component analysis in this section focuses on the concept and uses behind it. A complete description of principal component analysis can be found in Johnson and Wichern [1982].

Procedure "PRINCOMP" of SAS package [SAS/Statistics 1985] is used to perform Principal Component Analysis. The procedure is used to calculate a maximum of 11 principal components from 11 original predictor variables. One original variable, STGAS, is dropped in this analysis because it was absent from the final selection in Chapter 6. The PCA is carried out for each filtered data group — data groups that remained after influential analysis in Chapter 6. The following four data groups, one from each major highway class, have been selected to illustrate some concepts of PCA in this section and principal component regression in subsequent sections.

- a. Central Region of Rural Interstate.
- b. Central Region of Urban Interstate.
- c. City Group "A" and Central Region of Urban Principal Arterial.
- d. City Group "D" of Urban Minor arterial and Collector.

The important results of PCA for the above selected data groups are shown in Table 7.1.

In statistical analysis, a model containing a large number of independent variables is not uncommon. In most cases, statistical analyses reveal the appropriate model. Our analyses start with a large list of variables because we do not initially want to overlook the variables that may be explanatory factors in a model. However, the inclusion of a large number of variables in a regression model often results in multicollinearity. In Chapters 5 and 6, it has been mentioned how multicollinearity may inhibit the usefulness of the results. Principal Component Analysis (PCA) can be used to study the structure of multicollinearity, and the results of such study can be used to improve the results of regression analysis. This method (described below) produces a set of artificial, uncorrelated ($r = 0$) variables that can then be used in a regression model.

Starting with a data set with p numeric variables, which is usually large in number, the PCA tries to find if there exist k linear combinations $PC_1, \dots, PC_k$ of the original variables $X_1, \dots, X_p$ such that the PC_i 's account for most of the variation in the original X 's. For the PC 's to be useful as a dimension reduction technique, k should

Table 7.1: Eigen Values and Component Variances of Selected Data Groups

PC _j	Eigenvalue (λ_j)	PROP _j (Eq. 7.3)	CUM-PROP _j (Eq. 7.4)	PC _j	Eigenvalue (λ_j)	PROP _j (Eq. 7.3)	CUM-PROP _j (Eq. 7.4)
(a) Central Region of Rural Interstate				(b) Central Region of Urban Interstate			
PC1	5.01048	0.455498	0.45550	PC1	5.22058	0.474598	0.47460
PC2	3.76659	0.342417	0.79792	PC2	3.75920	0.341746	0.81634
PC3	1.08231	0.098392	0.89631	PC3	0.85521	0.077746	0.89409
PC4	0.60152	0.054684	0.95099	PC4	0.63882	0.058074	0.95216
PC5	0.44356	0.040323	0.99131	PC5	0.39720	0.036109	0.98827
PC6	0.06398	0.005816	0.99713	PC6	0.09699	0.008818	0.99709
PC7	0.01891	0.001719	0.99885	PC7	0.01815	0.001650	0.99874
PC8	0.00737	0.000670	0.99952	PC8	0.01050	0.000954	0.99970
PC9	0.00432	0.000393	0.99991	PC9	0.00272	0.000247	0.99994
PC10	0.00059	0.000053	0.99997	PC10	0.00049	0.000044	0.99999
PC11	0.00037	0.000034	1.00000	PC11	0.00014	0.000013	1.00000
(c) City Group "A" and Central Region of Urban Principal Arterial				(d) City Group "D" of Urban Minor Arterial & Collector			
PC1	5.64001	0.512728	0.51273	PC1	4.87349	0.443044	0.44304
PC2	4.26445	0.387678	0.90041	PC2	3.91262	0.355692	0.79874
PC3	0.61384	0.055803	0.95621	PC3	1.15912	0.105374	0.90411
PC4	0.30860	0.028054	0.98426	PC4	0.66483	0.060439	0.96455
PC5	0.09755	0.008868	0.99313	PC5	0.22961	0.020874	0.98542
PC6	0.03851	0.003500	0.99663	PC6	0.14004	0.012731	0.99815
PC7	0.02628	0.002389	0.99902	PC7	0.01052	0.000957	0.99911
PC8	0.00631	0.000573	0.99959	PC8	0.00724	0.000658	0.99977
PC9	0.00258	0.000234	0.99983	PC9	0.00239	0.000217	0.99999
PC10	0.00125	0.000113	0.99994	PC10	0.00010	0.000009	1.00000
PC11	0.00064	0.000058	1.00000	PC11	0.00005	0.000004	1.00000

be substantially smaller than p . At the end of this section, it is shown that the value of k in most of the data groups is 2 or 3, which is small compared to our 11 original variables used to derive Principal Components (PCs). Each principal component is a linear combination of the original variables, with coefficients equal to the eigenvectors of the correlation or covariance matrix. Let $\lambda_1 > \lambda_2 > \lambda_3 > \dots > \lambda_p > 0$ be the ordered eigenvalues of the variance-covariance matrix of X 's, and $\underline{\alpha}_1, \underline{\alpha}_2, \underline{\alpha}_3, \dots, \underline{\alpha}_p$ be the corresponding normalized eigenvector [Johnson & Wichern 1982]. Then the j -th Principal Component (PC j) is defined as

$$PCj = \sum_{i=1}^p \alpha_{ij} X_i = \underline{\alpha}_j' X \quad (7.1)$$

The PCs selected in the regression model (see Section 7.3.1) are presented in Appendix Tables D1, D2 and D3 for the data groups Interstate, Urban Principal Arterial, and Urban Minor Arterial and Collector, respectively. These tables show the elements of the eigenvectors, or the coefficients of the PCs. Means and standard deviations of the original variables are also shown in these tables. The first Principal Component (PC1) of $X_1, X_2, \dots, X_p$ (the original variables) is defined as the linear combination $\underline{\alpha}_1' X$ of $X_1, X_2, \dots, X_p$ that has the maximum variance among all possible linear combinations $\underline{\alpha}' X$, subject to the constraint $\underline{\alpha}' \underline{\alpha} < 1$. The second Principal Component (PC2) is defined as the linear combination, $\underline{\alpha}_2' X$, that has the maximum variance among all possible linear combinations $\underline{\alpha}' X$, is uncorrelated with PC1, and satisfies the constraint $\underline{\alpha}' \underline{\alpha} < 1$. At each

stage j , PC_j is uncorrelated with $PC_1, PC_2, \dots, PC(j-1)$. Thus, the principal components have the following properties:

- The principal component variables are jointly uncorrelated.
- The first principal component has the largest variance of any linear function of the original variables. The second component has the second largest variance, and so forth.

The zero correlation condition allows dimension reduction through the independent factors. As a result, the regression coefficients for PCs' are independent on the number of PCs' in the regression equation.

Principal components can be obtained by computing the eigenvalues and eigenvectors of the correlation or covariance matrix. In this study, the correlation matrix has been used so that the components are not affected by the scales of measurement of the original variables. Our original variables are qualitatively different variables and are measured/expressed in different units. In such cases, it is very difficult to construct a linear combination of original variables. The correlation option of the SAS PRINCOMP procedure has eliminated this problem by standardizing each original variable as

$$X_1^{std} = \frac{X_1 - \mu_1}{\sigma_1} \quad (7.2)$$

where, X_1^{std} is the standardized form of original variable X_1 ,

μ_1 and σ_1 are the mean and standard deviation of X_1 .

The values of the means and standard deviations of all the original

variables for the data groups are presented in Appendix Tables D1 to D3. The variables X_1^{std} are now unitless. The variable X_1 in Equation (7.1) is the standardized form of Equation (7.2). The above standardization carries out PCA on the correlation matrix of the original variables. Since all the diagonal elements in a correlation matrix are 1.0, the total variation is equal to number of variables (p). This implies that average variance of the Principal Component is $p/p = 1$. Because the average variance is 1, sometimes the following rule of thumb is used to determine the number of components to be retained:

Retain PC $_j$, if Variance(PC $_j$) > 1.

The principal components in Table 7.1 are sorted in descending order of the eigenvalues, λ_j , which are equal to the variances of the components. The above rule of thumb suggests that only 2 or 3 PCs in Table 7.1 with λ_j greater than 1 are to be retained in our four selected data groups. A similar result has been found for the rest of our data groups (results not shown). Because the correlation matrix is used, the sum of the variances of both the original and the principal component variables is equal to the number of variables. A set of eigenvalues of almost equal magnitudes suggests that there is little multicollinearity, while a wide variation of magnitudes indicates severe multicollinearity. The eigenvalues in Table 7.1 suggest that our data sets have severe multicollinearity. The number of large (usually greater than unity) eigenvalues may be taken as a crude indication of the factors needed to describe the behavior of the full set of variables. The eigenvectors are the coefficients for the linear transformation of the standardized variables with mean zero and

variance one. These coefficients are used to create observed values of the new component variables and can be used to interpret the structure of these variables.

The fraction of the total variation accounted for by the j -th Principal Component is

$$\frac{\lambda_j}{\sum_{j=1}^p \lambda_j} \quad [= \text{PROP}_j]. \quad (7.3)$$

The values of PROP_j for the four selected data groups in Table 7.1 suggest that the first 2 or 3 PCs account for most of the variation. The fraction of the total variation accounted for by the first k ($k \leq p$) Principal Components is

$$\frac{\sum_{j=1}^k \lambda_j}{\sum_{j=1}^p \lambda_j} \quad [= \text{CUM-PROP}_k]. \quad (7.4)$$

These fractions are calculated for each j . The first k components are retained if CUM-PROP_k is large (generally in the 90 percent neighborhood) and if the fraction PROP_j for $j > k$ does not provide enough contribution to CUM-PROP_k . Table 7.1 has presented the values of PROP_j and CUM-PROP_j for the four representative data groups selected at the start of this section. The stopping rule based on CUM-PROP_j of Equation (7.4) suggests that 2 or 3 PC's are enough to describe the data sets. While trying to decide upon a stopping point, the jumps in the

ratios of Equation (7.4) are also noticed. The results are same as those concluded by the rule of thumb for retaining PCs. The retained PCs of each data group are used in the following section to check their significance in regression analysis.

7.3 Principal Component Regression

The combination of principal component analysis and regression analysis presents the analyst with the means of reducing the number of significant variables and of expressing the remaining variables in a linear composite relationship [Harr 1987]. In principal component regression, the set of principal component variables (PCs), instead of the original variables, is used in a regression analysis. Since the principal components are uncorrelated, there is no multicollinearity in the regression. Thus, it is possible to determine the important coefficients without attempting any variable selection techniques. Regression analysis with the retained PCs of Section 7.2 is performed to determine the significance of the PCs. In addition, the different variable selection rules (see Section 5.3 and its subsections) are used to find the candidate models with PCs for each data group. The models with retained PCs in Section 7.2 are examined to see if they belong to the set of candidate models and if they can be selected finally after further diagnosis. In a forecast, users need the future values of all the original variables. Use of the results of principal component regression may be costly due to the forecasts of a large number of original variables. However, the principal component regression analysis provides a direct check on the standard regression

model and its derivative "elasticity model" to see how good the models in Chapter 6 compare to collinearity-free principal component regression. Because the principal component regression starts with data sets after influence analysis (Chapter 6), further influential diagnosis is not necessary. The residual plots in Section 7.3.1 have shown that there is no need for influence analysis for the filtered data, resulted after influence analysis in Chapter 6. At the same time, collinearity analysis can be skipped because, by definition, PCs are independent of each other and no problem of multicollinearity will arise. But the other tests of Chapter 6 (for example, significance test, normality and homoscedasticity, and model aptness) are used to find the best model from the group of candidate models.

7.3.1 Final Principal Component Regression Model

The PCA in Section 7.2 has resulted in the most useful PCs, based on the original predictor variables. But it has not been shown whether the retained components are significant in describing the response variable AADT. The "REG" procedure of SAS [SAS/Statistics] is used to perform the regression with the PC's. The validity of the regression assumptions and model aptness (see Section 6.3) are checked for all the candidate models of each data group. In addition, the significance tests of Section 6.4 are performed to determine the overall significance and the significance of each PC in the regression equation. The comparative evaluation (as was done in Chapter 6) of all these tests and the information on variance explained by the PCs in the PCA of Section 7.2 are used to select the final model for each

group of data under consideration. Some important model statistics -- R^2 (Coefficient of Multiple Determination), R_a^2 (Adjusted Coefficient of Multiple Determination), RMSE (Root Mean Square Error) and C.V. (Coefficient of Variation) -- for the final selected models are shown in Tables 7.2, 7.3, and 7.4 for Interstate, Urban Principal arterial and Urban Minor arterial and Collector, respectively. The models in these tables will provide three alternative options for Interstate Highways and only one option for non-interstate urban highways. The ranges of the various model statistics in Tables 7.2 to 7.4 are as follows:

Highway Category	R^2 [R^2](*)	R_a^2	RMSE	C.V.
Interstate Highways	61.46-90.26 [50.35-88.86]	59.51-89.23	1505-12616	12.33-33.33
Urban Principal Art.	52.87-97.57 [51.81-94.14]	49.72-96.91	762-2187	5.62-21.04
Urban Minor Arterial & Collector	66.87-89.31 [62.52-87.18]	59.51-86.64	695-2560	8.10-30.56

(*) R^2 ranges of the final selections in Chapter 6
(See Tables 6.23-6.25).

The above table also compares the ranges of R^2 values to the final selections of Chapter 6.

The P-values (PROB>F) of the significance statistics of Tables 7.2-7.4 show that the minimum α -levels at which a significant relation exists between PCs and AADT are 0.0001, 0.0003 and 0.0069 for Interstate, Urban Principal Arterial and Urban Minor Arterial & Collector, respectively. The significance at an α -level of 0.0001 indicates that

Table 7.2: Some Key Results of Principal Component Regression
for Interstate Highways

Region	Model Statistics		Significance Statistics				Normality Stat.	
	R ²	RMSE	F-Value	Model	t-	Prob>t	N	W/D (**)
	R _a ²	C.V.	Prob>F	PC(*)	value			(P-value)
A. Interstate Highways (Rural & Urban): Regional Model								
North	74.32	8229.5	70.418	PC1	9.691	0.0001	77	0.0841 (>0.15)
	73.26	30.206	0.0001	PC2	9.870	0.0001		
				PC4	-4.463	0.0001		
Central	76.08	5934.1	118.729	PC1	14.134	0.0001	14	0.0623 (>0.15)
	75.44	24.315	0.0001	PC2	12.100	0.0001		
				PC3	3.167	0.0020		
South	88.12	2905.4	96.430	PC1	13.730	0.0001	57	0.0789 (>0.15)
	87.21	20.658	0.0001	PC2	11.186	0.0001		
				PC3	-6.413	0.0001		
				PC5	5.563	0.0001		
B. Rural Interstate Highways: Statewide Model								
ALL	71.44	4021.7	97.545	PC1	12.276	0.0001	121	0.0817 (0.046)
	70.71	21.245	0.0001	PC2	10.135	0.0001		
				PC3	6.262	0.0001		
C. Rural Interstate Highways: Regional Model								
North	69.84	3311.3	23.930	PC1	6.869	0.0001	35	0.9481 (0.165)
	66.92	18.489	0.0001	PC3	3.127	0.0038		
				PC7	3.851	0.0006		
Central	61.46	5326.1	35.616	PC1	8.844	0.0001	71	0.0914 (0.147)
	59.73	22.156	0.0001	PC2	2.373	0.0205		
				PC3	4.796	0.0001		
South	90.26	1504.7	88.034	PC1	14.008	0.0001	43	0.9603 (0.269)
	89.23	12.893	0.0001	PC2	7.658	0.0001		
				PC3	-6.154	0.0001		
				PC4	-7.707	0.0001		

Table 7.2, continued

Region	Model Statistics			Significance Statistics			Normality Stat.	
	R ²	RMSE	F-Value	Model	t-	Prob>t	N	W/D (**) (P-value)
	R ² _a	C.V.	Prob>F	PC(*)	value			
D. Urban Interstate Highways: Statewide Model								
ALL	74.89	8751.7	98.438	PC1	14.619	0.0001	103	0.0543 (>0.15)
	74.13	27.653	0.0001	PC2	-8.272	0.0001		
				PC4	-3.629	0.0005		
E. Urban Interstate Highways: Regional Model								
North	61.89	12616.5	25.983	PC1	-4.167	0.0001	52	0.0983 (>0.15)
	59.51	33.334	0.0001	PC2	7.018	0.0001		
				PC4	-3.366	0.0015		
Central	86.27	7244.8	96.310	PC1	14.715	0.0001	50	0.9591 (0.186)
	85.37	22.742	0.0001	PC2	-8.202	0.0001		
				PC4	-2.265	0.0283		
South	89.30	3751.6	33.372	PC1	8.882	0.0001	16	0.9357 (0.358)
	86.62	12.229	0.0001	PC2	-3.443	0.0049		
				PC3	3.063	0.0099		

(*) See Table D1 for description of PCs (Principal Components).

(**) Wilk-Shapiro 'W' for N<51 or Kolmogorov 'D' for N>51, and
P-value = PROB>D or PROB<W.

Table 7.3: Some Key Results of Principal Component Regression
for Urban Principal Arterial

Region	Model Statistics			Significance Statistics			Normality Stat.	
	R^2	R_a^2	RMSE C.V.	F-Value Prob>F	Model PC(*)	t- value	Prob>t	N W/D (**) (P-value)
City Group "A" [City Population: 30,000 to 50,000]								
North	59.05	1841.1	12.980	PC3	3.075	0.0065	21	0.9360
	54.50	13.941	0.0003	PC4	4.063	0.0007		(0.240)
Central	93.05	761.5	44.634	PC1	8.983	0.0001	14	0.9243
	90.97	5.615	0.0001	PC3	6.585	0.0001		(0.326)
				PC4	-3.138	0.0106		
South	97.57	1157.4	147.500	PC1	11.384	0.0001	15	0.9587
	96.91	7.853	0.0001	PC2	11.501	0.0001		(0.640)
				PC3	-13.440	0.0001		
City Group "B" [City Population: 20,000 to 30,000]								
North	74.24	1010.8	14.407	PC1	4.474	0.0012	13	0.9589
	69.08	8.203	0.0011	PC2	2.966	0.0141		(0.692)
Central	93.61	1713.1	65.959	PC1	10.646	0.0001	12	0.8842
	92.19	11.344	0.0001	PC2	-4.310	0.0020		(0.108)
South	97.57	1157.4	147.500	PC1	11.384	0.0001	15	0.9587
	96.91	7.853	0.0001	PC2	11.501	0.0001		(0.640)
				PC3	-13.440	0.0001		
City Group "C" [City Population: 10,000 to 20,000]								
North	70.26	1543.4	14.173	PC1	4.901	0.0001	29	0.9750
	65.30	13.797	0.0001	PC3	4.578	0.0001		(0.725)
				PC5	-2.335	0.0282		
				PC6	-2.503	0.0195		
Central	77.26	2059.4	43.047	PC1	5.526	0.0001	42	0.9543
	75.47	16.614	0.0001	PC3	9.490	0.0001		(0.163)
				PC5	-2.924	0.0058		
South	97.57	1157.4	147.500	PC1	11.384	0.0001	15	0.9587
	96.91	7.853	0.0001	PC2	11.501	0.0001		(0.640)
				PC3	-13.440	0.0001		

Table 7.3, continued

Region	Model Statistics		Significance Statistics				Normality Stat.	
	R ²	RMSE C.V.	F-Value Prob>F	Model PC(*)	t- value	Prob>t	N	W/D (**) (P-value)
City Group "D" [City Population: 5,000 to 10,000]								
North	52.87	2186.7	16.825	PC1	5.130	0.0001	33	0.9449
	49.72	21.403	0.0001	PC2	-2.708	0.0111		(0.146)
Central	77.05	846.1	16.785	PC1	2.487	0.0218	25	0.9244
	72.46	10.253	0.0001	PC2	2.122	0.0465		(0.075)
				PC3	5.407	0.0001		
				PC4	5.217	0.0001		
South	55.01	1189.5	22.005	PC1	5.850	0.0001	39	0.9868
	52.51	11.667	0.0001	PC2	-3.129	0.0035		(0.946)

(*) See Table D2 for description of PCs' (Principal Components).

(**) Wilk-Shapiro 'W' for N<51 or Kolmogorov 'D' for N>51, and
P-value = PROB>D or PROB<W.

Table 7.4: Some Key Results of Principal Component Regression
for Urban Minor Arterial & Collector

Model Statistics		Significance Statistics				Normality Stat.	
R ²	RMSE	F-Value	Model	t-	Prob>t	N	W/D (**)
R ² _a	C.V.	Prob>F	PC(*)	value			(P-value)
City Group "A" [City Population: 30,000 to 50,000]							
89.31	1247.9	33.422	PC1	7.135	0.0001	16	0.9485 (0.469)
86.64	11.939	0.0001	PC3	3.564	0.0039		
			PC5	-6.054	0.0001		
City Group "B" [City Population: 20,000 to 30,000]							
66.87	2560.0	9.084	PC1	2.454	0.0365	12	0.9723 (0.891)
59.51	30.564	0.0069	PC3	3.485	0.0069		
City Group "C" [City Population: 10,000 to 20,000]							
85.59	694.8	29.702	PC1	6.413	0.0001	13	0.9604 (0.713)
82.71	8.096	0.0001	PC2	-4.275	0.0016		
City Group "D" [City Population: 5,000 to 10,000]							
72.09	945.68	16.356	PC1	2.783	0.0119	23	0.9838 (0.947)
67.68	20.938	0.0001	PC3	5.520	0.0001		
			PC5	3.294	0.0038		

(*) See Table D3 for description of PCs' (Principal Components).

(**) Wilk-Shapiro 'W' for $N < 51$ or Kolmogorov 'D' for $N \geq 51$, and
P-value = PROB>D or PROB<W.

9,999 out of 10,000 times a significant relationship exists between the selected PCs and AADT. The significance statistics for each individual PC in the models of Tables 7.2-7.4 state that the minimum P-values ($\text{PROB} > t$), for which the PCs are significant are 0.028, 0.0465 and 0.0365 for Interstate, Urban Principal Arterial and Urban Minor Arterial & Collector, respectively. So the PCs are significant at least at 95% level of confidence. Usually, the P-value for the PC is as low as 0.0001 (see Tables 7.2-7.4). Partial regression residual plots of PCs for the selected model, one from each major highway class, are presented in Appendix Figures D1.1-D1.12. These sample plots also suggest the PCs in the equation are significant and the plots do not suggest any observation to be outlier.

By definition, the PC's are uncorrelated, so there is no problem of multicollinearity. Since the principal components are linear combinations of the original variables, it is not unreasonable to expect them to be nearly normal [Johnson & Wichern 1982]. The P-values of normality statistics in Tables 7.2-7.4 show that the normality assumption is satisfied for α -level as low as 0.05 and the results are much better in most of the cases. Appendix Figures D2.1 to D2.4 show the normality plots for the four selected models, one from each major highway class. These sample normality plots, as well as the normality statistics in Tables 7.2-7.4, suggest that the normality assumption of the regression models has been satisfied.

The residual plots for each of the selected model groups (one from each major highway class) are drawn against

1. the predicted values of AADT (see Appendix Figures D3.1-D3.4),
2. the PCs in the model (see Appendix Figures D4.1-D4.12), and
3. the PC not in the model (see Appendix Figures D5.1-D5.4).

These plots do not suggest any gross departure from non-constancy of error variance and non-linearity of the regression relation. These residual plots also do not suggest any observation to be outlier. This is an expected result because PCA has performed with the filtered data sets after influential analysis in Chapter 6. The plots of residuals in Appendix Figures D3.1-D3.4 and D4.1-D4.2 also justify that the most appropriate PCs are entered into the model. The sample plots in Figures D5.1-D5.4 indicate that no additional PCs — rather than those already entered into the model — will provide any significant additional strength in the model. All these sample plots and some key regression statistics in Tables 7.2-7.4 show that the final selections are statistically significant and most appropriate. The regression equations of these final selected models for each data group are shown in Tables 7.5, 7.6 and 7.7 for Interstate, Urban Principal Arterial and Urban Minor Arterial & Collector, respectively. These tables show the R^2 and R_a^2 values for Principal Component based Regression (PSR) model and, for comparison, the R^2 values for the final models selected in Chapter 6. The comparison of these R^2 values for the two alternative model forms does not support one form over the other. According to the principle behind developing PCR models (see discussion in Section 3.4), further evaluations of these relatively complex PCR models

Table 7.5: Final Principal Component Regression (PCR) Equations
for Interstate Highways

A. Interstate Highways (Rural & Urban): Regional Model		
A1. <u>North Region</u>	PCR: $R^2=74.32$ [$R_a^2=73.26$]	(CH6: $R^2= 72.28$)
AADT = 27244.31 + 4366.87 PC1 + 4536.40 PC2 - 4613.70 PC4		
A2. <u>Central Region</u>	PCR: $R^2=76.08$ [$R_a^2=75.44$]	(CH6: $R^2= 73.84$)
AADT = 24404.76 + 3571.36 PC1 + 3419.14 PC2 + 1726.03 PC3		
A2. <u>South Region</u>	PCR: $R^2=88.12$ [$R_a^2=87.21$]	(CH6: $R^2= 74.60$)
AADT = 14064.26 + 2443.00 PC1 + 2362.87 PC2 - 2278.30 PC3 + 3237.59 PC5		

B. Rural Interstate Highways: Statewide Model		
B. <u>All Region</u>	PCR: $R^2=71.44$ [$R_a^2=70.71$]	(CH6: $R^2= 71.27$)
AADT = 18929.66 + 2153.61 PC1 + 1853.91 PC2 + 2016.10 PC3		

C. Rural Interstate Highways: Regional Model		
C1. <u>North Region</u>	PCR: $R^2=69.84$ [$R_a^2=66.92$]	(CH6: $R^2= 50.35$)
AADT = 17909.26 + 1831.51 PC1 + 1618.41 PC3 + 15306.91 PC7		
C2. <u>Central Region</u>	PCR: $R^2=61.46$ [$R_a^2=59.73$]	(CH6: $R^2= 61.62$)
AADT = 24038.84 + 2515.15 PC1 + 778.50 PC2 + 2934.67 PC3		
C3. <u>South Region</u>	PCR: $R^2=90.26$ [$R_a^2=89.23$]	(CH6: $R^2= 76.47$)
AADT = 11670.72 + 1499.15 PC1 + 1040.59 PC2 - 1113.89 PC3 - 1613.74 PC4		

Table 7.5, continued

D. Urban Interstate Highways: Statewide Model		
D. <u>All Region</u>	PCR: $R^2=74.89$ [$R_a^2=74.13$]	(CH6: $R^2=77.81$)
AADT = 31648.16 + 5675.98 PC1 - 3613.93 PC2 - 3903.12 PC4		
E. Urban Interstate Highways: Regional Model		
E1. <u>North Region</u>	PCR: $R^2=61.89$ [$R_a^2=59.51$]	(CH6: $R^2=55.27$)
AADT = 37848.12 - 3571.10 PC1 + 6165.24 PC2 - 6340.10 PC4		
E2. <u>Central Region</u>	PCR: $R^2=86.27$ [$R_a^2=85.37$]	(CH6: $R^2=84.75$)
AADT = 31855.82 + 6665.45 PC1 - 4378.18 PC2 - 2932.51 PC4		
E3. <u>South Region</u>	PCR: $R^2=89.30$ [$R_a^2=86.62$]	(CH6: $R^2=88.86$)
AADT = 30677.00 + 3431.21 PC1 - 1850.52 PC2 + 3304.89 PC3		

Note: See Table D1 for description of PCs (Principal Components).

Table 7.6: Final Principal Component Regression (PCR) Equations for Urban Principal Arterial

City Group "A" [City Population: 30,000 to 50,000]		
<u>North Region</u>	PCR: $R^2=59.05$ [$R_a^2=54.50$]	(CH6: $R^2=73.62$)
AADT = 13207.05 + 882.56 PC3 + 2010.54 PC4		
<u>Central Region</u>	PCR: $R^2=93.05$ [$R_a^2=90.97$]	(CH6: $R^2=89.84$)
AADT = 13563.21 + 798.94 PC1 + 1775.23 PC3 - 1192.98 PC4		
<u>South Region</u>	PCR: $R^2=97.57$ [$R_a^2=96.91$]	(CH6: $R^2=83.35$)
AADT = 14738.80 + 1522.73 PC1 + 1803.94 PC2 - 3864.17 PC3		

City Group "B" [City Population: 20,000 to 30,000]		
<u>North Region</u>	PCR: $R^2=74.24$ [$R_a^2=69.08$]	(CH6: $R^2=78.80$)
AADT = 12321.84 + 502.09 PC1 + 627.59 PC2		
<u>Central Region</u>	PCR: $R^2=93.61$ [$R_a^2=92.19$]	(CH6: $R^2=94.14$)
AADT = 15100.58 + 2195.76 PC1 - 1176.72 PC2		
<u>South Region</u>	PCR: $R^2=97.57$ [$R_a^2=96.91$]	(CH6: $R^2=83.35$)
AADT = 14738.80 + 1522.73 PC1 + 1803.94 PC2 - 3864.17 PC3		

Table 7.6, continued

City Group "C" [City Population: 10,000 to 20,000]		
<u>North Region</u>	PCR: $R^2=70.26$ [$R_a^2=65.30$]	(CH6: $R^2= 60.77$)
AADT = 11186.14 + 629.29 PC1 +1235.53 PC3 - 1662.56 PC5 -2617.91 PC6		
<u>Central Region</u>	PCR: $R^2=77.26$ [$R_a^2=75.47$]	(CH6: $R^2= 69.88$)
AADT = 12395.93 + 733.31 PC1 + 3102.18 PC3 - 1365.70 PC5		
<u>South Region</u>	PCR: $R^2=97.57$ [$R_a^2=96.91$]	(CH6: $R^2= 83.35$)
AADT = 14738.80 + 1522.73 PC1 + 1803.94 PC2 - 3864.17 PC3		

City Group "D" [City Population: 5,000 to 10,000]		
<u>North Region</u>	PCR: $R^2=52.87$ [$R_a^2=49.72$]	(CH6: $R^2= 51.81$)
AADT = 10216.70 + 835.70 PC1 - 576.47 PC2		
<u>Central Region</u>	PCR: $R^2=77.05$ [$R_a^2=72.46$]	(CH6: $R^2= 75.05$)
AADT = 8251.92 + 188.94 PC1 + 198.87 PC2 + 780.36 PC3 + 1108.25 PC4		
<u>South Region</u>	PCR: $R^2=55.01$ [$R_a^2=52.51$]	(CH6: $R^2= 52.85$)
AADT = 10195.59 + 525.87 PC1 - 309.23 PC2		

Note: See Table D2 for description of PCs' (Principal Components).

Table 7.7: Final Principal Component Regression (PCR) Equations
for Urban Minor Arterial & Collector

City Group "A" [City Population: 30,000 to 50,000]	
PCR: $R^2=89.31$ [$R_a^2=86.64$]	(CH6: $R^2=79.58$)
AADT = 10451.81 + 954.94 PC1 + 926.73 PC3 - 4712.88 PC5	

City Group "B" [City Population: 20,000 to 30,000]	
PCR: $R^2=66.87$ [$R_a^2=59.51$]	(CH6: $R^2=77.58$)
AADT = 8375.92 + 839.34 PC1 + 2372.89 PC3	

City Group "C" [City Population: 10,000 to 20,000]	
PCR: $R^2=85.59$ [$R_a^2=82.71$]	(CH6: $R^2=87.18$)
AADT = 8581.77 + 543.35 PC1 - 479.46 PC2	

City Group "D" [City Population: 5,000 to 10,000]	
PCR: $R^2=72.09$ [$R_a^2=67.68$]	(CH6: $R^2=62.52$)
AADT = 4516.65 + 254.15 PC1 + 1033.76 PC3 + 1386.16 PC5	

Note: See Table D3 for description of PCs (Principal Components).

are not warranted. The constant term of the models in Tables 7.5 to 7.7 represents the mean of the response variable, AADT. The PC values entered in each of these models in Tables 7.5-7.7 can be computed from their relation to the eigenvectors presented in Appendix Tables D1-D3. The absolute values of the coefficients of the PCs in Tables D1-D3 represent the importance of each original variable in defining the PCs.

7.4 Chapter Summary

Principal Component Regression (PCR) models have been developed for each data group, shown in Chapters 5 and 6. These alternative models are based on Principal Component Analysis (PCA). The PCA has reduced the dimension of the problem significantly. For example, it has formed only 2 or 3 useful uncorrelated variables (see the PCs with eigenvalues greater than one in Table 7.1) from 11 original variables. Each of the final PCR models is found to be statistically significant, with R^2 values similar to the final selections in Chapter 6. The concepts and uses of the PCA have been provided in this chapter. The complete model building approach of Chapter 6 has been used to find the PCR models. The key results are presented in the figures and tables. Since by definition, each of the principal components is independent of each other, the problem of multicollinearity -- a problem that often arises with socioeconomic variables -- has been completely eliminated. The alternative PCR models have also proved the suitability of models in Chapter 6 -- regression and its derivative elasticity model -- with fewer original variables.

CHAPTER 8

LAGGED TRAFFIC MODEL

8.1 Introduction

In this chapter, an inexpensive and simple model to forecast traffic will be developed, based on the traffic data and the rate at which traffic has changed over the years. The lagged traffic model developed in this chapter can be considered as a substitute for hundreds of "trend projections" employed often to forecast traffic at the project sites. The segment data bases (See Chapter 5) have been used to build the models. The lagged regression models have been developed with a full set of data. Statistical analyses and tests have been performed to find the quality of the models and to identify the strength of relation of the models. The partial lagged models are developed with the data set by omitting the last year of AADT for each highway segment in the data bases. The performance of the models has been evaluated by comparing the predicted last year AADT using the partial models with the observed AADT value of each highway segment.

8.2 Lagged Model Formulation

The statistical analysis of lagged regression is not uncommon in transportation planning, economics and forecasting. For example, Chan [1985] used this technique to estimate highway travel and fuel consumption. In his formulation, both lagged endogeneous (dependent) variable and current exogeneous (independent) variables were used.

8.2.1 Modeling Approach

Often in statistical and econometric models involving time, a change in an explanatory variable has an affect that is distributed over time. A part of the impact may occur immediately, but the additional effects may persist through time. Sometimes, there may be no immediate effect and a lag is required before a response occurs. The general form of the lag model with equal time intervals between observations can be represented as

$$Y_t = k_0 + \sum_{i=1}^P k_{yi} Y_{t-i} + \sum_{j=1}^Q k_{xj} X_{t-j} + \epsilon_t \quad (8.1)$$

Both explanatory (independent, X) and response (dependent, Y) variables can enter into the lag structure. In Equation (8.1), the k 's are constant and ϵ_t is the random error term. In general, more than one lag variable ($P > 1$ and/or $Q > 1$ in Equation (8.1)) will tend to be highly correlated and will not be able to obtain reliable estimates. At the same time, models with more than one lagged variable lead to more complicated models to estimate. On the other hand, no guidelines

are available as to an acceptable length of the lag. With the objective of building simple model, the analysis in this chapter has shown that the simple model -- $P=1$, no explanatory lag variable and a modification to account for unequal time interval between observations -- is enough to describe most of the variation in traffic data.

8.2.2 Model Formulation

The formulation of lagged regression is simple when the data are equally spaced (for example, data are available for each year). The original highway segment data bases (See Chapter 5 and the tables in Appendix A) are used in the analysis. Time intervals between AADT observations in these data bases are not the same. A modified formulation of the lagged regression of Equation (8.1) is warranted to account for these unequal time intervals. To make the model simple, only the first lagged value -- $P = 1$ in Equation (8.1) -- of AADT is used in this model. The models with exogeneous variables are developed in earlier chapters.

It has been postulated that the amount of traffic would follow this time-series pattern:

$$AADT_t = k_0 + k_m LAADT_{t-m} + k_r RAADT_{tm} + \epsilon_t \quad (8.2)$$

where,

$$AADT_t = \text{AADT in year } t,$$

$$LAADT_{t-m} = \text{Lagged AADT in year } t-m,$$

$$\begin{aligned}
 \text{RAADT}_{tm} &= \text{Rate of AADT change between years } t \text{ and } t-m, \\
 &= [\text{AADT}_t - \text{AADT}_{t-m}]/m, \text{ and} \\
 k_0, k_m \text{ and } k_r &\text{ are the coefficients.}
 \end{aligned}$$

Linear regression of SAS [SAS/STATISTICS 1985] has been used to determine the coefficients of the Equation (8.2). The term " k_0 " in Equation (8.2) represents the average effect of all excluded (not explicitly considered) factors in the model. The ϵ_t is the part of the model that is "unexplained" and is caused by the factors about which analysts remain ignorant. The expected value of ϵ_t is zero. Then on rearrangement, Equation (8.2) can be transformed to:

$$\text{AADT}_t = \frac{k_0 m}{m - k_r} + \frac{k_m m - k_r}{m - k_r} \text{LAADT}_{t-m} \quad (8.3)$$

The terms in Equation (8.3) are defined under Equation (8.2). Equation (8.3) will be used to predict AADT at any year by knowing the lag year AADT (LAADT) and m — the difference of year between lag year ($t-m$) and the year (t) at which forecast is desired. The term " m " will be referred as "forecast period".

8.3 Lagged Regression Model

For comparison, the groupings of data sets are unchanged with respect to those used in earlier chapters. The "REG" procedure of SAS [SAS/Statistics 1985] is used to perform the regression in Equation (8.2). The model using a full data set has been referred to as the

"full-lagged model" or simply as the "lagged model". To evaluate the performance of the models, models are formed by deleting the last year AADT observation for each roadway segment in the segment data bases. The model with this partial data sets is referred to as "Partial Lagged Model" in this chapter.

To depict the graphical plots associated with residual analyses, the following three models -- one from each major highway class -- have been selected:

Model 1: North Region of Urban Interstate,

Model 2: City Group "A" and North Region of
Urban Principal Arterial; and

Model 3: City Group "C" of Urban Minor
Arterial & Collector.

8.3.1 Full-Lagged Model

The estimates of the parameters and the other key regression results of the lagged regression model (Equation 8.2) for interstate, urban minor arterial & collector are presented in Tables 8.1, 8.2 and 8.3, respectively. The ranges of the various model statistics in these tables are as follows:

Table 8.1: Full-Lagged Regression Results of Interstate Highways

Region	Model Statistics		Significance Statistics & Parameter Values					Normality Stat.	
	R ²	RMSE	F-Value	Parameter		t-	Prob>t	N	W/D (*) (P-value)
	R ² _a	C.V.	Prob>F	Name	Estimate	value			
A. Interstate Highways (Rural & Urban): Regional Model									
North	99.46	2526.6	18488.8	CONST	250.05261	0.906	0.3663	204	0.1288 (<0.01)
	99.45	6.289	0.0001	LAADT	1.00029	177.514	0.0001		
				RAADT	2.36768	28.105	0.0001		
Central	98.42	2770.5	12962.6	CONST	62.02860	0.226	0.8211	419	0.1126 (<0.01)
	98.41	7.224	0.0001	LAADT	1.03957	146.955	0.0001		
				RAADT	1.54560	31.521	0.0001		
South	98.10	2021.4	4021.5	CONST	-846.55778	-2.965	0.0035	159	0.1557 (<0.01)
	98.07	10.222	0.0001	LAADT	1.10673	74.320	0.0001		
				RAADT	1.85193	17.914	0.0001		
B. Rural Interstate Highways: Statewide Model									
ALL	97.53	2088.0	9371.6	CONST	177.88057	0.895	0.3711	478	0.1462 (<0.01)
	97.52	8.925	0.0001	LAADT	1.02221	115.594	0.0001		
				RAADT	1.79409	32.858	0.0001		
C. Rural Interstate Highways: Regional Model									
North	94.61	1859.1	851.6	CONST	1097.59856	1.998	0.0485	100	0.1432 (<0.01)
	94.50	8.815	0.0001	LAADT	0.96235	34.289	0.0001		
				RAADT	2.14349	19.105	0.0001		
Central	97.16	2398.6	4411.3	CONST	-118.49997	-0.338	0.7356	261	0.1190 (<0.01)
	97.14	8.307	0.0001	LAADT	1.03520	79.899	0.0001		
				RAADT	1.70124	22.975	0.0001		
South	96.04	1271.5	1382.3	CONST	-207.38543	-0.736	0.4630	117	0.1761 (<0.01)
	95.97	9.675	0.0001	LAADT	1.05773	49.623	0.0001		
				RAADT	1.80581	15.789	0.0001		

Table 8.1, continued

Region	Model Statistics		Significance Statistics & Parameter Values				Normality Stat.		
	R ² R ² _a	RMSE C.V.	F-Value Prob>F	Parameter Name Estimate	t- value	Prob>t	N	W/D (*) (P-value)	
D. Urban Interstate Highways: Statewide Model									
ALL	98.62	3508.1	10787.4	CONST	1126.44461	2.752	0.0063	304	0.1383 (<0.01)
	98.61	6.572	0.0001	LAADT	1.01406	139.710	0.0001		
				RAADT	1.71911	26.825	0.0001		
E. Urban Interstate Highways: Regional Model									
North	99.43	3014.2	8737.1	CONST	275.78001	0.516	0.6070	104	0.1505 (<0.01)
	99.41	5.150	0.0001	LAADT	0.99805	123.550	0.0001		
				RAADT	2.46689	20.408	0.0001		
Central	98.11	3272.0	4021.4	CONST	687.12000	1.056	0.2926	158	0.1078 (<0.01)
	98.08	6.058	0.0001	LAADT	1.03300	84.480	0.0001		
				RAADT	1.46264	20.553	0.0001		
South	95.40	3322.0	404.3	CONST	-2548.4029	-1.646	0.1078	30	0.9726 (0.641)
	95.16	8.683	0.0001	LAADT	1.15547	25.168	0.0001		
				RAADT	1.86829	8.754	0.0001		

(*) Wilk-Shapiro "W" for N<51 or Kolmogorov "D" for N>51, and
P-value = PROB>D or PROB<W.

Table 8.2: Full-Lagged Regression Results of Urban Principal Arterial

Region	Model Statistics		Significance Statistics & Parameter Values					Normality Stat.	
	R ²	R ² _a	RMSE C.V.	F-Value Prob>F	Parameter Name Estimate	t- value	Prob>t	N	W/D (*) (P-value)
City Group "A" [City Population: 30,000 to 50,000]									
North	99.46		439.9	24800.5	CONST	27.83083	0.422 0.6737	273	0.1229 (<0.01)
	99.45		3.399	0.0001	LAADT	0.98818	212.149 0.0001		
					RAADT	3.61995	124.378 0.0001		
Central	99.18		511.8	13406.7	CONST	46.81155	0.526 0.5992	224	0.1161 (<0.01)
	99.18		3.889	0.0001	LAADT	0.99679	151.545 0.0001		
					RAADT	3.77805	61.846 0.0001		
South	99.35		247.7	3729.5	CONST	214.42029	1.650 0.1053	52	0.1631 (<0.01)
	99.32		2.379	0.0001	LAADT	0.97593	80.058 0.0001		
					RAADT	3.93023	41.882 0.0001		
City Group "B" [City Population: 20,000 to 30,000]									
North	99.98		86.5	259068	CONST	-6.30353	-0.332 0.7405	118	0.2710 (<0.01)
	99.98		0.706	0.0001	LAADT	1.00180	675.741 0.0001		
					RAADT	3.96802	266.187 0.0001		
Central	99.61		458.0	8886.8	CONST	-98.00552	-0.855 0.3952	72	0.0769 (<0.01)
	99.60		3.435	0.0001	LAADT	1.00303	132.321 0.0001		
					RAADT	3.45706	52.871 0.0001		
South	99.22		378.5	823.6	CONST	1757.29224	3.106 0.0084	16	0.9188 (0.212)
	99.10		1.552	0.0001	LAADT	0.93057	40.464 0.0001		
					RAADT	3.76437	20.326 0.0001		

Table 8.2, continued

Region	Model Statistics			Significance Statistics & Parameter Values				Normality Stat.	
	R ²	RMSE C.V.	F-Value	Parameter		t-	Prob>t	N	W/D (*) (P-value)
	R ² _a		Prob>F	Name	Estimate	value			
City Group "C" [City Population: 10,000 to 20,000]									
North	99.05	331.9	10838.3	CONST	331.91553	3.880	0.0001	210	0.1270 (<0.01)
	99.04	3.632	0.0001	LAADT	0.96816	128.524	0.0001		
				RAADT	3.63161	76.250	0.0001		
Central	99.07	530.0	13484.1	CONST	-3.43535	-0.042	0.9664	255	0.1389 (<0.01)
	99.07	4.487	0.0001	LAADT	1.00199	147.624	0.0001		
				RAADT	3.63089	66.623	0.0001		
South	98.12	619.2	756.9	CONST	378.46475	1.100	0.2802	32	0.7370 (<0.01)
	97.99	5.692	0.0001	LAADT	0.97113	28.834	0.0001		
				RAADT	3.23398	18.683	0.0001		
City Group "D" [City Population: 5,000 to 10,000]									
North	98.83	429.8	3679.6	CONST	106.51264	0.873	0.3848	90	0.2553 (<0.01)
	98.80	4.432	0.0001	LAADT	0.99136	81.650	0.0001		
				RAADT	3.95393	39.398	0.0001		
Central	99.57	217.4	9406.2	CONST	82.77866	1.121	0.2655	85	0.1648 (<0.01)
	99.56	2.405	0.0001	LAADT	0.99630	119.990	0.0001		
				RAADT	3.72608	58.926	0.0001		
South	99.13	359.1	8761.5	CONST	200.54730	2.270	0.0246	157	0.2548 (<0.01)
	99.12	3.344	0.0001	LAADT	0.99216	116.576	0.0001		
				RAADT	3.15041	53.639	0.0001		

(*) Wilk-Shapiro "W" for N<51 or Kolmogorov "D" for N>51, and
P-value = PROB>D or PROB<W.

Table 8.3: Full-Lagged Regression Results of Urban Minor Arterial & Collector

Model Statistics		Significance Statistics & Parameter Values					Normality Stat.	
R^2	RMSE	F-Value	Parameter	t-	Prob>t	N	W/D (*)	
R_a^2	C.V.	Prob>F	Name Estimate	value			(P-value)	
City Group "A" [City Population: 30,000 to 50,000]								
99.17	438.3	2446.1	CONST	69.41096	0.400 0.6909	44	0.9172	
99.13	3.910	0.0001	LAADT	0.99320	68.436 0.0001		(<0.01)	
			RAADT	3.54781	29.878 0.0001			
City Group "B" [City Population: 20,000 to 30,000]								
99.79	208.8	11018.3	CONST	16.41477	0.309 0.7585	50	0.9466	
99.78	3.201	0.0001	LAADT	0.99558	144.404 0.0001		(0.049)	
			RAADT	3.54817	48.193 0.0001			
City Group "C" [City Population: 10,000 to 20,000]								
99.17	358.5	3404.0	CONST	58.27245	0.507 0.6141	60	0.1460	
99.14	4.122	0.0001	LAADT	0.99339	80.610 0.0001		(<0.01)	
			RAADT	3.37950	33.157 0.0001			
City Group "D" [City Population: 5,000 to 10,000]								
99.26	368.3	9982.5	CONST	119.55407	1.884 0.0615	152	0.1616	
99.25	4.678	0.0001	LAADT	0.99490	123.902 0.0001		(<0.01)	
			RAADT	3.41341	39.682 0.0001			

(*) Wilk-Shapiro 'W' for $N < 51$ or Kolmogorov 'D' for $N > 51$, and
P-value = PROB>D or PROB<W.

Highway Class	R^2	R_a^2	RMSE	C.V.
Interstate Highways	94.61-99.46	94.50-99.45	1272-3508	5.15-10.22
Urban Principal Art.	98.12-99.98	97.99-99.98	87-619	0.71-5.69
Urban Minor Arterial & Collector	99.17-99.79	99.13-99.78	209-438	3.20-4.68

The high R^2 (Coefficient of Multiple Determination) and R_a^2 (Adjusted Coefficient of Multiple Determination) statistics of the lagged models imply that no additional variables is necessary to reduce the variation of traffic. The RMSE (Root Mean Square Error) and the C.V. (Coefficient of Variation) values of the models in Tables 8.1-8.3 also have been reduced significantly as compared to the models in the Chapters 6 and 7.

The parameter estimates, which correspond to parameter names CONST, LAADT and RAADT in Tables 8.1-8.3, represent the values of k_0 , k_m and k_r of Equations 8.2 and 8.3. In addition, the significance tests of Section 6.4 are performed to see the significance of overall regression relation and the significance of each term in Equation (8.1). The significance statistics (F-value, $\text{PROB}>F$, t-value and $\text{PROB}>t$) show that a strong overall relationship exists and the parameters (LAADT and RAADT) are highly significant in explaining traffic volumes (AADT). The P-values in most of these tests show that the overall regression relation and the variables in Equation (8.2) are significant at an α level of 0.0001.

Partial regression residual plots of LAADT and RAADT for the selected models, one from each major highway class, are presented in Appendix Figures E1.1-E1.6. These sample plots also show that the variables in the equation are significant. The "CONST" (Constant or Intercept) term has been found insignificant in most of the cases for an α level of 0.05. The "CONST" term in the model represents the average effect of all factors not explicitly considered in the model. The term has a meaning when the explicitly considered factors in the model can take a value of zero. Thus, nonsignificance of the "CONST" term is not taken as evidence to drop the term from the model.

Nonnormality of the error terms is found for most of the models of Tables 8.1-8.3 for an α level of 0.01. Three sample normal probability plots of the selected models, one from each major highway class, are presented in Appendix Figures E2.1-E2.3. The curvature of these plots also indicates that the errors are not normally distributed. Much of the curvature in these plots are due to the presence of outlier(s) in the data set. The normality of error terms is important to support the validity of the significance test. In Chapter 6, normality statistics have been found to be improved in the post-influence case. For segment data bases, influential analysis is done (results not shown) to identify the outlier(s), but the outliers are not deleted from the data sets because they are thought to be valid — our simple model has simply failed to model the outlier(s). Moreover, the high degree of significance of the variables in the model equation and the highly significant regression relation mean that the results of the significance test are not expected to be altered, whether or

not the error terms have a normal distribution or not.

The collinearity statistics of the models in Tables 8.1-8.3 , introduced in Chapter 6, are examined. Although, all the results of collinearity are not shown, the expected sign of the parameters (LAADT and RAADT) and their high probability of significance are enough to convince us that there is no problem of multicollinearity.

The residual plots for each of the selected model group (one from each major highway class) are drawn against --

1. predicted values (see Appendix Figures E3.1-E3.3) and
2. variables in the model -- LAADT and RAADT (see Appendix Figures E4.1-E4.6).

These plots do not suggest any gross departure from non-constancy of error variance and non-linearity of the regression relation. But, evidence of outlier(s) is present in these graphical plots. For example, an observation in these plots at a distance of more than 3 times the standard deviation (STD DEV) can be considered to be an outlier. In Chapter 6, outliers are removed, if possible, to eliminate their influence on the average county and city average AADT. But for segment AADT data base, the outliers are considered valid data and no modification except a check for coding error is done for the observation(s) suspected to be outlier(s). A trend of increasing the band width of residuals from near-zero values of RAADT to the higher absolute values of RAADT in the plots is an expected result, because at low rate of AADT change errors are expected to be small and vice-versa. Moreover, the usual transformations (for example, log,

square-root, log-log, etc.) to remove this trend will complicate the model structure and create a problem for some negative values of RAADT. Also, any transformations are not warranted from the sample scatterplots in Figures 8.1 and 8.2 of AADT against LAADT and RAADT, because a linear trend is evident in these plots. A sample residual plot against RAADT when the variable RAADT is not in model is shown in Figure 8.3. This sample residual plot also does not suggest any form but linear. It also shows that RAADT is an important variable. The model statistics of the three selected representative models, one from each major highway class, with and without RAADT, in the presence of LAADT in the models, are

Selected Model	RAADT in Model	R^2	R_a^2	RMSE	C.V.
Model 1	Absent	97.06	97.03	6789	11.60
	Present	99.43	99.41	3014	5.15
Model 2	Absent	68.44	68.32	3353	25.90
	Present	99.46	99.45	440	3.40
Model 3	Absent	83.16	82.87	1601	18.40
	Present	99.17	99.14	358	4.12

Thus, RAADT in the model has significantly improved all the model statistics and consequently will improve the predictive power of the model. This improvement with RAADT is applicable for all the lagged models.

The Prediction models of Equation (8.3) of the full-lagged regression models are shown in Tables 8.4, 8.5 and 8.6 for Interstate, Urban Principal Arterial and Urban Minor Arterial & Collector, respectively. These models are derived by using the values of parameter

Figure 8.1: Scatterplot of AADT against LAADT for City Group "A" and Region "n" of Urban Principal Arterial

Figure 8.2: Scatterplot of AADT against RAADT for City Group "A" and Region "n" of Urban Principal Arterial

Table 8.4: Lagged Traffic (Lag-AADT) Models for Interstate Highways

A. Interstate Highways (Rural & Urban): Regional Model	
A1. <u>North Region</u> :	$AADT_t = \frac{250.05261}{m - 2.36768} + \frac{1.00029}{m - 2.36768} LAADT_{t-m}$
A2. <u>Central Region</u> :	$AADT_t = \frac{62.02860}{m - 1.54560} + \frac{1.03957}{m - 1.54560} LAADT_{t-m}$
A3. <u>South Region</u> :	$AADT_t = \frac{-846.55778}{m - 1.85193} + \frac{1.10673}{m - 1.85193} LAADT_{t-m}$
B. Rural Interstate Highways: Statewide Model	
B. <u>All Region</u> :	$AADT_t = \frac{177.88057}{m - 1.79409} + \frac{1.02221}{m - 1.79409} LAADT_{t-m}$
C. Rural Interstate Highways: Regional Model	
C1. <u>North Region</u> :	$AADT_t = \frac{1097.59856}{m - 2.14349} + \frac{0.96235}{m - 2.14349} LAADT_{t-m}$
C2. <u>Central Region</u> :	$AADT_t = \frac{-118.49997}{m - 1.70124} + \frac{1.03520}{m - 1.70124} LAADT_{t-m}$
C3. <u>South Region</u> :	$AADT_t = \frac{-207.38543}{m - 1.80581} + \frac{1.05773}{m - 1.80581} LAADT_{t-m}$

Table 8.4, continued

D. Urban Interstate Highways: Statewide Model	
D. <u>All Region:</u>	$AADT_t = \frac{1126.44461 \text{ m}}{m - 1.71911} + \frac{1.01406 \text{ m} - 1.71911}{m - 1.71911} LAADT_{t-m}$
E. Urban Interstate Highways: Regional Model	
E1. <u>North Region:</u>	$AADT_t = \frac{275.78001 \text{ m}}{m - 2.46689} + \frac{0.99805 \text{ m} - 2.46689}{m - 2.46689} LAADT_{t-m}$
E2. <u>Central Region:</u>	$AADT_t = \frac{687.12000 \text{ m}}{m - 1.46264} + \frac{1.03300 \text{ m} - 1.46264}{m - 1.46264} LAADT_{t-m}$
E3. <u>South Region:</u>	$AADT_t = \frac{-2548.4029 \text{ m}}{m - 1.86829} + \frac{1.15547 \text{ m} - 1.86829}{m - 1.86829} LAADT_{t-m}$

Table 8.5: Lagged Traffic (Lag-AADT) Models for Urban Principal Arterial

City Group "A" [City Population: 30,000 to 50,000]	
<u>North Region:</u>	$AADT_t = \frac{27.83083}{m - 3.61995} m + \frac{0.98818}{m - 3.61995} m - 3.61995 LAADT_{t-m}$
<u>Central Region:</u>	$AADT_t = \frac{46.81155}{m - 3.77805} m + \frac{0.99679}{m - 3.77805} m - 3.77805 LAADT_{t-m}$
<u>South Region:</u>	$AADT_t = \frac{214.42029}{m - 3.93023} m + \frac{0.97593}{m - 3.93023} m - 3.93023 LAADT_{t-m}$
City Group "B" [City Population: 20,000 to 30,000]	
<u>North Region:</u>	$AADT_t = \frac{-6.30353}{m - 3.96802} m + \frac{1.00180}{m - 3.96802} m - 3.96802 LAADT_{t-m}$
<u>Central Region:</u>	$AADT_t = \frac{-98.00552}{m - 3.45706} m + \frac{1.00303}{m - 3.45706} m - 3.45706 LAADT_{t-m}$
<u>South Region:</u>	$AADT_t = \frac{1757.29224}{m - 3.76437} m + \frac{0.93057}{m - 3.76437} m - 3.76437 LAADT_{t-m}$

Table 8.5, continued

City Group "C" [City Population: 10,000 to 20,000]	
<u>North Region:</u>	
	$AADT_t = \frac{331.91553 m}{m - 3.63161} + \frac{0.96816 m - 3.63161}{m - 3.63161} LAADT_{t-m}$
<u>Central Region:</u>	
	$AADT_t = \frac{-3.43535 m}{m - 3.63089} + \frac{1.00199 m - 3.63089}{m - 3.63089} LAADT_{t-m}$
<u>South Region:</u>	
	$AADT_t = \frac{378.46475 m}{m - 3.23398} + \frac{0.97113 m - 3.23398}{m - 3.23398} LAADT_{t-m}$
City Group "D" [City Population: 5,000 to 10,000]	
<u>North Region:</u>	
	$AADT_t = \frac{106.51264 m}{m - 3.95393} + \frac{0.99136 m - 3.95393}{m - 3.95393} LAADT_{t-m}$
<u>Central Region:</u>	
	$AADT_t = \frac{82.77866 m}{m - 3.72608} + \frac{0.99630 m - 3.72608}{m - 3.72608} LAADT_{t-m}$
<u>South Region:</u>	
	$AADT_t = \frac{200.54730 m}{m - 3.15041} + \frac{0.99216 m - 3.15041}{m - 3.15041} LAADT_{t-m}$

Table 8.6: Lagged Traffic (Lag-AADT) Models for Urban Minor Arterial & Collector

City Group "A" [City Population: 30,000 to 50,000]
$\text{AADT}_t = \frac{69.41096 \text{ m}}{\text{m} - 3.54781} + \frac{0.99320 \text{ m} - 3.54781}{\text{m} - 3.54781} \text{LAADT}_{t-m}$
City Group "B" [City Population: 20,000 to 30,000]
$\text{AADT}_t = \frac{16.41477 \text{ m}}{\text{m} - 3.54817} + \frac{0.99558 \text{ m} - 3.54817}{\text{m} - 3.54817} \text{LAADT}_{t-m}$
City Group "C" [City Population: 10,000 to 20,000]
$\text{AADT}_t = \frac{58.27245 \text{ m}}{\text{m} - 3.37950} + \frac{0.99339 \text{ m} - 3.37950}{\text{m} - 3.37950} \text{LAADT}_{t-m}$
City Group "D" [City Population: 5,000 to 10,000]
$\text{AADT}_t = \frac{119.55407 \text{ m}}{\text{m} - 3.41341} + \frac{0.99490 \text{ m} - 3.41341}{\text{m} - 3.41341} \text{LAADT}_{t-m}$

from Tables 8.1 to 8.3 in Equation (8.3). Like elasticity models in Chapter 6, three options are present for interstate highways and for one option on non-interstate highways. The use of these models is simple and the only information needed is a one lag year AADT value and the forecast period. Further evaluations of these differently approached models will be carried out in Chapter 10. It is expected that lagged model will perform as well as the models developed in Chapter 6.

8.3.2 Partial-Lagged Model and Its Performance

The partial-lagged regression model of Equation (8.2) is formed by omitting the last year observation from each highway section of the segment data base. The major purpose of forming this partial model is to evaluate the performance of the lagged regression model. The partial models also verify the stability of the model parameter estimates and of their significance of relation.

8.3.2.1 Partial-Lagged Model

The results of partial lagged regression analysis are presented in Appendix Tables El.1 to El.3 for interstate, urban principal arterial and urban minor arterial & collector, respectively. The ranges of the various partial model statistics from Appendix Tables El.1- El.3 and their comparison with the full lagged model from Tables 8.1-8.3 are as follows:

Highway Class[(*)]	R^2	R_a^2	RMSE	C.V.
Interstate Highways	95.49-99.82 [94.61-99.46]	95.36-99.81 [94.50-99.45]	1051-3285 [1272-3508]	2.99-8.56 [5.15-10.22]
Urban Principal Arterial	96.53-99.97 [98.12-99.98]	96.20-99.97 [97.99-99.98]	101-568 [87-619]	0.86-6.96 [0.71-5.69]
Urban Minor Arterial & Collector	98.97-99.82 [99.17-99.79]	98.91-99.81 [99.13-99.78]	193-444 [209-438]	3.12-5.07 [3.20-4.68]

(*) Ranges of the full-lagged models statistics are shown in [].

No major change in the statistics is noticed for omitting the last observation from each segment. Thus, the stability of the lagged model is verified. The qualities of the statistics in Tables E1.1-E1.3 are almost identical to those for the full-lagged regression presented in Tables 8.1 to 8.3. The discussions about the statistics presented in Section 8.3.1 are also valid for these partial regression models.

8.3.2.2 Performance of Partial-Lagged Model

To evaluate the partial-lagged model, the forecast model form of Equation (8.3) has been used to forecast the last year of traffic data, which have been deleted during formulation of partial-lagged model. In using Equation (8.3) to forecast AADT, the users need only the information about one lag year traffic data (LAADT) -- which could be the present year AADT -- and the "forecast period" from the lagged year traffic data to the year for which the forecast is desired. A wide range of possible values of this "forecast period" has been used to capture the both short-term and long-term performance of the model.

To evaluate the efficiency of model forecasts, the following five forecast-measures have been used:

- a. Mean Error (ME)
- b. Mean Percentage Error (MPE)
- c. Mean Absolute Error (MAE)
- d. Mean Absolute Percentage Error (MAPE)
- e. Pearson Correlation Coefficients (r) between the observed and predicted values.

The formal definitions of these measures, as well as their comparison for use in forecast evaluation will be provided in Chapter 10. The forecast measures, the number of forecasts and ranges of "forecast period" of the partial-lagged prediction models for Interstate, Urban Principal Arterial, and Urban Minor Arterial & Collector are presented in Appendix Tables E2.1 to E2.3, respectively. The range of results from Appendix Tables E2.1 to E2.3 can be summarized as follows:

Highway Class	ME	MPE	MAE	MAPE	r
Interstate Highways	-1066, -5424	-3.96, -10.31	1311, 5472	7.30, 12.43	0.952, 0.995
Urban Prin- cipal Arterial	-114, -1588	-14.69, 0.41	656, 1588	5.32, 14.69	0.904, 0.986
Urban Minor Arterial & Collector	-558, -4	-4.40, 0.37	663, 1309	7.95, 11.20	0.941, 0.986

It is evident from the range of values of ME and MPE that the lagged models in general are underpredicting traffic. The positive and negative prediction errors are cancelled each other in ME and MPE. The MAE measure shows high values and ranges for interstate highways compared to those in noninterstate highways. But MAPE (Mean Absolute Percentage Error) shows that the values and their ranges have almost remained same for all highway classes. Pearson correlation coeffi-

cient (r) shows that a high degree of correlation exists between predicted and observed AADT values. In addition to these forecast measures, three selected sample plots — one from each major highway category — of Observed AADT and Predicted AADT are presented in Appendix Figures E5.1-E5.3. These plots and the forecast measures in Tables E2.1-E2.3 establish that model has performed well to predict the last year of each segment traffic data for a short to long term forecast period.

The sample plots, one from each major highway category, of change in predicted and observed AADT are presented in Appendix Figures E6.1-E6.3 to see if the variable, change in observed AADT, will be helpful to forecast the change in predicted AADT. The random nature of these plots of change in observed and predicted AADT, and their low correlation coefficients, suggest that the model with change in AADT will not be useful to capture the change in predicted AADT. It will not be as effective as with the lagged model with a change to account for unequal time intervals between observations.

8.4 Chapter Summary

Alternative time-series models, based on past AADT data and the rate at which AADT has been changing in past years to account for the unequal time spacing between observations, have been developed for each data group produced in Chapters 5 and 6. These alternative models are based on lagged regression analysis. Each of the models is found statistically significant with high R^2 values. The complete model building approach of Chapter 6 has been used to confirm the

suitability of the models. The performance evaluation of the models is tested by forming models with partial data. The partial lagged models show the stability of the model parameters. The comparison of the models developed in this chapter with those in earlier chapters will be done in Chapter 10.

CHAPTER 9

VEHICLE REGISTRATION AND CITY POPULATION FORECASTS

9.1 Introduction

Forecasts of predictor variables entered in the models in this study, other than vehicle registrations and city population, are available from outside sources (see Chapter 4). This chapter explores the application of Time Series Analysis to produce the forecasts of vehicle registrations at the state and county level. Following a brief introduction to Time Series Analysis, model development and fitting are discussed in some detail. This chapter addresses the development of computationally efficient models for forecasting of vehicle registrations based on the time series analysis framework. The combined forecasts of vehicle registration are based on two components: (1) forecasts produced by an Autoregressive procedure and (2) those produced using the Box-Jenkins ARIMA technique. The performance of the forecasting models produced in this study is evaluated. To forecast city population, a simple but widely accepted "ratio" method has been used. The terms prediction and forecasting have been used interchangeably in this chapter and throughout the report, although philosophical distinctions can be made.

9.2 Time Series Forecasts of Vehicle Registration

A time series is a sequence of observations arranged in order of some other variable, usually a time variable. Yearly vehicle registration data for the years 1950 to 1988 for the state of Indiana and each of its 92 counties are used to generate the independent forecasts of vehicle registration for the state and each county. Final results of the forecasts and models are presented for all 93 series of data. To illustrate model identification, estimation and validation, two counties (24-Franklin and 79-Tippecanoe) are highlighted in this chapter. In addition, 91-White County is used to show certain results of the time series analysis. The yearly total number of vehicle registrations have been used in this study, so each series of data is non-seasonal. The representative plots of series for 24-Franklin and 79-Tippecanoe are shown in Figures 9.1 and 9.2, respectively. Despite an occasional "shock" in the series, these plots show that there is an increasing trend in vehicle registrations and a lack of affinity towards the mean value of the series.

9.2.1 Introduction to Forecast Procedures and Estimation Method

Using other predictor variables in this study (for example, income, employment, population, and household) as a predictor variable(s) to forecast of Vehicle Registrations is possible. But, to obtain accurate forecasts and confidence limits, the input series must be independent of one another. Also, the past values of the response series cannot contain additional information about future values of the input series beyond that contained in the past values of the input

Figure 9.1: Observed Series of Franklin County Vehicle Registration

Figure 9.2: Observed Series of Tippecanoe County Vehicle Registration

series. That is, there should be no feedback loops between the response series and the input series. Thus, the time series analysis employed in this chapter, which depends on only on time, seems to be a more appropriate method to forecast vehicle registrations at county and state level. The following time series procedures appear to be appropriate for this study:

- a. ARIMA -- fits models that allow for an error term generated by an AutoRegressive Integrated Moving Average (ARIMA) process. A brief description of this method is presented in Section 9.2.2.
- b. AUTOREG -- does multiple regression allowing for a serially correlated error term that is generated by an AUTOREgressive (AUTOREG) process. The procedure has been addressed concisely in Section 9.2.3.

The estimation techniques [SAS/ETS 1984, Brocklebank & Dickey 1986] that can be used in the above procedures are as follows:

- a. Yule-Walker (YW)
- b. Unconditional Least Squares (ULS)
- c. Conditional Least Squares (CLS)
- d. Maximum Likelihood (ML)

The ULS estimates are also referred to as Nonlinear Least Squares (NLS) estimates or Exact Least Squares (ELS) estimates. A detailed description of these methods is beyond the scope of this study, but the following comparative evaluations from the literature [Brocklebank & Dickey 1986] are made to select the most accurate method.

- i. Computationally, YW estimation is the fastest.
- ii. The ULS technique more accurately computes prediction error variances and finite sample prediction than the CLS technique.
- iii. The CLS method assumes a constant variance and the same linear combination of past values as the optimum prediction.
- iv. In the ML method, the quantity to be minimized is not the sum of squares; instead, it is the negative log of the likelihood function.

The Ordinary Least Squares (OLS) estimates and YW estimates are used as starting values for the ML and ULS methods. Although the CLS, ULS, and ML methods should give similar results for reasonably large data sets, studies [SAS/ETS 1984] comparing the three methods suggest that ML is the most accurate method. Based on the literature and some pilot runs (results not shown) with different methods, this study has used the ML method in model estimation.

9.2.2 ARIMA Model

ARIMA is an acronym for AutoRegressive Integrated Moving-Average models, usually denoted by the notation $ARIMA(p,d,q)$, where

- p is the degree of the autoregressive part,
- d is the degree of the differencing, and
- q is the degree of the moving-average process.

The ARIMA procedure analyzes and forecasts univariate time series data using the autoregressive integrated moving average model developed by Box and Jenkins [1976].

ARIMA is an iterative method for modeling the dependence among the observations in a time series. It is a model building process rather than model fitting process, because the model is determined from the data rather than by assumption. The model determination stage, called identification, is followed by parameter estimation, and then diagnostic checking to determine if the model provides an adequate description of the data. If the checking stage shows that the model is deficient in some way, then it is necessary to go back to the identification stage and go through the process again. It is also desirable to develop a model that uses parameters parsimoniously, i.e., contains a small number of autoregressive and moving average terms.

The ARIMA procedure assumes that the time series is either stationary or can be made into a stationary time series after suitable differencing operations. Intuitively, the series needs to have a constant mean and to fluctuate about that mean with a constant variance. In other words, the covariance between two elements in the series depends only on the time difference between the two elements.

For the autocorrelated error terms, the usual ordinary least squares (OLS) estimates of regression parameters may not be enough, and the usual estimates of standard errors may be biased. Further, because of serial autocorrelation, past and present observations can be used to improve predictions in the near future. So, in the ARIMA model, as opposed to the normal assumption of stochastic independence of observations, we specifically assume that these observations are correlated. Fitting complicated models with the SAS ARIMA procedure

[SAS/ETS 1984] usually requires the user to provide input and judgment. The SAS ARIMA procedure can handle time series of moderate size. The procedure needs more than thirty observations and fewer than 2000. With fewer than thirty, the parameters are not estimated very well. With thousands of observations, the method requires excessive computer time and memory.

9.2.2.1 Model Formulation

Let $\{Z_t\}$ be observations on the state variable taken at equally spaced intervals. The observation at time t can be thought of as the sum of a deterministic component (f_t) plus a stochastic noise component (ϵ_t), i.e., $Z_t = f_t + \epsilon_t$. If the $\{Z_t\}$ series is stationary, then f_t can be represented by a mean level μ . The time series of vehicle registrations (see the representative plots in Figures 9.1 and 9.2) exhibits some degrees of non-stationarity. For simplicity, the differencing technique [Box-Jenkins 1976] has been used to overcome the problem of non-stationarity. Figures 9.3 and 9.4 show the plots of the first differences of the series presented in Figures 9.1 and 9.2, respectively. The increasing trend in the observed series has been eliminated in the first difference series.

The noise components $\{\epsilon_t\}$ in vehicle registration data are assumed to be serially correlated and they induce correlation in the $\{Z_t\}$ series. Therefore, the ARIMA process represents ϵ_t by a linear combination of a white noise sequence $\{a_t\}$, where the a 's are independent variables with zero mean and variance σ_a^2 .

Figure 9.3: First Difference Series of Franklin County Vehicle Registration

Figure 9.4: First Difference Series of Tippecanoe County Vehicle Registration

The mathematical representation of ARIMA (p,d,q), originally formulated by Box and Jenkins [1976], of the non-seasonal data, Z_t , is as follows:

$$\Phi_p(B) \nabla^d z_t = \theta_0 + \Theta_q(B) a_t \quad (9.1)$$

where,

$$\Phi_p(B) = 1 - \phi_1 B - \dots - \phi_p B^p$$

$$\Theta_q(B) = 1 - \theta_1 B - \dots - \theta_q B^q$$

$$B^m z_t = z_{t-m}$$

$$\nabla^m z_t = (1 - B)^m z_t$$

$$z_t = Z_t - E(Z_t)$$

$E(Z_t)$ -- Mean of the Process Z_t

a_t -- White noise with zero means and variance

ϕ -- An Autoregressive (AR) parameter

θ_0 -- Constant Term (MU)

θ -- A Moving Average (MA) parameter

p -- The order of the differenced or AR series

q -- The order of the white noise or MA series

d -- The order of differencing

Here, $\Phi_p(B)$ and $\Theta_q(B)$ are polynomials of degree p and q , respectively, in the backshift operator B . The models of Equation (9.1) have been formulated by Box and Jenkins (1976), and they are usually referred to as autoregressive integrated moving average (ARIMA) models of order (p,d,q), generally represented as ARIMA(p,d,q). The general form of

Equation (9.1) has been elaborated in Table 9.1 for a few representative ARIMA models being produced in this study (see Appendix Tables F1 and F2). An example for each of these representative models is also shown in Table 9.1.

The analysis to develop ARIMA models is divided into three stages (identification, estimation and forecast), corresponding to the stages described by Box and Jenkins [1976]. These stages to prescribe a ARIMA model are described in Sections 9.2.2.3 to 9.2.2.6. The overall steps involved in modeling the nonseasonal time series are outlined in Table 9.2.

9.2.2.2 Chi-Squared Check of Autocorrelation

One way of viewing the process of modeling time series is an attempt to find a transformation that reduces the observed data to random noise. To do that, one needs to examine the sample autocorrelations of the residuals as a diagnostic check. Autocorrelation, if evident in the residuals, may help to suggest the direction in which the model should be modified. Box and Pierce [1970] have developed a test (known as the Box-Pierce Q-statistic) that is capable of determining whether several autocorrelation coefficients are significantly different from zero. This test is based on the χ^2 (chi-square) distribution of the autocorrelation coefficients. If the computed value of the test is less than that from the table of values of the χ^2 statistic, the autocorrelations used to calculate the test are not significantly different from zero. This suggests that the data generating the autocorrelations are random. If the computed χ^2 -test

Table 9.1: Example of Selected ARIMA Models from General Form
[Equation (9.1)]

ARIMA(1,1,1)	
<u>MODEL:</u>	$Z_t = \theta_0 + (1 + \phi_1) Z_{t-1} - \phi_1 Z_{t-2} + a_t - \theta_1 a_{t-1}$
<u>EXAMPLE</u> [Hamilton County]:	$Z_t = 1968.82 + (1 + 0.6683) Z_{t-1} - 0.6683 Z_{t-2} + a_t - 0.8758 a_{t-1}$
ARIMA(1,1,0)	
<u>MODEL:</u>	$Z_t = \theta_0 + (1 + \phi_1) Z_{t-1} - \phi_1 Z_{t-2} + a_t$
<u>EXAMPLE</u> [Tippecanoe County]:	$Z_t = 1579.00 + (1 + 0.4190) Z_{t-1} - 0.4190 Z_{t-2} + a_t$
ARIMA(0,1,1)	
<u>MODEL:</u>	$Z_t = \theta_0 + Z_{t-1} + a_t - \theta_1 a_{t-1}$
<u>EXAMPLE</u> [STATE]:	$Z_t = 78722.3 + Z_{t-1} + a_t + 0.3730 a_{t-1}$

Table 9.1, continued

ARIMA(0,1,0)	
<u>MODEL:</u>	$Z_t = \theta_0 + Z_{t-1} + a_t$
<u>EXAMPLE</u> [<u>Franklin County</u>]:	$Z_t = 304.03 + Z_{t-1} + a_t$

ARIMA(2,1,0)	
<u>MODEL:</u>	$Z_t = \theta_0 + \phi_1(Z_{t-1} - Z_{t-2}) + \phi_2(Z_{t-2} - Z_{t-3}) + a_t$
<u>EXAMPLE</u> [<u>Kosciusko County</u>]:	$Z_t = 1146.29 + 0.4937 (Z_{t-1} - Z_{t-2}) - 0.4388 (Z_{t-2} - Z_{t-3}) + a_t$

ARIMA(2nd,1,0)	
<u>MODEL:</u>	$Z_t = \theta_0 + \phi_2(Z_{t-2} - Z_{t-3}) + a_t$
<u>EXAMPLE</u> [<u>Dearborn County</u>]:	$Z_t = 576.97 - 0.3169 (Z_{t-2} - Z_{t-3}) + a_t$

Table 9.2: Steps of ARIMA Model for Nonseasonal Univariate Series

1. Check for nonstationarity using
 - data plot to monitor slow level shifts in the data
 - ACF to monitor very slow decay

If any of these tests indicate nonstationarity, difference the series and repeat the steps above. If necessary, second differencing will be made.
2. Check the Q statistic (CHI SQUARE). If Q is small (in other words, PROB is fairly large) and if the first few autocorrelations are small, then one may assume that the original (possibly differenced) series is just white noise.
3. Check the ACF and PACF [Box and Jenkins 1976, Abraham and Leodolter 1983] to identify a model. If the ACF drops to zero after q lags, this indicates an MA(q) model. If the PACF drops after p lags, this indicates an AR(p) model.
4. Estimate the model (or several candidate models) of step 3.
5. Check the Q statistic (CHI-SQUARE) after estimation. If it is insignificant, the model fits reasonably well according to this criterion. Otherwise, return to the original ACF and PACF of the original (possibly differenced) data to determine if something has been missed. This is generally more advisable than plotting the ACF of the residuals from the misspecified model.
6. Forecast the series from the fitted model of step 5. It is a good idea to start the forecast a few steps before the end of series to compare the last forecasts to the data values at the end of the series. In case of a large discrepancy, the user may want to adjust the forecasts. In the final forecast, omit the start the forecast from few steps back. It is used only as a diagnostic tool.
7. Examine plots of residuals and possibly use PROC UNIVARIATE [SAS/Basics, 1985] to examine the distribution to test the white noise assumption further.

Sources: 1. SAS/ETS [1984] and SAS [1986].

2. Box and Jenkins [1976], and Abraham and Leodolter [1983].

statistics (i.e., Q-statistic) is larger than the value from the table, the autocorrelations are significantly different from zero, indicating the existence of some pattern. The Q-statistic is computed as

$$\chi^2\text{-test} = n \sum_{j=1}^k r_j^2, \quad (9.2)$$

where k is the largest time lag included. The smaller the autocorrelations (r_j), the smaller the value of χ^2 .

In the identification stage, the SAS ARIMA procedure uses autocorrelations to form a statistic whose approximate distribution is chi-squared under the null hypothesis that the series is white noise. The test is the Ljung modification of the Box-Pierce Q statistic. The formula for this statistic is

$$n(n+2) \sum_{j=1}^k \frac{r^2(j)}{(n-j)} \quad (9.3)$$

where $r(j)$ is the estimated autocorrelation at lag j and k is any positive integer. SAS ARIMA procedure uses several values of k to compute the χ^2 statistic. In the modeling stage, the SAS ARIMA procedure calculates the same statistic on the residuals to test the hypothesis that they are white noise. The statistic is compared to critical values from a chi-squared distribution. If the model is correct, the residuals should be white noise and the chi-squared statistic should be small (the probability value should be large). A

significant chi-square statistic concludes that the model does not fit well.

9.2.2.3 Model Identification

The IDENTIFY statement of the SAS ARIMA procedure [SAS/ETS 1984] has been used to identify the model. PROC ARIMA reads in the time series, differencing them if a trend is detected, and computes autocorrelations and partial autocorrelations. These results usually suggest one or more models that could be fit to the data. At the identification stage, Autocorrelated Function (ACF) and Partial Autocorrelated Function (PACF) [Box & Jenkins 1976] are the keys to model identification. The behavior of functions for different processes is summarized below:

	<u>MA(q)</u>	<u>AR(p)</u>	<u>ARMA(p,q)</u>	<u>White Noise</u>
ACF	D(q)	T	T	zero
PACF	T	D(p)	T	zero

where,

D(i) means the function drops off to zero after lag i.
 T means the function tails off exponentially.
 zero means the function is zero at all nonzero lags.

ACFs for the observed series of 24-Franklin and 79-Tippecanoe counties are shown in Figures 9.5 and 9.6, respectively. A slow decay of ACF and an increasing trend in the plots in Figures 9.1 and 9.2 suggest that the observed series of vehicle registrations are nonstationary. The PACFs of this observed series are presented in Figures 9.7 and 9.8. One may want to analyze AR(1) — an autoregressive model with lag 1 — based on identification rules. The chi-square statistic and

Franklin County Vehicle Registration
Series: Observed

Mean of the Series = 10956.2
Standard Deviation = 3513.24
No. of Observations = 39

AUTOCORRELATIONS

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error
0	1.00000												*****										0
1	0.92163												*****										0.160128
2	0.85258												*****										0.263058
3	0.77708												*****										0.326307
4	0.70054												*****										0.370733
5	0.62696												*****										0.403249
6	0.57036												*****										0.427513
7	0.49654												*****										0.446599
8	0.42027												*****										0.460537
9	0.34114												*****										0.470268
10	0.26269												*****										0.476571
11	0.18694												****										0.480269
12	0.11519												**										0.482131
13	0.04598												*										0.482836
14	-0.01886																						0.482949
15	-0.07935												**										0.482967

Note: ". " Marks two Standard Errors

Figure 9.5: Autocorrelation of Observed Series for Franklin
County Vehicle Registration

Tippecanoe County Vehicle Registration
Series: Observed

Mean of the Series = 58565.3
Standard Deviation = 21081.3
No. of Observations = 39

AUTOCORRELATIONS

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error
0	1.00000												*****										0
1	0.94202												*****										0.160128
2	0.88025												*****										0.266738
3	0.81081												*****										0.332993
4	0.73958												*****										0.38026
5	0.66655												*****										0.415509
6	0.59610												*****										0.442077
7	0.52085												*****										0.462227
8	0.44180												*****										0.477039
9	0.36126												*****										0.487418
10	0.28108												*****										0.494235
11	0.20078												****										0.498317
12	0.12473												**										0.500387
13	0.05292												*										0.501184
14	-0.01320																						0.501327
15	-0.07671												**										0.501336

Note: ". ." Marks two Standard Errors

Figure 9.6: Autocorrelation of Observed Series for Tippecanoe County Vehicle Registration

Franklin County Vehicle Registration
Series: Observed

(a) Box-Pierce Q-statistic:

AUTOCORRELATION CHECK FOR WHITE NOISE

To Lag	Chi- Square	df	P(White- Noise)	Autocorrelations					
6	150.65	6	0.000	0.922	0.853	0.777	0.701	0.627	0.570
12	184.87	12	0.000	0.497	0.420	0.341	0.263	0.187	0.115

(b) PARTIAL AUTOCORRELATIONS

Partial																									
Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1			
1	0.92163																								
2	0.02116																								
3	-0.07680																								
4	-0.05395																								
5	-0.02474																								
6	0.07156																								
7	-0.14165																								
8	-0.08749																								
9	-0.06955																								
10	-0.04604																								
11	-0.03287																								
12	-0.05851																								
13	-0.04384																								
14	-0.03370																								
15	-0.02814																								

Note: ^.^ Marks of Approx. two Standard Errors

Figure 9.7: (a) Q-statistic and (b) Partial Autocorrelation of Observed Series for Franklin County Vehicle Registration

Tippecanoe County Vehicle Registration
Series: Observed

(a) Box-Pierce Q-statistic:

AUTOCORRELATION CHECK FOR WHITE NOISE

To Lag	Chi- Square	df	P(White- Noise)	Autocorrelations					
6	163.13	6	0.000	0.942	0.880	0.811	0.740	0.667	0.596
12	201.29	12	0.000	0.521	0.442	0.361	0.281	0.201	0.125

(b) PARTIAL AUTOCORRELATIONS

Partial		Lag Correlation																				
		-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
1	0.94202																					
2	-0.06354													*								
3	-0.10024													**								
4	-0.05072													*								
5	-0.05235													*								
6	-0.01839																					
7	-0.08693																					
8	-0.08502													**								
9	-0.06316													**								
10	-0.05164													*								
11	-0.06116													*								
12	-0.02995													*								
13	-0.03022													*								
14	-0.01891														*							
15	-0.04739														*							

Note: '*' Marks of Approx. two Standard Errors

Figure 9.8: (a) Q-statistic and (b) Partial Autocorrelation of Observed Series for Tippecanoe County Vehicle Registration

the associated Prob(White Noise) presented in part (a) of PACFs of Figures 9.7 and 9.8 show that chi-square statistic are significant. The first difference series is tried because of nonstationarity of the observed series and a significant chi-square statistic. ACFs and PACFs for the first difference series (see Figures 9.3 and 9.4) are presented in Figures 9.9-9.10 and 9.11-9.12, respectively. ACFs in Figure 9.9 and 9.10 and plots in Figures 9.3 and 9.4 suggest that the first difference series is stationary. Further, the low chi-square statistics and the high probability of white noise in part (a) of Figures 9.11 and 9.12 suggest that the first difference series is appropriate. According to our identification rules from ACF and PACF, the following models are identified:

1. ARIMA(0,1,0) seems to be the most appropriate model for 24-Franklin County because of no significant lags in ACF and PACF in Figures 9.9 and 9.11. Although not warranted, two other models -- ARIMA(1,1,0) and ARIMA(0,1,1) -- have been examined to make the most appropriate selection.
2. From the plots of ACF and PACF in Figures 9.10 and 9.12, it appears that ARIMA(1,1,0) is a good model for Tippecanoe County. But the other possibilities -- ARIMA(0,1,1), ARIMA(1,1,1) and ARIMA(0,1,0) -- also need to be investigated to make a good final selection. ARIMA(0,1,0) is not warranted, based on the ACF and PACF plots, but it will be the appropriate model when there are no significant autoregressive or moving average parameters in other ARIMA models.

Franklin County Vehicle Registration
Series: First Difference

Mean of the Series = 304.026
Standard Deviation = 348.483
No. of Observations = 38

AUTOCORRELATIONS

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error
0	1.00000																						0
1	-0.07353									*													0.162221
2	-0.09935									**													0.163096
3	-0.07115									*													0.164681
4	0.19828																						0.165488
5	-0.07131									*													0.171626
6	0.03567									*													0.172404
7	-0.05452									*													0.172598
8	-0.01340																						0.173051
9	-0.07698									**													0.173078
10	-0.02184																						0.173977
11	-0.00350																						0.174049
12	0.14593																						0.174051
13	0.09804																						0.177241
14	-0.06982									*													0.178662
15	-0.14890									***													0.179379

Note: '*' Marks two Standard Errors

Figure 9.9: Autocorrelation of First Difference Series for Franklin County Vehicle Registration

Tippecanoe County Vehicle Registration
Series: First Difference

Mean of the Series = 1608.79
Standard Deviation = 1060.15
No. of Observations = 38

AUTOCORRELATIONS

Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1	Std Error
0	1.00000																						0
1	0.38190									.													0.162221
2	0.14201									.													0.184369
3	0.07239									.													0.187225
4	0.16620									.													0.18796
5	0.02764									.													0.191788
6	0.03347									.													0.191893
7	0.00868									.													0.192047
8	0.00145									.													0.192057
9	-0.12615									.													0.192057
10	-0.10449									.													0.194226
11	-0.12317									.													0.195699
12	0.02922									.													0.197729
13	0.02926									.													0.197843
14	-0.20256									.													0.197956
15	-0.15564									.													0.203338

Note: '.' Marks two Standard Errors

Figure 9.10: Autocorrelation of First Difference Series for Tippecanoe County Vehicle Registration

Franklin County Vehicle Registration
Series: First Difference

(a) Box-Pierce Q-statistic:

AUTOCORRELATION CHECK FOR WHITE NOISE

To Lag	Chi- Square	df	P(White- Noise)	Autocorrelations						
6	2.91	6	0.820	-0.074	-0.099	-0.071	0.198	-0.071	0.036	
12	4.65	12	0.969	-0.055	-0.013	-0.077	-0.022	-0.003	0.146	

(b) PARTIAL AUTOCORRELATIONS

Partial Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1
1	-0.07353									*												
2	-0.10532								.	**					.							
3	-0.08842								.	**					.							
4	0.17847								.						.							
5	-0.06045								.	*			****		.							
6	0.06118								.				*		.							
7	-0.03610								.	*					.							
8	-0.05728								.	*					.							
9	-0.06357								.	*					.							
10	-0.07068								.	*					.							
11	-0.00523								.						.							
12	0.14368								.				***		.							
13	0.15119								.				***		.							
14	-0.01397								.						.							
15	-0.13288								.	***					.							

Note: . . Marks of Approx. two Standard Errors

Figure 9.11: (a) Q-statistic and (b) Partial Autocorrelation of First Difference Series for Franklin County Vehicle Registration

Tippecanoe County Vehicle Registration
Series: First Difference

(a) Box-Pierce Q-statistic:

AUTOCORRELATION CHECK FOR WHITE NOISE

To Lag	Chi- Square	df	P(White- Noise)	Autocorrelations					
6	8.39	6	0.211	0.382	0.142	0.072	0.166	0.028	0.033
12	10.73	12	0.552	0.009	0.001	-0.126	-0.104	-0.123	0.029

(b) PARTIAL AUTOCORRELATIONS

Partial																									
Lag	Correlation	-1	9	8	7	6	5	4	3	2	1	0	1	2	3	4	5	6	7	8	9	1			
1	0.38190																								
2	-0.00450																								
3	0.02299																								
4	0.15407																								
5	-0.10612																								
6	0.04932																								
7	-0.01619																								
8	-0.03067																								
9	-0.12357																								
10	-0.02562																								
11	-0.07277																								
12	0.12749																								
13	0.02686																								
14	-0.28412																								
15	0.06480																								

Note: . Marks of Approx. two Standard Errors

Figure 9.12: (a) Q-statistic and (b) Partial Autocorrelation of First Difference Series for Tippecanoe County Vehicle Registration

9.2.2.4 Model Estimation

The ESTIMATE statement of the SAS ARIMA procedure [SAS/ETS 1984] is used to estimate the parameters and to diagnosis the fit. The maximum likelihood technique is used in this estimation.

The following diagnostic information and statistics are used to check the model or to compare the alternative models produced in the identification stage.

1. Chi-Square statistics and/or Probability of White Noise — The description of these statistics was provided in Section 9.2.2.3.
2. Root Mean Square Error (RMSE) -- Section 5.4 has a concise description of this statistic.
3. Akaike's information criterion (AIC) [Akaike 1981] -- Section 5.3.5 has a succinct description of this information.
4. t-statistic and significance of parameters of model -- Section 6.4.2 has a brief description of these statistics.
5. Correlation between parameters — A description can be found in Section 6.4.2.

The above statistics and information on the different ARIMA models produced in the identification stage for the few selected counties are presented in Tables 9.3 and 9.4. The models with nonsignificant parameters and high correlation between parameters (if applicable) have been dropped in making the final model selections. Table 9.4 shows that some or all parameters of any overfitted model are nonsig-

Table 9.3: Statistics of ARIMA Models for Few Selected Counties

County No. Name	Model:	Model Characteristics			Normality	
	ARIMA(p,d,q)	P(White- Noise) [**]	RMSE	AIC	W-Value	PROB<W
24 Franklin	ARIMA(1,1,0)	0.653-0.928	357.0	556.50	0.9421	0.073
	ARIMA(0,1,1)	0.678-0.933	356.7	556.44	0.9470	0.100
	ARIMA(0,1,0) [*]	0.714-0.963	353.2	554.71	0.9208	0.015
79 Tippecanoe	ARIMA(1,1,0) [*]	0.592-0.924	995.5	634.62	0.9587	0.295
	ARIMA(0,1,1)	0.557-0.917	1009.8	635.65	0.9464	0.097
	ARIMA(1,1,1)	0.531-0.879	1009.6	636.62	0.9589	0.298
	ARIMA(0,1,0)	0.123-0.466	1074.4	639.27	0.9450	0.089
91 White	ARIMA(1,1,0) [*]	0.771-0.921	314.7	547.15	0.9773	0.694
	ARIMA(0,1,1)	0.546-0.970	288.4	543.93	0.9602	0.320
	ARIMA(1,1,1)	0.539-0.909	291.9	545.24	0.9841	0.901
	ARIMA(0,1,0)	0.066-0.336	347.4	553.47	0.9903	1.000

[*] Model Selected.

[**] Range of values with lags 6, 12, 18 and 24.

Table 9.4: Significance and Correlation of Parameters of ARIMA Models for Few Selected Counties

County No. Name	ARIMA Model: (p,d,q)	Parameter-			Correlation		
		Name	Estimate	t-value	Parameter	AR1	MA1
24 Franklin	(1,1,0)	MU	302.77	5.61	MU	0.020	NA(**)
		AR1	-0.0756	-0.45 (*)			
	(0,1,1)	MU	302.47	5.77	MU	NA	-0.019
		MA1	0.0961	0.58 (*)			
	(0,1,0)	MU	304.03	5.31	-	NA	NA
79 Tippecanoe	(1,1,0)	MU	1579.00	5.80	MU	0.023	NA
		AR1	0.4190	2.78			
	(0,1,1)	MU	1606.59	7.29	MU	NA	-0.041
		MA1	-0.3556	-2.12			
	(1,1,1)	MU	1578.40	5.69	MU AR1	-0.043	-0.056 0.922
		AR1	0.4243	1.08 (*)			
		MA1	0.0063	0.01 (*)			
	(0,1,0)	MU	1608.79	9.23	-	NA	NA
91 White	(1,1,0)	MU	343.07	3.75	MU	0.052	NA
		AR1	0.4546	3.03			
	(0,1,1)	MU	366.35	4.15	MU	NA	-0.060
		MA1	-0.9993	-0.07 (*)			
	(1,1,1)	MU	356.48	5.01	MU AR1	-0.057	-0.018 0.646
		AR1	-0.9995	-0.04 (*)			
		MA1	-0.2737	-1.06 (*)			
	(0,1,0)	MU	345.00	6.12	-	NA	NA

(*) Not Significant at $\alpha = 0.05$.

(**) NA = Not Applicable.

nificant. For Franklin County, $ARIMA(0,1,0)$ — identified in Section 9.2.2.3 — is the only model with no significant parameter. $ARIMA(0,1,0)$ is only a difference model with no autoregressive or moving average parameters. Table 9.3 shows that $ARIMA(0,1,0)$ has the lowest values of RMSE and AIC among the alternative models for Franklin County. Thus, $ARIMA(0,1,0)$ has been finally selected to forecast vehicle registrations for Franklin County.

For 79-Tippecanoe County; the parameters of $ARIMA(1,1,0)$, $ARIMA(0,1,1)$ and $ARIMA(1,1,1)$ are found to be significant. $ARIMA(1,1,0)$ is the most warranted model in the identification stage. The overfitted $ARIMA(1,1,1)$ model has nonsignificant AR and MA parameters with high correlation between these parameters. The RMSE and AIC values of $ARIMA(1,1,0)$ are lowest among all the candidate models, and the probability of white noise of $ARIMA(1,1,0)$ is high. Thus, $ARIMA(1,1,0)$ is selected to forecast Tippecanoe County vehicle registrations.

For 91-White County, the overfitted $ARIMA(1,1,1)$ and $ARIMA(0,1,1)$ have nonsignificant AR or MA parameters, and a high correlation exists between AR and MA parameters for the $ARIMA(1,1,1)$ model. Unlike 24-Franklin and 79-Tippecanoe, the RMSE and AIC values of the overfitted $ARIMA(1,1,1)$ and unwarranted $ARIMA(0,1,1)$ are smaller than those for $ARIMA(1,1,0)$ and $ARIMA(0,1,0)$. But the $ARIMA(1,1,0)$ has lower RMSE and AIC values than the $ARIMA(0,1,0)$ model. The significance of the parameters in the model is a primary consideration in model selection. Thus, $ARIMA(1,1,0)$ has been selected to forecast White County vehicle registrations.

The final models from the Box-Jenkins procedure and their key statistics for each of the 93 series (92 counties and the entire state) are presented in Appendix Table F1. The estimates of the parameters and their t-values for the ARIMA models are presented in Table F2.

9.2.2.5 Model Forecast and Validation

The FORECAST statement of the SAS ARIMA procedure [SAS/ETS 1984] was used to forecast future values at years 1989 to 2015, using estimates of the model. The same maximum-likelihood method as used in model estimation is used in model forecasts. The results of these forecasts from ARIMA models for all 92 counties and state vehicle registrations are shown in Appendix Table F3. The forecasts at years 1989-2015 are generated from the last observation (Year 1988) of the series. In addition to these forecasts, one-step ahead forecasts [Abraham & Leodolter 1983, Box & Jenkins 1976] are generated for each series at years 1951 to 1988. These one-step ahead forecasts are used to compute the residuals. Normality of these residuals are tested by using the SAS univariate procedure [SAS/Basics 1985]. A detailed discussion of this normality test can be found in Section 6.3.4 of Chapter 6. The Shapiro-Wilk W-value and the P-value are for each model are presented in Appendix Table F1. Table 9.3 also shows these normality statistics for all candidate models of the three selected representative counties. The normality assumption of residuals is satisfied for most of the series. There are a few series having very low W and probability value. The normality assumption has been

violated in those cases. The normal probability plots of the three selected counties are presented in Appendix Figures F1.1-F1.3. These plots depict the presence of one or a few outliers (if any) from the expected straight line pattern and thus identify the cause of violation of normality with a low P-value.

By analogy to the plots of residuals against predictor variables in earlier chapters, the plots of residuals are generated against the time variable, Year. Those plots for the three selected counties are presented in Appendix Figures F2.1-F2.3. In spite of the presence of a few outliers (lying more than 2-3 times STD DEV from the zero residual line), the randomness of the residual plots is apparent in these plots. Normality statistics can be improved by deleting the suspected outliers from the series (See Chapter 6). Because of the problem of estimation with missing data in a series and overall high quality of other results of the models, model refitting by deleting the suspected outliers (if any) has not been tried.

9.2.3 Autoregression Procedure

The AUTOREGression (AUTOREG) procedure [SAS/ETS 1984] fits a multiple linear regression model to a selected response time series, with corrections for serial correlation. Unlike the ARIMA procedure, this procedure works even if some values of the independent or dependent variables are missing. The AUTOREG procedure has been used to alleviate the shortcomings of the Ordinary Least Squares regression estimates (see Section 5.2) for the effects of serial correlation. It has also been used to generate forecasts.

9.2.3.1 First Order Autocorrelation Check of Residuals

Most regression procedures can print a Durbin-Watson statistic that tests for the presence of first-order autocorrelation. When autocorrelation is present, the ordinary least-squares (OLS) parameter estimates are not efficient and the standard error estimates are biased. A common way of detecting a certain type of serial correlation is the Durbin-Watson test [Draper & Smith 1981]. The alternate hypothesis to detect departures from the null hypothesis (true errors are uncorrelated) is

$$H_a: \epsilon_t = \rho \epsilon_{t-1} + e_t \quad (9.4)$$

where $|\rho| < 1$ and e_t is an uncorrelated series, and the errors e_t are assumed to be $N(0, \sigma^2)$ variables. This type of error term, in which ϵ_t is related to ϵ_{t-1} , is called an AR error of the first order. The Durbin-Watson statistic (d) is given by

$$d = \frac{\sum_{t=2}^n (\hat{\epsilon}_t - \hat{\epsilon}_{t-1})^2}{\sum_{t=1}^n \hat{\epsilon}_t^2} \quad (9.5)$$

where $\hat{\epsilon}_t = Y_t - \hat{Y}_t$. If the actual errors ϵ_t are uncorrelated, the numerator of d in Equation (9.2) has an expected value of about $2(n-1)\sigma^2$ and the denominator has an expected value of about $n\sigma^2$. Thus, if the errors ϵ_t are uncorrelated, the ratio d should be about 2. Positive autocorrelation means that ϵ_t is closer to ϵ_{t-1} than in the

independent case, so $|\varepsilon_t - \varepsilon_{t-1}|$ should be smaller. It follows that d should also be less. The smallest possible value for d is zero. If d is significantly less than 2, positive autocorrelation is present. When is a Durbin-Watson statistic significant? The answer depends on the number of independent variables in the regression and the number of observations. The critical boundary values of the Durbin-Watson test have been taken from the tables in Draper and Smith [1981]. The tables use $k' = k-1$, where k' is the number of explanatory variables, and n (number of observations) to obtain the bounds d_L (lower bound) and d_U (upper bound) for any given regression [Draper & Smith 1981]. A Durbin-Watson statistic $d > 2$ is evidence of negative autocorrelation. To see that the evidence is true, one needs to compute $d' = 4-d$ and use the standard Durbin-Watson test on d' . In Section 9.2.3.3, the Durbin-Watson statistic will be used to compare the OLS and AUTOREG procedures for forecasting vehicle registrations.

Three caveats apply to the Durbin-Watson test. First, it is designed to detect first-order AR errors. Although this type of autocorrelation is only one possibility, it seems to be the most common. The test has some power against other types of autocorrelation. Second, the Durbin-Watson bounds are not valid when the lagged values of the dependent variable appear on the right side of the regression. Third, the Durbin-Watson statistic often lies in the critical region, $d_L < d < d_U$, even though no real autocorrelation is present.

9.2.3.2 Model Description

Parameter estimates produced by the AUTOREG procedure are usually similar to ordinary least-square estimates, but the standard errors can be very different, affecting significance tests. AUTOREG is a useful tool for forecasting. It uses the time series part of the model as well as the systematic part in generating predicted values. The AUTOREG procedure estimates the parameters of a linear model whose error term is assumed to be an autoregressive process of a given order p , denoted $AR(p)$. The model for time t is as follows:

$$y_t = x_t' \beta + v_t \quad (9.6)$$

where v_t is assumed to be generated by an autoregressive process of order p ($AR(p)$). That is

$$v_t = \varepsilon_t - \alpha_1 v_{t-1} - \dots - \alpha_p v_{t-p} \quad (9.7)$$

where

y_t are the dependent values,

x_t is a vector of regression values,

β is a vector of structural parameters, and

α_i 's ($i=1, \dots, p$) are the autoregressive parameters.

The ε_t are normally and independently distributed with a mean of zero and a variance of σ^2 .

An autoregressive model can be specified for the error term. Its parameters can be estimated in one of four ways, depending on what method is used in estimates. As mentioned in Section 9.2.1, the maximum likelihood method usually provides the most accurate estimates of model error autocorrelation parameters. After an OLS fit of the dependent series, the residuals are used to estimate the error autocorrelation parameters. These parameters are then used to reestimate the regression parameters by generalized least squares. After the regression parameters and the autoregression parameters are estimated, the autoregressive model has been used to forecast future observations. A Durbin-Watson statistic is computed from the OLS residuals. AUTOREG procedure also computes Akaike's information criterion (AIC) [Akaike 1981].

9.2.3.3 Model Estimation

To determine the number of autoregressive parameters of residuals after the OLS fit, a number of trial runs with a large number of autocorrelation lags in the models for different series have been made. The results of these trial runs show that only the first lag autoregressive parameter (AR1) is significant with a constant term and time variable in the model. For 24-Franklin County, Table 9.5 shows the significance of parameters for an overfitted autoregressive model with 8 lags.

Table 9.5: Nonsignificance of Overfitted Autoregressive Lags for Franklin County Vehicle Registrations

Variable	Estimate	t	Prob>t
Constant	-597216	-13.460	0.0001
Year	308.88	13.740	0.0001
AR1	-0.8298	-4.313	0.0002
AR2	0.0403	0.164	0.8709
AR3	-0.0197	-0.082	0.9352
AR4	-0.2289	-0.948	0.3508
AR5	0.2396	0.990	0.3302
AR6	-0.2351	-0.955	0.3476
AR7	0.2374	0.949	0.3502
AR8	0.0351	0.177	0.8605

This table shows that only AR1 with a constant term and Year is significant (i.e., Prob>t or P-value is very low, usually less than 0.05).

The following statistics and diagnostic measures are obtained for each Autoregressive model.

1. Durbin-Watson d statistic for OLS and AUTOREG procedures. A description of this statistic was provided in Section 9.2.3.1.
2. Coefficient of Multiple Determination (R^2). Section 5.3 has the definition of R^2 .
3. RMSE or $\sqrt{\text{MSE}}$. A brief description of this statistic can be found in Section 5.4.
4. Akaike's Information Criterion (AIC) [Akaike 1981]. Section 5.3.5 has described this statistic.
5. t-value of the parameters and their significance. Section 6.4.2 has a concise description.

The results of items 1 to 4 in the above listing are shown in Appendix Table F4 for all 93 series. The estimation of the model parameters and their t-values are presented in Appendix Table F5. The computed t-values of the parameters of the models indicate that almost all parameters are significant at an α -level as low as 0.0001. Table F4 shows very high R^2 values (about 99 percent) for all AUTOREG models. A significant increase in the d-statistic is noticed in the AUTOREG model with respect to that in the OLS model. Usually, the problem of first-order autocorrelation associated with OLS model has been removed in AUTOREG model. The control statistics have been provided in the footnote to Table F4. Even when autocorrelation has not been removed completely, a significant improvement in the d-statistic can be found in the AUTOREG model over the OLS model.

Table 9.6 has compared the D-W d, R^2 , $\sqrt{\text{MSE}}$, and AIC between the OLS with time, AUTOREG with time and AR1, and the resulting ARIMA model (see Section 9.2.2.4) for the three selected counties. In spite of close and high R^2 values, a significant improvement has achieved in D-W's d, $\sqrt{\text{MSE}}$ and AIC in the AUTOREG model with respect to OLS model. Although R^2 is not possible for the ARIMA model, the $\sqrt{\text{MSE}}$ and AIC statistics imply that there is no significant difference in the quality of results between the AUTOREG and ARIMA models.

Table 9.6: Key Statistics of OLS, AUTOREG and ARIMA Model for Few Selected Counties Vehicle Registrations

County No.	County Name	Model [*]	D-W (d) [**]	R ² [***]	\ MSE	AIC
24	Franklin	OLS	0.282	96.80	665.5	619.67
		AUTOREG	1.925	99.10	347.6	571.22
		ARIMA(0,1,0)	-	NA	353.2	554.71
79	Tippecanoe	OLS	0.197	98.68	2488.0	722.53
		AUTOREG	1.214	99.76	1079.9	660.40
		ARIMA(1,1,0)	-	NA	995.5	634.62
91	White	OLS	0.186	97.17	823.3	636.26
		AUTOREG	1.077	99.51	348.7	572.17
		ARIMA(1,1,0)	-	-	347.4	553.47

[*] OLS = Ordinary Least Square, AUTOREG = Autoregressive with AR parameter at Lag 1; ARIMA = Box-Jenkins Model.

[**] [$\alpha=0.01$] OLS: $(d_L, d_U)=(1.24, 1.34)$;
AUTOREG: $(d_L, d_U)=(1.19, 1.39)$

[***] NA = Not Available.

9.2.3.4 Model Forecast and Validation

The AUTOREG models from Section 9.2.3.3 are used to forecast the future values of county and state vehicle registrations for years 1989 to 2015. The results of these forecasts are shown in Appendix Table F6. These forecasts consist of both the structural (part 1 of Equation 9.6) and autoregressive (part 2 of Equation 9.6) parts of the autoregressive model. Forecasts are also made for the time series at years 1951 to 1988. These forecasts were used to evaluate the performance of the models. The normality assumption of these residuals is tested by using the SAS UNIVARIATE procedure [SAS/Basics 1985]. Appendix Table F4 has presented the results of the normality statistics — Shapiro-Wilk W-value and the associated P-value. The quality

of the results of the normality of these AUTOREG models and the ARIMA models in Section 9.2.2.5 is similar. For those series with very low probability results, the normality assumption has been violated for the presence of at least one outlier. The normal probability plots of the three selected counties are shown in Appendix Figures F1.4-F1.6. Once again, these plots are similar to those shown for ARIMA models in Figures F1.1-F1.3. However, a slight improvement in the P-value has been achieved for the three selected AUTOREG models. The plots of residuals against time, presented in Appendix Figures F2.4-F2.6, show the evidence of presence outliers. Randomness in the residuals can be noted in these plots.

9.2.4 Combination of Forecasts and Comparison of Models

The combination of forecasts is thought to be a practical and simple way to produce better forecasts. An extensive literature review supports the combination of forecasts. Although there is currently general agreement that combination can increase accuracy, there is still concern about the preferred method of combination.

Armstrong [1984] recommended developing several simple methods and combining the forecasts rather than developing one complex model. He said "If one does not know which of a set of forecasts is most accurate, then combining forecasts produces dramatic gain. Given that we know little about the best way to weight the components of a combined forecast, use methods that are as different as possible, and simply weight each forecast equally. One should not introduce complexities unless absolutely necessary."

A number of researchers have found advantages in combining models. The combination could be based on any criterion — for example, Mean Absolute Percentage Error (MAPE), Root Mean Square Percentage Error (RMSPE), Accuracy Ratio ($\bar{Q}$), etc.) or a simple average. Granger and Ramanathan [1984] said, "In theory, a combined forecast will usually be superior to its constituent models and never be worse than the worse of the constituents". This means that one should never lose by combination and will usually gain.

Both academics and practitioners often recommend combining forecasts. This is considered especially useful if the methods are different. Combinations of forecasts are intuitively appealing. They guard against mistakes and unreasonable assumptions, and thus help to avoid large errors. They also use more information. A statistical summary [Table 2, p. 96 of Armstrong 1986] shows that the combination of forecasts from two different methods yielded a 6.6 percent reduction in error compared to the average component. The error reduction ranged from 0 to 23 percent across the eight studies. Combinations of forecasts from three methods are expected to yield further improvements, but the two studies available on combining three methods found no gain and an 18 percent error reduction. Combinations of forecasts derived by similar methods also help. Armstrong [1984] found an average error reduction of 42 percent when two methods were combined (averaged over four studies). Makridakis and Winkler [1983], in their study of 111 time series, found a 7.2 percent reduction for two methods, with continuing gains as methods were added (for example, a 16.3 percent reduction with five methods). Research to date suggests

that equal weighting of the various forecasts is sufficient.

Both the Box-Jenkins and Autoregressive procedures in this study have been found to deliver quality forecasts in this study. The procedures can hardly be blamed for failing to deliver more than is possible from a scanty data base. The optimality of these forecasts rests on two assumptions: that the model is correct and the model structure does not change over time (particularly in the future).

Based on the quality of the statistics of both Box-Jenkins and Autoregressive procedures, and lessons from the literature on combining forecasts, the combination of forecasts in this study has been done with a simple average of the individual forecasts. Appendix Tables F7 shows the results of this combination. It is highly recommended that combined forecasts, rather than a single forecast of vehicle registration (if required) be used by the traffic model.

The performance measures -- ME, MPE, MAE, MAPE, RMSPE, and $\bar{Q}$ -- of the forecasts from Box-Jenkins, Autoregressive and their combination for the two selected representative counties are shown in Table 9.7. Some of these forecast measures have been introduced in earlier chapters and their full description is provided in next chapter. Despite the merits and demerits of these forecast measures, all the measures suggest that both Box-Jenkins and Autoregressive have produced forecasts similar in quality. The high quality of their forecasts is verified by (1) very low values of MPE, MAPE, RMSPE, and (2) an accuracy ratio ($\bar{Q}$) close to 1 -- a value that reflects good forecasts.

Table 9.7: Forecast Measures of Time Series Models for Two Selected Counties Vehicle Registrations

County	Model	Forecast Measures					
		ME	MPE	MAE	MAPE	RMSPE	$\bar{Q}$
Franklin	Box-Jenkin	-1.74	0.216	244.7	2.602	4.154	1.027
	Autoreg.	21.05	0.434	245.5	2.602	3.960	1.027
	Combined	9.66	0.325	242.2	2.575	4.023	1.027
Tippecanoe	Box-Jenkin	-23.55	0.049	779.0	1.430	1.951	1.014
	Autoreg.	56.82	0.387	809.7	1.562	2.202	1.016
	Combined	16.58	0.218	762.3	1.428	2.001	1.014

The forecast measures of combined forecasts also illustrate the high quality forecasts of vehicle registration. It is also proved from Table 9.7 that there is no absolute superiority of the autoregressive or the Box-Jenkins procedure over the other.

It is expected that a combination of forecasts will continue to produce good forecasts, even if one constituent forecast is faulty. Appendix Figures F3.1-F3.3 and F3.4-F3.6 present the plots of observed values of vehicle registration vs. their forecasts from Autoregressive, Box-Jenkins and their combination for the two selected counties 24-Franklin and 79-Tippecanoe, respectively. The points in these plots lie very close to the 45° line. Appendix Figures F4.1-F4.3 and F4.4-F4.6 show the plots of observed values of vehicle registration and forecasts from Autoregressive, Box-Jenkins and their combination for the two selected counties 24-Franklin and 79-Tippecanoe, respectively. Although different forecasts for each of these counties are drawn on separate plots, use of the same scale allows one to see that

the forecasts from different procedures are almost same or close to each other.

9.3 City Population Forecasts

Forecasts of city population, like vehicle registration in Section 9.2, are not available from any source, to date. This study has used a very simple but commonly-used method to forecast city population. The method uses the "ratio" of city population to county population to forecast the city population from the forecasts of county population available from other sources. Forecasts of city population will be used mainly to forecast traffic by the elasticity model (if required) of Chapter 6. No model in Chapter 6 has both county and city population in its equation at the same time. Thus, the ratio method of forecasting city population will not violate the independence of the variables in the model.

9.3.1 Ratio Method of City Population Forecasts

The underlying idea of the "ratio" technique [Krueckeberg & Silvers 1974] can be summarized as follows: The population growth of a city (CTY) is highly dependent on what happens to the population in its surrounding region, e.g., a township or county (CNTY/TWN). The "ratio" technique assumes that the nature of this interdependence is likely to persist in the near future. If a surrounding region's population projections are available, then one can estimate the city's share of the region's projected total. Algebraically, the "ratio" technique can be represented as:

$$\frac{POP_{CTY}^{t+n}}{POP_{CNTY/TWN}^{t+n}} = \frac{POP_{CTY}^t}{POP_{CNTY/TWN}^t} \quad (9.8)$$

where,

POP_{CTY}^j = City Population at year j

$POP_{CNTY/TWN}^j$ = Township(s) or County(ies) Population at year j

For projection purposes, the terms can be rearranged as follows:

$$POP_{CTY}^{t+n} = \left| \frac{POP_{CTY}^t}{POP_{CNTY/TWN}^t} \right| POP_{CNTY/TWN}^{t+n} \quad (9.9)$$

Equation (9.9) simply says that the future city population will be some fraction ($POP_{CTY}^t / POP_{CNTY/TWN}^t$) of the future population of the region ($POP_{CNTY/TWN}^{t+n}$). Equation (9.9) appears similar to a linear model of general form $Y = a + bX$; where a (the intercept) is assumed to be zero, and the independent variable is the population size of the surrounding township or county, and the b coefficient is the ratio of population sizes. The only historical data required in this "ratio" method is the population of the city and its surrounding township or county at one recent point in time. One may think that this "ratio" technique is inferior to the linear model based on a series of historical data. To guard against that possibility, the method can be improved by looking at several points in time and take an average or trend of the ratios. County or township population projections are often based on "cohort survival technique" [Krueckeberg & Silvers

1974]. Using that sophisticated technique's population projection as input to the "ratio" method, one can easily see the efficiency of this simple but popular method.

In this study, only one point (Year 1980) has been used to determine the ratio for Equation (9.9). This ratio can be modified and/or calibrated as soon as 1990 census population data at the city and county levels become available, by determining the trend of ratio or average ratio. The 1970 census year data are thought to be distant in time and have not been considered in determining the trend of the ratio or the average ratio. This study has projected the city population for all the cities in the State of Indiana with a 1980 population of 5000 or more. In the ratio technique, the appropriate surrounding area to serve as a defining context for a city is based on the following considerations:

1. the size of the city — the bigger the city, the bigger the surrounding region, and
2. the location of the city within a township and/or county. For example, if a city is located very close to the boundary of another county/township, then the adjacent county/township is also included in the surrounding region.

The surrounding townships or counties used in this study are given in Appendix Table F8. The cities in Table F8 have been listed alphabetically, where rank of a city is based on the city's 1980 population size. Table F8 also shows the county name and its number for each city. Finally, Equation (9.9) has used to forecast the city popula-

tion. The results for these forecasts at years 1985-2020 at every 5 years are shown in Table F9. The forecasts from Table F9 will be used in any traffic model that uses city population as a predictor variable.

9.4 Chapter Summary

The main purpose of this chapter is to produce reliable forecasts of input variables for the traffic models when no forecasts are available from outside sources. This chapter has described the techniques used to forecast those input variables -- vehicle registration and city population. To forecast vehicle registrations, the popular Box-Jenkins time-series analysis and a comparatively simple Autoregressive time series procedure have been used. The Autoregressive method was found to be as accurate as the Box-Jenkins method. The results of these two methods have been compared and combined to produce better forecasts. The performance measures of the methods have been evaluated and the results show the high quality of the forecasts for county and state vehicle registration. City population has been predicted by using a ratio technique, which is very simple but uses the input of more sophisticated methods. The results of all forecasts have been shown in tabular form. The model building process has been demonstrated with tables and figures.

CHAPTER 10

MODEL EVALUATION, COMBINATION AND CALIBRATION

10.1 Introduction

The most important rule for choosing a forecasting method is its accuracy, or how well the forecast matches the actual future value. In this chapter, several measures to determine the accuracy of forecasting models are summarized from the forecasting literature. Some of those measures are used to evaluate the performance of the models developed in this study. Based on the performance of individual models, forecasts from different models have been combined. Finally, a method to determine when there will be a need to change or recalibrate a forecasting model or its parameters is presented.

10.2 Performance Measures Criteria

The performance of a forecast can be checked against its actual value it becomes known. The selection of forecast criteria is usually arbitrary, but has for the most part been limited to those that are frequently seen in statistics and econometrics: coefficient of multiple determination (R^2), standard error of estimate, mean absolute error, range, and mean error. The major difficulty is the absence of

a single universally accepted measure of forecasting accuracy.

This section describes some measures of forecast accuracy [Ahlburg 1989, Armstrong 1978, Chisholm & Whitaker 1971, Meyer & Glauber 1964, and Montgomery & Johnson 1976], discusses their advantages and disadvantages, then decides on their uses and roles in this study. The following notation has been adapted for this section:

- A_i is the i th actual value.
- F_i is the i th forecast.
- n is the number of forecasts made in the forecast horizon.

Mean Error (ME)

The Mean Error (ME) and Mean Percentage Error (MPE) are calculated from

$$ME = \frac{\sum_{i=1}^n (F_i - A_i)}{n} \quad (10.1)$$

$$MPE = \frac{\sum_{i=1}^n (F_i - A_i)}{n} (100) \quad (10.2)$$

They should not be used alone because one could have a ME or MPE equal to zero when large errors are present if the large errors had different signs and canceled one another. This study has used these measures primarily to prove this weakness.

Mean Absolute Deviation (MAD or MAE)

The mean absolute deviation (MAD or MAE) is calculated from

$$\text{MAD or MAE} = \frac{\sum_{i=1}^n |F_i - A_i|}{n} \quad (10.3)$$

MAD is appropriate when the cost function is linear and symmetric. An example is when the cost of an error of 10 units is twice that of an error of 5 units, regardless of the sign of $F_i - A_i$. It does not have the "cancellation" problem associated with ME and MPE. Because of its simplicity, this study has used MAE as a measure of forecast accuracy.

Mean Squared Error (MSE)

Mean Squared Error (MSE) is commonly used in many statistical methods of forecasting. MSE is defined as

$$\text{MSE} = \frac{\sum_{i=1}^n (F_i - A_i)^2}{n} \quad (10.4)$$

This measure has two major drawbacks. First, it refers to fitting a model to historical data. An MSE of zero can always be obtained in the fitting phase by using a polynomial of sufficiently high order. The MSE calculated during the fitting phase of forecasting may give little indication of the accuracy of the model in forecasting. A second drawback of the MSE as a measure of forecasting accuracy is that different methods often use MSE in the different procedures in

their model fitting phase. Thus, comparison of the methods that use MSE in their fitting procedure in different ways is of limited value.

In the forecasting phase, the use of MSE as a measure of accuracy can also create problems. MSE does not represent absolute measure and is not particularly appropriate for making comparisons among formal forecasting methods (for example, methods based on statistical theory) and naive methods (for example, ad hoc methods). Thus, one should look for alternate measures of accuracy that seek to: (a) express accuracy in relative terms and (b) allow comparison among formal methods and naive methods of forecasting [Armstrong 1978].

Root Mean Square Error (RMSE)

The Root Mean Square Error (RMSE) is calculated from

$$RMSE = \left[\frac{\sum_{i=1}^n (F_i - A_i)^2}{n} \right]^{1/2} \quad (10.5)$$

RMSE is similar to MAD. A good approximate relationship is: $RMSE = 0.8MAD$. It is difficult to visualize what the RMSE means in practical terms, but all one need to do is multiply the RMSE by 1.25 to get an approximation of the MAD. One should avoid the RMSE when there are outliers, because the outliers will have an excessively strong effect on the measure. One legitimate reason for using the RMSE arises when the cost associated with an error increases as the square of the error.

Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error (MAPE) is calculated from

$$\text{MAPE} = \left[\frac{\sum_{i=1}^n \left| \frac{F_i - A_i}{A_i} \right|}{n} \right] \quad (100) \quad (10.6)$$

The MAPE is similar to the MAD except that it is dimensionless. This is helpful in making comparisons among forecasts from different situations. The MAPE is appropriate when the cost of errors is more closely related to the percentage error than to units of error. This assumption is often reasonable. Problems may arise if A_i values are close to zero, but this problem does not arise in this study. Consequently, this study uses MAPE as one measure of forecasting model accuracy.

Root Mean Square Percentage Error (RMSPE)

The Root Mean Square Percentage Error (RMSPE) is calculated from

$$\text{RMSPE} = \left[\frac{\sum_{i=1}^n \left[\frac{F_i - A_i}{A_i} \right]^2}{n} \right]^{1/2} \quad (100) \quad (10.7)$$

The RMSPE is similar to MAPE, except it uses the square of the error in its cost function instead of a linear error term. Use of RMSPE

arises may be appropriate when the cost associated with an error increases as the square of the error. Because this type of error function seems applicable in this study, RMSPE is used as a measure of accuracy.

Theil's measure of inequality (U)

The literature reflects some confusion regarding the mathematical representation of Theil's U statistic. There are actually two measures (U1 and U2). Theil proposed both, but at different times and under the same symbol. This section will present the different forms of the U statistic and determine its applicability to this study.

Theil's U1 statistic [Armstrong 1978, Meyer & Glauber 1964, Chisholm & Whitkar 1971] is based on a comparison of the predicted change with the observed change. It is a measure of the degree to which the forecasted value approximates the actual one, or more precisely, the amount by which α and β differ from 1 and 0, respectively, in the equation $F_i = \alpha A_i + \beta$. The Theil U1 coefficient, originally proposed by Theil in 1958, is estimated by

$$U1 = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (F_i - A_i)^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^n F_i^2} + \sqrt{\frac{1}{n} \sum_{i=1}^n A_i^2}} \quad (10.8)$$

The denominator of this statistic normalizes it so that its domain is the closed interval of zero to one. Obviously, $U1 = 0$ is a perfect

forecast, since $F_i - A_i = 0$ for all i . At the other extreme, $U1 = 1$ is the case of the worst possible forecasts. Ahlburg [1989] dropped the first term of the denominator in Equation (10.8).

The definition of the U2 statistic developed by Theil [1966] and presented by Makridakis and Wheelwright [1978] is different from Equation (10.8). Their definition of the U2 statistic is as follows:

$$U2 = \frac{\sqrt{\frac{1}{n-1} \sum_{i=1}^{n-1} (FPE_{i+1} - APE_{i+1})^2}}{\sqrt{\frac{1}{n-1} \sum_{i=1}^{n-1} (APE_{i+1})^2}} \quad (10.9)$$

where,

$$FPE_{i+1} = \frac{F_{i+1} - A_i}{A_i}, \text{ the predictive relative change), and}$$

$$APE_{i+1} = \frac{A_{i+1} - A_i}{A_i} \text{ the actual relative change.}$$

The Equation (10.9) can be simplified to the form shown in Equation (10.10), by substituting the values of FPE_{i+1} and APE_{i+1} , as

$$U2 = \frac{\sqrt{\sum_{i=1}^{n-1} \left[\frac{F_{i+1} - A_{i+1}}{A_i} \right]^2}}{\sqrt{\sum_{i=1}^{n-1} \left[\frac{F_{i+1} - A_{i+1}}{A_i} \right]^2}} \quad (10.10)$$

A major difference between Equation (10.10) and the U2 statistic [Theil 1966] is that Theil mentioned predicted and observed changes,

while Equation (10.10) [Makridakis & Wheelwright 1978] shows relative changes. The definition of U_2 presented by Armstrong [1978] is same as that of Theil [1966]. There are also differences between the Equations (10.8) and (10.10). In Equation (10.8), the denominator represents the sum of the squares of predicted and actual values over the number of forecasts n . In Equation (10.10), the denominator represents sum of the squares of the relative change in actual values. Comparing the numerator of Equation (10.10) with Equation (10.8) shows that the numerator of Equation (10.8) is the sum of change of predicted and actual values (after, $1/n$ is being factored out from numerator and denominator) and that of Equation (10.10) is the sum of relative changes.

Ahlburg's definition of the second Theil inequality statistic, U_2' , is completely different from Equation (10.9) or (10.10). The U_2' statistic has been defined as

$$U_2' = \left[\frac{\sum_{i=1}^n (F'_i - \bar{A}')^2}{\sum_{i=1}^n (\bar{A}' - A'_i)^2} \right]^{1/2} \quad (10.11)$$

where, $\bar{A}'$ is the sample mean of the A'_i 's and

$$F'_i = \ln(F_i) - \ln(F_{i-1})$$

$$A'_i = \ln(A_i) - \ln(A_{i-1})$$

U2 seems reasonable and is easier to interpret because the U2 = 1.0 benchmark is based on a no-change model. However, U2 does not pick up errors in forecasting levels, but measures only errors in changes. Despite the advantages of U2 over U1, U1 has been more widely advocated. The confusion of U1 and U2 implies that these measures are not well understood. Armstrong [1978] drew the conclusion that there is little need for Theil's U, when other measures can do the job and do it more simply.

Coefficient of Variation (CV)

The coefficient of variation (CV) is calculated from

$$CV = \frac{RMSE}{\sum_{i=1}^n A_i / n} \quad (10.12)$$

The definition of RMSE (Root Mean Square Error) appeared in Equation (10.5). The CV relates the RMSE to the average value of the actual data. This unitless measure is similar to the MAPE, but the MAPE is easier to interpret.

Coefficient of determination (R^2)

The coefficient of determination (R^2) is calculated from

$$R^2 = \frac{\sum_{i=1}^n [(F_i - \bar{F})(A_i - \bar{A})]^2}{[\sum_{i=1}^n (F_i - \bar{F})^2][\sum_{i=1}^n (A_i - \bar{A})^2]} \quad (10.13)$$

where $\bar{A}$ is the average of A_i and $\bar{F}$ is the average of F_i . R^2 is the most popular measure used by researchers in forecasting problems. R^2 is interpreted as the "proportion of variance" explained. An R^2 of zero means that the model is not useful in explaining fluctuations, but it does not reflect its ability to forecast levels; thus, $R^2 = 0$ may not be completely bad forecast. Similarly, an R^2 of 1.0 does not represent a perfectly good forecast.

Sometimes, R_a^2 (the adjusted R^2) is used instead of R^2 . R_a^2 compensates for the loss in degrees of freedom in the model. R_a^2 can be negative [Saha 1986]. For more than one variable, R_a^2 is preferable to R^2 . R^2 has meaning primarily when comparing different models in a given situation. Because of its popularity, the simple correlation coefficient (r) — represented as the square root of R^2 in Equation (10.13) — is used in this study.

Accuracy ratio ($\bar{Q}$)

The accuracy ratio ($\bar{Q}$) is calculated from

$$\bar{Q} = \frac{\sum_{i=1}^n Q_i}{n} \quad (10.14)$$

where

$$Q_i = \begin{cases} A_i/F_i & \text{if } A_i > F_i \\ F_i/A_i & \text{if } F_i > A_i \end{cases}$$

$\bar{Q}$ is similar to the MAPE. One key difference is that it is not bounded on both sides; it can range from 1 to infinity. Therefore, the accuracy ratio is preferable to the $\overline{\text{MAPE}}$ when dealing with large errors. Because of it is simple, easy-to-understand, and free of units, this study has used $\bar{Q}$ as a measure of accuracy.

10.3 Evaluation and Combination

The elasticity models developed in this study (see Tables 6.26-6.28), by their nature, use growth of areawide variables to determine the traffic growth. Because of this, they do not account for localized impacts, such as land use changes, that affect traffic. The various computer-based travel demand forecasting procedures (Section 2.3) also depend on forecasts of socioeconomic variables to forecast traffic. Therefore, no matter which traffic forecasting method is used, results should be interpreted cautiously, and should possibly consider the use of several methods to determine the range of a reasonable forecast.

Although there are other measures of accuracy than those presented in Section 10.2, one can argue that the list of measures presented in the previous section should be enough for most forecast-

ing problems. The typical procedure is to compare the various forecasting models using each of the selected measures [Armstrong 1978]. The selection of a measure of accuracy depends to a great extent on the situation. The MAPE provides a good measure for most situations. R^2 is a popular measure, but with all its problems, using it alone to evaluate a forecasting method may be misleading. It appears, from the discussion in Section 10.2, that many measures could be redundant to each other. In the absence of any universally accepted criteria, this study has considered the following list of measures to evaluate and compare the traffic models developed in this study.

1. Mean Error (ME)
2. Mean Percentage Error (MPE)
3. Mean Absolute Error (MAE)
4. Mean Absolute Percentage Error (MAPE)
5. Correlation Coefficient (r)
6. Root Mean Square Percentage Error (RMSPE)
7. Accuracy Ratio ($\bar{Q}$)

The results of these forecasting measures for Interstate, Urban Principal Arterial and Urban Minor Arterial & Collector are presented in Tables 10.1, 10.2 and 10.3, respectively. The Principal Component Analysis (PCA) based models presented in Chapter 7 have not been evaluated or compared in this chapter because of their complexity. The large number of original variables in PCA based models has not improved the model statistics in PCA based regression models significantly as compared to the model statistics in elasticity models (see

Table 10.1: Forecast Measures from Regression, Elasticity and Lag-AADT Models of Interstate Highways

Region	N	Fore- cast Period	Model (*)	Forecast Measures						
				ME	MPE	MAE	MAPE	r	RMSPE	$\bar{Q}$
Interstate Highways (Rural & Urban)										
North	41	1-15	Regression	-10963	8.15	23859	52.92	0.56882	69.97	1.73
			Elasticity	-1861	-6.33	1978	6.70	0.99915	9.13	1.08
			Lag-AADT	-4214	-10.74	4259	10.95	0.99602	13.81	1.13
			Combined	-3037	-8.54	3094	8.75	0.99846	11.01	1.10
Central	82	2-16	Regression	-4661	3.51	14491	36.64	0.74306	49.91	1.45
			Elasticity	-1107	-4.70	2973	7.65	0.99367	9.52	1.09
			Lag-AADT	-2373	-6.96	3237	8.30	0.99109	10.33	1.10
			Combined	-1740	-5.83	2854	7.41	0.99420	9.08	1.08
South	39	1-12	Regression	-8850	-18.69	10467	35.95	0.84438	41.96	1.62
			Elasticity	-1499	-6.17	1987	8.05	0.99431	9.66	1.09
			Lag-AADT	-585	-4.87	1826	7.98	0.99400	8.77	1.09
			Combined	-1042	-5.52	1446	6.96	0.99640	8.37	1.08
Rural Interstate Highways										
ALL	89	1-16	Regression	15929	65.61	23182	88.69	0.45243	151.05	1.95
			Elasticity	-244	-1.47	1861	9.23	0.98567	12.32	1.11
			Lag-AADT	-1700	-7.57	2200	9.17	0.98305	11.35	1.11
			Combined	-972	-4.50	1518	7.13	0.99090	9.33	1.08
North	18	3-15	Regression	-3020	-3.81	6284	23.72	0.96470	33.79	1.31
			Elasticity	-223	-0.46	2575	11.35	0.94685	13.42	1.12
			Lag-AADT	-2965	-11.35	2965	11.35	0.95196	14.08	1.14
			Combined	-1594	-5.85	2132	8.80	0.96539	10.86	1.10
Central	44	2-16	Regression	-1569	9.78	9909	38.57	0.47785	50.06	1.46
			Elasticity	-904	-3.63	1918	6.88	0.98741	8.39	1.08
			Lag-AADT	-1895	-8.26	2495	9.58	0.98944	11.48	1.11
			Combined	-1400	-5.95	1761	6.95	0.99332	8.73	1.08
South	27	1-12	Regression	-2886	-9.44	4558	27.73	0.74949	32.63	1.40
			Elasticity	-1032	-6.96	1383	8.62	0.97994	10.10	1.10
			Lag-AADT	-987	-5.89	1223	7.43	0.98780	8.52	1.08
			Combined	-1009	-6.42	1240	7.71	0.98512	9.00	1.09

Table 10.1, continued

Region	N	Fore- cast Period	Model (*)	Forecast Measures						
				ME	MPE	MAE	MAPE	r	RMSPE	$\bar{Q}$
Urban Interstate Highways										
ALL	73	1-16	Regression	-15685	-10.78	20959	34.50	0.56628	47.77	1.55
			Elasticity	-549	-1.74	2616	5.04	0.99525	6.42	1.05
			Lag-AADT	-2900	-4.81	4013	7.30	0.99048	9.20	1.08
			Combined	-1725	-3.27	2822	5.26	0.99473	6.57	1.06
North	23	1-13	Regression	-23608	-3.44	33999	57.95	0.52171	73.12	1.89
			Elasticity	-4170	-8.16	4170	8.16	0.99862	10.54	1.10
			Lag-AADT	-5219	-9.59	5313	9.95	0.99513	12.56	1.12
			Combined	-4694	-8.88	4723	9.01	0.99755	11.38	1.11
Central	38	2-16	Regression	-9053	-10.78	12469	19.65	0.84385	23.99	1.26
			Elasticity	-2255	-5.03	2747	5.65	0.99695	7.51	1.06
			Lag-AADT	-2580	-5.41	3880	7.10	0.98930	8.86	1.08
			Combined	-2418	-5.22	3178	6.19	0.99491	7.71	1.07
South	12	1-7	Regression	-9401	-11.99	12160	23.23	0.86034	25.48	1.31
			Elasticity	-243	-0.36	1918	4.78	0.99091	6.71	1.05
			Lag-AADT	1056	0.62	3678	8.15	0.98053	9.98	1.09
			Combined	406	0.14	2323	5.56	0.98949	7.41	1.06

- (*) i. See Tables 6.23, 6.26 and 8.4 for Elasticity, Regression and Lag-AADT models, respectively.
 ii. Combined model forecasts are equal to average forecasts of Elasticity and Lag-AADT models.

Table 10.2: Forecast Measures from Regression, Elasticity and Lag-AADT Models of Urban Principal Arterial

Region	N	Fore- cast Period	Model (*)	Forecast Measures						
				ME	MPE	MAE	MAPE	r	RMSPE	Q
City Group "A"										
North	59	3-15	Regression	-559	11.00	4826	37.72	0.24944	47.62	1.45
			Elasticity	-42	0.19	815	6.11	0.98537	7.59	1.06
			Lag-AADT	-834	-4.53	1231	8.41	0.97840	9.96	1.09
			Combined	-438	-2.20	854	6.05	0.98824	7.14	1.06
Central	55	3-16	Regression	156	20.73	4460	40.50	0.38113	62.29	1.45
			Elasticity	619	5.86	1170	9.23	0.98137	11.00	1.09
			Lag-AADT	-830	-4.58	1054	6.69	0.98427	8.38	1.08
			Combined	-105	0.65	787	5.83	0.98541	7.56	1.06
South	13	7-16	Regression	3271	43.88	3668	46.21	0.00000	71.97	1.46
			Elasticity	1241	11.43	1348	12.30	0.97481	13.64	1.12
			Lag-AADT	-274	0.45	742	8.40	0.97031	11.81	1.09
			Combined	483	5.91	724	7.86	0.97801	9.96	1.08
City Group "B"										
North	31	4-15	Regression	-378	22.21	4963	48.08	0.10432	68.76	1.55
			Elasticity	-391	-1.78	983	7.50	0.98360	8.91	1.08
			Lag-AADT	-672	-4.06	1149	8.09	0.97583	9.85	1.09
			Combined	-531	-2.93	1009	7.23	0.98400	8.29	1.08
Central	19	6-14	Regression	338	17.26	5076	43.94	0.32467	55.68	1.50
			Elasticity	-649	-3.90	817	5.59	0.99223	6.56	1.06
			Lag-AADT	-1374	-8.54	1409	8.96	0.98571	10.73	1.10
			Combined	-1012	-6.27	1074	7.08	0.99176	8.25	1.08
South	4	7	Regression	-2003	-6.40	3409	13.35	0.00000	14.27	1.15
			Elasticity	42	0.36	341	1.53	0.99412	2.09	1.02
			Lag-AADT	-120	-0.12	1330	5.33	0.90356	5.39	1.05
			Combined	-39	0.11	833	3.43	0.96538	3.60	1.03

Table 10.2, continued

Region	N	Fore- cast Period	Model (*)	Forecast Measures						
				ME	MPE	MAE	MAPE	r	RMSPE	$\bar{Q}$
City Group "C"										
North	51	3-17	Regression	86	12.83	2624	27.80	0.62233	45.52	1.30
			Elasticity	310	2.10	963	7.90	0.97384	8.99	1.08
			Lag-AADT	-645	-4.80	1086	9.27	0.95862	11.10	1.10
			Combined	-168	-1.32	800	6.74	0.97155	8.33	1.07
Central	61	3-14	Regression	-123	14.04	3582	33.97	0.67284	47.46	1.38
			Elasticity	50	0.10	1053	8.41	0.98054	9.89	1.09
			Lag-AADT	-1145	-7.63	1342	9.43	0.97315	11.54	1.11
			Combined	-547	-3.73	939	7.11	0.98205	9.06	1.08
South	8	3-17	Regression	-3624	-12.81	5009	34.68	0.00000	40.32	1.60
			Elasticity	-220	-0.08	870	6.68	0.98437	8.15	1.07
			Lag-AADT	-220	-0.55	1021	6.67	0.96953	8.08	1.07
			Combined	-220	-0.31	848	5.53	0.97914	7.38	1.06
City Group "D"										
North	20	4-14	Regression	-1044	5.65	3209	37.74	0.31932	54.61	1.44
			Elasticity	-1455	-13.98	1455	13.98	0.95211	16.91	1.18
			Lag-AADT	-679	-0.21	1861	20.97	0.76915	34.31	1.23
			Combined	-1067	-7.10	1472	14.33	0.92081	17.99	1.17
Central	20	4-16	Regression	742	19.36	2216	32.92	0.12065	51.71	1.35
			Elasticity	191	2.80	750	9.01	0.93910	10.62	1.09
			Lag-AADT	-373	-2.96	665	7.03	0.95824	8.37	1.08
			Combined	-91	-0.08	510	5.78	0.95593	7.56	1.06
South	38	4-12	Regression	-292	8.94	3138	30.05	-0.01143	38.59	1.35
			Elasticity	-623	-4.86	932	8.13	0.97483	9.60	1.09
			Lag-AADT	-1421	-11.29	1421	11.29	0.96646	13.57	1.14
			Combined	-1022	-8.07	1091	8.80	0.97719	10.57	1.10

- (*) i. See Tables 6.24, 6.27 and 8.5 for Elasticity, Regression and Lag-AADT models, respectively.
 ii. Combined model forecasts are equal to average forecasts of Elasticity and Lag-AADT models.

Table 10.3: Forecast Measures from Regression, Elasticity and Lag-AADT Models of Urban Minor Arterial & Collector

City Group	N	Fore-cast Period	Model (*)	Forecast Measures						
				ME	MPE	MAE	MAPE	r	RMSPE	$\bar{Q}$
A	12	3-16	Regression	-468	6.92	3203	29.12	0.37517	39.70	1.34
			Elasticity	2092	15.00	2675	20.20	0.93524	24.81	1.20
			Lag-AADT	125	1.49	1286	11.47	0.93675	14.46	1.12
			Combined	1109	8.25	1458	11.15	0.96852	14.01	1.11
B	14	3-14	Regression	823	85.72	3508	109.01	0.56514	170.24	2.14
			Elasticity	180	15.79	1315	25.66	0.93452	33.85	1.27
			Lag-AADT	-564	-5.25	632	7.44	0.97563	11.14	1.09
			Combined	-192	5.27	886	14.91	0.96471	18.95	1.16
C	18	3-17	Regression	-1121	7.17	3107	40.85	0.28198	58.44	1.51
			Elasticity	-310	-1.87	755	9.44	0.96558	15.40	1.10
			Lag-AADT	-282	-1.53	759	9.35	0.96519	15.23	1.10
			Combined	-296	-1.70	754	9.34	0.96556	15.30	1.10
D	33	3-16	Regression	-4167	-16.11	5283	65.20	0.00932	75.73	2.66
			Elasticity	830	9.58	1013	12.21	0.98426	15.22	1.13
			Lag-AADT	-536	-5.58	714	8.77	0.98688	10.84	1.10
			Combined	147	1.92	545	6.99	0.98949	9.04	1.07

- (*) 1. See Tables 6.25, 6.28 and 8.6 for Elasticity, Regression and Lag-AADT models, respectively.
 ii. Combined model forecasts are equal to average forecasts of Elasticity and Lag-AADT models.

Chapter 6). The second and third columns of Tables 10.1-10.3 show the number of forecasts and the range of the forecast period — the time difference between the year of forecast and the base period (if any). Base period information (as required) has been used by all models except the regression model. For elasticity and lag-AADT models, each forecast has been made for a roadway segment at its last year of traffic data with an earlier year AADT for that segment as its base year AADT. Also, the base and forecast years (and hence the forecast period) for a forecast are kept same for all the models. Different forecast periods have resulted for the following reasons:

- a. The traffic volume data are not available at an equal spacing over time.
- b. Different forecast periods allow testing the model performance over a short term (say, < 5 years), medium term (say, 5-15 years), and long term (say, > 15 years).

With enough forecasts for each case, a separate analysis at different forecast ranges could be done to see the model's performance over the short, medium and long term separately. However, for comparing different forecasting models, using a wide range of forecast periods is not expected to change the conclusions, as long as the same base and future years are used among the competing models.

The forecast measures MAE, MAPE, RMSPE and $\bar{Q}$ have been primarily used in this study for model evaluation and comparison. In addition, the error function of each of these measures is different. By comparing all these measures in Tables 10.1 to 10.3, one can see that the

regression model does not provide good forecasts. The elasticity model (the variant of the regression model) and the lag-AADT model are clearly superior to the regression model because of the significant improvement seen in

1. low values of MAE, MAPE and RMSPE,
2. high values of r , and
3. accuracy ratio ($\bar{Q}$) of close to unity.

The ranges of forecast measures for models in the three major highway categories are shown in Table 10.4. This summary table also shows the clear margin of improvement in the elasticity and the lag-AADT models over the regression model. The main reason for this improvement is that the elasticity and lag-AADT models recognize the impacts of non-resident travel in the form of base year and lag year AADT. Based on performance, this study does not recommend the use of regression models to forecast traffic.

The results of ME, MPE and r show that they are either ineffective or redundant to other measures. The use of ME and MPE can be misleading. For example, the following results show that, although the regression models are as good as the other models based on ME or MPE, the other measures (MAE, MAPE, RMSPE and $\bar{Q}$) show that the regression models are much inferior to the other models.

- i. MPE for the north and central regions of Interstate Highways, and for the north region of both rural and urban interstate highways.
(See Table 10.1)
- ii. ME for the central region of city groups "A" and "B", the north

Table 10.4: Ranges of Forecast Measures of Models for Major Highway Categories

Highway Category	Models	MAE		MAPE		RMSPE		$\bar{Q}$	
		Lower	Upper	Lower	Upper	Lower	Upper	Lower	Upper
Inter-state Highways	Regression	4558	33999	19.65	88.69	23.99	151.05	1.26	1.95
	Elasticity	1383	4170	4.78	11.35	6.42	13.42	1.05	1.12
	Lag-AADT	1223	5313	7.10	11.35	8.52	14.08	1.08	1.14
	Combined	1240	4713	5.26	9.01	6.57	11.38	1.06	1.11
Urban Principal Arterial	Regression	2216	5076	13.35	48.08	14.27	71.97	1.15	1.60
	Elasticity	341	1455	1.53	13.98	2.09	16.91	1.02	1.18
	Lag-AADT	665	1861	5.33	20.97	5.39	34.31	1.05	1.23
	Combined	510	1472	3.43	14.33	3.60	17.99	1.03	1.17
Urban Minor Art. & Collector	Regression	3107	5283	29.12	109.01	39.70	170.24	1.34	2.66
	Elasticity	755	2675	9.44	25.66	15.21	33.85	1.10	1.27
	Lag-AADT	632	1286	7.44	11.47	10.84	15.23	1.09	1.12
	Combined	545	1458	6.99	14.91	9.04	18.95	1.07	1.16

Note: Lower = Lower value of the forecast measure, and
Upper = Upper value of the forecast measure.

- and central regions of city group "C", and the south region of city group "D" of urban principal arterial. (See Table 10.2)
- iii. MPE for north region of city group "D" of urban principal arterial. (See Table 10.2)
- iv. ME and MPE of city group "A" of urban minor arterial & collector. (See Table 10.3)

Although the correlation coefficient (r) is redundant to other measures (MAE, MAPE, RMSPE and $\bar{Q}$), the values of r show a very high degree of correlation between the predicted and observed AADT for both elasticity and lag-AADT models. The inferiority of regression models is also reflected in the low values of r for most of the cases of Tables 10.1 to 10.3.

By comparing the values of MAE, MAPE, RMSPE, and $\bar{Q}$ from Tables 10.1-10.3 and their ranges in Table 10.4, one can see that both elasticity and lag-AADT models have forecasted traffic equally well. Recall that the lag-AADT model was built by using the traffic data only, while the elasticity model was built based on regression analysis using economic and demographic variables and AADT in the model formulation. The MAE measures in Tables 10.1-10.3 show the expected value of error in absolute terms. Table 10.4 has shown the ranges of these values. Although some high values of MAE are noted for Interstate highways, the percentage error in absolute values (MAPE) are in most of those cases less than 10 percent. On the other hand, despite the high value of MAPE for some cases of noninterstate highways, a low value of MAE has resulted from forecasts. The RMSPE,

which uses square of the error in the cost function, shows that the values of RMSPE are usually below 10 percent, but some high values are noticed in noninterstate cases with low traffic volumes. The accuracy ratio ($\bar{Q}$) in Tables 10.1-10.4 shows that expected values of prediction are usually within 10 percent of the observed AADT values.

"One can never lose by combining the forecasts". This statement has first mentioned in Section 9.2.4. Based on the comparable performance of elasticity and lag-AADT models, this study has combined the forecasts from these constituent models by applying equal weights to each. The following cases show an improvement in forecast measures (MAE, MAPE, RMSPE and $\bar{Q}$) for combined forecasts versus any of their constituent models' forecasts:

A. Interstate Highways (See Table 10.1):

- Central and south regional model of Interstate highways.
- North and statewide (the "ALL" case) of rural Interstate highways.

B. Noninterstate Highways (See Tables 10.2 & 10.3):

- Central and south regional model for city group "A" of urban principal arterial.
- North, central and south regional model for city group "C" of urban principal arterial.
- Central region of city group "D" of urban principal arterial.

- City group "D" model of urban minor arterial & collector.

The above list indicates a clear margin of improvement in all four forecast measures for 11 out of 27 models in the three highway categories. Moreover, an improvement in some of the forecast measures was noticed in the following cases:

- MAE and $\bar{Q}$ for the central region and MAE of the south region of rural interstate (See Table 10.1).
- MAPE, RMSPE and $\bar{Q}$ for the north region of city groups "A" and "B" of urban principal arterial (See Table 10.2).

For the rest of the cases, the performance measures of combined forecasts are between the performance measures of the constituent models. In other words, the combined forecasts can never be worse than the worst forecast of the constituent models. In fact the combined forecast often better than the forecast of any of the constituent models. Based on the study results in this section, the combined forecasts that resulted from a simple average of the elasticity and lag-AADT model forecasts are highly recommended to be used to forecast traffic on state highways.

10.4 Calibration and Tracking Signal

In most forecasting systems, it is important to monitor the forecast errors to ensure that the system remains valid. The accuracy of a forecasting method is determined by analyzing forecasting errors experienced. A combination of forecast models may have been used to generate forecasts. The accuracy of the forecasts is measured at

every period, when the actual data are available, by a tracking signal test. For unbiased forecasts, the tracking signal will lie within certain limits with a preset probability; otherwise (for biased forecasts), the signal will fall outside the limits. If the forecasting system yields unbiased estimates, the tracking signal should be within the preset limit. When the tracking signal deviates from the limit by more than a prescribed amount, an investigation is made to determine if the forecasting model should be modified by recalibrating the model(s).

The first tracking signal used in forecasting was the simple cumulative sum (cumsum) of the errors [Thomopoulos 1980]. The simple cumsum is defined by the ratio of the sum of errors at the end of each period to the mean absolute deviation (MAD) of the errors. The ratio should fluctuate around zero if the errors are unbiased. Users should take note if the ratio exceeds a control limit. Control limits for tracking signal test can be set according to the probability of getting a false report, defined as a Type I error — a case where the control limit is exceeded due to chance.

This study has used the confidence interval of four forecast measures (MAE, MAPE, RMSPE, and $\bar{Q}$) from Section 10.4 to install a tracking signal test and thus determine the need for changes in the forecasting model(s) and/or parameter(s). The description follows. The standard deviation of the errors, measured from the performance analysis of the individual forecast methods and the combined forecast method has been used to determine the 90- and 95-percent probability limits of the errors. The use of 90-percent probability limits

accepts a risk of error of 10 percent (i.e., 10 out of 100 forecast results may lie outside the boundary set by a 90-percent limit). Confidence limits of 90-percent and 95-percent have been proposed because different users may be willing to accept different risks of error. Even the same user can take different risks for different cases, for example, a lower level of risk for a higher level of highway. Also, the risk taking behavior may change with time for an individual. However, the 5 percent and 10 percent risks of error (or 95-percent and 90-percent) are believed to be the most common level of risk that a user will choose, and are commonly used in statistical control. However, if the errors of the combined forecasts were found exceed the 90- or 95-percent limit, errors of the individual forecasts will be checked to determine whether the component models need to be modified.

Appendix Tables G1-G6 present the 90-percent and 95-percent confidence limits of the four forecast measures (MAE, MAPE, RMSPE and $\bar{Q}$) for the combined and constituent models of all groups of highways. The following list shows the description of all those tables of confidence limits for the forecast measures.

1. Table G1: 90-percent confidence limits for models of Interstate Highways.
2. Table G2: 95-percent confidence limits for models of Interstate Highways.
3. Table G3: 90-percent confidence limits for models of Urban Principal Arterial.
4. Table G4: 95-percent confidence limits for models of Urban Principal Arterial.
5. Table G5: 90-percent confidence limits for models of Urban Minor Arterial & Collector.
6. Table G6: 95-percent confidence limits for models of Urban Minor Arterial & Collector.

The minimum possible value of $\bar{Q}$ is 1.0. For MAE, MAPE and RMSPE, it is zero. The lower limits (L90 or L95) in Tables G1-G6 are not controlling factor, but the upper limits (U90 or U95) will be used as control points for the monitoring procedure or tracking signal. It may possible that one or two of the forecast measures may exceed the control limit for a forecast made from a model, while the others are not. In that case, the user or modeler needs to apply his (her) judgment to decide whether that particular forecast will be counted to see if the the risk level has exceeded. But, if 3 out of 4 forecast measures exceed the control limit, then it is probably necessary to change or to calibrate the involved model, if the user risk level is also exceeded. For example, with a 10 percent level of risk, if at least three forecast measures exceed their control limits in more than 10 percent of the forecasts, then it has to taken as a signal to change or calibrate the models. This test should be applied primarily to the combined forecasts. When a necessity to calibrate or to change the combined forecast appears, the proposed tracking signal test will be applied to the errors of the component models to see whether one or both component models need to be fixed.

10.5 Chapter Summary

The performances of all the traffic forecasting models developed in earlier chapters, except the PCR models, have been tested in this chapter. Because no criteria are universally accepted, several performance measuring criteria have been checked. Comparison of these criteria among the models has concluded that the forecasts from the

regression model are consistently inferior to the forecasts of the elasticity model (the variant of regression model) and the lag-AADT model. On the other hand, both elasticity and the lag-AADT models have showed almost equal performance. Combined forecasts — the simple average of the elasticity and lag-AADT model forecasts — usually have demonstrated better performance than any of the constituent models. Thus, combined forecasts are highly recommended to forecast traffic on the state highway system. Finally, a procedure is suggested to monitor the forecasts and to see if there is a need to change or to recalibrate the models or their parameters based on model performance measures and the user's (or modelers) willingness to accept a certain level of risk.

CHAPTER 11

SUMMARY AND CONCLUSIONS

11.1 Introduction

The primary purpose of this research was to develop a procedure to forecast traffic volumes on urban segments of the state and interstate highway systems for the Indiana Department of Transportation. In this study, a detailed statistical analysis was conducted to develop alternative models to forecast traffic. The models and the procedures described in this study are intended to provide highway planners with a tool for simple, fast and inexpensive estimation of traffic projections. Emphasis was also placed on achieving reliable input information for the forecasts of any background factors (independent variables) used in the models. This study improves on previous efforts to build simple and reliable procedures to forecast traffic. Among the several models developed in this study, elasticity and lag-AADT models are finally selected because of their simplicity and better performance. Accurate forecasts of the input variables are ensured for the success of the elasticity models. In the absence of any universally-accepted forecasting measuring criteria, this study has employed several measures to evaluate the forecasting models.

Often, the combined forecasts developed in this study were found to perform better than the forecasts from any of the constituent models. This chapter summarizes the study's analysis and conclusions. Some problems and limitations of the models -- and suggestions to overcome them -- are discussed. This chapter also presents guidelines on how to implement the models and makes recommendations for further studies.

11.2 Summary of Findings

The analyses conducted in this study were performed with traffic data gathered from the paper files of INDOT. Other input data were obtained from a variety of sources, for example, the libraries at Purdue, Census Publications, IU Business Center, and W&P Economics. The nationwide survey on "Forecasting Traffic on State Highways" (ITE Technical Council Committee 6F-41, informational report) showed the lack of any universally accepted method to address the issue of traffic forecasts in small- to medium-sized urban areas. This study has developed an efficient, inexpensive and easy-to-use method to forecast the traffic on state highways. The greatest strength of this study is the application and description of different statistics, ranging from simple to sophisticated. This report contains a full description of the entire model building process. The major findings of the research are summarized in the following sections.

11.2.1 Data Evaluation and Candidate Elasticity Model

The variables and the data bases used in this study have been described in Chapter 4. Table 4.7 contains a summary of the quality (cost, availability and reliability) of the variables. The details of the analyses and their results for the evaluation of data and for selection of the candidate regression/elasticity models are presented in Chapter 5. The framework of the analyses for interstate and noninterstate highways are presented in Figures 5.1 and 5.2, respectively. Several variable selection criteria (R_p^2 , R_a^2 , C_p , PC, AIC) have been employed to select the most appropriate model. Despite the merits and demerits of using the R^2 (R_p^2) criterion, it has been adopted by the researchers as the single most useful criterion to gauge the "goodness" of a statistical model. However, analyses in this research were aided by other statistics. The data structure of this study includes the two data bases (segment and county/city average) and the four formats (raw, raw E&L, density, and density E&L). A sensitivity analysis of the "maximum" R^2 value among the competing models that are without any inconsistency in the sign of regression coefficients identifies the combination of county/city average data base and raw format as the best combination from all possible combination of the data structure. A significant improvement in model statistics was found in county/city average data bases over segment data bases. Because all the predictor variables used in this study are totals at either the city, county, or state level, it was not surprising to have traffic data on a county/city average basis perform better than traffic data on a more localized basis.

A similar sensitivity analysis among the data groups revealed the following:

- For Interstate Highways: (1) For separate analysis of rural and urban interstate highways, both statewide and regional (north, central and south regions) models are found to be suitable. (2) A statewide model for the entire interstate network in Indiana was not satisfactory. (3) The improvement of the model statistics is better in case of analysis by geographical region than by the extent of roadway mileage and city group.
- For Urban Principal Arterial: (1) The combination of city group and geographic region performs better than any other possible combination. This second-level stratification by geographical region under each city group has been established as superior to grouping by city group alone. (2) Results improved when the data of city groups A, B and C in the south region were pooled. The alternate was having unstable results with too few observations in each city group.
- For Minor Arterial & Collector: The second-level stratification by geographic region and extent of highway mileage resulted in poor results and groups with too few observations. However, the analysis at this level of stratification identified areas of weakness in the data. After pooling data by city group, the quality of model statistics improved.

The candidate models resulted from narrowing down a list of possible candidate models by comparing the model statistics (R^2 , R_a^2 , PC, RMSE,

AIC and C_p) and by applying judgment on the quality (availability, cost and reliability) of the data for the predictor variables in the model. The list of those candidate models are shown in Chapter 5.

11.2.2 Elasticity Based Traffic Model

The final regression equations and the elasticity models developed in this study were shown in Chapter 6. The influential analysis identified the individual outliers and the outlier groups and their effect on model statistics. The diagnostic statistics employed to do influential analysis were shown in Section 6.2.1. Modification of the data (if necessary) or deletion of outliers (if justified) was found to improve the quality of model statistics significantly. For example, it improved the statistics for the normality assumption of errors. Validity of the regression assumptions (linearity, constant variance, and normality of errors) were checked through formal tests and graphical plots — residual and normal probability plots. Results of significance tests showed that the model parameters are highly significant. A significance of relation also resulted for all the models. The collinearity test found that no significant relationship existed between the variables of each model. The final regression equations of each group, shown in Tables 6.23–6.25, were produced by comparing the results of the above tests and some model statistics (R^2 , R_a^2 , RMSE, and CV) of the candidate models, and by applying judgment regarding the quality of predictor variables. The R^2 values for the regression models of interstate highways, urban principal arterial, and urban minor arterial & collector have ranges 50.35–

88.86, 51.81-94.14 and 62.52-87.18 percent, respectively, with one or two variables in each equation. Each of these models is simple and does not contain more than two predictor variables. The elasticity models developed from the regression models are shown in Tables 6.26-6.28. These models are statistically sound and simple. They require the base year traffic data and base and future year data for the predictor variable(s).

11.2.3 Principal Component Based Traffic Model

The procedure and results for Principal Component Analysis (PCA) were shown in Chapter 7. The PCA was carried out for each group of filtered data which resulted from the influential analysis of Chapter 6. The PCA used 11 predictor variables, but had eliminated the problem of multicollinearity by computing the artificial variables (principal components) which are independent to each other. Some key results of the Principal Component Regression (PSR) model with PCs in the equation are shown in Tables 7.2-7.4. Appendix Tables D1-D3 show the relationship between the PCs entered in the equation and the original variables. The PCR equations for interstate highways, urban principal arterial and urban minor arterial & collector are shown in Tables 7.5, 7.6 and 7.7, respectively. These tables show a one-to-one comparison of R^2 values between the PCR models and the regression or elasticity models from Chapter 6. The R^2 values for the PCR models had ranges 61.46-90.26, 52.87-97.57 and 66.87-89.31 percent for the three major highway categories in this study. The R^2 ranges for the regression/elasticity models are 50.35-88.86, 51.81-94.14 and 62.52-

87.18 percent. This range comparison, plus one-to-one comparisons for each model shown in Tables 7.5-7.7, do not show any significant improvement from the complex PCR model over the simple regression or elasticity model developed in Chapter 6. However, the complex PCR models, which need all variables to compute PCs in the model equation, certified the goodness of the model statistics for the regression or elasticity models that have fewer variables in their equations.

11.2.4 Lagged Traffic (Lag-AADT) Model

The information of traffic data itself and the rate at which traffic had changed were used to develop the inexpensive and simple lagged traffic model. The segment data base of Chapter 4 with a "raw" format (see Chapter 5) was used to build this model. Although Equation (8.2) had used "rate of AADT change", in its rearranged form, Equation (8.3) needs only one AADT value to forecast traffic on a highway segment. Because the data bases used to build lag-AADT models are different from those used in Chapters 6 and 7, the model statistics of the lag models are not directly compared to the other models. However, the traffic forecasting performance of the lag-AADT models were compared with the others in Chapter 10. The lag traffic models for interstate, urban principal arterial and urban minor arterial and collector were presented in Tables 8.1, 8.2 and 8.3, respectively. These tables show, as expected, a very high R^2 values (about 99 percent). The parameters of the models and the regression relationships were found highly significant at very low α levels. The nonnormality of the error terms were because of the presence of

outliers. The forecasting performance of these models was tested by skipping the last year of AADT values from each segment, reformulating the models, and comparing the resulting forecasts against the skipped values. Very high forecasting quality performance measures and model statistics were found for the models (shown in Appendix E) built with partial data.

11.2.5 Time Series and Ratio Method Forecasts

No forecasts of vehicle registrations and city population are available from outside sources. The structure and results of procedures developed to make these forecasts are shown in Chapter 9 and Appendix F. A ratio method of forecasting city population was described in Section 9.3.1. Its forecasts for the cities of Indiana were shown in Appendix F. Forecasts of vehicle registration were made through two time series analysis techniques — the Box-Jenkins ARIMA model and the autoregressive procedure. Parameters of the models were found to be significant at 5 percent level of significance. Both autoregressive and ARIMA procedures produce high quality forecasts in this study. Use of these two different types of models also increased confidence in the forecasts. A combined forecast of vehicle registrations was made by simple averaging of the forecasts from the Box-Jenkins and the autoregressive procedures. The forecast measures of the combined forecasts and the forecasts from the constituent models for the two selected counties were shown in Table 9.7. The values of the performance criteria verified the reliability of the vehicle registration forecasts.

11.2.6 Traffic Model Evaluation

Level of accuracy is a primary concern for the users of traffic forecasts. Inaccurate forecasts can lead to under or over-designed facilities. To determine the tolerable errors in forecast, one needs to know how much error a traffic forecast can have without causing major design changes. However, boundary cases must be examined more carefully. In that case, it will be wise to develop forecasts from several methods to arrive at a "consensus range" of the traffic estimate.

Usually, the error in various travel forecasting methods can be estimated by testing the methods against the actual counts and comparing the results. An extensive study has determined that errors from mainframe traffic simulation are about 10 percent [Trombly & Ouderkirk 1986].

This study used several forecasting measuring criteria (Section 10.2) to evaluate the performance of the traffic models. The results, shown in Tables 10.1-10.3, show that the mean absolute percentage errors, defined in Section 10.2, are usually less than 10 percent. Regression models developed in Chapter 6 were found to be ineffective in forecasting project site traffic. Despite the difference in model statistics and procedures, both elasticity and lag-AADT models were found to be highly efficient models for forecasting traffic. They were found to work equally well. The combined forecasts, formed by simple averaging of the forecasts from the elasticity and lag-AADT models, did better than either the constituent model in many cases.

Combined forecasts are recommended to forecast traffic on the state highway segments. Forecasts from several models provides the opportunity to assess the sensitivity of the forecasts to different model forms. Finally, a procedure, shown in Section 10.4, was developed to monitor the forecasts and to see if there will be any need in the future to recalibrate the models and their parameters.

11.3 Implementation Guidelines

One purpose of this research was to prepare guidelines for the use of the models developed in this study. The work elements undertaken to accomplish that purpose included review of the related literature, preparation of the data bases, testing different data bases and their formats and stratification, analysis and development of different types of traffic models, forecasts of input variables for which no outside source is available, evaluation of different models, and development of a monitoring procedure to determine the need for model recalibration. Figures 11.1, 11.2 and 11.3 present the process for implementation of the models to forecast traffic on interstate highways, urban principal arterial, and urban minor arterial & collector, respectively.

The steps that are recommended for the implementation of the elasticity and lag-AADT models to predict the future traffic for urban segment of the state highways and interstate highways of Indiana are listed below.

1. Find the exact location (i.e., city & county) of the roadway for

Figure 11.1: Process for Implementation of the Model on Interstate Highways

Figure 11.2: Process for Implementation of the Model on Urban Principal Arterial

Figure 11.3: Process for Implementation of the Model on Urban Minor Arterial & Collector

which the forecast is needed.

2. Select the traffic models that will be used to predict traffic.

a. Determine the functional class of roadway.

This will determine which models are applicable to the project site. To determine the functional class, the functional classification system map — prepared by Program Development Division of INDOT — and the road inventory file of INDOT, will be the two best guides. Moreover, the definitions provided in Table 4.1 of this study would be helpful to find the appropriate highway class. The project site will be classified into one of the four categories of highways provided listed Table 4.1. If the classification is not clear-cut, then personal judgment should be used, and documentation provided.

b. Examine the area type.

Check if the project site is rural or urban in nature. If the project site is in a rural area for noninterstate highways, then the models developed in the rural phase of this study (Fricker & Saha, 1987) will be applicable to that site. Otherwise, the procedures described in this section will be applied. Suburban segments can be identified as urban segments, because data from suburban segments were included with urban segments in the model building process.

c. Find the geographical region.

Consult Figure 4.2 of this dissertation to determine the geographical region (north, central and south) of the project site. This finding will be used to select the appropriate model for urban principal arterial models and the regional model of interstate highways.

d. Determine the city group.

Find the city group (A, B, C or D) based on the size of the city population. Section 4.6.1 of this study introduced the city group based on 1980 city population. In using the forecasting models, population in the base year can be used to determine the city group. If the population is not known, a population estimate from the closest census year population to the base year either by ratio method in Section 9.3.1 or by linear interpolation or extrapolation from city population forecasts in Table F9. The city group information will be used to select models for noninterstate urban highways.

e. Select appropriate models.

The information from steps 2a to 2d are used to find the appropriate model(s). Steps 2a and 2b are used to determine highway class and its area type.

1. Interstate Highways: Find the appropriate elasticity models from Table 6.26, by using the the information

obtained on area type (step 2b) and geographical region (2c). For each project site, three alternative models — regional interstate model, statewide rural or urban interstate model, and regional rural or urban interstate model — will be identified in this table. Figure 11.1 shows those appropriate models for each case. For instance, if the project site is identified as being in the northern region and in a rural area, then the models A1, B and C1 from Table 6.26 will be the selected for that project site. Similarly, three alternative lag-AADT models will be selected from Table 8.4.

- ii. Urban Principal Arterial: The information on geographical region (step 2c) and on city group (step 2d) of the project site will be used to find the appropriate elasticity model from Table 6.27. Similarly, the lag-AADT will be used identified from Table 8.5.
- iii. Urban Minor Arterial & Collector: The city group (step 2d) is the only basis for selecting the appropriate model for this highway category, if the area type (step 2b) and the functional class (step 2a) had identified the project site as "Urban Minor Arterial & Collector". The appropriate elasticity and lag-AADT models will be identified from Tables 6.28 and 8.6, respectively.

3. Collect the base year AADT ($AADT_b$) and the lag year AADT ($LAADT$).

The base or lag year may be different from the present/current year, but it is the year for which most recent data needed by the are available. $AADT_b$ (required by the elasticity model) or LAADT (required by the lag-AADT model) for a project site can be one value for a small project (e.g., intersections) or a series of estimates for roadway sections for a larger project (e.g., lane widening). The primary source of data is the Highway Department's Traffic Volume Book. If this source fails to provide such information, then it could be determined from short-term counts at the project site, using the procedures described in section 2.7.

4. Collect the base and future year data for the predictor variables used in the elasticity models.

The description of the predictor variables in Section 4.6.3 is a guide to the sources of the required predictor variables. Except vehicle registration and city population forecasts, the forecasts of the predictor variables used in the models are available from outside sources. The combined vehicle registration forecasts developed by time series analysis and presented in Appendix Table F7 will serve as future year values for vehicle registration at the county and state level. The ratio method of making city population forecasts presented in Appendix Table F9 can be used as required by any model. The lag-AADT models need only the estimate of city population in the base year (if required) to select the appropriate model for noninterstate high-

ways. They do not need any other information for the predictor variables, to forecast traffic.

5. Estimate the future year AADT.

- a. Calculate the future year AADT by using the appropriate elasticity model(s) (Tables 6.26-6.28), as determined in step 2e, with the values found in steps 3 and 4. Denote the future ("f"-year) AADT estimate from the elasticity (E) model as $AADT_f^E$. For each interstate highway segment, the average forecasts from the three alternative models will be designated as $AADT_f^E$. Only one forecast will be computed for each noninterstate highway segment.
- b. Calculate the future year AADT by using appropriate lag-AADT model(s) (Tables 8.4-8.6), as determined in step 2e with the values found in steps 3 and 4. Denote the AADT estimate from the lag-AADT (or "L") model as $AADT_f^L$.
- c. Find the average of the two AADT estimates found in steps 5a and 5b.

$$AADT_f = \left[AADT_f^E + AADT_f^L \right] * 0.5 \quad (11.1)$$

where,

$AADT_f$ = Future year AADT estimate,

$AADT_f^E$ = Future year AADT estimate by Elasticity model(s),

$AADT_f^L$ = Future year AADT estimate by Lag-AADT model(s).

The AADT forecast ($AADT_f$) from Equation (11.1) will be used as the "future year AADT" for the project site. The user may give different weight to the AADT found in step 5a or step 5b, based on model performance. The Equation (11.1) would then be modified to be

$$AADT_f^w = w * AADT_f^E + (1 - w) * AADT_f^L \quad (11.2)$$

where,

$AADT_f^w$ = Weighted AADT estimate,

w = Weight given to AADT estimate from

Elasticity model, $0 < w < 1.00$,

other terms are as defined in Equation (11.1).

In the future, the performance of the models can be used to determine the weight "w" in Equation (11.2). But, based on comparable values of the forecasting measuring criteria (MAE, MAPE, RMSPE and $\bar{Q}$) for the elasticity and lag-AADT models, and improved performance of the combined forecasts, a simple average, shown in Equation (11.1), is recommended at present.

6. Adjust the estimated future year AADT.

If necessary, the forecast from step 5 can be adjusted by using information on changes in fuel price, fuel supply (energy crisis), fleet fuel efficiency (miles per gallon), household

size, inflation rate, etc., which have not been included in model formulation because of insufficient information and future uncertainty about those factors. Empirical results [see Chapter 9 of Trombly & Ouderkirk 1986] can be useful in incorporating such adjustments, if the users have a "feel" for any of these factors. This step is completely optional and it is left to the user to decide whether to modify the forecast values obtained in step 5. Because of its optional nature, this step was not shown in the process for implementation in Figures 11.1 to 11.3.

11.4 Problems, Limitations and Suggestions

The results from this research should be generalized very cautiously outside the bounds of the data and analysis methods described in this report. An important limitation is that the traffic data are from Indiana highways and streets.

A few problems may appear as soon as users begin to use the models to predict traffic. The most serious problem is one that is common to all forecasting processes: the accuracy of the model is determined to a large extent by the accuracy of the input, especially the future values of the predictor variables, as required by the elasticity models. However, this study has focussed on obtaining reliable data as much as possible, either from outside sources or by developing its own forecast of the input variables.

Applicability of the models to some locations may also cause problems. How can a user decide whether the project area, for which

future forecast of traffic is needed, is "rural" enough for the model(s)? It is difficult to provide guidelines to assist in this issue, but suggestions [TRB/Special Report 209 1985] exist. Judgment is required in making this determination. In approximate terms, highways with more than 10 uncontrolled access points per mile (on one side) would be considered to be "suburban". Also, any highway on which left or right turns cause appreciable delay to through vehicles would also be classified as "suburban". Multilane suburban highways and rural roads differ from suburban arterials in the following features: (1) their roadside development is not as intense, (2) the density of traffic access points is not as high, and (3) signalized intersections are more than 2 miles apart. In fact, highways with signal spacing of 2 miles or more could be treated as "rural" highways. Increased use of the developed models will lessen this problem. In the meantime, and in the spirit of this study, it may be wise in such borderline cases generate both a rural and an urban forecast.

The elasticity model formulation in Chapter 3 assumes that elasticities are constant over time. A similar linear assumption has been made in the formulation of the lag-AADT model. Historically, travel has been growing at a fairly constant rate for many years. Although fuel shortages interrupted this rate of increase for a while, it has resumed. Therefore, any assumption of constant elasticities would not introduce substantial errors. On the other hand, variable elasticities are not very common in traffic forecasting. They involve more sophisticated and expensive analysis [Kanafani 1983]. This sophistication and expense are against this study's philosophy that the models

should be easy to understand and inexpensive to use. Elasticities could be recalculated periodically as new information become available, and the appropriateness of earlier values could be checked. If the elasticities seem to change significantly (for example, more than 10 percent), then the new set of elasticities should be used in the model. A similar check could be made on the coefficients of the lag-AADT models.

Users are expected to weigh the results of the forecasting models in terms of the local situation, and adjust them according to their professional judgment.

11.5 Future Research Direction

The methodologies presented in this report were based on and tested against coverage station traffic counts. The aggregate and disaggregate traffic forecasting models for rural roads of Indiana were developed using only the elasticity method, by using the traffic data from continuous count stations [Fricker & Saha 1987]. Continuous count stations are the only locations where "true" historic AADT counts are available. Because of the few useful data points from continuous stations data, this study was carried out using traffic data from coverage count stations. The success of this study can be attributed to the determination of data format, data bases and their stratification scheme, and the filtering of traffic data through influential diagnostics. However, further traffic forecasting studies will be helped by the availability of more traffic data, because of the installation of more continuous count stations at locations

representing a variety of highway categories and traffic characteristics. It is expected that traffic data from the increased number of continuous count stations and from the coverage count stations will provide better statistical results and model performance by using the methodologies of this study.

The data bases and models developed in this study can be updated as new counts become available. Efforts to convert the raw information electronically (automatically) to the form needed by the data base of this study are needed to reduce the bulk of amount of time spent preparing data manually.

Another useful extension of this study would be the use of the methodologies in the rural area by using the traffic count from coverage count stations as well as from continuous count stations and providing more weight on data from continuous stations. The earlier rural study [Fricker & Saha 1987], which was based on only continuous stations at rural area, suffered from inadequate traffic data. The preliminary analysis, presented in Chapter 5 and early parts of Chapter 6 of this report regarding data format, data bases and their stratification scheme and data filtering, were impossible with the scanty rural data base. The time constraints of that study did not allow a test of alternative models (for example, lag-AADT, PSR) and the exhaustive performance evaluation that was done in this study. Similarly, this study's methodologies can be tested on the local roads as well as on the noninterstate highways of urban areas with populations more than 50,000. And, if possible, the results from such a study could be compared to the results of any sophisticated 4-step

sequential modeling process.

An area that needs special attention is the development of the formal procedure to incorporate the factors which can not be addressed in the model formulation, either because of incompatibility in the model formulation or the lack of enough data. A few of these factors were mentioned in the last (optional) step of the implementation guidelines in Section 11.3.

A possible application as well as an useful extension of this study is to use the results of this study to estimate and forecast of Vehicle Miles of Travel (VMT). Among other studies, the highway cost-allocation study is very much dependent on VMT. The Appendix B of the 1988 Update of the Indiana Highway Cost-Allocation Study [Sinha et al. 1989] showed an disaggregate approach to compute and forecast VMT based on AADT estimate and forecast. An implementation of that approach can be undertaken to estimate and forecast of VMT by using the results of the present study.

Another future effort should be to determine the best weights to use in combining forecasts, as discussed in Chapter 10 of this study, by automatically updating the weights as the actual data for the forecast years become available. Also, policies and sensitivity levels with which to define acceptable forecast accuracy need to be established. Perhaps a nationwide survey of experts and an analysis the performance of different forecasting studies could be undertaken. This study has identified a policy to gauge or monitor forecast accuracy for its own forecast measures.

Time series analysis could be used to forecast future traffic, given the availability of enough data as required by the procedure. According to Armstrong [1984 and 1986], the time series approach could be combined with the present approaches to obtain reliable traffic forecasts. Time series analysis treats traffic volume as a function of time and uses land use development as the starting point to formulate the traffic growth — as time passes, more land is developed and traffic increases proportionally. Time series analysis is also a way to introduce time lags, especially with respect to economic predictor variables, to see if better ADT forecasting models are possible.

The area that the researchers feel will be useful to investigate is the model transferability — the applicability of the models developed in this study to similar states like Indiana. Hartgen [1990] has identified a procedure to determine the similarities among the financial, infrastructure, and organizational structures of the state highway systems, and to group states according to these similarities. His study has identified states that are based on similar systems, rather than classifying them by closeness and geography. If the performance of the traffic models developed in this study and tested in a "similar" state have been found to be similar to the current study, then the models in this study can be applied directly to that "similar" state without going through the modeling process. Although, the resulting parameters of the models reflect the validity of the model in the State of Indiana, the procedures discussed in this study were not specific to Indiana. The transferability of the model can be tested in states not similar to Indiana, either directly or by

developing models using the methodologies of this study on the data of that other state. This consideration may help to fill the gap in the unification of the modeling process, especially to rural and small- to medium-sized urban area, where enough funds are not usually available to do extensive studies.

11.6 Conclusions

The principal objective of this study was to develop simple, fast and inexpensive traffic forecasting models for the urban segments of the state and interstate highway network in Indiana. This study has developed two different types of data bases and then tested four forms of data and different data groupings to select the best suitable data structure. The study has identified and developed different suitable methodologies and then applied various statistical analyses to find the best models. Alternative models have been developed in this study to use them at the project level. The choice of predictor variables for the models was based on a combination of various statistical analyses and subjective judgment regarding quality of those variables.

The analyses done to develop the elasticity-based as well as the lag-AADT models are as reliable as possible within the limitations of the data. The developed models could be updated as new data becomes available. The developed elasticity models provide better statistical results than those found in a previous, similar study [Trombly & Ouderkirk 1986]. Although the variable selection criteria used in this study are not based solely on the statistical results, this study is based on extensive statistical analysis. The study serve be as a

stand-alone guide to building and testing the various statistical models to forecast traffic. The variables used in the models were found to be statistically significant. It was found that no other variables will provide additional significant predictive power in the models.

The step-by-step instructions in Section 11.3 are provided to give a structured approach to implementing the models. The developed models are expected to provide highway planners with a simple, fast, and inexpensive estimation procedure to predict future traffic.

In most states, the task of traffic forecasting is heavily dependent on AADT counts from continuous count stations. This study has shown that reliable traffic forecasting models are possible even with traffic data from coverage counts. Much of the credit can be attributed to the data sufficiency, and improved model specification and structure. The reliability of the models is reflected in the values of the selected forecasting measures in Chapter 10. Any state with adequate historical traffic data from coverage and continuous count stations can use this model building approach to determine future year AADT on state highway and interstate segments of small- to medium-size urban areas.

Many of the results summarized elsewhere in this study are mutually supportive. For instance, different forecasting measures (see Chapter 10) showed that quality of the forecast measures remained unchanged in spite of different error functions implicit in the measures. Other examples of this "mutual support" were the variable

selection criteria in Chapters 5 and 6 and the model statistics of Chapters 5 through 9. Such results increased confidence in the procedures and analysis methods employed to build models throughout the study.

Some of the results of this research did not apply directly to forecasting traffic but were found useful in selecting efficient models and in gauging model quality. For instance, the principal component models of Chapter 7 with eleven predictor variables validated the simple elasticity model with for fewer (viz. ≤ 2) variables without any major change in model statistics. This study has also developed forecasts for input variables that required by the elasticity model, but for which no forecasts are available from outside sources.

The most obvious and direct use of a traffic forecasting model is for the estimation of the benefits from alternate highway system improvement projects. A second application would be as an aid to the appropriate design of a project (for example, number of lanes or type of traffic control). The identification of potential problem segments in the state highway system could be accomplished by using the models to identify rapid traffic growth areas. Undoubtedly, more work must be done in this area to improve the accuracy and reliability of a traffic projection model. It is important to note that the developed models in this report are not purported to be perfect forecasting tools, if such a model could ever exist. Users are expected to weigh the results in terms of the local situation, and make adjustments using their professional judgment.

The use of different models to forecast traffic has provided an opportunity to search for some degree of consensus. The results of different models developed in this study were compared by observing their performance as well as their model statistics (if applicable). The efficient traffic models (elasticity and lag-AADT) forecasts are combined based on the performance of the individual models. The results of computations will not be more accurate than the input data on which they were based. In the absence of any predictor variables other than AADT itself, the lag-AADT model with lower data requirements, can be expected to perform better than the other models developed in this study. Travel demand can increase rapidly in some part because of steady growth in employment, population, etc. In such cases, it is expected that the elasticity model will outperform the lag-AADT model, which does not account for such explosions in past traffic volumes. This study has verified that combined forecasts from the lagged and elasticity models outperform the forecasts from the best individual model alone, in many cases. Finally, it is expected that the suggested procedure of combining the forecasts from the elasticity and the lag-AADT models will provide more reliable traffic forecasts to highway planners.

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APPENDICES

Appendix A

Table A1: Segment AADT Raw Data Base for Urban Minor Arterial & Collector

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OBS	CT	CTYNM	CTY	PCTY	CTY	CN	CNTYNM	CNTYAR	GRE	PCNT	FUNC
	YN		AR	80	GR	TYN			GION	Y80	
1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
-1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
42	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma
42	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma
42	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma
-2	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma

(1)	(2)	(7)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
OBS	CT	CN	M88TOT	M88	PM88	FAS	HWY	SEC	YEAR	AADT	CTYPOP	CNTY	CNTY
	YN	TYN		FUNC	FUNC							POP	HH
1	13	89	235.29	58.54	24.88	fau	sr121	1n	70	7111	43999	79109	25243
1	13	89	235.29	58.54	24.88	fau	sr121	1n	75	5658	43898	77351	26191
1	13	89	235.29	58.54	24.88	fau	sr121	1n	79	8291	42395	76300	27164
1	13	89	235.29	58.54	24.88	fau	sr121	1n	82	8820	40752	75000	27172
-1	13	89	235.29	58.54	24.88	fau	sr121	1n	85	10020	39030	72200	26418
42	87	80	40.17	10.47	26.06	fau	sr19	7b	73	3254	5028	16700	5529
42	87	80	40.17	10.47	26.06	fau	sr19	7b	77	3728	4756	16900	5831
42	87	80	40.17	10.47	26.06	fau	sr19	7b	80	3754	5004	16819	5993
-2	87	80	40.17	10.47	26.06	fau	sr19	7b	84	4090	4694	16200	5700

Table A1, continued

(1)	(2)	(7)	(19)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
OBS	CT	CN	YEAR	CNTYVR	CNTY	CNTY	STPOP	STHH	STVR	STEMP	STINC	STGAS
YN	TYN				EMP	INC						
1	13	89	70	46259	26456	9381	5195392	1609443	3134244	1580100	9374	2366
1	13	89	75	52634	26412	9539	5309147	1747281	3772173	1603117	10344	2644
1	13	89	79	57978	27575	10716	5475000	1896477	4319035	1929580	11556	2757
1	13	89	82	57679	24275	9543	5485000	1946384	4342071	1719673	10292	2336
-1	13	89	85	57560	24895	10743	5503000	1990746	4533362	1892613	11562	2424
42	87	80	73	14114	2020	12022	5329000	1711108	3652567	1702849	10978	2732
42	87	80	77	15615	2355	11830	5405000	1824325	4071356	1727408	11311	2795
42	87	80	80	16151	2677	11423	5490224	1927052	4362862	1844200	10830	2538
-2	87	80	84	16424	2278	12336	5493000	1970890	4388881	1795825	11000	2405

Note: See Table 4.3 for description of columns.

Table A2: Segment AADT Density Data Base for Urban Minor Arterial & Collector

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OBS	CT	CTYNM	CTY	PCTY	CTY	CN	CNTYNM	CNTYAR	GRE	PCNT	FUNC
	YN		AR	80	GR	TYN			GION	Y80	
1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
-1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
42	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma
42	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma
42	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma
-2	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma

(1)	(2)	(7)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
OBS	CT	CN	M88TOT	M88	PM88	FAS	HWY	SEC	YEAR	AADT	CTYPOP	CNTY	CNTY
	YN	TYN		FUNC	FUNC							POP	HH
1	13	89	235.29	58.54	24.88	fau	sr121	1n	70.	7111.0	2699.3	195.7	62.4
1	13	89	235.29	58.54	24.88	fau	sr121	1n	75.	5658.0	2693.1	191.3	64.8
1	13	89	235.29	58.54	24.88	fau	sr121	1n	79.	8291.0	2600.9	188.7	67.2
1	13	89	235.29	58.54	24.88	fau	sr121	1n	82.	8820.0	2500.1	185.5	67.2
-1	13	89	235.29	58.54	24.88	fau	sr121	1n	85.	10020.0	2394.5	178.6	65.4
42	87	80	40.17	10.47	26.06	fau	sr19	7b	73.	3254.0	3142.5	64.0	21.2
42	87	80	40.17	10.47	26.06	fau	sr19	7b	77.	3728.0	2972.5	64.8	22.4
42	87	80	40.17	10.47	26.06	fau	sr19	7b	80.	3754.0	3127.5	64.5	23.0
-2	87	80	40.17	10.47	26.06	fau	sr19	7b	84.	4090.0	2933.7	62.1	21.9

Table A2, continued

(1)	(2)	(7)	(19)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
OBS	CT	CN	YEAR	CNTYVR	CNTY	CNTY	STPOP	STHH	STVR	STEMP	STINC	STGAS
	YN	TYN			EMP	INC						
1	13	89	70.	58.5	65.4	9381.0	144.4	44.7	60.4	43.9	9374.0	2366.0
1	13	89	75.	68.0	65.3	9539.0	147.6	48.6	71.1	44.6	10344.0	2644.0
1	13	89	79.	76.0	68.2	10716.0	152.2	52.7	78.9	53.6	11556.0	2757.0
1	13	89	82.	76.9	60.0	9543.0	152.5	54.1	79.2	47.8	10292.0	2336.0
-1	13	89	85.	79.7	61.6	10743.0	153.0	55.3	82.4	52.6	11562.0	2424.0
42	87	80	73.	84.5	7.7	12022.0	148.1	47.6	68.5	47.3	10978.0	2732.0
42	87	80	77.	92.4	9.0	11830.0	150.2	50.7	75.3	48.0	11311.0	2795.0
42	87	80	80.	96.0	10.3	11423.0	152.6	53.6	79.5	51.3	10830.0	2538.0
-2	87	80	84.	101.4	8.7	12336.0	152.7	54.8	79.9	49.9	11000.0	2405.0

Note: See Table 4.3 for description of columns.

Table A3: Segment AADT, Earlier & Later Years Density Data Base for Urban Minor Arterial & Collector

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OBS	CT	CTYNM	CTY	PCTY	CTY	CN	CNTYNM	CNTYAR	GRE	PCNT	FUNC
YN			AR	80	GR	TYN			GION	Y80	
1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
2	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
2	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
41	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma
41	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma
42	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma
42	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma

(1)	(2)	(7)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
OBS	CT	CN	M88TOT	M88	PM88	FAS	HWY	SEC	YEAR	AADT	CTYPOP	CNTY	CNTY
YN		TYN		FUNC	FUNC							POP	HH
1	13	89	235.29	58.54	24.88	fau	sr121	1n	72.50	6384.5	2696.2	193.5	63.6
1	13	89	235.29	58.54	24.88	fau	sr121	1n	82.00	9043.7	2498.5	184.3	66.6
2	13	89	235.29	58.54	24.88	fau	sr121	2n	72.50	5529.0	2696.2	193.5	63.6
2	13	89	235.29	58.54	24.88	fau	sr121	2n	82.00	5732.7	2498.5	184.3	66.6
41	87	80	40.17	10.47	26.06	fau	sr19	6b	75.00	4337.0	3057.5	64.4	21.8
41	87	80	40.17	10.47	26.06	fau	sr19	6b	82.00	5170.5	3030.6	63.3	22.4
42	87	80	40.17	10.47	26.06	fau	sr19	7b	75.00	3491.0	3057.5	64.4	21.8
42	87	80	40.17	10.47	26.06	fau	sr19	7b	82.00	3922.0	3030.6	63.3	22.4

Table A3, continued

(1)	(2)	(7)	(19)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
OBS	CT	CN	YEAR	CNTYVR	CNTY	CNTY	STPOP	STHH	STVR	STEMP	STINC	STGAS
	YN	TYN			EMP	INC						
1	13	89	72.50	63.3	65.4	9460.0	146.0	46.7	65.8	44.3	9859.0	2505.0
1	13	89	82.00	77.5	63.3	10334.0	152.6	54.0	80.2	51.3	11136.7	2505.7
2	13	89	72.50	63.3	65.4	9460.0	146.0	46.7	65.8	44.3	9859.0	2505.0
2	13	89	82.00	77.5	63.3	10334.0	152.6	54.0	80.2	51.3	11136.7	2505.7
41	87	80	75.00	88.4	8.3	11926.0	149.2	49.2	71.9	47.7	11144.5	2763.5
41	87	80	82.00	98.7	9.5	11879.5	152.7	54.2	79.7	50.6	10915.0	2471.5
42	87	80	75.00	88.4	8.3	11926.0	149.2	49.2	71.9	47.7	11144.5	2763.5
42	87	80	82.00	98.7	9.5	11879.5	152.7	54.2	79.7	50.6	10915.0	2471.5

Note: See Table 4.3 for description of columns.

Table A4: County or City Average Raw Data Base for
Urban Minor Arterial & Collector

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OBS	CT	CTYNM	CTY	PCTY	CTY	CN	CNTYNM	CNTYAR	GRE	PCNT	FUNC
YN	YN		AR	80	GR	TYN			GION	Y80	
2	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
2	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
2	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
2	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
-1	13	richmond	16.3	41349	a	89	wayne	404.25	c	76058	uma
42	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma
42	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma
42	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma
-2	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	uma

(1)	(2)	(7)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
OBS	CT	CN	M88TOT	M88	PM88	FAS	HWY	SEC	YEAR	AADT	CTYPOP	CNTY	CNTY
YN	YN	TYN		FUNC	FUNC							POP	HH
2	13	89	235.29	58.54	24.88	fau	sr121	2	70.00	6516	43999	79109	25243
2	13	89	235.29	58.54	24.88	fau	sr121	2	75.00	5397	43898	77351	26191
2	13	89	235.29	58.54	24.88	fau	sr121	2	79.00	6994	42395	76300	27164
2	13	89	235.29	58.54	24.88	fau	sr121	2	82.00	7330	40752	75000	27172
-1	13	89	235.29	58.54	24.88	fau	sr121	2	85.00	7840	39030	72200	26418
42	87	80	40.17	10.47	26.06	fau	sr19	4	73.00	6338	5028	16700	5529
42	87	80	40.17	10.47	26.06	fau	sr19	4	77.00	7247	4756	16900	5831
42	87	80	40.17	10.47	26.06	fau	sr19	4	80.00	7242	5004	16819	5993
-2	87	80	40.17	10.47	26.06	fau	sr19	4	84.00	7870	4694	16200	5700

Table A4, continued

(1)	(2)	(7)	(19)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
OBS	CT	CN	YEAR	CNTYVR	CNTY	CNTY	STPOP	STHH	STVR	STEMP	STINC	STGAS
YN	TYN				EMP	INC						
2	13	89	70.00	46259	26456	9381	5195392	1609443	3136244	1580100	9374	2366
2	13	89	75.00	52634	26412	9539	5309147	1747281	3772173	1603117	10344	2644
2	13	89	79.00	57978	27575	10716	5475000	1896477	4319035	1929580	11556	2757
2	13	89	82.00	57679	24275	9543	5485000	1946384	4342071	1719673	10292	2336
-1	13	89	85.00	57560	24895	10743	5503000	1990746	4533362	1892613	11562	2424
42	87	80	73.00	14114	2020	12022	5329000	1711108	3652567	1702849	10978	2732
42	87	80	77.00	15615	2355	11830	5405000	1824325	4071356	1727408	11311	2795
42	87	80	80.00	16151	2677	11423	5490224	1927052	4362862	1844200	10830	2538
-2	87	80	84.00	16424	2278	12336	5493000	1970890	4388881	1795825	11000	2405

Note: See Table 4.3 for description of columns.

Table A5: County or City Average Raw Data Base for
Urban Principal Arterial

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OBS	CT	CTYNM	CTY	PCTY	CTY	CN	CNTYNM	CNTYAR	GRE	PCNT	FUNC
YN			AR	80	GR	TYN			GION	Y80	
11	11	kokomo	14.5	47808	a	34	howard	293.00	n	86896	upa
11	11	kokomo	14.5	47808	a	34	howard	293.00	n	86896	upa
11	11	kokomo	14.5	47808	a	34	howard	293.00	n	86896	upa
11	11	kokomo	14.5	47808	a	34	howard	293.00	n	86896	upa
-1	11	kokomo	14.5	47808	a	34	howard	293.00	n	86896	upa
98	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	upa
98	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	upa
98	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	upa
-2	87	tipton	1.6	5004	d	80	tipton	260.75	c	16819	upa

(1)	(2)	(7)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
OBS	CT	CN	M88TOT	M88	PM88	FAS	HWY	SEC	YEAR	AADT	CTYPOP	CNTY	CNTY
YN		TYN		FUNC	FUNC						POP	POP	HH
11	11	34	296.52	17.47	5.89	fap	us31	11	73.00	17336	51915	85700	27338
11	11	34	296.52	17.47	5.89	fap	us31	11	77.00	18283	52109	87100	29907
11	11	34	296.52	17.47	5.89	fap	us31	11	80.00	17384	47808	86896	31050
11	11	34	296.52	17.47	5.89	fap	us31	11	83.00	19926	45714	84900	30560
-1	11	34	296.52	17.47	5.89	fap	us31	11	87.00	20701	45723	83750	30620
98	87	80	40.17	4.81	11.97	fap	sr28	2	73.00	6714	5028	16700	5529
98	87	80	40.17	4.81	11.97	fap	sr28	2	77.00	7416	4756	16900	5831
98	87	80	40.17	4.81	11.97	fap	sr28	2	80.00	7587	5004	16819	5993
-2	87	80	40.17	4.81	11.97	fap	sr28	2	84.00	9815	4694	16200	5700

Table A5, continued

(1)	(2)	(7)	(19)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
OBS	CT YN	CN TYN	YEAR	CNTYVR	CNTY EMP	CNTY INC	STPOP	STHH	STVR	STEMP	STINC	STGAS
11	11	34	73.00	64291	39793	12622	5329000	1711108	3652567	1702849	10978	2732
11	11	34	77.00	70848	38728	12359	5405000	1824325	4071356	1727408	11331	2795
11	11	34	80.00	73529	36942	11334	5490224	1927052	4362862	1844200	10830	2538
11	11	34	83.00	71313	32599	10811	5476000	1953931	4276264	1679775	10445	2381
-1	11	34	87.00	69622	36198	13322	5532700	2009770	4451900	1945174	11593	2630
98	87	80	73.00	14114	2020	12022	5329000	1711108	3652567	1702849	10978	2732
98	87	80	77.00	15615	2355	11830	5405000	1824325	4071356	1727408	11311	2795
98	87	80	80.00	16151	2677	11423	5490224	1927052	4362862	1844200	10830	2538
-2	87	80	84.00	16424	2278	12336	5493000	1970890	4388881	1795825	11000	2405

Note: See Table 4.3 for description of columns.

Table A6: County or City Average Raw Data Base for Interstate Highways

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
OBS	CT	CTYNM	CTY	PCTY	CTY	CN	CNTYNM	CNTYAR	GRE	PCNT	FUNC
YN			AR	80	GR	TYN			GION	Y80	
2	12	lafayette	11.5	43011	a	79	tippecanoe	501.50	c	121702	ui
2	12	lafayette	11.5	43011	a	79	tippecanoe	501.50	c	121702	ui
2	12	lafayette	11.5	43011	a	79	tippecanoe	501.50	c	121702	ui
2	12	lafayette	11.5	43011	a	79	tippecanoe	501.50	c	121702	ui
-1	12	lafayette	11.5	43011	a	79	tippecanoe	501.50	c	121702	ui
117	12	lafayette	11.5	43011	a	91	white	503.75	n	23867	ri
117	12	lafayette	11.5	43011	a	91	white	503.75	n	23867	ri
117	12	lafayette	11.5	43011	a	91	white	503.75	n	23867	ri
-2	12	lafayette	11.5	43011	a	91	white	503.75	n	23867	ri

(1)	(2)	(7)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
OBS	CT	CN	M88TOT	M88	PM88	FAS	HWY	SEC	YEAR	AADT	CTYPOP	CNTY	CNTY
YN		TYN		FUNC	FUNC							POP	HH
2	12	79	1283.95	23.62	1.84	fa1	165	2	75.00	19886	48894	112408	35231
2	12	79	1283.95	23.62	1.84	fa1	165	2	79.00	23659	46286	121600	40113
2	12	79	1283.95	23.62	1.84	fa1	165	2	82.00	25929	43914	123900	41294
2	12	79	1283.95	23.62	1.84	fa1	165	2	85.00	30610	44150	124500	41031
-1	12	79	1283.95	23.62	1.84	fa1	165	2	87.00	35276	44331	126800	40940
117	12	91	1137.14	15.22	1.34	fa1	165	2	71.00	9866	45905	21300	7051
117	12	91	1137.14	15.22	1.34	fa1	165	2	80.00	17915	43011	23867	8798
117	12	91	1137.14	15.22	1.34	fa1	165	2	85.00	18855	44150	23400	8817
-2	12	91	1137.14	15.22	1.34	fa1	165	2	87.00	31126	44331	23840	9050

Table A6, continued

(1)	(2)	(7)	(19)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)	(32)
OBS	CT	CN	YEAR	CNTYVR	CNTY	CNTY	STPOP	STHH	STVR	STEMP	STINC	STGAS
YN	TYN				EMP	INC						
2	12	79	75.00	70800	31945	9624	5309197	1747281	3772173	1603117	10344	2644
2	12	79	79.00	81786	39198	10513	5475000	1896477	4319035	1929580	11566	2757
2	12	79	82.00	84509	37998	9886	5485000	1946384	4342071	1719673	10292	2336
2	12	79	85.00	87094	39237	10593	5500000	1981498	4460976	1847252	11157	2424
-1	12	79	87.00	87164	42395	11347	5532700	2009770	4451900	1945174	11593	2630
117	12	91	71.00	16164	4332	9889	5250000	1645683	3210180	1531495	9669	2468
117	12	91	80.00	22321	6059	10186	5490224	1927052	4362862	1844200	10830	2538
117	12	91	85.00	25368	6036	10219	5500000	1981498	4460976	1847252	11157	2424
-2	12	91	87.00	26078	5863	12169	5532700	2009770	4451900	1945174	11593	2630

Note: See Table 4.3 for description of columns.

Appendix B

Table B1: City Number, Name and Land Area

City No.	City Name	Area in sq. mile	City No.	City Name	Area in sq. mile
1	INDIANAPOLIS	352.0	44	BEECH GROVE	4.1
2	FORT WAYNE	52.6	45	WABASH	5.6
3	GARY	39.4	46	MADISON	8.3
4	EVANSVILLE	37.3	47	NOBLESVILLE	5.9
5	SOUTH BEND	36.3	48	FRANKLIN	6.1
6	HAMMOND	23.8	49	LEBANON	6.0
7	MUNCIE	21.9	50	GREENFIELD	5.1
8	ANDERSON	37.3	51	WASHINGTON	4.1
9	TERRE HAUTE	26.3	52	MARTINSVILLE	3.2
10	BLOOMINGTON	10.6	53	ELWOOD	4.1
11	KOKOMO	14.5	54	WARSAW	7.3
12	LAFAYETTE	11.5	55	GREENSBURG	3.0
13	RICHMOND	16.3	56	JASPER	5.7
14	ELKHART	15.9	57	PRINCETON	3.5
15	MISHAWAKA	13.2	58	BLUFFTON	5.0
16	EAST CHICAGO	11.2	59	TELL CITY	3.8
17	NEW ALBANY	13.2	60	DECATUR	3.1
18	MICHIGAN CITY	19.6	61	GREENCASTLE	3.7
19	MARION	10.4	62	AUBURN	3.8
20	COLUMBUS	17.1	63	BRAZIL	2.6
21	PORTAGE	22.4	64	PLYMOUTH	5.8
22	LAWRENCE	20.9	65	MT. VERNON	2.2
23	HOBART	14.5	66	HARTFORD CITY	3.3
24	VALPARAISO	7.6	67	KENDALLVILLE	4.3
25	LAPORTE	11.9	68	PORTLAND	2.4
26	WEST LAFAYETTE	4.7	69	NEW HAVEN	2.7
27	JEFFERSONVILLE	6.1	70	GAS CITY	2.4
28	VINCENNES	7.4	71	LINTON	5.0
29	NEW CASTLE	5.9	72	BOONVILLE	2.8
30	GOSHEN	10.0	73	RUSHVILLE	1.8
31	GREENWOOD	8.4	74	ALEXANDRIA	2.4
32	CARMEL	7.8	75	NORTH VERNON	4.1
33	LOGANSPOUT	4.9	76	WINCHESTER	2.4
34	CONNERSVILLE	6.4	77	WHITING	1.9
35	CROWN POINT	7.0	78	CHARLESTOWN	2.2
36	HUNTINGTON	6.6	79	ANGOLA	2.1
37	FRANKFORT	4.4	80	HUNTINGBURG	2.9
38	SEYMOUR	6.5	81	SALEM	2.9
39	SHELBYVILLE	7.1	82	CLINTON	2.0
40	BEDFORD	11.9	83	MONTICELLO	2.6
41	LAKE STATION	7.6	84	COLUMBIA CITY	2.1
42	PERU	3.6	85	SCOTTSBURG	3.5
43	CRAWFORDSVILLE	5.9	86	ROCHESTER	2.5
			87	TIPTON	1.6

Source: (i) County and City Data Book, Bureau of Census.

(ii) Statistical Information system (STATIS), The Economic Development Information Network (EDIN), Indiana University.

Table B2: County Number, Name and Land Area

County No.	Name	Area in sq. mile	County No.	Name	Area in sq. mile
1	adams	341.25	48	madison	453.00
2	allen	662.00	49	marion	395.00
3	bartholomew	407.25	50	marshall	443.75
4	benton	407.50	51	martin	340.50
5	blackford	166.25	52	miami	371.00
6	boone	424.25	53	monroe	385.25
7	brown	313.75	54	montgomery	505.50
8	carroll	372.50	55	morgan	408.25
9	cass	414.25	56	newton	404.00
10	clark	378.00	57	noble	412.75
11	clay	361.00	58	ohio	87.00
12	clinton	405.50	59	orange	407.25
13	crawford	308.25	60	owen	387.00
14	daviess	431.50	61	parke	444.25
15	dearborn	306.75	62	perry	382.00
16	decatur	372.25	63	pike	339.50
17	dekalb	364.50	64	porter	420.25
18	delaware	393.00	65	posey	410.00
19	dubois	430.00	66	pulaski	434.50
20	elkhart	466.50	67	putnam	484.00
21	fayette	215.00	68	randolph	454.75
22	floyd	149.75	69	ripley	445.75
23	fountain	397.75	70	rush	408.25
24	franklin	387.25	71	st. joseph	460.75
25	fulton	368.75	72	scott	192.00
26	gibson	492.00	73	shelby	411.50
27	grant	416.50	74	spencer	399.00
28	greene	546.75	75	starke	309.25
29	hamilton	398.75	76	steuben	308.25
30	hancock	306.50	77	sullivan	453.25
31	harrison	484.25	78	switzerland	223.00
32	hendricks	411.00	79	tippecanoe	501.50
33	henry	396.00	80	tipton	260.75
34	howard	293.00	81	union	164.00
35	huntington	366.75	82	vanderburgh	237.25
36	jackson	515.25	83	vermillion	260.75
37	jasper	561.25	84	vigo	407.50
38	jay	384.50	85	wabash	398.00
39	jefferson	363.75	86	warren	366.50
40	jennings	377.75	87	warrick	391.00
41	johnson	319.50	88	washington	516.00
42	knox	519.00	89	wayne	404.25
43	kosciusko	540.00	90	wells	369.50
44	lagrange	380.25	91	white	503.75
45	lake	504.00	92	whitley	336.25
46	laporte	601.75			
47	lawrence	453.75		STATE	35973.25

Source: (i) County and City Data Book, Bureau of Census.

(ii) Statistical Information system, The Economic Development Information Network (EDIN), Indiana University.

Table B3: 1988 County Functional Class Mileage of State of Indiana

County No.	County Name	Total	Rural total	Urban total	UMAC	ZUMAC	UPA	ZUPA	INT	ZINT
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1	ADAMS	875.86	819.27	56.59	16.70	29.51	5.58	9.86	0.00	0.00
2	ALLEN	2458.03	1393.66	1064.37	237.75	22.34	59.02	5.55	30.46	1.24
3	BARTHOLOMEW	1009.88	767.47	242.41	47.86	19.74	22.29	9.20	22.52	2.23
4	BENTON	833.95	833.95	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	BLACKFORD	431.63	372.65	58.98	11.94	20.24	6.87	11.65	0.00	0.00
6	BOONE	1077.94	992.75	85.19	19.63	23.04	7.76	9.11	35.02	3.25
7	BROWN	453.91	453.91	0.00	0.00	0.00	0.00	0.00	0.00	0.00
8	CARROLL	915.29	915.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00
9	CASS	1108.65	970.43	138.22	23.92	17.31	11.77	8.52	5.50	0.50
10	CLARK	875.49	587.26	288.23	80.03	27.77	18.49	6.42	28.55	3.26
11	CLAY	870.21	779.74	90.47	18.18	20.10	9.46	10.46	12.53	1.44
12	CLINTON	999.65	921.87	77.78	19.76	25.40	9.53	12.25	10.47	1.05
13	CRAWFORD	587.81	587.81	0.00	0.00	0.00	0.00	0.00	16.98	2.89
14	DAVIESS	976.55	895.45	81.10	25.53	31.48	5.43	6.70	0.00	0.00
15	DEARBORN	678.62	678.62	0.00	0.00	0.00	0.00	0.00	17.01	2.51
16	DECATUR	805.81	750.14	55.67	14.36	25.79	5.49	9.86	22.72	2.82
17	DEKALB	961.35	903.01	58.34	14.24	24.41	2.99	5.13	18.21	1.89
18	DELAWARE	1346.18	794.25	551.93	152.31	27.60	41.37	7.50	32.54	2.42
19	DUBOIS	886.12	766.06	120.06	33.29	27.73	12.56	10.46	3.32	0.37
20	ELKHART	1603.62	915.09	688.53	164.66	23.91	56.81	8.25	21.33	1.33
21	FAYETTE	482.49	399.41	83.08	16.90	20.34	12.25	14.74	0.00	0.00
22	FLOYD	518.84	309.06	209.78	49.01	23.36	12.35	5.89	16.23	3.13
23	FOUNTAIN	878.67	878.67	0.00	0.00	0.00	0.00	0.00	16.95	1.93
24	FRANKLIN	745.82	745.82	0.00	0.00	0.00	0.00	0.00	4.36	0.58
25	FULTON	938.69	894.40	44.29	8.19	18.49	2.90	6.55	0.00	0.00
26	GIBSON	1238.51	1175.47	63.04	14.05	22.29	4.63	7.34	4.74	0.38
27	GRANT	1257.11	970.27	286.84	78.59	27.40	22.99	8.01	19.77	1.57
28	GREENE	1130.37	1082.33	48.04	9.86	20.52	4.11	8.56	0.00	0.00
29	HAMILTON	1281.80	1006.28	275.52	67.53	24.51	18.32	6.65	13.43	1.05
30	HANCOCK	835.35	753.25	82.10	22.96	27.97	8.99	10.95	19.12	2.29
31	HARRISON	989.41	989.41	0.00	0.00	0.00	0.00	0.00	17.33	1.75
32	HENDRICKS	1045.74	917.35	128.39	22.50	17.52	16.72	13.02	26.75	2.56
33	HENRY	1077.92	960.77	117.15	26.26	22.42	11.11	9.48	20.31	1.88
34	HOWARD	953.21	656.69	296.52	91.39	30.82	17.47	5.89	0.00	0.00
35	HUNTINGTON	970.46	859.19	111.27	29.04	26.10	13.05	11.73	23.96	2.47
36	JACKSON	1030.05	915.22	114.83	31.27	27.23	5.97	5.20	22.01	2.14
37	JASPER	1155.71	1155.71	0.00	0.00	0.00	0.00	0.00	32.01	2.77
38	JAY	929.89	879.97	49.92	14.75	29.55	4.21	8.43	0.00	0.00
39	JEFFERSON	735.91	662.28	73.63	17.33	23.54	12.59	17.10	0.00	0.00
40	JENNINGS	760.75	714.30	46.45	10.14	21.83	8.60	18.51	0.00	0.00
41	JOHNSON	876.83	648.80	228.03	49.16	21.56	20.09	8.81	17.23	1.97
42	KNOX	1200.50	1060.51	139.99	30.58	21.84	8.24	5.89	8.71	0.73
43	KOSCIUSKO	1481.42	1355.91	125.51	22.58	17.99	11.12	8.86	4.22	0.28

Table B3, continued

County No.	Name	Total	Rural total	Urban total	UMAC	ZUMAC	UPA	ZUPA	INT	ZINT
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
44	LAGRANGE	942.24	942.24	0.00	0.00	0.00	0.00	0.00	24.78	2.63
45	LAKE	2447.36	445.45	2001.91	428.78	21.42	134.64	6.73	79.69	3.26
46	LAPORTE	1621.55	1219.09	402.46	91.63	22.77	40.35	10.03	37.79	2.33
47	LAWRENCE	919.76	788.70	131.06	36.10	27.54	9.60	7.32	6.08	0.66
48	MADISON	1556.02	980.56	575.46	149.01	25.89	42.86	7.45	17.89	1.15
49	MARION	3336.12	0.00	3336.12	801.86	24.04	199.77	5.99	130.83	3.92
50	MARSHALL	1180.47	1110.86	69.61	15.99	22.97	3.17	4.55	3.80	0.32
51	MARTIN	472.51	472.51	0.00	0.00	0.00	0.00	0.00	0.00	0.00
52	MIAMI	977.14	878.49	98.65	20.94	21.23	10.01	10.15	1.56	0.16
53	MONROE	930.62	668.40	262.22	71.40	27.23	20.31	7.75	6.33	0.68
54	MONTGOMERY	1095.51	1017.67	77.84	24.86	31.94	7.18	9.22	23.20	2.12
55	MORGAN	905.00	809.24	95.76	20.96	21.89	10.60	11.07	11.34	1.25
56	NEWTON	828.71	828.71	0.00	0.00	0.00	0.00	0.00	2.88	0.35
57	NOBLE	1019.89	970.98	48.91	12.83	26.23	4.02	8.22	0.00	0.00
58	OHIO	174.91	174.91	0.00	0.00	0.00	0.00	0.00	0.00	0.00
59	ORANGE	751.39	751.39	0.00	0.00	0.00	0.00	0.00	0.00	0.00
60	OWEN	733.07	733.07	0.00	0.00	0.00	0.00	0.00	0.00	0.00
61	PARKE	877.36	877.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00
62	PERRY	698.77	644.24	54.53	9.39	17.22	5.00	9.17	12.64	1.81
63	PIKE	658.17	658.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00
64	PORTER	1308.12	789.42	518.70	132.31	25.51	54.74	10.55	32.16	2.46
65	POSEY	864.45	808.99	55.46	15.09	27.21	6.05	10.91	17.44	2.02
66	PULASKI	1004.76	1004.76	0.00	0.00	0.00	0.00	0.00	0.00	0.00
67	PUTNAM	962.05	904.85	57.20	12.74	22.27	6.68	11.68	20.34	2.11
68	RANDOLPH	1075.72	1042.48	33.24	9.20	27.68	3.37	10.14	1.35	0.13
69	RIPLEY	930.01	930.01	0.00	0.00	0.00	0.00	0.00	8.40	0.90
70	RUSH	883.24	840.14	43.10	8.14	18.89	7.32	16.98	0.00	0.00
71	ST. JOSEPH	1867.02	750.97	1116.05	173.78	15.57	71.06	6.37	39.38	2.11
72	SCOTT	453.49	417.94	35.55	8.85	24.89	0.00	0.00	11.55	2.55
73	SHELBY	1018.46	936.90	81.56	23.56	28.89	8.59	10.53	27.21	2.67
74	SPENCER	935.96	935.96	0.00	0.00	0.00	0.00	0.00	9.25	0.99
75	STARKE	839.39	839.39	0.00	0.00	0.00	0.00	0.00	0.00	0.00
76	STEBEN	838.24	795.35	42.89	7.99	18.63	4.58	10.68	41.19	4.91
77	SULLIVAN	1072.28	1072.28	0.00	0.00	0.00	0.00	0.00	0.00	0.00
78	SWITZERLAND	435.43	435.43	0.00	0.00	0.00	0.00	0.00	0.00	0.00
79	TIPPECANOE	1283.95	923.63	360.32	92.01	25.54	45.89	12.74	23.63	1.84
80	TIPTON	664.93	624.76	40.17	10.47	26.06	4.81	11.97	0.00	0.00
81	UNION	325.05	325.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00
82	VANDEBURGH	1063.40	359.98	703.42	178.89	25.43	37.47	5.33	7.16	0.67
83	VERMILION	561.02	502.35	58.67	9.09	15.49	5.18	8.83	8.31	1.48
84	VIGO	1332.56	827.94	504.62	113.57	22.51	45.25	8.97	16.43	1.23

Table B3, continued

County No.	Name	Total	Rural total	Urban total	UMAC	ZUMAC	UPA	ZUPA	INT	ZINT
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
85	WABASH	972.45	857.54	114.91	35.68	31.05	10.39	9.04	2.40	0.25
86	WARREN	680.08	680.08	0.00	0.00	0.00	0.00	0.00	0.00	0.00
87	WARRICK	834.34	699.85	134.49	28.24	21.00	6.20	4.61	25.00	3.00
88	WASHINGTON	938.05	891.50	46.55	6.56	14.09	7.57	16.26	0.00	0.00
89	WAYNE	1094.49	859.20	235.29	58.54	24.88	21.24	9.03	23.03	2.10
90	WELLS	891.31	832.93	58.38	17.08	29.26	4.23	7.25	1.05	0.12
91	WHITE	1137.14	1079.37	57.77	18.65	32.28	3.53	6.11	15.22	1.34
92	WHITLEY	816.95	780.42	36.53	8.74	23.93	3.33	9.12	0.00	0.00
STATE		91482.91	73811.26	17671.65	4145.18	23.46	1336.12	7.56	1233.6	1.35

Note:

- i. UMAC (col.6) = Urban Minor Arterial & Collector
 iv. col.7 (ZUMAC) = (col.7/col.5)*100
 ii. UPA (col.8) = Urban Principal Arterial
 v. col.9 (ZUPA) = (col.8/col.5)*100
 iii. INT (col.10) = Interstate
 vi. col.11 (ZINT) = (col.10/col.3)*100
 vii. Total (col.3), Rural total (col.4) & Urban total (col.5) mileage include both state and local mileage

Source: InDOT, Division of Program Development, Mileage Report.

Table B4: Traffic Data Retrieval Form

City # : 12		City Name : Lafayette		1980 Popu-		(a) City: 43,011	
County #: 79		County Name : Tippecanoe		lation:		(b) County:121,702	
Hwy. Name	Section Number	Section Description FROM TO		Month	Year	ADT	AADT
					1960		8152
					1966		11824
SR25	3K	9th St.	18th St.	12	1970	17422	16760
					1971		
					1972		
					1973		
				8	1974	18405	16435
					1975		
					1976		
					1977		
				12	1978	14114	13972
					1979		
					1980		
					1981		
				10	1982	17722	14570
					1983		
1984							
1985							
	1986	18608	18161				
	1987						
	1988						
					1960		18656
					1966		21983
US52	5C	SR26 (Laf.)	SR38/ Main St.	12	1970	19958	19200
					1971		
					1972		
					1973		
				7	1974	28434	25591
					1975		
					1976		
					1977		
				12	1978	26384	26120
					1979		
					1980		
					1981		
				10	1982	28592	27180
					1983		
1984							
1985							
	1986	27091	26440				
	1987						
	1988						

Appendix C

Table C1: Best Models for Interstate Highways
[Data Format: Raw and County Avg. by Year]

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
RI+UI ALL N=313	1 2 3 4	0.5030 0.5229	0.5014 0.5199	0.5034 0.4863	13714 13457	5965.4 5954.5	61.64 48.75	CNTYPOP CNTYPOP STMP	0.0629 0.0631 0.0242
RI+UI CTYGR=A N=79	1 2 3 4	0.2376 0.2998	0.2277 0.2814	0.8020 0.7555	8105 7818	1424.0 1419.3	201.68 181.12	CNTYINC CNTYINC CNTYPOP	3.2232 2.2224 0.0630
RI+UI CTYGR=A+ N=76	1 2 3 4	0.3917 0.4028	0.3835 0.3864	0.6412 0.6463	19887 19839	1506.4 1507.0	40.50 40.44	CNTYPOP CNTYPOP STINC	0.0587 0.0584 4.8356
RI+UI CTYGR=B N=41	1 2 3 4	0.3851 0.6015 0.6295 0.6415	0.3693 0.5806 0.5994 0.6017	0.6780 0.4614 0.4506 0.4581	15940 12999 12703 12668	795.4 779.6 778.7 779.3	18.47 0.95 0.43 1.34	CNTYEMP CNTYHH CTYPOP CNTYHH CTYPOP STHH CNTYHH CTYPOP STHH CNTYINC	0.1030 0.1102 3.5719 0.1079 3.3942 0.0381 0.0924 2.9945 0.0419 2.4143
RI+UI CTYGR=C N=61	1 2 3 4	0.6404 0.6712 0.6745	0.6343 0.6598 0.6574	0.3840 0.3628 0.3712	11242 10842 10882	1139.9 1136.5 1137.8	7.79 4.24 5.65	CNTYPOP CNTYPOP CNTYINC CNTYPOP CNTYINC STINC	0.0617 0.0578 3.4664 0.0588 2.7105 2.4688
RI+UI CTYGR=D N=56	1 2 3 4	0.1290	0.1129	0.9355	4597	946.5	55.40	STMP	0.0151
RI+UI MFUNC=F1 N=47	1 2 3 4	0.5186 0.5298	0.5079 0.5085	0.5242 0.5343	5545 5542	812.3 813.2	40.11 40.17	CNTYHH CNTYPOP STMP	0.8658 0.2965 0.0081
RI+UI MFUNC=F2 N=62	1 2 3 4	0.6896 0.7281 0.7497 0.7559	0.6844 0.7188 0.7387 0.7387	0.3311 0.2996 0.2848 0.2870	7640 7211 6977 6951	1110.7 1104.5 1101.3 1101.8	18.67 11.16 7.81 8.30	CNTYVR CNTYEMP CTYPOP CNTYVR CTYPOP CNTYEMP CNTYVR CTYPOP CNTYEMP STINC	0.5484 1.4499 0.0230 0.2870 0.0168 0.7476 0.2595 0.0170 0.7852 2.0981

Table C1, continued

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
RI+UI MFUNC=F3 N=68	1 2 3 4	0.4722 0.5255	0.4642 0.5109	0.5598 0.5183	4165 3980	1135.5 1130.2	97.94 83.60	CNTYINC CNTYINC STMP	2.9892 2.7625 0.0110
RI+UI MFUNC=F4 N=136	1 2 3 4	0.4288 0.4466	0.4245 0.4382	0.5882 0.5784	18134 17917	2669.1 2666.8	20.53 17.79	CNTYPOP CNTYPOP STMP	0.0586 0.0594 0.0298
RI+UI GREGN=c N=132	1 2 3 4	0.6629 0.7202 0.7308	0.6603 0.7159 0.7245	0.3475 0.2928 0.2860	9359 8560 8429	2416.0 2394.4 2390.3	39.87 13.34 10.05	CNTYVR CNTYHH CNTYINC CNTYHH CNTYINC STMP	0.0685 0.1175 3.2177 0.1193 2.5994 0.0154
RI+UI GREGN=n N=104	1 2 3 4	0.4533 0.4731	0.4479 0.4626	0.5681 0.5582	18132 17889	2041.5 2039.7	19.04 16.74	CNTYHH CNTYPOP STINC	0.2274 0.0773 6.7586
RI+UI GREGN=s N=77	1 2 3 4	0.6142 0.6177	0.6090 0.6074	0.4064 0.4133	7837 7853	1382.8 1384.1	39.02 39.99	CNTYHH CNTYHH STMP	1.1019 1.0917 0.0068
RI ALL N=186	1 2 3 4	0.3101 0.3782 0.4060	0.3064 0.3714 0.3962	0.7049 0.6422 0.6201	7872 7494 7344	3339.2 3321.9 3315.4	53.45 32.21 24.73	CNTYINC CNTYINC CNTYVR CNTYINC CNTYVR CTYPOP	3.5472 2.9472 0.0252 2.5574 0.0218 0.0072
RI CTYGR=A N=51	1 2 3 4	0.3896 0.4706	0.3772 0.4485	0.6602 0.5956	7351 6917	910.0 904.7	228.70 194.11	CNTYINC CNTYINC CNTYPOP	3.7421 2.4670 0.0726
RI CTYGR=A+ N=57	1 2 3 4	0.4010 0.5910 0.6483 0.6609	0.3901 0.5758 0.6284 0.6348	0.6426 0.4545 0.4048 0.4043	8554 7134 6677 6620	1034.1 1014.4 1007.8 1007.7	48.95 18.61 10.86 10.72	CNTYINC CNTYINC CTYPOP CNTYINC CTYPOP CNTYEMP CNTYINC CTYPOP CNTYEMP STHH	4.2921 3.3436 0.0178 3.0399 0.0159 0.0252 2.7841 0.0168 0.0243 0.0127
RI CTYGR=B N=13	1 2 3 4	0.2646 0.3079	0.1977 0.1695	1.0028 1.1073	5154 5244	224.1 225.3	N/A N/A	CNTYINC CNTYINC STHH	2.7998 3.0185 0.0138

Table C1, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIG	C _p	Variables in Model	b-coefficients
RI CTYGR=C N=26	1 2 3 4	0.7344 0.7506	0.7233 0.7290	0.3099 0.3144	5052 5001	445.4 445.7	58.58 55.66	CNTYVR CNTYVR STINC	0.4643 0.4426 2.2716
RI CTYGR=D N=39	1 2 3 4	0.0967	0.0723	1.0001	4779	662.8	34.84	STEMP	0.0133
RI MFUNC=F1 N=37	1 2 3 4	0.3503 0.3726	0.3317 0.3357	0.7240 0.7381	4494 4481	624.3 625.0	59.26 58.09	CNTYPOP CNTYPOP STEMP	0.2032 0.1946 0.0070
RI MFUNC=F2 N=44	1 2 3 4	0.6083 0.7493 0.7640 0.7677	0.5989 0.7371 0.7464 0.7439	0.4290 0.2874 0.2831 0.2919	6749 5464 5367 5393	777.9 760.2 759.6 760.9	22.50 1.99 1.65 3.06	CNTYVR CNTYVR CTYPOP CNTYVR CTYPOP CNTYINC CNTYPOP CTYPOP CNTYINC STHH	0.4678 0.4490 0.0135 0.4237 0.0130 1.3552 0.3285 0.0141 1.4977 0.0102
RI MFUNC=F3 N=44	1 2 3 4	0.4522 0.5041	0.4392 0.4799	0.5999 0.5685	4213 4058	736.4 734.0	50.82 44.22	CNTYINC CNTYINC STHH	2.7733 2.6681 0.0113
RI MFUNC=F4 N=61	1 2 3 4	0.2571 0.3581 0.3775	0.2445 0.3360 0.3447	0.7932 0.7083 0.7099	9361 8776 8718	1117.6 1110.7 1110.8	9.29 2.28 2.55	CNTYINC CNTYINC CNTYHH CNTYINC CNTYHH STHH	3.7682 3.4083 0.0422 3.1957 0.0416 0.0158
RI GREGN=c N=80	1 2 3 4	0.3838 0.4873 0.5112	0.3759 0.4740 0.4919	0.6478 0.5527 0.5402	7352 6749 6633	1426.4 1413.7 1411.9	27.40 12.04 10.01	CNTYINC CNTYINC CNTYVR CNTYINC CNTYVR CTYPOP	3.8903 3.3085 0.0239 2.9988 0.0203 0.0052
RI GREGN=n N=47	1 2 3 4	0.2779 0.3064	0.2619 0.2749	0.7863 0.7882	7504 7438	840.7 840.8	67.66 65.29	CNTYINC CNTYINC STHH	3.6207 3.4723 0.0141
RI GREGN=s N=59	1 2 3 4	0.4088 0.4176	0.3984 0.3968	0.6327 0.6448	4982 4989	1006.6 1007.7	42.93 43.47	CNTYHH CNTYHH STEMP	0.5870 0.5779 0.0058

Table C1, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
UI	1	0.5338	0.5301	0.4811	16704	2471.7	15.10	CNTYPOP	0.0671
ALL	2	0.5557	0.5485	0.4658	16373	2467.6	10.63	CNTYPOP STMP	0.0673 0.0324
N=127	3								
	4								
UI	1	0.2013	0.1706	0.9216	7221	499.5	71.19	STHH	0.0304
CTYGR=A	2								
N=28	3								
	4								
UI	1	0.0748	0.0204	1.1429	32070	396.2	22.07	CNTYPOP	0.0517
CTYGR=A+	2								
N=19	3								
	4								
UI	1	0.5491	0.5318	0.5202	10099	518.3	60.87	CNTYHH	0.1086
CTYGR=B	2	0.7990	0.7829	0.2492	6876	496.6	15.83	CNTYEMP STHH	0.0752 0.0818
N=28	3	0.8083	0.7844	0.2556	6853	498.3	16.08	CNTYEMP STHH CNTYINC	0.0690 0.0817 1.4102
	4								
UI	1	0.6450	0.6342	0.3981	13113	665.6	-0.94	CNTYPOP	0.0603
CTYGR=C	2	0.6715	0.6510	0.3900	12809	664.9	-1.19	CNTYPOP CNTYINC	0.0586 3.9495
N=35	3	0.6727	0.6410	0.4118	12991	666.8	0.71	CNTYPOP CNTYINC STMP	0.0588 3.6115 0.0079
	4								
UI	1	0.3444	0.3007	0.8305	3650	280.8	149.54	STINC	4.3596
CTYGR=D	2	0.3463	0.2529	0.9339	3772	282.7	151.07	STINC STMP	3.7673 0.0033
N=17	3								
	4								
UI	1	0.8362	0.8157	0.2457	3918	167.2	N/A	CNTYEMP	1.5011
MFUNC=F1	2	0.9157	0.8916	0.1566	3005	162.6	N/A	CNTYEMP STVR	1.2253 0.0070
N=10	3								
	4								
UI	1	0.7630	0.7482	0.2962	8127	326.0	9.37	CNTYEMP	1.6145
MFUNC=F2	2	0.7947	0.7673	0.2874	7812	325.4	8.24	CNTYEMP STHH	1.5650 0.0275
N=18	3								
	4								
UI	1	0.6353	0.6188	0.4310	3660	395.8	37.84	CNTYINC	4.3110
MFUNC=F3	2	0.6777	0.6470	0.4144	3522	394.8	33.12	CNTYINC STMP	4.0185 0.0109
N=24	3								
	4								

Table C1, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
UI MFUNC=F4 N=75	1	0.4350	0.4273	0.5959	19863	1486.5	4.31	CNTYPOP	0.0658
	2	0.4526	0.4374	0.5930	19686	1486.1	3.96	CNTYPOP STMP	0.0663 0.0330
	3								
	4								
UI GREGN=c N=52	1	0.8452	0.8421	0.1672	8567	943.7	9.73	CNTYEMP	0.1188
	2	0.8652	0.8597	0.1513	8074	938.5	4.26	CNTYEMP STMP	0.1173 0.0273
	3	0.8677	0.8594	0.1543	8081	939.6	5.32	CNTYEMP STMP CNTYINC	0.1129 0.0217 1.3908
	4								
UI GREGN=n N=57	1	0.4879	0.4785	0.5494	20333	1132.9	2.20	CNTYHH	0.2656
	2	0.5003	0.4818	0.5552	20270	1133.4	2.86	CNTYPOP STINC	0.0902 6.7759
	3								
	4								
UI GREGN=s N=18	1	0.7311	0.7143	0.3361	7720	324.1	76.27	CNTYVR	0.5237
	2	0.8134	0.7886	0.2612	6641	319.6	50.63	CNTYEMP STHH	1.0169 0.0531
	3								
	4								

Note: Cases for N < 5 have not been recorded

Table C2: Best Models for Interstate Highways
[Data Format: Raw E&L and County Avg. by Year]

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
RI+UI ALL N=126	1 2 3 4	0.5058 0.5170	0.5018 0.5092	0.5102 0.5065	13413 13313	2396.9 2396.1	18.65 17.44	CNTYPOP CNTYPOP STINC	0.0612 0.0608 5.3241
RI+UI CTYGR=A N=34	1 2 3 4	0.1855 0.2072	0.1601 0.1560	0.9163 0.9463	7823 7842	611.5 612.6	81.24 80.29	CNTYINC CNTYINC STMP	2.8206 2.6889 0.0122
RI+UI CTYGR=A+ N=30	1 2 3 4	0.4115 0.4159	0.3905 0.3727	0.6726 0.7139	19645 19929	595.1 596.8	9.94 11.67	CNTYPOP CNTYPOP STINC	0.0590 0.0594 6.0357
RI+UI CTYGR=B N=18	1 2 3 4	0.4025 0.6163 0.6332	0.3651 0.5652 0.5546	0.7469 0.5372 0.5764	15551 12870 13025	349.3 343.4 344.6	24.71 12.85 13.76	CNTYEMP CNTYHH CTYPOP CNTYVR CTYPOP STHH	0.1031 0.1067 3.6898 0.0560 3.4727 0.0338
RI+UI CTYGR=C N=24	1 2 3 4	0.6329 0.6584	0.6162 0.6258	0.4339 0.4392	11345 11202	450.1 450.3	-3.09 -2.27	CNTYPOP CNTYPOP CNTYINC	0.0577 0.0536 3.6698
RI+UI CTYGR=D N=20	1 2 3 4								
RI+UI MFUNC=F1 N=18	1 2 3 4	0.5374 0.5453	0.5085 0.4847	0.5782 0.6365	5466 5597	311.7 313.4	5.57 7.24	CNTYHH CNTYPOP STMP	0.8399 0.2845 0.0071
RI+UI MFUNC=F2 N=26	1 2 3 4	0.7236 0.7463	0.7121 0.7242	0.3224 0.3199	7408 7251	465.3 465.0	2.09 2.12	CNTYHH CNTYHH CTYPOP	1.2525 1.2716 0.0082

Table C2, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
RI+UI MFUNC=F3 N=24	1 2 3 4	0.4651 0.5214	0.4407 0.4758	0.6322 0.6154	3594 3480	394.9 394.2	100.50 89.80	CNTYINC CNTYINC STHH	2.7222 2.7951 0.0104
RI+UI MFUNC=F4 N=58	1 2 3 4	0.4557 0.4648	0.4460 0.4454	0.5832 0.5935	17341 17350	1134.0 1135.0	2.79 3.84	CNTYPOP CNTYPOP STINC	0.0594 0.0596 6.8199
RI+UI GREGN=c N=50	1 2 3 4	0.7107 0.7452 0.7591	0.7047 0.7343 0.7433	0.3134 0.2873 0.2828	8691 8243 8102	909.0 904.6 903.8	14.24 9.06 8.17	CNTYVR CNTYVR CNTYINC CNTYHH CNTYINC STHH	0.0686 0.0616 2.7363 0.1165 2.2871 0.0186
RI+UI GREGN=n N=44	1 2 3 4	0.4385 0.4532	0.4251 0.4265	0.6150 0.6268	17941 17919	863.9 864.7	4.99 5.81	CNTYPOP CNTYPOP STINC	0.0744 0.0719 7.9142
RI+UI GREGN=s N=32	1 2 3 4	0.6468	0.6350	0.4003	7846	575.9	12.33	CNTYHH	1.1131
RI ALL N=74	1 2 3 4	0.2583 0.3369 0.3714	0.2480 0.3182 0.3445	0.7829 0.7192 0.7004	7710 7342 7199	1326.6 1320.3 1318.4	17.07 9.85 7.78	CNTYINC CNTYINC CNTYVR CNTYINC CNTYVR CTYPOP	3.3529 2.5843 0.0256 2.1420 0.0221 0.0079
RI CTYGR=A N=22	1 2 3 4	0.3504 0.3831	0.3179 0.3182	0.7795 0.8117	7177 7176	392.6 393.4	130.15 124.68	CNTYINC CNTYINC CNTYPOP	3.4859 2.6365 0.0425
RI CTYGR=A+ N=22	1 2 3 4	0.4514 0.6179 0.6862	0.4240 0.5777 0.6339	0.6583 0.5028 0.4532	7812 6689 6228	396.3 390.3 388.0	8.85 2.70 1.36	CTYPOP CTYPOP CNTYINC CTYPOP CNTYINC CNTYEMP	0.0243 0.0188 3.1816 0.0170 2.7477 0.0255
RI CTYGR=B N=6	1 2 3 4	0.2887 0.5251	0.1109 0.2086	1.4225 1.4246	5566 5252	105.1 104.6	N/A N/A	CNTYINC CNTYINC CTYPOP	3.2363 8.9719 2.9147

Table C2, continued

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
RI CTYGR=C N=10	1	0.8085	0.7846	0.2873	4535	170.2	N/A	CNTYVR	0.4709
	2	0.8176	0.7654	0.3388	4732	171.7	N/A	CNTYVR STHH	0.4513 0.0080
	3								
	4								
RI CTYGR=D N=14	1								
	2								
	3								
	4								
RI MFUNC=F1 N=14	1	0.3690	0.3164	0.8413	4463	237.1	29.69	CNTYPOP	0.1967
	2	0.3781	0.2651	0.9610	4627	238.9	31.11	CNTYPOP STEMP	0.1883 0.0044
	3								
	4								
RI MFUNC=F2 N=18	1	0.6172	0.5931	0.4787	6518	318.0	7.02	CNTYHH	0.9949
	2	0.7496	0.7162	0.3505	5443	312.4	1.75	CNTYPOP CTYPOP	0.3315 0.0139
	3	0.7527	0.6997	0.3886	5599	314.2	3.58	CNTYPOP CTYPOP CNTYINC	0.3236 0.0137 0.7770
	4								
RI MFUNC=F3 N=16	1	0.4747	0.4372	0.6754	3612	264.0	39.03	CNTYINC	2.6055
	2	0.5403	0.4695	0.6719	3506	264.0	34.66	CNTYINC STHH	2.7129 0.0109
	3								
	4								
RI MFUNC=F4 N=26	1	0.2553	0.2242	0.8689	8962	475.0	1.01	CTYPOP	0.0210
	2	0.3343	0.2764	0.8393	8655	474.0	0.57	CNTYINC CNTYHH	3.2133 0.0451
	3	0.3541	0.2660	0.8808	8718	475.0	1.96	CNTYINC CNTYHH STVR	2.9361 0.0430 0.0044
	4								
RI GREGN=c N=30	1	0.3806	0.3585	0.7079	7158	534.5	10.55	CNTYINC	4.0629
	2	0.5077	0.4711	0.6017	6498	529.6	5.05	CNTYINC CNTYVR	3.2793 0.0247
	3	0.5621	0.5116	0.5726	6245	528.1	3.83	CNTYINC CNTYPOP STHH	2.7541 0.0168 0.0194
	4								
RI GREGN=n N=20	1	0.2299	0.1872	0.9412	7356	358.0	210.47	CNTYINC	3.2932
	2	0.2732	0.1877	0.9833	7354	358.9	199.75	CNTYINC STINC	2.5461 4.4233
	3								
	4								
RI GREGN=s N=24	1	0.4469	0.4218	0.6536	4931	410.1	25.01	CNTYHH	0.5830
	2								
	3								
	4								

Table C2, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
UI	1	0.5197	0.5101	0.5187	16598	1012.5	2.13	CNTYPOP	0.0646
ALL	2	0.5363	0.5174	0.5204	16474	1012.7	2.40	CNTYPOP STVR	0.0620 0.0099
N=52	3								
	4								
UI	1								
CTYGR=A	2								
N=12	3								
	4								
UI	1	0.1293	-0.0158	1.4511	33460	168.4	75.12	CNTYPOP	0.0652
CTYGR=A+	2								
N=8	3								
	4								
UI	1	0.6252	0.5877	0.5248	8870	219.9	84.78	CNTYHH	0.1059
CTYGR=B	2	0.8512	0.8181	0.2480	5892	210.9	30.84	CNTYEMP STPOP	0.0738 0.1189
N=12	3	0.8946	0.8550	0.2108	5259	208.8	22.09	CNTYEMP STVR STINC	0.0873 0.0352 32.8320
	4								
UI	1	0.6291	0.5982	0.4945	13448	268.0	-0.93	CNTYPOP	0.0568
CTYGR=C	2	0.6548	0.5921	0.5334	13551	269.0	0.45	CNTYPOP CNTYINC	0.0548 5.1102
N=14	3								
	4								
UI	1	0.3118	0.1398	1.3763	3081	97.9	N/A	STHH	0.0130
CTYGR=D	2								
N=6	3								
	4								
UI	1	0.7699	0.7315	0.3835	8416	146.3	32.84	CNTYEMP	1.5084
MFUNC=F2	2	0.7965	0.7151	0.4477	8670	147.3	30.58	CNTYEMP STHH	1.3792 0.0263
N=8	3								
	4								
UI	1	0.6911	0.6397	0.5148	3071	130.2	N/A	CNTYINC	4.8178
MFUNC=F3	2	0.7248	0.6147	0.6055	3176	131.2	N/A	CNTYINC STHH	4.7991 0.0087
N=8	3								
	4								
UI	1	0.4620	0.4441	0.6097	19363	633.7	-3.66	CNTYPOP	0.0674
MFUNC=F4	2	0.4707	0.4342	0.6388	19534	635.2	-2.05	CNTYPOP STINC	0.0670 7.8636
N=32	3								
	4								

Table C2, continued

Case & N	# of Var	R^2	R_a^2	PC	RMSE	AIC	C_p	Variables in Model	b-coefficients
UI GREGN=c N=20	1	0.8736	0.8666	0.1544	7858	360.7	-2.99	CNTYHH	0.1582
	2	0.8834	0.8697	0.1577	7767	361.1	-1.99	CNTYHH STHH	0.1521 0.0213
	3								
	4								
UI GREGN=n N=24	1	0.4563	0.4316	0.6425	20838	479.2	-2.78	CNTYPOP	0.0871
	2	0.4673	0.4166	0.6849	21112	480.8	-1.13	CNTYPOP STINC	0.0845 9.4675
	3								
	4								
UI GREGN=s N=8	1	0.7825	0.7462	0.3625	7332	144.1	23.97	CNTYVR	0.5316
	2	0.8523	0.7932	0.3249	6618	143.0	16.98	CNTYVR STHH	0.4641 0.0384
	3								
	4								

Note: Cases for $N < 5$ have not been recorded

Table C3: Best Models for Interstate Highways
[Data Format: Density and County Avg. by Year]

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
RI+UI ALL N=313	1 2 3 4	0.4752 0.4942	0.4735 0.4910	0.5316 0.5155	14093 13856	5982.4 5972.8	88.63 76.18	CNTYPOP CNTYPOP CNTYINC	26.496 24.479 2.069
RI+UI CTYGR=A N=79	1 2 3 4	0.2477 0.3274	0.2380 0.3097	0.7913 0.7257	8051 7663	1422.9 1416.1	82.02 67.40	CNTYPOP CNTYPOP CNTYINC	37.880 26.036 2.131
RI+UI CTYGR=A+ N=76	1 2 3 4	0.3316	0.3226	0.7045	20846	1513.6	60.48	CNTYPOP	22.549
RI+UI CTYGR=B N=41	1 2 3 4	0.4065 0.4703 0.5313	0.3913 0.4424 0.4932	0.6544 0.6133 0.5700	15661 14988 14288	794.0 791.3 788.3	26.98 22.10 17.53	CNTYHH CNTYHH CNTYINC CNTYEMP CNTYINC STHH	56.878 41.361 5.031 29.318 5.252 2104.020
RI+UI CTYGR=C N=61	1 2 3 4	0.6077 0.6316	0.6010 0.6188	0.4189 0.4065	11742 11477	1145.2 1143.4	26.26 23.19	CNTYPOP CNTYPOP CNTYINC	25.787 24.097 3.090
RI+UI CTYGR=D N=56	1 2 3 4	0.1301 0.2132	0.1140 0.1835	0.9343 0.8759	4595 4411	946.4 942.8	63.39 54.37	STEMP STEMP CNTYPOP	542.920 493.170 75.625
RI+UI MFUNC=F1 N=47	1 2 3 4	0.6227 0.6353	0.6143 0.6187	0.4108 0.4144	4909 4881	800.8 801.2	23.49 23.28	CNTYPOP CNTYPOP STEMP	43.534 42.016 270.520
RI+UI MFUNC=F2 N=62	1 2 3 4	0.6864 0.7142 0.7176	0.6812 0.7046 0.7030	0.3345 0.3148 0.3213	7678 7392 7411	1111.3 1107.5 1108.8	18.28 13.51 14.69	CNTYHH CNTYHH CNTYVR CNTYHH CNTYVR STINC	434.059 465.943 404.640 454.404 343.720 1.660

Table C3, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
RI+UI MFUNC=F3 N=68	1	0.4716	0.4642	0.5598	4165	1135.5	97.16	CNTYINC	2.989
	2	0.5259	0.5113	0.5178	3978	1130.2	82.76	CNTYINC STMP	2.761 398.040
	3								
	4								
RI+UI MFUNC=F4 N=136	1	0.3903	0.3858	0.6279	18735	2677.9	36.64	CNTYPOP	23.106
	2	0.4045	0.3955	0.6224	18585	2676.8	34.73	CNTYPOP STMP	23.344 956.560
	3								
	4								
RI+UI GREGN=c N=132	1	0.6622	0.6596	0.3482	9369	2416.3	59.57	CNTYHH	52.520
	2	0.7234	0.7192	0.2894	8510	2319.9	27.57	CNTYHH CNTYINC	46.573 3.175
	3	0.7347	0.7285	0.2819	8368	2388.4	23.33	CNTYHH CNTYINC STMP	47.359 2.537 568.600
	4								
RI+UI GREGN=n N=104	1	0.4728	0.4677	0.5478	17805	2038.0	10.98	CNTYHH	119.648
	2	0.4898	0.4797	0.5405	17603	2036.0	9.42	CNTYHH STINC	118.375 5.901
	3								
	4								
RI+UI GREGN=s N=77	1	0.5645	0.5587	0.4587	8326	1392.2	36.87	CNTYEMP	304.974
	2	0.5667	0.5549	0.4685	8361	1393.8	38.32	CNTYEMP STVR	302.827 135.540
	3								
	4								
RI ALL N=186	1	0.3101	0.3064	0.7049	7872	3339.2	53.45	CNTYINC	3.547
	2	0.3904	0.3837	0.6296	7420	3318.2	29.31	CNTYINC CNTYPOP	2.966 8.291
	3	0.4019	0.3920	0.6244	7370	3316.7	27.38	CNTYINC CNTYPOP STMP	2.727 8.569 333.890
	4								
RI CTYGR=A N=51	1	0.3896	0.3772	0.6602	7351	910.0	228.70	CNTYINC	3.742
	2	0.4254	0.4051	0.6464	7206	908.9	70.27	CNTYINC CNTYPOP	2.996 16.761
	3								
	4								
RI CTYGR=A+ N=57	1	0.4010	0.3901	0.6426	8554	1034.1	48.95	CNTYINC	4.292
	2	0.5192	0.5014	0.5342	7734	1023.6	62.96	CNTYINC CNTYHH	3.696 19.453
	3								
	4								
RI CTYGR=B N=13	1	0.2646	0.1977	1.0028	5154	224.1	N/A	CNTYINC	2.800
	2	0.5438	0.4526	0.7298	4257	219.8	N/A	CNTYHH CTYPOP	141.278 16.966
	3	0.7061	0.6081	0.5551	3602	216.1	N/A	CNTYPOP CTYPOP STHH	64.993 23.173 1330.820
	4								

Table C3, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
RI CTYGR=C N=26	1 2 3 4	0.8253 0.8830 0.9107 0.9169	0.8181 0.8728 0.8986 0.9010	0.2038 0.1475 0.1217 0.1227	4097 3425 3059 3022	434.5 426.0 421.0 421.2	55.50 31.91 21.60 20.88	CNTYHH CNTYHH CTYPOP CNTYHH CTYPOP STINC CNTYPOP CTYPOP STHH STINC	383.628 414.203 0.144 396.711 0.134 2.913 128.477 0.120 450.490 1.954
RI CTYGR=D N=39	1 2 3 4	0.0979 0.1637 	0.0736 0.1172 	0.9996 0.9757 	4776 4662 	662.7 661.8 	36.46 33.25 	STEMP STEMP CTYPOP 	478.900 481.350 0.145
RI MFUNC=F1 N=37	1 2 3 4	0.4664 0.4842 	0.4511 0.4538 	0.5946 0.6069 	4073 4063 	617.0 617.8 	38.12 37.75 	CNTYPOP CNTYPOP STGAS 	30.650 30.067 5.199
RI MFUNC=F2 N=44	1 2 3 4	0.6884 0.7220 	0.6810 0.7084 	0.3413 0.3187 	6020 5754 	767.8 764.8 	50.54 42.77 	CNTYHH CNTYHH CNTYVR 	380.771 407.324 351.740
RI MFUNC=F3 N=44	1 2 3 4	0.4522 0.5047 	0.4392 0.4805 	0.5999 0.5678 	4213 4055 	736.4 733.9 	68.32 59.95 	CNTYINC CNTYINC STEMP 	2.773 2.568 375.320
RI MFUNC=F4 N=61	1 2 3 4	0.2571 0.3712 0.3900 	0.2445 0.3495 0.3579 	0.7932 0.6939 0.6956 	9361 8686 8630 	1117.6 1109.4 1109.6 	9.29 7.73 7.85 	CNTYINC CNTYINC CNTYHH CNTYINC CNTYHH STHH 	3.768 3.315 18.548 3.104 18.304 560.150
RI GREGN=c N=80	1 2 3 4	0.3838 0.4906 0.5149 	0.3759 0.4774 0.4957 	0.6478 0.5491 0.5362 	7352 6727 6608 	1426.4 1413.2 1411.3 	27.40 28.41 25.53 	CNTYINC CNTYINC CNTYPOP CNTYINC CNTYPOP STEMP 	3.890 3.349 7.030 2.905 7.239 458.950
RI GREGN=n N=47	1 2 3 4	0.2779 0.3060 	0.2619 0.2745 	0.7863 0.7866 	7504 7440 	840.7 840.9 	67.66 27.86 	CNTYINC CNTYINC STHH 	3.621 3.472 500.220
RI GREGN=s N=59	1 2 3 4	0.5047 0.5111 	0.4961 0.4936 	0.5300 0.5413 	4559 4571 	996.1 997.4 	33.19 34.06 	CNTYEMP CNTYEMP STEMP 	177.924 175.623 177.800

Table C3, continued

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
UI ALL N=127	1 2 3 4	0.4878 0.5075	0.4837 0.4996	0.5286 0.5163	17510 17239	2483.7 2480.7	36.09 31.96	CNTYPOP CNTYPOP CNTYPOP	27.663 27.656 4.019
UI CTYGR=A N=28	1 2 3 4	0.1993	0.1685	0.9239	7230	499.5	210.19	STHH	1086.800
UI CTYGR=A+ N=19	1 2 3 4	0.0572 0.3841	0.0018 0.3071	1.1646 0.8468	32372 26970	396.5 390.4	11.68 4.43	CNTYPOP CNTYPOP CNTYHH	9.196 35.022 132.796
UI CTYGR=B N=28	1 2 3 4	0.5672 0.7864 0.8026	0.5506 0.7693 0.7779	0.4993 0.2648 0.2632	9894 7089 6955	517.1 499.3 499.1	61.27 20.09 18.89	CNTYHH CNTYHH STHH CNTYHH STHH CNTYINC	45.806 40.435 2772.630 36.372 2780.240 1.818
UI CTYGR=C N=35	1 2 3 4	0.5937 0.6072	0.5814 0.5827	0.4555 0.4664	14027 14006	670.4 671.2	14.90 15.37	CNTYPOP CNTYPOP CNTYINC	24.563 23.773 2.850
UI CTYGR=D N=17	1 2 3 4	0.4338 0.6064	0.3961 0.5502	0.7172 0.5623	3392 2927	278.3 274.1	34.02 21.68	CNTYHH CNTYPOP STINC	854.620 217.949 3.750
UI MFUNC=F1 N=10	1 2 3 4	0.8277 0.9328	0.8061 0.9136	0.2585 0.1247	4019 2682	167.7 160.3	N/A N/A	CNTYEMP CNTYEMP STHH	210.448 167.119 948.270
UI MFUNC=F2 N=18	1 2 3 4	0.7393 0.7814	0.7231 0.7523	0.3258 0.3060	8523 8061	327.7 326.5	12.83 10.50	CNTYEMP CNTYEMP CNTYVR	651.336 679.137 577.750
UI MFUNC=F3 N=24	1 2 3 4	0.6353 0.6774	0.6188 0.6467	0.4310 0.4148	3660 3523	395.8 394.8	26.18 22.85	CNTYINC CNTYINC STEMP	4.311 4.018 389.520

Table C3, continued

Case & N	# of Var	R^2	R_a^2	PC	RMSE	AIC	C_p	Variables in Model	b-coefficients
UI MFUNC=F4 N=75	1	0.3742	0.3657	0.6600	20904	1494.1	21.69	CNTYPOP	24.513
	2	0.3909	0.3740	0.6598	20766	1494.1	21.22	CNTYPOP STVR	23.817 801.950
	3								
	4								
UI GREGN=c N=52	1	0.8457	0.8427	0.1666	8550	943.5	101.42	CNTYEMP	46.791
	2	0.8661	0.8607	0.1503	8046	938.2	83.67	CNTYEMP STMP	46.204 990.250
	3	0.8681	0.8599	0.1539	8069	939.4	83.75	CNTYEMP STMP CNTYINC	44.676 810.120 1.237
	4								
UI GREGN=n N=57	1	0.5056	0.4966	0.5304	19979	1130.8	8.02	CNTYHH	138.443
	2	0.5163	0.4984	0.5374	19943	1131.6	8.69	CNTYHH STINC	137.266 5.493
	3								
	4								
UI GREGN=s N=18	1	0.5472	0.5189	0.5660	10017	333.5	62.23	CTYPOP	11.803
	2	0.7705	0.7399	0.3213	7366	323.3	26.64	CTYPOP CNTYVR	8.753 1255.440
	3								
	4								

Note: Cases for $N < 5$ have not been recorded

Table C4: Best Models for Interstate Highways
[Data Format: Density E&L and County Avg. by Year]

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
RI+UI ALL N=126	1 2 3 4	0.4860 0.4956	0.4819 0.4874	0.5306 0.5290	13678 13605	2402.0 2402.0	27.55 26.76	CNTYPOP CNTYPOP STINC	26.115 25.912 4.913
RI+UI CTYGR=A N=34	1 2 3 4	0.2069 0.2578	0.1821 0.2099	0.8922 0.8859	7719 7587	610.6 610.4	45.41 42.58	CNTYPOP CNTYPOP CNTYINC	31.861 22.116 1.735
RI+UI CTYGR=A+ N=30	1 2 3 4	0.3546	0.3315	0.7376	20573	597.8	16.94	CNTYPOP	22.857
RI+UI CTYGR=B N=18	1 2 3 4	0.4287 0.4905	0.3930 0.4226	0.7141 0.7133	15206 14831	348.5 348.5	26.54 24.15	CNTYHH CNTYINC STVR	56.744 12.452 2810.790
RI+UI CTYGR=C N=24	1 2 3 4	0.6129 0.6304	0.5953 0.5952	0.4575 0.4752	11651 11652	451.3 452.2	0.12 1.21	CNTYPOP CNTYPOP CNTYINC	24.670 22.975 3.093
RI+UI CTYGR=D N=20	1 2 3 4	0.1269	0.0784	1.0671	4263	336.2	71.22	CNTYHH	239.749
RI+UI MFUNC=F1 N=18	1 2 3 4	0.6466 0.6540	0.6245 0.6078	0.4418 0.4844	4778 4883	306.9 308.5	1.30 2.98	CNTYPOP CNTYPOP STHH	42.374 41.172 188.600
RI+UI MFUNC=F2 N=26	1 2 3 4	0.7214 0.7326	0.7098 0.7093	0.3250 0.3372	7437 7444	465.5 466.4	6.35 7.22	CNTYHH CNTYHH CNTYVR	441.771 456.149 265.440

Table C4, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
RI+UI MFUNC=F3 N=24	1 2 3 4	0.4651 0.5213	0.4407 0.4757	0.6322 0.6155	3594 3480	394.9 394.2	74.80 66.84	CNTYINC CNTYINC STHH	2.722 2.795 375.800
RI+UI MFUNC=F4 N=58	1 2 3 4	0.4226 0.4306	0.4123 0.4099	0.6186 0.6315	17860 17896	1137.6 1138.8	8.94 10.07	CNTYPOP CNTYPOP STVR	23.742 22.927 444.250
RI+UI GREGN=c N=50	1 2 3 4	0.7100 0.7481 0.7630	0.7040 0.7373 0.7476	0.3141 0.2841 0.2782	8701 8196 8035	909.1 904.1 902.9	16.51 10.31 9.08	CNTYHH CNTYHH CNTYINC CNTYHH CNTYINC STHH	52.624 47.167 2.857 46.232 2.208 686.710
RI+UI GREGN=n N=44	1 2 3 4	0.4616 0.4719	0.4488 0.4461	0.5896 0.6054	17567 17610	862.0 863.2	0.77 1.99	CNTYPOP CNTYPOP STINC	39.174 37.976 6.637
RI+UI GREGN=s N=32	1 2 3 4	0.5765 0.5767	0.5624 0.5476	0.4799 0.5108	8592 8736	581.7 583.7	9.98 11.96	CNTYEMP CNTYEMP STHH	315.784 315.397 78.650
RI ALL N=74	1 2 3 4	0.2583 0.3568 0.3661	0.2480 0.3387 0.3389	0.7829 0.6975 0.7063	7710 7231 7229	1326.6 1318.1 1319.0	18.59 8.83 9.72	CNTYINC CNTYINC CNTYPOP CNTYINC CNTYPOP STMP	3.353 2.582 8.691 2.451 8.748 326.730
RI CTYGR=A N=22	1 2 3 4	0.3504 0.3765	0.3179 0.3108	0.7795 0.8204	7177 7214	392.6 393.7	130.15 24.65	CNTYINC CNTYINC STINC	3.486 3.283 3.178
RI CTYGR=A+ N=22	1 2 3 4	0.3803 0.5319	0.3493 0.4827	0.7437 0.6159	8303 7404	398.9 394.8	38.35 26.56	CNTYINC CNTYINC CNTYHH	4.507 3.631 20.341
RI CTYGR=B N=6	1 2 3 4	0.2887 0.6586	0.1109 0.4311	1.4225 1.0241	5566 4453	105.1 102.6	N/A N/A	CNTYINC CNTYHH CTYPOP	3.236 158.912 19.175

Table C4, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
RI CTYGR=C N=10	1 2 3 4	0.8999 0.9492 0.9481	0.8874 0.9346 0.9522	0.1502 0.0944 0.0743	3279 2498 2135	163.7 158.9 156.2	N/A N/A N/A	CNTYHH CNTYHH CTYPOP CNTYPOP STHH CTYPOP	394.685 420.041 0.137 127.760 516.310 0.011
RI CTYGR=D N=14	1 2 3 4								
RI MFUNC=F1 N=14	1 2 3 4	0.5039 0.5085	0.4626 0.4192	0.6615 0.7595	3957 4114	233.8 235.6	116.70 117.52	CNTYPOP CNTYPOP STVR	29.918 29.306 50.455
RI MFUNC=F2 N=18	1 2 3 4	0.7255 0.7327	0.7083 0.6971	0.3431 0.3742	5518 5624	312.0 313.6	22.19 23.24	CNTYHH CNTYHH CNTYVR	363.303 372.421 153.640
RI MFUNC=F3 N=16	1 2 3 4	0.4747 0.5397	0.4372 0.4689	0.6754 0.6728	3612 3509	264.0 263.9	39.03 26.27	CNTYINC CNTYINC STHH	2.606 2.713 390.980
RI MFUNC=F4 N=26	1 2 3 4	0.2231 0.3536	0.1907 0.2974	0.9064 0.8150	9154 8529	476.3 473.5	15.76 11.41	CNTYHH CNTYHH CNTYINC	24.460 20.105 3.090
RI GREGN=c N=30	1 2 3 4	0.3806 0.5121	0.3585 0.4760	0.7079 0.5963	7158 6469	534.5 529.3	23.04 14.63	CNTYINC CNTYINC CNTYPOP	4.063 3.319 7.283
RI GREGN=n N=20	1 2 3 4	0.2299 0.2732	0.1872 0.1877	0.9412 0.9833	7356 7354	358.0 358.9	9.83 10.38	CNTYINC CNTYINC STINC	3.293 2.546 4.418
RI GREGN=s N=24	1 2 3 4	0.5246	0.5030	0.5618	4571	406.4	11.22	CNTYEMP	178.909

Table C4, continued

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
UI ALL N=52	1 2 3 4	0.4855 0.5086	0.4753 0.4885	0.5556 0.5516	17179 16961	1016.1 1015.7	8.68 8.14	CNTYPOP CNTYPOP CTYPOP	27.016 2727.164 4.116
UI CTYGR=A N=12	1 2 3 4	0.1266	0.0392	1.2228	7562	216.2	N/A	STEMP	878.930
UI CTYGR=A+ N=8	1 2 3 4	0.1136	-0.0341	1.4773	33761	168.5	8.52	STVR	2861.920
UI CTYGR=B N=12	1 2 3 4	0.6495 0.8431 0.8869 0.9074	0.6145 0.8083 0.8445 0.8544	0.4907 0.2615 0.2262 0.2250	8577 6049 5447 5270	219.2 211.5 209.6 209.2	84.03 35.19 25.69 22.32	CNTYHH CNTYPOP STPOP CNTYHH STVR STINC CNTYPOP STPOP STINC CTYPOP	45.072 14.806 4246.290 47.655 2180.100 35.614 21.897 4667.860 45.963 3.640
UI CTYGR=C N=14	1 2 3 4	0.5921 0.6006	0.5582 0.5280	0.5438 0.6173	14103 14577	269.4 271.1	-6.37 -4.45	CNTYPOP CNTYPOP CNTYINC	23.608 22.811 2.993
UI CTYGR=D N=6	1 2 3 4	0.5857	0.4821	0.8286	2391	94.9	N/A	CNTYHH	586.566
UI MFUNC=F2 N=8	1 2 3 4	0.7395 0.7807	0.6961 0.6930	0.4342 0.4824	8954 8999	147.3 147.9	47.85 41.64	CNTYEMP CNTYEMP CNTYVR	602.260 593.598 657.120
UI MFUNC=F3 N=8	1 2 3 4	0.6911 0.7694	0.6397 0.6771	0.5148 0.5074	3071 2907	130.2 129.8	N/A N/A	CNTYINC CNTYINC CTYPOP	4.818 5.940 7.443
UI MFUNC=F4 N=32	1 2 3 4	0.4082 0.4178	0.3884 0.3776	0.6707 0.7027	20309 20487	636.7 638.2	2.78 4.28	CNTYPOP CNTYPOP STINC	25.555 25.387 8.288

Table C4, continued

Case & N	# of Var	R^2	R_a^2	PC	RMSE	AIC	C_p	Variables in Model	b-coefficients
UI GREGN=c N=20	1	0.8753	0.8684	0.1524	7805	360.4	32.07	CNTYHH	62.320
	2	0.8852	0.8717	0.1553	7705	360.3	30.25	CNTYHH STHH	59.901 776.520
	3								
	4								
UI GREGN=n N=24	1	0.4768	0.4530	0.6183	20442	478.3	-0.57	CNTYPOP	45.398
	2	0.4863	0.4374	0.6605	20732	479.9	1.07	CNTYPOP CTYPOP	44.361 2.962
	3								
	4								
UI GREGN=s N=8	1	0.6504	0.5921	0.5827	9295	147.9	51.88	CNTYVR	2166.470
	2	0.8294	0.7612	0.3752	7112	144.2	25.26	CNTYVR CTYPOP	1528.160 7.597
	3								
	4								

Note: Cases for $N < 5$ have not been recorded

Table C5: Best Models for Urban Principal Arterial
[Data Format: Raw and City Avg. by Year]

Case & N	# of Var	R ²	-R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
ALL N=255	1	0.2055	0.2023	0.8071	3530	4168.3	68.45	CNTYINC	1.2913
	2	0.2957	0.2901	0.7211	3331	4139.6	38.19	CNTYINC CNTYEMP	1.0547 0.0223
	3	0.3557	0.3480	0.6649	3192	4118.9	12.06	CNTYINC CNTYEMP CTYPOP	0.9352 0.0187 0.0814
	4	0.3711	0.3610	0.6541	3160	4114.7	7.87	CNTYINC CNTYEMP CTYPOP STHH	0.8322 0.0182 0.0846 0.0046
CTYGR=A N=43	1	0.2215	0.2025	0.8545	2675	680.6	16.70	CNTYINC	1.2644
	2	0.3314	0.2980	0.7689	2509	676.1	10.83	CNTYINC CTYPOP	1.2109 0.1696
	3	0.3448	0.2944	0.7896	2515	677.2	11.87	CNTYINC CTYPOP STHH	1.0885 0.1826 0.0031
	4								
CTYGR=B N=30	1	0.3424	0.3189	0.7516	4652	508.6	16.54	CNTYEMP	0.0314
	2	0.3684	0.3217	0.7719	4643	509.4	16.86	CNTYEMP STEMP	0.0310 0.0078
	3								
	4								
CTYGR=C N=80	1	0.4021	0.3945	0.6285	2994	1282.7	32.92	CNTYINC	1.5627
	2	0.4977	0.4847	0.5414	2762	1270.8	17.50	CNTYINC CTYPOP	1.3804 0.3617
	3	0.4989	0.4791	0.5538	2777	1272.6	19.29	CNTYINC CTYPOP STHH	1.3359 0.3579 0.0012
	4								
CTYGR=D N=102	1	0.2180	0.2102	0.8132	2304	1581.5	23.55	CNTYVR	0.0177
	2	0.3594	0.3464	0.6795	2097	1563.2	3.58	CNTYEMP STHH	0.0306 0.0084
	3	0.3857	0.3669	0.6645	2063	1560.9	1.49	CNTYEMP STHH CTYPOP	0.0316 0.0081 0.2804
	4	0.3967	0.3718	0.6655	2055	1561.1	1.78	CNTYEMP STHH STINC STVR	0.0314 0.0066 0.5534 0.2869
CTYGR=A MFUNC=F3 N=15	1	0.7037	0.6810	0.3874	1217	214.9	50.09	CNTYINC	1.7212
	2								
	3								
	4								
CTYGR=A MFUNC=F4 N=28	1	0.4243	0.4022	0.6642	2396	437.7	17.39	CTYPOP	0.4237
	2	0.5352	0.4981	0.5763	2196	433.7	11.42	CTYPOP STHH	0.5122 0.0098
	3	0.5357	0.4787	0.6178	2238	435.6	13.32	CTYPOP STHH CNTYPOP	0.5169 0.0099 0.0008
	4								
CTYGR=B MFUNC=F4 N=26	1	0.3225	0.2943	0.7904	4990	444.7	26.08	CNTYEMP	0.0304
	2	0.3531	0.2969	0.8156	4981	445.5	25.91	CNTYEMP STEMP	0.0299 0.0085
	3								
	4								

Table C5, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
CTYGR=C MFUNC=F2 N=28	1	0.3297	0.3039	0.7734	1189	398.5	38.02	STINC	1.4139
	2	0.4579	0.4146	0.6722	1191	394.5	28.15	STINC CNTYHH	1.0418 0.3301
	3								
	4								
CTYGR=C MFUNC=F3 N=26	1	0.5089	0.4885	0.5728	2889	416.3	60.51	CNTYHH	0.5136
	2	0.7667	0.7464	0.2942	2034	398.9	19.21	CNTYVR CTYPOP	0.1913 0.6040
	3	0.8064	0.7799	0.2641	1895	396.1	14.53	CNTYPOP CTYPOP CNTYEMP	0.1087 0.6992 0.3571
	4	0.8114	0.7754	0.2785	1914	397.4	15.70	CNTYPOP CTYPOP CNTYEMP STINC	0.1110 0.6897 0.3100 0.4624
CTYGR=C MFUNC=F4 N=26	1	0.6379	0.6229	0.4224	2749	413.7	13.34	CNTYINC	1.9709
	2	0.6627	0.6334	0.4252	2710	413.9	12.92	CNTYINC CTYPOP	1.8779 0.1797
	3								
	4								
CTYGR=D MFUNC=F1 N=41	1	0.0906	0.0673	1.0026	2299	636.6	30.66	STHH	0.0066
	2								
	3								
	4								
CTYGR=D MFUNC=F2 N=27	1	0.7961	0.7879	0.2366	1055	377.8	81.24	CNTYVR	0.3221
	2	0.8376	0.8240	0.2030	961	375.7	62.03	CNTYVR CTYPOP	0.2679 0.4764
	3	0.8629	0.8450	0.1848	902	371.1	51.10	CNTYVR CTYPOP STINC	0.2252 0.5589 0.6803
	4								
CTYGR=D MFUNC=F3 N=15	1	0.5571	0.5230	0.5792	1777	226.3	26.08	CNTYEMP	0.5384
	2	0.8651	0.8426	0.2023	1021	210.5	2.29	CTYPOP STHH	0.8359 0.0122
	3	0.8971	0.8690	0.1777	931	208.4	1.61	CNTYEMP CTYPOP STHH	0.1848 0.7450 0.0089
	4								
CTYGR=D MFUNC=F4 N=19	1	0.5644	0.5388	0.5381	1940	289.5	4.19	CNTYVR	0.0200
	2	0.6379	0.5927	0.4978	1823	288.1	2.95	CNTYEMP STPOP	0.0338 0.0093
	3	0.6801	0.6161	0.4906	1769	287.7	3.10	CNTYHH CTYPOP STEMP	0.0375 1.4908 0.0082
	4								
CTYGR=A GREGN=c N=15	1	0.5771	0.5446	0.5530	1760	226.0	244.72	CNTYEMP	0.3753
	2	0.8230	0.7935	0.2655	1185	214.9	98.04	CNTYPOP CNTYINC	0.0970 2.2656
	3								
	4								
CTYGR=A GREGN=n N=23	1	0.4630	0.4385	0.6381	2445	360.8	18.72	CTYPOP	0.4496
	2	0.5284	0.4813	0.6131	2351	359.9	16.19	CTYPOP STHH	0.5121 0.0080
	3	0.5303	0.4561	0.6675	2406	361.8	18.06	CTYPOP STHH CNTYPOP	0.5163 0.0081 0.0009
	4								

Table C5, continued

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
CTYGR=A GREGN=s N=5	1 2 3	0.8909	0.8545	0.2546	149	51.5	N/A	CNTYPOP	0.1111
CTYGR=B GREGN=c N=12	1 2 3	0.9436 0.9530	0.9379 0.9426	0.0789 0.0783	1527 1469	177.8 177.6	N/A N/A	CNTYVR CNTYVR CNTYINC	0.0260 0.0226 0.9065
CTYGR=B GREGN=n N=13	1 2 3 4	0.5908 0.7879 0.8395	0.5536 0.7455 0.7861	0.5580 0.3393 0.3031	1214 917 841	186.5 179.9 178.3	7.99 1.81 1.66	CNTYINC CNTYINC STHH CNTYVR CNTYINC STEMP	0.1150 1.0547 0.0105 0.0754 0.5855 0.0051
CTYGR=B GREGN=s N=5	1 2 3	0.9897 0.9930	0.9863 0.9861	0.0241 0.0279	374 377	60.7 60.7	N/A N/A	STPOP CNTYPOP CNTYEMP	0.0234 0.5703 0.2238
CTYGR=C GREGN=c N=45	1 2 3 4	0.4395 0.6165 0.6204	0.4264 0.5982 0.5927	0.6127 0.4383 0.4536	3403 2848 2868	733.9 718.8 720.3	74.19 39.81 41.00	CNTYINC CNTYINC CTYPOP CNTYINC CTYPOP CNTYPOP	1.8733 1.5943 0.5668 1.5531 0.5571 0.0094
CTYGR=C GREGN=n N=30	1 2 3	0.3179 0.4016	0.2936 0.3572	0.7795 0.7314	2260 2155	465.3 463.4	7.56 5.44	CNTYINC CNTYINC CTYPOP	1.3858 1.1870 0.2576
CTYGR=C GREGN=s N=5	1 2 3	0.7119 0.8168	0.6158 0.6337	0.6723 0.7326	1062 1037	71.1 70.9	N/A N/A	CNTYPOP CNTYPOP CNTYINC	1.1137 1.3107 1.4523
CTYGR=D GREGN=c N=26	1 2 3 4	0.3676 0.5888 0.6550	0.3412 0.5530 0.6079	0.7378 0.5185 0.4705	1293 1065 997	374.5 365.3 362.7	14.93 4.01 2.15	CTYPOP CTYPOP STEMP CTYPOP STHH CNTYINC	0.6729 0.7327 0.0073 0.9459 0.5176 0.0048
CTYGR=D GREGN=n N=34	1 2 3 4	0.4382 0.4725 0.4928	0.4206 0.4385 0.4421	0.6321 0.6296 0.6425	2410 2372 2364	531.5 531.3 532.0	-0.64 -0.43 -0.51	CNTYVR CNTYHH CNTYINC CNTYHH CNTYINC STHH	0.0194 0.0284 1.0012 0.0281 0.8564 0.0041
CTYGR=D GREGN=s N=42	1 2 3 4	0.3985 0.4303 0.4520	0.3834 0.4010 0.4087	0.6617 0.6574 0.6634	1727 1702 1692	628.1 627.8 628.2	-0.49 -0.47 0.17	STPOP STPOP STINC STPOP STINC CTYPOP	0.0155 0.0118 0.8937 0.0113 0.8484 0.1910

Note: Cases for N < 5 have not been recorded

Table C5.1: Best Models for Urban Principal Arterial by Region
[Data Format: Raw and City Avg. by Year]

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
GREGN=c N=98	1	0.3489	0.3421	0.6782	3668	1610.6	87.60	CNTYVR	0.0285
	2	0.5565	0.5472	0.4715	3043	1575.0	31.70	CNTYPOP CNTYINC	0.0175 1.4136
	3	0.6601	0.6492	0.3689	2679	1550.9	4.81	CNTYVR CNTYINC CTYPOP	0.0197 1.4408 0.1370
	4	0.6610	0.6491	0.3758	2690	1552.8	6.64	CNTYPOP CNTYINC CTYPOP STHH	0.0142 1.4542 0.1334 0.0015
GREGN=n N=100	1	0.3400	0.3333	0.6869	2566	1572.0	21.32	CNTYINC	1.6632
	2	0.4123	0.4002	0.6241	2434	1562.4	10.47	CNTYINC CTYPOP	1.3369 0.0659
	3	0.4412	0.4237	0.6054	2385	1559.3	7.34	CNTYINC CTYPOP CNTYVR	1.1702 0.0654 0.0053
	4								
GREGN=s N=57	1	0.2935	0.2806	0.7579	3584	934.9	9.26	CNTYVR	0.1323
	2	0.3264	0.3015	0.7484	3532	934.3	8.35	CNTYVR STEMP	0.1270 0.0067
	3	0.3767	0.3414	0.7174	3429	931.8	5.92	CNTYEMP STPOP CTYPOP	0.2331 0.0122 0.1048
	4	0.3815	0.3340	0.7374	3449	933.4	7.50	CNTYEMP STHH CTYPOP STINC	0.2328 0.0068 0.1037 0.7858
GREGN=s CTYGR=A+B +C N=15	1	0.8108	0.7963	0.2474	2961	241.7	87.28	CNTYVR	0.6020
	2	0.8553	0.8312	0.2170	2696	239.6	66.16	CNTYEMP STHH	0.6090 0.0110
	3								
	4								

Table C6: Best Models for Urban Principal Arterial
[Data Format: Raw E&L and City Avg. by Year]

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
ALL N=116	1	0.2191	0.2122	0.8083	3451	1891.9	27.30	CNTYEMP	0.0289
	2	0.3156	0.3034	0.7208	3245	1878.7	12.08	CNTYEMP CNTYINC	0.0222 1.0259
	3	0.3766	0.3599	0.6679	3111	1869.8	3.19	CNTYEMP CNTYINC CTYPOP	0.0194 0.8961 0.0821
	4	0.3915	0.3695	0.6633	3087	1869.1	2.54	CNTYEMP CNTYINC CTYPOP STHH	0.0189 0.8319 0.0853 0.0045
CTYGR=A N=18	1	0.2808	0.2359	0.8989	2429	282.5	14.47	CNTYINC	1.5926
	2	0.4169	0.3391	0.8164	2259	280.7	11.09	CNTYINC CTYPOP	1.5756 0.1747
	3	0.4285	0.3061	0.8980	2315	282.4	12.62	CNTYINC CTYPOP STHH	1.4401 0.1835 0.0028
	4								
CTYGR=B N=14	1	0.4952	0.4531	0.6730	4241	235.7	399.74	CNTYEMP	0.0325
	2	0.5075	0.4180	0.7611	4375	237.4	391.76	CNTYEMP STEM	0.0324 0.0067
	3								
	4								
CTYGR=C N=36	1	0.3542	0.3352	0.7217	2991	578.2	10.41	CNTYINC	1.6291
	2	0.4620	0.4294	0.6358	2771	573.6	5.34	CNTYINC CTYPOP	1.4639 0.4004
	3	0.4673	0.4174	0.6659	2800	575.3	6.99	CNTYINC CTYPOP STHH	1.4253 0.3950 0.0026
	4								
CTYGR=D N=48	1	0.2987	0.2834	0.7623	2184	740.1	4.50	CNTYVR	0.0182
	2	0.3962	0.3962	0.6843	2049	734.9	-0.24	CNTYEMP STPOP	0.0316 0.0102
	3	0.4125	0.3724	0.6944	2044	735.6	0.63	CNTYEMP STPOP CTYPOP	0.0324 0.0098 0.2249
	4								
CTYGR=A MFUNC=P3 N=6	1	0.8590	0.8238	0.2820	906	83.3	N/A	CNTYINC	1.9942
	2	0.8876	0.8127	0.3371	934	83.9	N/A	CNTYINC CNTYEMP	1.8220 0.0510
	3								
	4								
CTYGR=A MFUNC=P4 N=12	1	0.5252	0.4777	0.6648	2039	184.7	N/A	CTYPOP	0.4390
	2	0.6980	0.6308	0.5034	1714	181.3	N/A	CTYPOP STHH	0.5509 0.0121
	3	0.7031	0.5918	0.5938	1803	183.1	N/A	CTYPOP STHH CNTYPOP	0.5592 0.0121 0.0013
	4								

Table C6, continued

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
CTYGR=B MFUNC=F4 N=12	1 2 3 4	0.4728 0.4892	0.4201 0.3756	0.7381 0.8514	4619 4792	204.3 205.9	N/A N/A	CNTYEMP CNTYEMP STEMP	0.0317 0.0313 0.0079
CTYGR=C MFUNC=F2 N=12	1 2 3 4	0.4203 0.5132	0.3623 0.4050	0.8116 0.8114	967 934	166.8 166.7	N/A N/A	CNTYVR STEMP CNTYPOP	0.1392 0.0056 0.1037
CTYGR=C MFUNC=F3 N=12	1 2 3 4	0.5167 0.8186 0.8527	0.4684 0.7783 0.7975	0.6766 0.3023 0.2946	3027 1955 1868	194.2 184.4 183.9	N/A N/A N/A	CNTYPOP CNTYVR CTYPOP CNTYPOP CTYPOP CNTYEMP	0.1637 0.2029 0.6639 0.1064 0.7743 0.4244
CTYGR=C MFUNC=F4 N=12	1 2 3 4	0.5378 0.5607	0.4916 0.4631	0.6471 0.7321	3067 3152	194.5 195.9	N/A N/A	CNTYINC CNTYINC CTYPOP	2.0978 2.0443 0.2100
CTYGR=D MFUNC=F1 N=20	1 2 3 4								
CTYGR=D MFUNC=F2 N=12	1 2 3 4	0.8592 0.9008 0.9236	0.8451 0.8787 0.8949	0.1972 0.1654 0.1528	867 767 714	164.2 161.9 160.8	N/A N/A N/A	CNTYVR CNTYVR CTYPOP CNTYVR CTYPOP STEMP	0.3156 0.2654 0.4441 0.2270 0.4983 0.0038
CTYGR=D MFUNC=F3 N=6	1 2 3 4	0.5836 0.9418 0.9534	0.4795 0.9029 0.8834	0.8329 0.1747 0.2332	1783 770 844	91.4 81.6 82.3	N/A N/A N/A	CNTYEMP CTYPOP STHH CNTYEMP CTYPOP CNTYVR	0.5224 0.7813 0.0121 0.2958 0.6958 0.1595
CTYGR=D MFUNC=F4 N=10	1 2 3 4	0.5754 0.6131 0.6601	0.5223 0.5026 0.4902	0.6369 0.7185 0.7930	2036 2077 2103	154.1 155.2 155.9	N/A N/A N/A	CNTYEMP CNTYEMP STINC CNTYHH STINC CTYPOP	0.0346 0.0302 1.4310 0.0329 1.8138 1.3940

Table C6, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	ATC	C _p	Variables in Model	b-coefficients
CTYGR=A GREGN=c N=6	1 2 3 4	0.6014 0.9638	0.5018 0.9396	0.7972 0.1087	1843 642	91.8 79.4	N/A N/A	CNTYEMP CNTYPOP CNTYINC	0.3938 0.1100 2.7755
CTYGR=A GREGN=n N=10	1 2 3 4								
CTYGR=B GREGN=c N=6	1 2 3 4	0.9812 0.9943	0.9765 0.9905	0.0376 0.0172	1053 670	85.1 79.9	N/A N/A	CNTYVR CNTYEMP STINC	0.0262 0.0368 1.7909
CTYGR=B GREGN=n N=6	1 2 3 4	0.6390 0.8873	0.5488 0.8122	0.7220 0.3381	1058 683	85.1 80.2	N/A N/A	STEMP CNTYINC CNTYHH	0.0169 1.5229 0.3422
CTYGR=C GREGN=c N=20	1 2 3 4	0.4266 0.6982 0.6985	0.3947 0.6627 0.6420	0.7009 0.4083 0.4522	3337 2491 2566	326.4 315.6 317.5	82.48 37.84 39.78	CNTYINC CNTYINC CTYPOP CNTYINC CTYPOP STINC	2.0692 1.8319 0.7613 1.8117 0.7542 1.7712
CTYGR=C GREGN=n N=14	1 2 3 4	0.1425 0.2053	0.0711 0.0608	1.1433 1.2282	2510 2524	221.0 221.9	484.91 447.89	CNTYINC CNTYINC CTYPOP	1.1002 0.9182 0.2215
CTYGR=D GREGN=c N=12	1 2 3 4	0.4984 0.7279 0.7905 0.7961	0.4482 0.6675 0.7719 0.6796	0.7023 0.4534 0.4190 0.4951	1068 829 772 814	169.2 163.8 162.7 164.4	N/A N/A N/A N/A	CTYPOP CTYPOP STEMP CTYPOP STEMP CNTYINC CTYPOP STEMP CNTYINC CNTYVR	0.7162 0.7656 0.0092 0.9511 0.0083 0.4397 0.9484 0.0079 0.4138 0.0032
CTYGR=D GREGN=n N=18	1 2 3 4	0.4876 0.5037	0.4556 0.4375	0.6405 0.6948	2344 2382	281.2 282.6	2.63 4.10	CNTYVR CNTYHH CNTYINC	0.0191 0.0268 1.0108
CTYGR=D GREGN=s N=18	1 2 3 4	0.5104 0.5138	0.4798 0.4490	0.6121 0.6807	1484 1527	264.8 266.6	-5.45 -3.51	STEMP STEMP CTYPOP	0.0186 0.0186 0.0714

Note: Cases for N < 5 have not been recorded

Table C7: Best Models for Urban Principal Arterial
[Data Format: Density and City Avg. by Year]

Case & N	# of Var	R ²	R ² _a	PC	RMSE	ATC	C _p	Variables in Model	b-coefficients
ALL N=255	1	0.2055	0.2023	0.8071	3530	4168.3	61.33	CNTYINC	1.291
	2	0.3210	0.3156	0.6952	3270	4130.2	17.91	CNTYINC CNTYEMP	1.024 11.281
	3	0.3360	0.3280	0.6852	3240	4126.5	14.02	CNTYINC CNTYEMP CTYPOP	1.040 11.309 0.647
	4	0.3498	0.3393	0.6763	3213	4123.2	10.61	CNTYINC CNTYEMP CTYPOP STHH	0.953 11.200 0.668 146.000
CTYGR=A N=43	1	0.2215	0.2025	0.8545	2675	680.6	16.70	CNTYINC	1.264
	2	0.3291	0.2955	0.7716	2514	676.2	5.83	CNTYINC CTYPOP	1.390 1.298
	3	0.3343	0.2831	0.8023	2536	677.9	7.50	CNTYINC CTYPOP STHH	1.320 1.324 67.305
	4								
CTYGR=B N=30	1	0.3675	0.3449	0.7229	4563	507.5	6.14	CNTYHH	17.056
	2	0.4358	0.3940	0.6896	4388	506.0	4.67	CNTYEMP CNTYVR	12.921 192.670
	3	0.5050	0.4479	0.6472	4188	504.1	3.15	CNTYEMP CNTYVR CTYPOP	15.703 244.333 1.452
	4								
CTYGR=C N=80	1	0.4021	0.3945	0.6285	2994	1282.7	-1.31	CNTYINC	1.563
	2	0.4063	0.3908	0.6400	3003	1284.2	0.17	CNTYINC STHH	1.513 77.850
	3								
	4								
CTYGR=D N=102	1	0.2050	0.1971	0.8268	2324	1583.2	26.38	CNTYVR	17.741
	2	0.3484	0.3352	0.6911	2115	1564.9	5.95	CNTYEMP STHH	16.445 302.388
	3	0.3570	0.3374	0.6954	2111	1565.5	6.59	CNTYEMP STHH STINC	16.360 252.329 0.534
	4								
CTYGR=A MFUNC=F3 N=15	1	0.7037	0.6810	0.3874	1217	214.9	258.15	CNTYINC	1.721
	2								
	3								
	4								
CTYGR=A MFUNC=F4 N=28	1	0.1041	0.0697	1.0340	2989	450.1	0.23	CTYPOP	1.359
	2	0.2357	0.1745	0.9478	2816	447.6	-1.33	CTYPOP CNTYINC	1.594 1.001
	3	0.2440	0.1495	1.0080	2858	449.3	0.49	CTYPOP CNTYINC STHH	1.689 0.959 94.190
	4								
CTYGR=B MFUNC=F4 N=26	1	0.3498	0.3227	0.7586	4889	443.6	177.27	CNTYHH	16.553
	2	0.4634	0.4168	0.6765	4537	440.6	144.44	CNTYEMP CNTYVR	12.145 272.512
	3	0.5785	0.5210	0.5747	4111	436.4	111.17	CNTYEMP CNTYVR CTYPOP	15.440 368.460 1.899
	4								

Table C7, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
CTYGR=C MFUNC=F2 N=28	1 2 3 4	0.3297 0.4616 0.4875	0.3039 0.4186 0.4234	0.7734 0.6676 0.6834	1189 1087 1082	398.5 394.3 394.9	27.99 19.76 19.76	STINC STINC CNTYHH STINC CNTYHH CNTYEMP	1.414 1.269 72.590 1.152 50.990 72.146
CTYGR=C MFUNC=F3 N=26	1 2 3 4	0.5215 0.5878 0.5915 0.5971	0.5015 0.5520 0.5357 0.5203	0.5583 0.5197 0.5571 0.5948	2852 2704 2753 2798	415.6 413.7 415.5 417.2	-2.23 -2.97 -1.12 0.64	CNTYEMP CNTYEMP CTYPOP CNTYEMP CTYPOP CNTYPOP CNTYEMP CTYPOP CNTYPOP STINC	280.609 322.355 1.530 268.960 1.435 8.917 236.506 1.438 12.585 0.501
CTYGR=C MFUNC=F4 N=26	1 2 3 4	0.6379 0.6664	0.6229 0.6157	0.4224 0.4458	2749 2775	413.7 415.1	9.08 10.36	CNTYINC CNTYINC CNTYVR	1.971 1.774 55.350
CTYGR=D MFUNC=F1 N=41	1 2 3 4	0.0906	0.0673	1.0026	2299	636.6	14.28	STHH	238.133
CTYGR=D MFUNC=F2 N=27	1 2 3 4	0.3112 0.3767 0.4212	0.2837 0.3248 0.3457	0.7990 0.7791 0.7801	1939 1883 1853	410.7 410.0 410.0	44.21 39.82 37.48	STEMP STEMP CNTYINC STEMP CNTYINC CTYPOP	374.610 249.557 0.833 213.999 1.097 1.682
CTYGR=D MFUNC=F3 N=15	1 2 3 4	0.5876 0.6196	0.5559 0.5562	0.5392 0.5706	1715 1714	225.3 226.1	-2.83 -1.46	CNTYEMP CNTYEMP CNTYHH	260.864 261.813 79.846
CTYGR=D MFUNC=F4 N=19	1 2 3 4	0.5319 0.6069 0.6208	0.5043 0.5567 0.5450	0.5783 0.5418 0.5814	2011 1902 1927	290.9 289.7 290.9	26.81 22.19 22.86	CNTYEMP CNTYEMP STPOP CNTYEMP CNTYINC CTYPOP	20.641 19.091 324.480 8.978 1.277 5.087
CTYGR=A GREGN=c N=15	1 2 3 4	0.4340 0.7131	0.3905 0.6652	0.7400 0.4304	2035 1509	230.4 222.2	312.25 154.88	CNTYEMP CNTYINC CTYPOP	241.653 2.613 2.567
CTYGR=A GREGN=n N=23	1 2 3 4	0.2181 0.2620	0.1809 0.1882	0.9308 0.9594	2954 2940	369.5 370.2	7.62 8.13	CNTYINC CNTYINC CTYPOP	1.430 1.335 0.994

Table C7, continued

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
CTYGR=A GREGN=s N=5	1 2 3	0.8911	0.8548	0.2541	148	51.5	N/A	CNTYPOP	16.637
CTYGR=B GREGN=c N=12	1 2 3	0.9470 0.9585	0.9417 0.9493	0.0742 0.0691	1481 1380	177.0 176.1	N/A N/A	CNTYEMP CNTYPOP CNTYVR	14.811 7.424 76.796
CTYGR=B GREGN=n N=13	1 2 3 4	0.7524 0.8377 0.9066 0.9290	0.7298 0.8052 0.8755 0.8935	0.3377 0.2597 0.1763 0.1597	945 802 641 593	179.9 176.5 171.3 169.7	9.00 4.80 1.79 2.16	CNTYVR CNTYEMP STMP CNTYEMP STMP CTYPOP CNTYVR CTYPOP STINC CNTYPOP	278.025 109.382 251.064 99.192 258.901 0.651 126.780 0.640 1.094 11.166
CTYGR=B GREGN=s N=5	1 2 3	0.9898 0.9930	0.9863 0.9859	0.0239 0.0283	372 379	60.7 60.8	N/A N/A	STPOP STPOP CNTYPOP	839.340 566.436 68.686
CTYGR=C GREGN=c N=45	1 2 3	0.4395 0.4924	0.4264 0.4682	0.6127 0.5801	3403 3277	733.9 731.4	8.96 6.24	CNTYINC CNTYINC CNTYPOP	1.873 1.696 13.813
CTYGR=C GREGN=n N=30	1 2 3	0.3179 0.3666	0.2936 0.3196	0.7795 0.7742	2260 2218	465.3 465.1	14.84 13.93	CNTYINC CNTYEMP CNTYVR	1.386 15.461 178.936
CTYGR=C GREGN=s N=5	1 2 3	0.7168 0.8225	0.6224 0.6450	0.6608 0.7099	1053 1021	71.0 70.7	N/A N/A	CNTYPOP CNTYPOP CNTYINC	484.737 570.452 1.457
CTYGR=D GREGN=c N=26	1 2 3	0.1587 0.2053	0.1236 0.1361	0.9816 1.0021	1492 1481	381.9 382.4	10.00 10.22	STEMP STHH CTYPOP	219.581 211.226 1.051
CTYGR=D GREGN=n N=34	1 2 3 4	0.5272 0.6576 0.6636 0.6690	0.5124 0.6355 0.6299 0.6234	0.5319 0.4087 0.4261 0.4451	2211 1911 1926 1943	525.6 516.6 518.0 519.5	7.43 -0.89 0.63 2.20	CTYPOP CTYPOP CNTYINC CTYPOP CNTYINC CNTYHH CTYPOP CNTYINC CNTYHH STPOP	6.401 5.299 1.397 4.823 1.231 3.666 4.725 1.153 3.692 105.210
CTYGR=D GREGN=s N=42	1 2 3	0.3985 0.4299	0.3834 0.4006	0.6617 0.6578	1727 1703	628.1 627.9	1.27 1.22	STPOP STPOP STINC	554.750 422.380 0.890

Note: Cases for N < 5 have not been recorded

Table C8: Best Models for Urban Principal Arterial
[Data Format: Density E&L and City Avg. by Year]

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
ALL N=116	1	0.2579	0.2514	0.7681	3364	1886.1	20.85	CNTYEMP	13.855
	2	0.3478	0.3362	0.6868	3168	1873.1	6.77	CNTYEMP CNTYINC	11.068 0.987
	3	0.3579	0.3407	0.6879	3157	1873.3	6.96	CNTYEMP CNTYINC STHH	10.931 0.937 133.550
	4								
CTYGR=A N=18	1	0.2809	0.2359	0.8989	2429	282.5	11.35	CNTYINC	1.593
	2	0.4090	0.3302	0.8274	2274	280.9	8.84	CNTYINC CTYPOP	1.804 1.307
	3	0.4109	0.2846	0.9257	2350	282.9	10.75	CNTYINC CTYPOP STHH	1.751 1.308 40.158
	4								
CTYGR=B N=14	1	0.5163	0.4760	0.6450	4152	235.1	N/A	CNTYEMP	12.999
	2	0.5496	0.4677	0.6961	4184	236.1	N/A	CNTYEMP CNTYVR	13.268 144.054
	3	0.6049	0.4863	0.7112	4110	236.3	N/A	CNTYEMP CNTYVR CTYPOP	15.918 202.059 1.367
	4								
CTYGR=C N=36	1	0.3542	0.3352	0.7217	2991	578.2	-5.23	CNTYINC	1.629
	2	0.3627	0.3241	0.7532	3016	579.7	-3.58	CNTYINC STHH	1.577 116.140
	3								
	4								
CTYGR=D N=48	1	0.2891	0.2736	0.7727	2199	740.7	8.81	CNTYEMP	18.088
	2	0.3883	0.3611	0.6933	2062	735.5	3.44	CNTYEMP STPOP	16.953 368.980
	3								
	4								
CTYGR=A MFUNC=F3 N=6	1	0.8590	0.8238	0.2820	906	83.3	N/A	CNTYINC	1.994
	2								
	3								
	4								
CTYGR=A MFUNC=F4 N=12	1	0.1024	0.0127	1.2566	2803	192.3	N/A	CNTYINC	1.022
	2	0.2554	0.0899	1.2409	2691	192.1	N/A	CNTYINC CTYPOP	1.343 1.559
	3	0.2659	-0.0094	1.4682	2835	193.9	N/A	CNTYINC CTYPOP STHH	1.299 1.642 102.138
	4								

Table C8, continued

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
CTYGR=B MFUNC=F4 N=12	1 2 3 4	0.4959 0.5580 0.6635	0.4455 0.4597 0.5374	0.7057 0.7367 0.6729	4516 4458 4125	203.8 204.2 202.9	N/A N/A N/A	CNTYEMP CNTYEMP CNTYVR CNTYEMP CNTYVR CTYPOP	12.680 12.665 218.590 16.049 347.159 1.960
CTYGR=C MFUNC=F2 N=12	1 2 3 4	0.3956 0.5173	0.3351 0.4101	0.8462 0.8044	987 930	167.3 166.6	N/A N/A	CNTYEMP CNTYEMP STEMP	193.888 149.068 164.492
CTYGR=C MFUNC=F3 N=12	1 2 3 4	0.5351 0.6083 0.6547 0.6731	0.4886 0.5212 0.5253 0.4864	0.6509 0.6529 0.6905 0.7938	2969 2873 2860 2975	193.7 193.7 194.1 195.5	N/A N/A N/A N/A	CNTYEMP CNTYEMP CTYPOP CNTYEMP CTYPOP STGAS CNTYEMP CTYPOP STGAS STEMP	293.254 342.554 1.681 364.644 2.271 7.453 348.096 2.505 8.525 244.910
CTYGR=C MFUNC=F4 N=12	1 2 3 4	0.5378 0.5680	0.4916 0.4721	0.6471 0.7199	3067 3126	194.5 195.7	N/A N/A	CNTYINC CNTYINC CNTYVR	2.098 1.735 101.993
CTYGR=D MFUNC=F1 N=20	1 2 3 4								
CTYGR=D MFUNC=F2 N=12	1 2 3 4	0.4459 0.5047 0.5708	0.3905 0.3946 0.4099	0.7757 0.8255 0.8583	1719 1713 1692	180.6 181.3 181.5	N/A N/A N/A	STINC STEMP STGAS STEMP STGAS CNTYEMP	4.078 625.087 10.385 636.545 12.678 99.901
CTYGR=D MFUNC=F3 N=6	1 2 3 4	0.6138 0.6620	0.5173 0.4367	0.7724 1.0139	1717 1855	90.9 92.1	N/A N/A	CNTYEMP CNTYEMP CNTYVR	254.855 145.496 139.464
CTYGR=D MFUNC=F4 N=10	1 2 3 4	0.5528 0.6053	0.4969 0.4926	0.6708 0.7330	2089 2098	154.7 155.4	N/A N/A	CNTYEMP CNTYINC CTYPOP	19.088 1.757 6.703

Table C8, continued

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
CTYGR=A GREGN=c N=6	1	0.4431	0.3038	1.1138	2178	92.8	N/A	CNTYEMP	268.305
	2	0.9702	0.9504	0.0893	582	78.2	N/A	CNTYINC CTYPOP	3.666 3.349
	3	0.9783	0.9458	0.1085	608	78.3	N/A	CNTYINC CTYPOP STGAS	3.648 3.437 5.801
	4								
CTYGR=A GREGN=n N=10	1	0.3495	0.2682	0.9757	2539	158.6	N/A	CNTYINC	2.455
	2	0.3600	0.1772	1.1886	2692	160.4	N/A	CNTYINC STHH	2.502 109.940
	3								
	4								
CTYGR=B GREGN=c N=6	1	0.9856	0.9820	0.0288	921	83.5	N/A	CNTYHH	20.049
	2	0.9979	0.9964	0.0064	410	74.1	N/A	CNTYPOP CNTYVR	7.445 91.623
	3	0.9999	0.9999	0.0003	78	53.6	N/A	CNTYEMP CNTYVR STGAS	14.804 88.641 3.277
	4								
CTYGR=B GREGN=n N=6	1	0.8320	0.7900	0.3360	722	80.6	N/A	CNTYVR	273.717
	2	0.9524	0.9207	0.1427	444	75.0	N/A	CNTYVR CTYPOP	261.012 0.679
	3	0.9934	0.9836	0.0328	202	65.1	N/A	CNTYHH STINC CTYPOP	53.551 3.663 0.647
	4								
CTYGR=C GREGN=c N=20	1	0.4266	0.3947	0.7009	3337	326.4	0.25	CNTYINC	2.069
	2	0.4721	0.4099	0.7142	3295	326.8	0.96	CNTYINC CNTYPOP	1.918 11.772
	3	0.4805	0.3832	0.7792	3369	328.4	2.72	CNTYINC CNTYPOP STINC	1.826 10.269 1.625
	4								
CTYGR=C GREGN=n N=14	1	0.1426	0.0711	1.1433	2510	221.0	-4.75	CNTYINC	1.100
	2	0.2404	0.1023	1.1739	2468	221.3	-3.35	CNTYEMP CNTYVR	11.904 173.867
	3								
	4								
CTYGR=D GREGN=c N=12	1	0.1647	0.0811	1.1695	1379	175.3	N/A	STEMP	278.037
	2	0.2292	0.0579	1.2847	1396	176.3	N/A	STEMP CTYPOP	294.737 1.053
	3								
	4								
CTYGR=D GREGN=n N=18	1	0.5797	0.5534	0.5254	2123	277.7	0.24	CTYPOP	6.574
	2	0.6980	0.6577	0.4228	1858	273.7	-1.77	CTYPOP CNTYINC	5.137 1.480
	3	0.7010	0.6369	0.4699	1914	275.5	0.13	CTYPOP CNTYINC STPOP	5.075 1.434 77.700
	4								
CTYGR=D GREGN=s N=18	1	0.5048	0.4739	0.6190	1493	264.9	-7.11	STEMP	685.716
	2								
	3								
	4								

Note: Cases for N < 5 have not been recorded

Table C9: Best Models for Urban Minor Arterial & Collector
[Data Format: Raw and City Avg. by Year]

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
ALL N=119	1	0.2409	0.2344	0.7851	3411	1938.1	16.44	CTYPOP	0.1560
	2	0.3157	0.3039	0.7197	3252	1927.7	5.48	CTYPOP STEMP	0.1540 0.0097
	3	0.3330	0.3156	0.7134	3225	1926.7	4.49	CTYPOP STEMP CNTYVR	0.1380 0.0093 0.0059
	4	0.3383	0.3151	0.7197	3226	1927.7	5.56	CTYPOP STEMP CNTYPOP CNTYINC	0.1339 0.0084 0.0033 0.2335
CTYGR=A N=18	1	0.5357	0.5067	0.5804	2541	284.1	87.60	CNTYINC	2.0930
	2	0.6594	0.6139	0.4769	2247	280.6	62.54	CNTYINC CNTYEMP	1.5457 0.0248
	3								
	4								
CTYGR=B N=13	1	0.6695	0.6394	0.4507	2313	203.2	N/A	CNTYINC	2.4080
	2	0.6950	0.6340	0.4879	2330	204.2	N/A	CNTYINC CTYPOP	2.0280 0.6171
	3								
	4								
CTYGR=C N=30	1	0.0940	0.0616	1.0355	3440	490.5	2.71	STEMP	0.0095
	2								
	3								
	4								
CTYGR=D N=58	1	0.1461	0.1309	0.9148	3002	930.8	17.63	CTYPOP	0.7764
	2	0.1890	0.1596	0.8994	2954	929.8	16.03	CTYPOP CNTYINC	0.6061 0.5617
	3	0.2140	0.1703	0.9025	2993	929.9	15.93	CTYPOP CNTYINC STEMP	0.5340 0.4518 0.0053
	4								
CTYGR=A MFUNC=F3 N=10	1	0.2790	0.1888	1.0815	1772	151.4	N/A	CNTYINC	1.3591
	2								
	3								
	4								
CTYGR=A MFUNC=F4 N=8	1	0.1716	0.0336	1.3806	1699	120.7	N/A	CNTYINC	0.5846
	2	0.4274	0.1983	1.2597	1548	119.7	N/A	CTYPOP STPOP	0.3364 0.0159
	3								
	4								
CTYGR=B MFUNC=F4 N=13	1	0.6695	0.6394	0.4507	2313	203.2	N/A	CNTYINC	2.4080
	2	0.6950	0.6340	0.4879	2330	204.2	N/A	CNTYINC CTYPOP	2.0280 0.6171
	3								
	4								

Table C9, continued

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
CTYGR=C MFUNC=F2 N=14	1 2 3 4	0.1745	0.1057	1.1007	4589	237.9	33.22	STEMP	0.0169
CTYGR=C MFUNC=F3 N=5	1 2 3 4	0.1634	0.1155	1.9521	463	62.8	N/A	STEMP	0.0010
CTYGR=C MFUNC=F4 N=11	1 2 3 4	0.7830 0.8180 0.8363	0.7588 0.7725 0.7662	0.3135 0.3185 0.3507	1178 1144 1160	157.4 157.4 158.3	N/A N/A N/A	CNTYHH CNTYEMP STPOP CNTVHH STPOP CNTYEMP	0.0329 0.0331 0.0111 0.0162 0.0094 0.0172
CTYGR=D MFUNC=F1 N=30	1 2 3 4								
CTYGR=D MFUNC=F2 N=9	1 2 3 4	0.9379 0.9678	0.9291 0.9570	0.0974 0.0645	686 534	119.3 115.4	N/A N/A	CNTYEMP CNTYPOP STGAS	1.1835 0.5219 2.6181
CTYGR=D MFUNC=F3 N=10	1 2 3 4	0.6737 0.8171	0.6329 0.7649	0.4895 0.3395	1310 1048	145.3 141.5	N/A N/A	STHH STHH CNTYEMP	0.0130 0.0083 0.2840
CTYGR=D MFUNC=F4 N=9	1 2 3 4	0.9484 0.9830 0.9840	0.9410 0.9774 0.9744	0.0811 0.0339 0.4160	475 294 313	112.7 104.7 106.1	N/A N/A N/A	CNTYVR CTYPOP CNTYINC CTYPOP CNTYINC CNTYEMP	0.0218 0.6939 2.1797 2.0122 0.5934 0.0040
CTYGR=A GREGN=c N=5	1 2 3 4	0.5165	0.3553	1.1281	745	67.5	N/A	STHH	0.0042
CTYGR=A GREGN=n N=8	1 2 3 4	0.1716 0.4274	0.0336 0.1984	1.3806 1.2597	1700 1548	120.7 119.7	N/A N/A	CNTYINC CTYPOP STPOP	0.5846 0.3364 0.0159

Table C9, continued

Case & N	# of Var	R^2	R_a^2	PC	RMSF	AIC	C_p	Variables in Model	b-coefficients
CTYGR=A GREGN=s N=5	1 2 3 4	0.7965	0.7287	0.4747	810	68.4	N/A	CNTYHH	0.6484
CTYGR=B GREGN=c N=5	1 2 3 4	0.2099	-0.0534	1.8435	509	63.8	N/A	CNTYPOP	0.0351
CTYGR=B GREGN=n N=8	1 2 3 4	0.3389	0.2286	1.1018	2146	124.4	N/A	CNTYINC	1.2822
CTYGR=C GREGN=c N=12	1 2 3 4								
CTYGR=C GREGN=n N=13	1 2 3 4	0.7574 0.7869	0.7353 0.7443	0.3309 0.3409	975 958	180.8 181.1	N/A N/A	CNTYHH CNTYHH STHH	0.0250 0.0236 0.0027
CTYGR=C GREGN=s N=5	1 2 3 4	0.8893 0.9940	0.8525 0.9880	0.2581 0.0239	1393 397	73.8 61.2	N/A N/A	CNTYHH CNTYEMP STINC	3.6792 6.3572 2.8209
CTYGR=D GREGN=c N=8	1 2 3 4	0.8806	0.8606	0.1991	834	109.3	N/A	CNTYINC	1.5171
CTYGR=D GREGN=n N=16	1 2 3 4	0.2997 0.3588	0.2497 0.2601	0.9004 0.9372	1097 957	225.9 226.5	-3.24 -1.97	CNTYVR CNTYVR STVR	0.0074 0.0070 0.0008
CTYGR=D GREGN=s N=34	1 2 3 4	0.1897	0.1644	0.9115	3430	555.5	14.58	CTYPOP	0.9395

Note: Cases for $N < 5$ have not been recorded

Table C10: Best Models for Urban Minor Arterial & Collector
[Data Format: Raw E&L and City Avg. by Year]

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
ALL	1	0.2850	0.2713	0.7699	3286	876.5	18.84	CTYPOP	0.1675
	2	0.3899	0.3660	0.6818	3065	869.9	10.74	CTYPOP STINC	0.1646 2.7789
	3	0.4075	0.3720	0.6873	3051	870.4	11.05	CTYPOP STINC CNTYHH	0.1469 2.5373 0.0107
N=54	4								
CTYGR=A	1	0.7894	0.7543	0.3509	1834	121.9	N/A	CNTYINC	2.7506
N=8	2	0.8348	0.7687	0.3634	1779	121.9	N/A	CNTYINC CNTYVR	2.3356 0.0070
	3								
	4								
CTYGR=B	1	0.7279	0.6598	0.5442	2313	94.5	N/A	CNTYINC	2.6321
N=6	2	0.7806	0.6343	0.2171	2399	95.2	N/A	CNTYINC STHH	2.5786 0.0081
	3								
	4								
CTYGR=C	1	0.1256	0.0528	1.1658	3350	229.1	0.41	CNTYHH	0.0211
N=14	2								
	3								
	4								
CTYGR=D	1	0.1313	0.0951	1.0135	2864	415.8	16.16	CTYPOP	0.7041
N=26	2	0.1711	0.0990	1.0451	2858	416.6	16.41	CTYPOP CNTYINC	0.5610 0.5372
	3								
	4								
CTYGR=B	1	0.7279	0.6598	0.5442	2313	94.5	N/A	CNTYINC	2.6321
MFUNC=F4	2	0.7806	0.6343	0.2171	2399	95.2	N/A	CNTYINC STHH	2.5786 0.0081
N=6	3								
	4								
CTYGR=C	1	0.4160	0.2701	1.1679	4114	101.4	N/A	STINC	7.2863
MFUNC=F2	2								
N=6	3								
	4								
CTYGR=C	1	0.8379	0.7974	0.3241	1253	86.9	N/A	CNTYHH	0.0349
MFUNC=F4	2	0.8417	0.7361	0.4750	1408	88.8	N/A	CNTYHH STGAS	0.0347 0.7693
N=6	3								
	4								

Table C10, continued

Case & N	# of Var	R^2	R_a^2	PC	RMSE	AIC	C_p	Variables in Model	b-coefficients
CTYGR=D MFUNC=F1 N=14	1 2 3 4								
CTYGR=C GREGN=c N=6	1 2 3 4	0.3548	0.1935	1.2904	3799	100.5	N/A	STINC	6.5713
CTYGR=C GREGN=n N=6	1 2 3 4	0.8597	0.8246	0.2806	875	82.8	N/A	CNTYHH	0.0253 0.0027
CTYGR=D GREGN=n N=8	1 2 3 4	0.3068 0.3581	0.1913 0.1013	1.1553 1.4122	1154 1216	114.5 115.9	N/A N/A	CNTYVP CNTYVR STVR	0.0074 0.0069 0.0008
CTYGR=D GREGN=s N=14	1 2 3 4	0.1906	0.1231	1.0792	3394	229.5	66.47	CTYPOP	0.9117

Note: Cases for $N < 5$ have not been recorded

Table C11: Best Models for Urban Minor Arterial & Collector
[Data Format: Density and City Avg. by Year]

Case & N	# of Var	R ²	R _a ²	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
ALL N=119	1	0.1343	0.1269	0.8953	3643	1953.7	12.24	CNTYEMP	14.788
	2	0.1996	0.1858	0.8418	3518	1946.4	4.64	CNTYEMP STEMP	13.973 328.640
	3	0.2133	0.1927	0.8414	3503	1946.3	4.63	CNTYPOP STEMP CNTYINC	4.356 269.920 0.404
	4								
CTYGR=A N=18	1	0.5357	0.5067	0.5804	2541	284.1	87.60	CNTYINC	2.093
	2	0.7829	0.7539	0.3040	1795	272.5	105.57	CNTYEMP CNTYVR	26.032 224.098
	3								
	4								
CTYGR=B N=13	1	0.6695	0.6394	0.4507	2313	203.2	N/A	CNTYINC	2.408
	2	0.7255	0.6682	0.4423	2218	202.9	N/A	CNTYINC CNTYVR	1.766 163.760
	3								
	4								
CTYGR=C N=30	1	0.0930	0.0606	1.0355	3441	490.6	10.65	STEMP	340.430
	2								
	3								
	4								
CTYGR=D N=58	1	0.1125	0.0967	0.9509	3060	933.0	59.40	CNTYINC	0.843
	2	0.1569	0.1263	0.9351	3010	932.0	55.73	CNTYINC STEMP	0.657 250.800
	3								
	4								
CTYGR=A MFUNC=F3 N=10	1	0.7835	0.7565	0.3247	971	139.3	N/A	CNTYHH	45.092
	2	0.8849	0.8521	0.2137	757	135.0	N/A	CNTYHH STHH	41.893 155.040
	3								
	4								
CTYGR=A MFUNC=F4 N=8	1	0.2216	0.0918	1.2974	1648	120.2	N/A	CNTYVR	90.507
	2	0.7539	0.6554	0.5414	1015	113.0	N/A	CNTYVR CNTYEMP	346.900 26.599
	3								
	4								
CTYGR=B MFUNC=F4 N=13	1	0.6695	0.6394	0.4507	2313	203.2	N/A	CNTYINC	2.408
	2	0.7255	0.6682	0.4423	2218	202.9	N/A	CNTYINC CNTYVR	1.766 163.760
	3								
	4								

Table C11, continued

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
CTYGR=C MFUNC=F2 N=14	1 2 3 4	0.1716	0.1026	1.1045	4597	237.9	191.60	STEMP	603.110
CTYGR=C MFUNC=F3 N=5	1 2 3 4	0.1635	-0.1154	1.9518	463	62.8	N/A	STEMP	36.037
CTYGR=C MFUNC=F4 N=11	1 2 3 4	0.7800 0.8109	0.7556 0.7637	0.3177 0.3308	1186 1166	157.5 157.8	N/A N/A	CNTYHH CNTYHH STPOP	17.229 16.664 267.980
CTYGR=D MFUNC=F1 N=30	1 2 3 4	0.4744 0.5018	0.4556 0.4649	0.6007 0.6089	2201 2181	463.7 464.1	85.69 81.87	CNTYHH CNTYPOP CNTYVR	318.726 105.852 71.317
CTYGR=D MFUNC=F2 N=9	1 2 3 4	0.8478	0.8260	0.2392	1075	127.4	N/A	CNTYEMP	802.442
CTYGR=D MFUNC=F3 N=10	1 2 3 4	0.7085 0.8168	0.6721 0.7645	0.4372 0.3402	1238 1049	144.2 141.6	N/A N/A	CNTYEMP CNTYEMP STHH	236.261 147.759 259.540
CTYGR=D MFUNC=F4 N=9	1 2 3 4	0.9370 0.9642 0.9862	0.9279 0.9522 0.9780	0.0991 0.0766 0.0358	525 427 291	114.5 111.4 104.8	N/A N/A N/A	CNTYHH CNTYHH CTYPOP CNTYEMP CTYPOP CNTYINC	46.924 52.050 3.136 24.679 5.365 0.639
CTYGR=A GREGN=c N=5	1 2 3 4	0.5103	0.3471	1.1426	750	67.7	N/A	STHH	151.752
CTYGR=A GREGN=n N=8	1 2 3 4	0.2216 0.7539	0.0918 0.6554	1.2974 0.5414	1648 1015	120.2 113.0	N/A N/A	CNTYVR CNTYVR CNTYEMP	90.507 346.897 26.600

Table C11, continued

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
CTYGR=A GREGN=s N=5	1 2 3 4	0.7966	0.7288	0.4746	810	68.4	N/A	CNTYHH	97.047
CTYGR=B GREGN=c N=5	1 2 3 4	0.2103	-0.0530	1.8427	509	63.8	N/A	CNTYPOP	17.535
CTYGR=B GREGN=n N=8	1 2 3 4	0.8549 0.8972	0.8307 0.8560	0.2419 0.2263	1005 927	112.3 111.3	N/A N/A	CTYPOP CTYPOP CNTYVR	3.037 1.615 155.009
CTYGR=C GREGN=c N=12	1 2 3 4	0.1425	0.0568	1.2005	4043	201.1	N/A	STINC	2.720
CTYGR=C GREGN=n N=13	1 2 3 4	0.7547 0.8707 0.9325	0.7324 0.8448 0.9099	0.3345 0.2069 0.1275	981 747 568	180.8 174.6 168.2	N/A N/A N/A	CNTYHH CNTYEMP CTYPOP CNTYEMP CTYPOP STHH	12.870 18.920 1.683 18.184 1.752 141.189
CTYGR=C GREGN=s N=5	1 2 3 4	0.8831 0.9926	0.8442 0.9851	0.2727 0.0297	1432 442	74.1 62.3	N/A N/A	CNTYHH CNTYEMP STINC	1577.910 2699.420 2.855
CTYGR=D GREGN=c N=8	1 2 3 4	0.8806	0.8606	0.1991	834	109.3	N/A	CNTYINC	1.517
CTYGR=D GREGN=n N=16	1 2 3 4	0.2654 0.5492	0.2130 0.4799	0.9444 0.6589	1124 914	227.0 221.0	32.72 17.44	CNTVHH CNTYHH CNTYVR	11.351 16.586 91.996
CTYGR=D GREGN=s N=34	1 2 3 4	0.1778 0.2052	0.1521 0.1539	0.9450 0.9486	3445 3451	555.9 556.8	40.07 39.73	CNTYINC CNTYINC STEM	1.173 0.945 220.820

Note: Cases for N < 5 have not been recorded

Table C12: Best Models for Urban Minor Arterial & Collector
[Data Format: Density E&L and City Avg. by Year]

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
ALL N=54	1	0.1852	0.1696	0.8774	3508	883.6	17.13	CNTYEMP	15.323
	2	0.2524	0.2231	0.8355	3393	880.9	13.59	CNTYHH STINC	14.331 2.324
	3								
	4								
CTYGR=A N=8	1	0.7896	0.7545	0.3507	1834	121.9	N/A	CNTYINC	2.750
	2	0.8735	0.8230	0.2782	1557	119.8	N/A	CTYPOP CNTYVR	8.242 339.141
	3								
	4								
CTYGR=B N=6	1	0.7279	0.6598	0.5442	2313	94.5	N/A	CNTYINC	2.632
	2	0.8312	0.7187	0.5064	2104	93.7	N/A	CNTYINC CNTYVR	1.765 222.666
	3								
	4								
CTYGR=C N=14	1	0.1152	0.0415	1.1797	3371	229.3	1134.28	STEMP	454.310
	2								
	3								
	4								
CTYGR=D N=26	1	0.0978	0.0602	1.0526	2918	416.8	38.55	CNTYINC	0.790
	2								
	3								
	4								
CTYGR=B MFUNC=F4 N=6	1	0.7279	0.6598	0.5442	2313	94.5	N/A	CNTYINC	2.632
	2	0.8312	0.7187	0.5064	2104	93.7	N/A	CNTYINC CNTYVR	1.765 222.666
	3								
	4								
CTYGR=C MFUNC=F2 N=6	1	0.4160	0.2701	1.1679	4114	101.4	N/A	STINC	7.286
	2								
	3								
	4								
CTYGR=C MFUNC=F4 N=6	1	0.8313	0.7891	0.3375	1259	87.2	N/A	CNTYHH	18.291
	2	0.8359	0.7265	0.4923	1434	89.0	N/A	CNTYHH CNTYEMP	14.001 4.433
	3								
	4								

Table C12, continued

Case & N	# of Var	R ²	R ² _a	PC	RMSE	AIC	C _p	Variables in Model	b-coefficients
CTYGR=D MFUNC=F1 N=14	1	0.3752	0.3231	0.8330	2314	218.7	454.50	CNTYHH	284.450
	2	0.4294	0.3257	0.8818	2310	219.5	416.21	CNTYPOP STMP	87.173 279.180
	3								
	4								
CTYGR=C GREGN=c N=6	1	0.3544	0.1930	1.2918	3800	100.5	N/A	STINC	6.568
	2								
	3								
	4								
CTYGR=C GREGN=n N=6	1	0.8566	0.8207	0.2868	884	83.0	N/A	CNTYHH	13.008
	2	0.9497	0.9162	0.1509	605	78.7		CNTYHH CTYPOP	0.880 15.566
	3								
	4								
CTYGR=D GREGN=n N=8	1	0.2734	0.1523	1.2110	1180	114.9	N/A	CNTYHH	11.273
	2	0.5514	0.3720	0.9869	1016	113.0	N/A	CNTYHH CNTYVR	16.725 94.691
	3								
	4								
CTYGR=D GREGN=s N=14	1	0.1682	0.0989	1.1091	3440	229.9	49.26	CNTYINC	1.185
	2	0.2011	0.0558	1.2347	3521	231.3	48.92	CNTYINC STMP	0.950 275.010
	3								
	4								

Note: Cases for N < 5 have not been recorded

Appendix D

Table D1: Eigenvectors or Coefficients of Principal Components (PCs)
of Final Regression Equations for Interstate Highways

Region	Item	Mean and Standard Deviation of Original variables, and Eigenvectors or Coefficient of PCs										
		Original Variable (*)						STPOP	STHH	STVR	STEMP	STINC
		CTYPOP	CNTYPOP	CNTYHH	CNTYVR	CNTYEMP	CNTYINC					
A. Interstate Highways (rural & Urban): Regional Model												
North	Mean	50246.8	161963.0	55370.9	115239.0	55739.7	10769.90	5463753	1915931	4244392	1787838	10887.40
	ST DEV	47208.0	187428.0	64049.4	121979.0	64959.3	1177.30	73850	101396	314980	111256	535.80
	PC1	0.093310	0.241740	0.254962	0.264509	0.260412	0.263182	0.359910	0.360483	0.374372	0.372773	0.349583
	PC2	0.201785	0.409886	0.400070	0.399652	0.402000	0.056115	-0.284016	-0.265802	-0.245879	-0.258625	-0.167591
	PC4	0.969960	-0.135167	-0.126151	-0.089653	-0.057927	-0.063243	0.052520	0.048295	0.031893	0.005613	-0.058838
Central	Mean	201925.0	111886.0	40076.3	84999.0	42932.7	11121.00	5450189	1899642	4197051	1779412	10910.60
	ST DEV	279822.0	194402.0	73265.9	142722.0	97747.7	1217.30	85070	113195	367897	120987	585.40
	PC1	0.067306	0.266859	0.269790	0.275387	0.268677	0.264246	0.377129	0.368567	0.377032	0.349479	0.302095
	PC2	0.121369	0.410937	0.408938	0.405158	0.407615	-0.006345	-0.249695	-0.248259	-0.243855	-0.280280	-0.238379
	PC3	0.826206	-0.087652	-0.089343	-0.073570	-0.108734	0.470602	-0.109923	-0.127922	-0.101147	-0.009440	0.155724
South	Mean	48130.7	36824.8	12688.6	29860.1	8835.7	9904.32	5474736	1932770	4311075	1805614	10995.10
	ST DEV	48528.3	22815.3	7873.9	17167.1	7486.3	1146.55	60215	80192	217769	103990	530.60
	PC1	-0.121932	0.395466	0.382287	0.373883	0.397111	0.123465	-0.331166	-0.318029	-0.307073	-0.220398	-0.127217
	PC2	-0.009562	0.262454	0.285506	0.302477	0.239342	0.270393	0.335132	0.321129	0.350682	0.412745	0.344746
	PC3	0.698956	-0.073755	-0.068613	-0.054305	-0.090459	0.611607	-0.131355	-0.185173	-0.165171	0.034489	0.190012
	PC5	0.543566	0.084603	0.090041	0.047689	0.180494	-0.722195	-0.076954	-0.122444	-0.049454	0.236353	0.231583
B. Rural Interstate Highways: Statewide Model												
ALL	Mean	150532.0	44846.7	15223.6	35643.2	10812.7	10331.00	5461745	1914220	4241194	1787151	10901.80
	ST DEV	232514.0	29605.6	9895.4	21642.0	9574.4	1431.90	75086	102171	327104	116205	559.10
	PC1	0.024409	0.284202	0.294231	0.316012	0.298408	0.238884	0.346978	0.338560	0.354609	0.356726	0.313155
	PC2	0.173925	0.390781	0.382410	0.367027	0.333256	0.158873	-0.313970	-0.308347	-0.297371	-0.273686	-0.206894
	PC3	0.712069	-0.124455	-0.125196	-0.022559	-0.312295	0.554461	-0.058917	-0.070360	-0.056737	0.068555	0.199948

Table D1, continued

Region	Item	Mean and Standard Deviation of Original variables, and Eigenvectors or Coefficient of PCs										
		Original Variable (*)										
		CTYPOP	CNTYPOP	CNTYHH	CNTYVR	CNTYEMP	CNTYINC	STPOP	STHH	STVR	STEMP	STINC
C. Rural Interstate Highways: Regional Model												
North	Mean	603793.3	133985.0	46027.1	98123.0	48596.2	10536.30	5459582	190120	4226480	1781128	10848.30
	ST DEV	50665.7	180731.0	61896.1	121324.0	65673.2	1138.00	76707	105711	338475	108278	523.20
	PC1	0.046337	0.244855	0.255769	0.264870	0.262240	0.287420	0.360176	0.360329	0.368969	0.368051	0.346093
	PC3	0.560907	-0.146782	-0.149353	-0.097786	-0.038850	0.577617	-0.200249	-0.234942	-0.260292	0.151825	0.332746
	PC7	0.043441	0.092604	0.276407	0.006830	-0.340710	-0.059578	-0.054363	0.632823	-0.617602	-0.008823	0.092340
Central	Mean	326194.0	106103.0	37945.0	81546.0	39545.6	11158.80	5450048	18993661	4191864	1778012	10904.50
	ST DEV	308819.0	186814.0	70760.2	137789.0	95620.1	1559.70	85712	114094	375670	126069	599.60
	PC1	0.138757	0.287438	0.288970	0.296079	0.287073	0.254201	0.357152	0.349759	0.356206	0.338020	0.298162
	PC2	0.178011	0.388224	0.386785	0.381716	0.383605	-0.022419	-0.276257	-0.274028	-0.272256	-0.294105	-0.250196
	PC3	0.703526	-0.119306	-0.125219	-0.099950	-0.157214	0.609630	-0.130034	-0.143310	-0.111439	-0.032464	0.133650
South	Mean	58044.2	31156.9	10787.4	25438.3	7091.1	9711.26	5476730	1932560	4313329	1795019	10925.90
	ST DEV	51908.3	19683.6	6822.5	14877.6	6136.9	1155.88	49014	71444	190660	90054	514.50
	PC1	-0.090147	0.414238	0.404040	0.401427	0.410200	0.181919	-0.297916	-0.288390	-0.279701	-0.188885	-0.093258
	PC2	0.136396	0.238827	0.263938	0.274492	0.219872	0.239464	0.402539	0.373663	0.411315	0.384446	0.234565
	PC3	0.240714	-0.099055	-0.108101	-0.099887	-0.090510	0.422379	-0.237371	-0.315005	-0.253527	0.364543	0.609299
	PC4	0.756205	-0.047877	-0.029964	-0.000835	-0.087177	0.415951	0.040620	0.066309	0.014176	-0.328748	-0.360590
D. Urban Interstate Highways: Statewide Model												
ALL	Mean	67387.0	222901.0	79322.5	161178.0	89738.0	10993.90	5454917	1906236	4226265	1781637	10888.30
	ST DEV	151857.0	264311.0	97081.4	188303.0	123837.0	1222.20	80790	104011	323104	112957	563.70
	PC1	0.228526	0.336819	0.345370	0.349301	0.348498	0.308240	0.292568	0.284408	0.295791	0.257500	0.237260
	PC2	-0.196178	-0.318618	-0.310323	-0.306738	-0.306551	0.031103	0.349968	0.343324	0.337112	0.395850	0.290061
	PC4	0.951446	-0.176924	-0.156729	-0.150499	-0.106938	-0.048423	-0.001157	-0.001134	-0.029338	0.039877	0.000524

Table D1, continued

Region	Item	Mean and Standard Deviation of Original variables, and Eigenvectors or Coefficient of PCs										
		Original Variable (*)										
		CTYPOP	CNTYPOP	CNTYHH	CNTYVR	CNTYEMP	CNTYINC	STPOP	STHH	STVR	STEMP	STINC
E. Urban Interstate Highways: Regional Model												
North	Mean	44730.8	286608.0	98425.9	196656.0	96940.0	11043.90	5463905	1918376	4262974	1787788	10914.80
	ST DEV	55117.1	215583.0	74020.7	137269.0	72302.6	1008.80	69915	94211	275364	104922	533.20
	PC1	-0.149261	-0.336848	-0.314178	-0.316579	-0.331466	0.052767	0.371212	0.348322	0.335697	0.352069	0.238534
	PC2	0.130015	0.347029	0.365359	0.371566	0.357705	0.208292	0.274856	0.281748	0.308083	0.296508	0.286391
	PC4	0.924476	-0.126039	-0.110230	-0.064660	-0.024383	-0.030525	0.123698	0.134290	0.088007	-0.078964	-0.253543
Central	Mean	91302.0	247273.0	91017.0	183998.0	112006.0	11446.60	5455537	1905831	4223731	1784388	10927.00
	ST DEV	208998.0	315481.0	119241.0	232426.0	159841.0	1033.00	80958	106634	334551	112019	563.90
	PC1	0.224985	0.339951	0.344082	0.345785	0.345985	0.306846	0.307679	0.297693	0.303560	0.252732	0.206605
	PC2	-0.206394	0.315620	0.310501	0.307767	0.307879	0.038420	0.334817	0.333675	0.329176	0.378647	0.308573
	PC4	0.944366	-0.136504	-0.133591	-0.136685	-0.128459	-0.153183	-0.022680	-0.012383	-0.020290	0.075412	0.079286
South	Mean	21399.2	58239.3	20056.7	44765.2	15146.2	9648.06	5440118	1890307	4186146	1776511	10791.30
	ST DEV	13282.0	28979.3	10169.7	22843.3	10176.4	1283.00	99861	115556	374602	137326	697.50
	PC1	0.307087	0.300205	0.314334	0.318355	0.260426	0.359868	0.291789	0.278049	0.303326	0.282115	0.289904
	PC2	-0.086342	-0.359251	-0.335772	-0.322627	-0.387249	-0.025499	0.337306	0.344138	0.310801	0.317924	0.257220
	PC3	-0.478276	0.118278	0.122706	0.161621	0.221958	-0.455552	0.318544	0.325524	0.320707	-0.211305	-0.323035

(*) See Table 4.3 of Chapter 4 for description of Original variables

Table D2: Eigenvectors or Coefficients of Principal Components (PCs)
of Final Regression Equations for Urban Principal Arterial

Region	Item	Mean and Standard Deviation of Original variables, and Eigenvectors or Coefficient of PCs'										
		Original Variable (*)										
		CTYPOP	CNTYPOP	CNTYHH	CNTYVR	CNTYEMP	CNTYINC	STPOP	STHH	STVR	STEMP	STINC
City Group "A" [City Population: 30,000 to 50,000]												
North	Mean	41985.8	184855.0	62634.1	132696.0	69628.5	11331.20	5442145	1882983	4175026	1767658	10979.40
	ST DEV	5008.2	169470.0	56634.7	105396.0	55349.5	982.80	72169	102372	287127	91605	411.00
	PC3	0.353476	0.008524	0.007572	0.038664	0.115924	0.638445	0.005027	-0.045747	-0.017592	0.337877	0.579475
	PC4	0.667093	-0.037438	-0.025738	0.000509	0.052353	0.228652	0.231154	0.272747	0.231628	-0.197699	-0.526632
	Central	Mean	38863.4	86392.7	28798.4	61157.2	29938.4	10533.40	5403535	1845014	4015922	1724947
	ST DEV	7706.5	25930.1	7907.0	14637.8	5440.4	1094.10	117344	142321	513686	144671	731.90
	PC1	0.054854	0.169026	0.231217	0.321267	0.294509	0.158099	0.381860	0.372993	0.384625	0.376790	0.353793
	PC3	-0.391462	0.160610	0.042494	0.116283	0.523122	0.556841	-0.208676	-0.295426	-0.288704	-0.051267	0.071451
	PC4	0.422657	-0.040925	-0.062611	-0.184236	-0.093580	0.032814	-0.307573	-0.284776	-0.185369	0.398216	0.635100
South	Mean	23412.1	57616.8	19726.2	42923.3	14895.9	9632.67	5403418	1848838	4041886	1752719	10681.60
	ST DEV	11297.6	24427.2	8339.3	19564.0	9813.8	915.99	126268	147759	522547	141390	849.10
	PC1	0.110765	0.250630	0.290312	0.325062	0.204427	0.324942	0.344784	0.341793	0.358549	0.336851	0.331463
	PC2	0.237269	0.406293	0.367958	0.318280	0.392272	0.141461	-0.286155	-0.279808	-0.263436	-0.258473	-0.267696
	PC3	0.757189	-0.121656	-0.118935	-0.158328	-0.363881	0.478435	-0.062623	-0.072370	-0.035332	0.001224	0.030535
City Group "B" [City Population: 20,000 to 30,000]												
North	Mean	23286.3	111175.0	36318.2	83978.9	30383.2	11690.20	5441148	1879797	4161632	1773192	10931.20
	ST DEV	2555.1	9586.0	4260.6	12150.8	3121.7	1126.80	74170	110411	350337	109362	603.40
	PC1	0.215837	0.316054	0.347710	0.356031	0.263403	0.054259	0.362274	0.360062	0.374415	0.288475	0.221916
	PC2	-0.025468	-0.252397	-0.296452	-0.031083	-0.113722	0.630114	-0.023661	-0.092822	0.020379	0.395226	0.520602
Central	Mean	23286.3	111175.0	36318.2	83978.9	30383.2	11690.20	5441148	1879797	4161632	1773192	10931.20
	ST DEV	2555.1	9586.0	4260.6	12150.8	3121.7	1126.80	74170	110411	350337	109362	603.40
	PC1	0.355433	0.357384	0.360982	0.362250	0.360139	0.343566	0.242777	0.231910	0.238948	0.192110	0.173057
	PC2	-0.206873	-0.228450	-0.218044	-0.214424	-0.221297	-0.082748	0.393868	0.388013	0.404086	0.436492	0.310125
South	Mean	23412.1	57616.8	19726.2	42923.3	14895.9	9632.67	5403418	1848838	4041886	1752719	10681.60
	ST DEV	11297.6	24427.2	8339.3	19564.0	9813.8	915.99	126268	147759	522547	141390	849.10
	PC1	0.110765	0.250630	0.290312	0.325062	0.204427	0.324942	0.344784	0.341793	0.358549	0.336851	0.331463
	PC2	0.237269	0.406293	0.367958	0.318280	0.392272	0.141461	-0.286155	-0.279808	-0.263436	-0.258473	-0.267696
	PC3	0.757189	-0.121656	-0.118935	-0.158328	-0.363881	0.478435	-0.062623	-0.072370	-0.035332	0.001224	0.030535

Table D2, continued

Region	Item	Mean and Standard Deviation of Original variables, and Eigenvectors or Coefficient of PCs'										
		Original Variable (*)										
		CTYPOP	CNTYPOP	CNTYHH	CNTYVR	CNTYEMP	CNTYINC	STPOP	STHH	STVR	STEMP	STINC
City Group "C" [City Population: 10,000 to 20,000]												
North	Mean	15561.1	156814.0	53704.0	111561.0	56063.1	10882.60	5428020	1870793	4124551	1767027	10864.00
	ST DEV	3190.4	190959.0	65147.2	122965.0	64123.3	1066.80	96473	123747	410463	118360	657.20
	PC1	0.046423	0.257111	0.265353	0.274762	0.272769	0.284369	0.374678	0.367707	0.382885	0.329240	0.316183
	PC3	0.768395	-0.071711	-0.083263	-0.045757	0.053817	0.528159	-0.165437	-0.180529	-0.178029	0.007166	0.147806
	PC5	0.204035	0.078380	0.118462	0.046379	-0.058514	-0.492302	-0.176925	-0.194633	-0.188060	0.752377	0.140125
	PC6	0.143988	0.080193	0.064821	0.002746	-0.096822	-0.379081	-0.067760	-0.126593	0.194724	-0.451842	0.743543
Central	Mean	13476.5	58439.0	19665.5	48101.6	13009.4	11830.30	540180	1867771	4123813	1753963	10889.90
	ST DEV	3040.0	29493.4	10297.4	25366.8	9700.8	1619.60	84042	115302	399729	115814	584.60
	PC1	0.124816	0.287261	0.300728	0.322389	0.304509	0.231354	0.345353	0.335180	0.353954	0.348274	0.288225
	PC3	0.648420	0.041413	-0.021451	0.068354	-0.085346	0.631080	-0.225219	-0.248027	-0.182862	-0.098116	0.108866
	PC5	0.277294	-0.000082	0.018805	-0.072533	0.202654	-0.544854	-0.199916	-0.275852	-0.119473	0.189366	0.642934
South	Mean	23412.1	57616.8	19726.2	42923.3	14895.9	9632.67	5403418	1848838	4041886	1752719	10681.60
	ST DEV	11297.6	24427.2	8339.3	19564.0	9813.8	915.99	126268	147759	522547	141390	849.10
	PC1	0.110765	0.250630	0.290312	0.325062	0.204427	0.324942	0.344784	0.341793	0.358549	0.336851	0.331463
	PC2	0.237269	0.406293	0.367958	0.318280	0.392272	0.141461	-0.286155	-0.279808	-0.263436	-0.258473	-0.267696
	PC3	0.757189	-0.121656	-0.118935	-0.158328	-0.363881	0.478435	-0.062623	-0.072370	-0.035332	0.001224	0.030535
City Group "D" [City Population: 5,000 to 10,000]												
North	Mean	6311.1	106788.0	36689.6	79466.0	38313.1	10401.90	5422841	1857278	4092834	1747745	10825.70
	ST DEV	1285.5	157128.0	54173.8	109166.0	58836.4	870.80	85161	116190	386917	103745	464.60
	PC1	-0.005251	0.326345	0.328878	0.333479	0.327188	0.319431	0.316055	0.308132	0.317404	0.311938	0.268565
	PC2	0.108624	-0.337831	-0.330767	-0.330478	-0.341586	-0.147193	0.339313	0.344021	0.339056	0.342199	0.227064
Central	Mean	6399.7	42162.2	14706.7	33954.2	10893.0	10011.80	5422582	1855616	4086697	1759172	10876.80
	ST DEV	1424.8	42568.6	15010.3	33947.1	14720.5	1120.70	90423	121198	415317	105936	627.40
	PC1	-0.123839	0.300443	0.306011	0.320231	0.312760	0.255366	0.333554	0.318448	0.342760	0.341591	0.297223
	PC2	0.062372	-0.388774	-0.382321	-0.364867	-0.375642	0.002811	0.313572	0.310992	0.311275	0.282096	0.230301
	PC3	0.631416	0.115786	0.112301	0.105128	0.070646	-0.600174	0.181517	0.243129	0.147053	0.014358	-0.291811
	PC4	0.688302	0.020796	-0.010271	-0.001040	0.030003	0.263066	-0.205186	-0.267691	-0.168656	-0.173238	0.532337
South	Mean	6610.9	37053.2	12572.9	29830.3	10528.8	9964.64	5434029	1876976	4147053	1771152	10884.60
	ST DEV	1681.2	20018.3	6952.5	15454.9	7957.2	1337.37	90975	118104	378395	103890	584.70
	PC1	0.078036	0.160098	0.192474	0.239374	0.163180	0.274203	0.414137	0.409120	0.416829	0.394434	0.322341
	PC2	-0.092799	0.475768	0.455093	0.433834	0.449591	0.053806	-0.179485	-0.154179	-0.169548	-0.173522	-0.223252

(*) See Table 4.3 of Chapter 4 for description of Original variables

Table D3: Eigenvectors or Coefficients of Principal Components (PCs) of
Final Regression Equations for Urban Minor Arterial & Collector

Item	Mean and Standard Deviation of Original variables, and Eigenvectors or Coefficient of PCs										
	Original Variable (*)										
	CTYPOP	CNTYPOP	CNTYHH	CNTYVR	CNTYEMP	CNTYINC	STPOP	STHH	STVR	STEMP	STINC
City Group "A" [City Population: 30,000 to 50,000]											
Mean	40760.8	164644.0	56574.2	116267.0	58429.6	10856.40	5414552	1860979	4088967	1764531	10831.10
ST DEV	3275.4	175984.0	60523.0	116590.0	61859.7	1325.50	111288	130777	461333	132619	792.00
PC1	-0.049195	0.289685	0.294276	0.305549	0.300768	0.275397	0.354566	0.343587	0.348127	0.320493	0.315786
PC3	0.736706	-0.076655	-0.098670	-0.041425	0.100700	0.528354	-0.141393	-0.182627	-0.177140	0.063451	0.248775
PC5	0.332173	0.102665	0.108639	0.038107	-0.053098	-0.720309	-0.072742	-0.228842	0.067011	0.352611	0.397136
City Group "B" [City Population: 20,000 to 30,000]											
Mean	21843.1	217097.0	72048.6	145492.0	66402.7	10878.50	5426052	1871766	4129497	1740344	10680.40
ST DEV	1326.7	182747.0	62944.5	114903.0	61282.8	1273.50	93365	119781	410781	116739	602.70
PC1	0.348056	0.214252	0.232374	0.246820	0.212255	0.200051	0.367682	0.372303	0.388553	0.343665	0.300139
PC3	0.371966	0.009140	-0.026858	0.004340	-0.004512	0.699643	-0.302868	-0.361661	-0.252039	-0.025108	0.290887
City Group "C" [City Population: 10,000 to 20,000]											
Mean	18273.5	187452.0	64622.8	136511.0	72721.3	11300.20	5436076	1881567	4148950	1777262	10924.80
ST DEV	1765.8	191913.0	65888.2	125027.0	64875.4	1236.60	100402	125309	397876	122111	679.60
PC1	-0.144338	0.320183	0.323090	0.330544	0.331702	0.203075	0.340163	0.317934	0.347858	0.299169	0.290580
PC2	0.302255	-0.361475	-0.354387	0.340033	-0.307233	0.210830	0.272838	0.267283	0.243667	0.330665	0.288669
City Group "D" [City Population: 5,000 to 10,000]											
Mean	5715.4	68277.0	23703.4	55303.1	25813.7	10562.80	5423516	1855136	4099983	1752213	10863.00
ST DEV	1189.4	104099.0	36021.6	81550.5	47707.3	1077.70	76585	108332	354745	90346	451.90
PC1	0.236726	0.352241	0.358650	0.361874	0.352248	0.264258	0.295384	0.288787	0.292839	0.273271	0.187915
PC3	-0.656270	-0.020887	-0.027277	-0.020087	-0.006546	0.665828	-0.076797	-0.068519	-0.038509	-0.011206	0.334894
PC5	0.511734	-0.155525	-0.149227	-0.143894	-0.185232	0.684970	0.067755	0.066889	-0.026583	-0.139916	-0.371650

(*) See Table 4.3 of Chapter 4 for description of Original variables

Figure D1.2: Partial Regression Residual Plot of PC2 for Central Region of Rural Interstate Highways

Figure D1.3: Partial Regression Residual Plot of PC3 for Central Region of Rural Interstate Highways

Figure D1.4: Partial Regression Residual Plot of PC1 for Central Region of Urban Interstate Highways

Figure D1.5: Partial Regression Residual Plot of PC2 for Central Region of Urban Interstate Highways

Figure D1.6: Partial Regression Residual Plot of PC4 for Central Region of Urban Interstate Highways

Figure D1.7: Partial Regression Residual Plot of PC1 for City Group "A" and Region "c" of Urban Principal Arterial

Figure D1.8: Partial Regression Residual Plot of PC3 for City Group "A" and Region "c" of Urban Principal Arterial

Figure D1.9: Partial Regression Residual Plot of PC4 for City Group "A" and Region "c" of Urban Principal Arterial

Figure D1.10: Partial Regression Residual Plot of PC1 for City Group
"D" of Urban Minor Arterial & Collector

Figure D1.11: Partial Regression Residual Plot of PC3 for City Group
"D" of Urban Minor Arterial & Collector

Figure D1.12: Partial Regression Residual Plot of PC5 for City Group
"D" of Urban Minor Arterial & Collector

Figure D2.1: Normal Probability Plot for Central Region of Rural Interstate Highways

Figure D2.2: Normal Probability Plot for Central Region of Urban Interstate Highways

Figure D2.3: Normal Probability Plot for City Group "A" and Region "c" of Urban Principal Arterial

Figure D2.4: Normal Probability Plot for City Group "D" of Urban Minor Arterial & Collector

Figure D3.1: Residual Plot against Predicted value for Central Region of Rural Interstate Highways

Figure D3.2: Residual Plot against Predicted value for Central Region of Urban Interstate Highways

Figure D3.3: Residual Plot against Predicted value for City Group
"A" and Region "c" of Urban Principal Arterial

Figure D3.4: Residual Plot against Predicted value for City Group "D" of Urban Minor Arterial & Collector

Figure D4.1: Residual Plot against PC1 for Central Region

Figure D4.2: Residual Plot against PC2 for Central Region

Figure D4.3: Residual Plot against PC3 for Central Region

Figure D4.4: Residual Plot against PC1 for Central Region of Urban Interstate Highway

Figure D4.5: Residual Plot against PC2 for Central Region of Urban Interstate Highways

Figure D4.6: Residual Plot against PC4 for Central Region

Figure D4.7: Residual Plot against PC1 for City Group "A"
and Region "c" of Urban Principal Arterial

LEGEND: A = 1 OBS, B = 2 OBS, ETC.

Figure D4.8: Residual Plot against PC3 for City Group "A" and Region "c" of Urban Principal Arterial

LEGEND: A = 1 OBS, B = 2 OBS, ETC.

Figure D4.9: Residual Plot against PC4 for City Group "A" and Region "c" of Urban Principal Arterial

LEGEND: A = 1 OBS, B = 2 OBS, ETC.

Figure D4.10: Residual Plot against PC1 for City Group "D" of Urban Minor Arterial & Collector

LEGEND: A = 1 OBS, B = 2 OBS, ETC.

Figure D4.11: Residual Plot against PC3 for City Group "D" of Urban Minor Arterial & Collector

LEGEND: A = 1 OBS, B = 2 OBS, ETC.

Figure D4.12: Residual Plot against PC5 for City Group "D" of Urban Minor Arterial & Collector

Figure D5.1: Residual Plot against PC8 (not in model) for
Central Region of Rural Interstate Highways

Figure D5.2: Residual Plot against PC8 (not in model) for Central Region of Urban Interstate Highways

Figure D5.3: Residual Plot against PC8 (not in model) for City Group "A" and Region "c" of Urban Principal Arterial

LEGEND: A = 1 OBS, B = 2 OBS, ETC.

Figure D5.4: Residual Plot against PC8 (not in model) for City Group "D" of Urban Minor Arterial & Collector

Appendix E

Table E1.1: Partial-Lagged Regression Results of Interstate Highways

Region	Model Statistics			Significance Statistics & Parameter Values				Normality Stat	
	R ²	R ² _a	RMSE C.V.	F-Value Prob>F	Parameter Name Estimate	t- value	Prob>t	N	W/D (*) (P-value)
A. Interstate Highways (Rural & Urban): Regional Model									
North	99.79	1605.2	34083.2	CONST	-19.49398	-0.098	0.9219	149	0.1268 (<0.01)
	99.78	4.143	0.0001	LAADT	1.00458	226.650	0.0001		
				RAADT	2.98118	40.429	0.0001		
Central	98.50	2485.7	10376.6	CONST	350.01753	1.238	0.2166	320	0.1112 (<0.01)
	98.49	6.992	0.0001	LAADT	1.02776	132.038	0.0001		
				RAADT	1.36517	27.684	0.0001		
South	98.81	1343.5	4714.6	CONST	-108.99377	-0.468	0.6404	117	0.1602 (<0.01)
	98.78	7.474	0.0001	LAADT	1.03591	72.149	0.0001		
				RAADT	2.21005	18.300	0.0001		
B. Rural Interstate Highways: Statewide Model									
ALL	97.52	1862.6	7027.6	CONST	640.19078	3.067	0.0023	361	0.1448 (<0.01)
	97.50	8.562	0.0001	LAADT	0.99501	100.818	0.0001		
				RAADT	1.68258	24.894	0.0001		
C. Rural Interstate Highways: Regional Model									
North	95.49	1495.9	740.3	CONST	185.11105	0.355	0.7238	73	0.1626 (<0.01)
	95.36	7.835	0.0001	LAADT	1.00078	37.594	0.0001		
				RAADT	2.73211	12.201	0.0001		
Central	96.96	2167.8	3159.3	CONST	840.56657	2.270	0.0243	201	0.1424 (<0.01)
	96.93	8.094	0.0001	LAADT	0.99257	67.753	0.0001		
				RAADT	1.59519	18.524	0.0001		
South	96.51	1051.3	1159.8	CONST	120.19918	0.431	0.6678	87	0.2074 (<0.01)
	96.42	8.495	0.0001	LAADT	1.02032	46.099	0.0001		
				RAADT	1.88571	12.951	0.0001		

Table E1.1, continued

Region	Model Statistics		Significance Statistics & Parameter Values					Normality Stat.	
	R ²	RMSE	F-Value	Parameter		t-	Prob>t	N	W/D (*)
	R ² _a	C.V.	Prob>F	Name	Estimate	value			(P-value)
D. Urban Interstate Highways: Statewide Model									
ALL	98.75	3284.7	8739.6	CONST	515.12102	1.176	0.2409	225	0.1345 (<0.01)
	98.73	6.483	0.0001	LAADT	1.02651	124.878	0.0001		
				RAADT	1.62377	24.210	0.0001		
E. Urban Interstate Highways: Regional Model									
North	99.82	1720.9	19758.7	CONST	-113.20860	-0.322	0.7481	225	0.1345 (<0.01)
	99.81	2.986	0.0001	LAADT	1.00492	178.844	0.0001		
				RAADT	3.01027	35.829	0.0001		
Central	98.33	2888.3	3418.4	CONST	372.50506	0.558	0.5777	119	0.1046 (<0.01)
	98.30	5.735	0.0001	LAADT	1.03337	77.206	0.0001		
				RAADT	1.29483	19.517	0.0001		
South	97.42	1937.5	509.0	CONST	731.22153	0.644	0.5253	30	0.9726 (0.641)
	97.22	5.662	0.0001	LAADT	1.00116	25.395	0.0001		
				RAADT	2.40671	9.653	0.0001		

(*) Wilk-Shapiro 'W' for $N \leq 51$ or Kolmogorov 'D' for $N > 51$, and
P-value = $\text{PROB} > D$ or $\text{PROB} < W$.

Table El.2: Partial-Lagged Regression Results of Urban Principal Arterial

Region	Model Statistics			Significance Statistics & Parameter Values					Normality Stat.	
	R ²	RMSE C.V.	F-Value Prob>F	Parameter		t- value	Prob>t	N	W/D (*) (P-value)	
	R ² _a			Name	Estimate					
City Group "A" [City Population: 30,000 to 50,000]										
North	99.36	459.8	15249.1	CONST	27.75357	0.341	0.7334	200	0.1365 (<0.01)	
	99.35	3.687	0.0001	LAADT	0.98467	167.541	0.0001			
				RAADT	3.61682	107.280	0.0001			
Central	99.05	537.4	8615.7	CONST	-16.36854	-0.151	0.8802	168	0.1498 (<0.01)	
	99.04	4.204	0.0001	LAADT	1.00096	121.059	0.0001			
				RAADT	3.94064	52.842	0.0001			
South	99.11	281.8	2003.1	CONST	322.05516	1.827	0.0761	39	0.9577 (0.269)	
	99.06	2.727	0.0001	LAADT	0.96382	57.059	0.0001			
				RAADT	3.92732	30.153	0.0001			
City Group "B" [City Population: 20,000 to 30,000]										
North	99.97	101.4	124971	CONST	-6.16070	-0.237	0.8132	85	0.2414 (<0.01)	
	99.97	0.864	0.0001	LAADT	1.00205	488.078	0.0001			
				RAADT	3.95342	176.114	0.0001			
Central	99.87	248.4	18172.8	CONST	36.87571	0.491	0.6240	50	0.8329 (<0.01)	
	99.87	2.033	0.0001	LAADT	0.99978	186.890	0.0001			
				RAADT	3.87413	76.484	0.0001			
South	99.20	415.6	558.9	CONST	2116.79778	3.125	0.0122	12	0.9485 (0.573)	
	99.20	1.726	0.0001	LAADT	0.91194	31.102	0.0001			
				RAADT	3.83773	16.353	0.0001			

Table E1.2, continued

Region	Model Statistics		Significance Statistics & Parameter Values					Normality Stat.	
	R ²	RMSE	F-Value	Parameter		t-	Prob>t	N	W/D (*) (P-value)
	R ² _a	C.V.	Prob>F	Name	Estimate	value			
City Group "C" [City Population: 10,000 to 20,000]									
North	99.20	366.2	7561.9	CONST	292.60243	3.023	0.0029	153	0.1681 (<0.01)
	99.00	3.348	0.0001	LAADT	0.96857	111.348	0.0001		
				RAADT	3.70205	67.347	0.0001		
Central	98.81	568.4	7483.1	CONST	107.53486	1.029	0.3049	184	0.1887 (<0.01)
	98.79	5.070	0.0001	LAADT	0.99093	109.667	0.0001		
				RAADT	3.67712	48.916	0.0001		
South	96.53	720.6	292.1	CONST	456.57292	0.805	0.4301	24	0.7506 (<0.01)
	96.20	6.958	0.0001	LAADT	0.96474	16.026	0.0001		
				RAADT	3.25878	14.685	0.0001		
City Group "D" [City Population: 5,000 to 10,000]									
North	99.55	246.7	6201.7	CONST	78.21203	0.899	0.3726	59	0.0942 (>0.15)
	99.53	2.727	0.0001	LAADT	0.99380	111.342	0.0001		
				RAADT	3.43147	37.050	0.0001		
Central	99.42	227.3	4964.9	CONST	173.05329	1.870	0.0665	61	0.1076 (0.079)
	99.40	2.602	0.0001	LAADT	0.98695	94.978	0.0001		
				RAADT	3.46190	37.466	0.0001		
South	98.75	393.9	4385.0	CONST	227.37756	1.943	0.0546	114	0.2295 (<0.01)
	98.73	3.835	0.0001	LAADT	0.99171	84.986	0.0001		
				RAADT	3.17555	39.837	0.0001		

(*) Wilk-Shapiro 'W' for N<51 or Kolmogorov 'D' for N>51, and
P-value = PROB>D or PROB<W.

Table E1.3: Partial-Lagged Regression Results of Urban Minor Arterial & Collector

Model Statistics			Significance Statistics & Parameter Values					Normality Stat.	
R^2	R_a^2	RMSE C.V.	F-Value Prob>F	Parameter Name Estimate	t- value	Prob>t	N	W/D (*) (P-value)	
City Group "A" [City Population: 30,000 to 50,000]									
99.19		443.9	1766.2	CONST	184.46788	0.919	0.3657	32	0.9541
99.13		4.077	0.0001	LAADT	0.97128	54.414	0.0039		(0.294)
				RAADT	3.76751	26.163	0.0001		
City Group "B" [City Population: 20,000 to 30,000]									
99.82		193.4	9157.8	CONST	62.59623	1.105	0.2771	36	0.9322
99.81		3.121	0.0001	LAADT	0.98893	128.482	0.0001		(0.044)
				RAADT	3.70737	48.015	0.0001		
City Group "C" [City Population: 10,000 to 20,000]									
98.97		408.7	1867.9	CONST	126.70698	0.845	0.4034	42	0.8061
98.91		4.899	0.0001	LAADT	0.98316	57.762	0.0001		(<0.01)
				RAADT	3.40414	25.390	0.0001		
City Group "D" [City Population: 5,000 to 10,000]									
99.10		386.5	5898.9	CONST	127.02978	1.567	0.1201	110	0.1068
99.08		5.065	0.0001	LAADT	0.99379	89.854	0.0001		(<0.01)
				RAADT	3.71034	30.463	0.0001		

(*) Wilk-Shapiro 'W' for $N < 51$ or Kolmogorov 'D' for $N \geq 51$, and
P-value = PROB>D or PROB<W.

Table E2.1: Forecast Measures from Partial-Lagged Model of Interstate Highways

Region	No. of Forecasts	Forecast Period Range	Forecast Measures				
			ME	MPF	MAE	MAPE	r
Interstate Highways (Rural & Urban)							
North	41	1-15	-2783	-3.96	4673	12.43	0.99084
Central	82	2-16	-3156	-8.11	3509	8.68	0.99135
South	39	1-12	-1414	-5.62	1815	7.30	0.99326
Rural Interstate Highways							
ALL	89	1-16	-2334	-8.72	2469	9.69	0.98738
North	18	3-15	-2649	-10.31	2762	10.76	0.95204
Central	44	2-16	-2774	-9.38	2829	9.65	0.99134
South	27	1-12	-1066	-6.14	1311	7.70	0.97964
Urban Interstate Highways							
ALL	73	1-16	-3359	-6.19	4255	7.72	0.99011
North	23	1-13	-5424	-9.96	5472	10.17	0.99461
Central	38	2-16	-3915	-7.52	4706	8.53	0.98473
South	12	1-7	-3284	-5.90	3966	7.64	0.97832

Table E2.2: Forecast Measures from Partial-Lagged Model of
Urban Principal Arterial

Region	No. of Forecasts	Forecast Period Range	Forecast Measures				
			ME	MPE	MAE	MAPE	r
City Group "A"							
North	59	3-15	-905	-4.93	1301	8.73	0.97317
Central	55	3-16	-905	-5.40	1053	6.97	0.98501
South	13	7-16	-304	0.41	778	8.86	0.97048
City Group "B"							
North	31	4-15	-731	-4.38	1168	8.16	0.97710
Central	19	6-14	-1205	-6.98	1302	8.27	0.98618
South	4	7-7	-361	-1.02	1326	5.32	0.90361
City Group "C"							
North	51	3-17	-663	-4.93	1109	9.33	0.95686
Central	61	3-14	-1281	-8.01	1441	9.94	0.97099
South	8	3-17	-114	0.23	1028	6.92	0.96878
City Group "D"							
North	20	4-14	-1588	-14.69	1588	14.69	0.95353
Central	20	4-16	-469	-4.05	656	6.70	0.96045
South	38	4-12	-1375	-10.84	1377	10.86	0.96637

Table E2.3: Forecast Measures from Partial-Lagged Model of
Urban Minor Arterial & Collector

City Group	No. of Fore- casts	Forecast Period Range	Forecast Measures				
			ME	MPE	MAE	MAPE	r
A	12	3-16	-4	0.37	1309	11.20	0.94132
B	14	3-14	-558	-4.40	663	7.95	0.97496
C	18	3-17	-221	-0.86	768	9.28	0.96290
D	33	3-16	-426	-4.05	690	8.69	0.98643

Figure E1.1: Partial Regression Residual Plot of LAADT for
North Region of Urban Interstate Highways

Figure E1.3: Partial Regression Residual Plot of LAADT for City Group "A" and Region "n" of Urban Principal Arterial

Figure E1.4: Partial Regression Residual Plot of RAADT for City Group "A" and Region "n" of Urban Principal Arterial

Figure E1.5: Partial Regression Residual Plot of LAADT for City Group "C" of Urban Minor Arterial & Collector

Figure El.6: Partial Regression Residual Plot of RAADT for City Group "C" of Urban Minor Arterial & Collector

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
P-value: <0.01

Figure E2.1: Normal Probability Plot for North Region
of Urban Interstate Highways

Figure E2.2: Normal Probability Plot for City Group "A" and Region "n" of Urban Principal Arterial

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
P-value: <0.01

Figure E2.3: Normal Probability Plot for City Group "C"
of Urban Minor Arterial & Collector

Figure E3.1: Residual Plot against Predicted value for
North Region of Urban Interstate Highways

Figure E3.2: Residual Plot against Predicted value for City Group "A" and Region "n" of Urban Principal Arterial

Figure E3.3: Residual Plot against Predicted value for City Group "C" of Urban Minor Arterial & Collector

Figure E4.1: Residual Plot against LAADT for North Region of Urban Interstate Highways

Figure E4.2: Residual Plot against RAADT for North Region of Urban Interstate Highways

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
STD DEV: 438

Figure E4.3: Residual Plot against LAADT for City Group "A" and Region "n" of Urban Principal Arterial

Figure E4.4: Residual Plot against RAADT for City Group "A" and Region "n" of Urban Principal Arterial

Figure E4.5: Residual Plot against LAADT for City Group
"C" of Urban Minor Arterial & Collector

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
 STD DEV: 352

Figure E4.6: Residual Plot against RAADT for City Group
 "C" of Urban Minor Arterial & Collector

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
 Pearson Correlation Coefficient (r) = 0.99461

Figure E5.1: Plot of Observed against Predicted AADT from Lagged Regression for North Regional Model of Urban Interstate Highways

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
 Pearson Correlation Coefficient (r) = 0.97317

Figure E5.2: Plot of Observed against Predicted AADT from Lagged Regression for City Group "A" and Region "n" of Urban Principal Arterial

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
 Pearson Correlation Coefficient (r) = 0.96290

Figure E5.3: Plot of Observed against Predicted AADT from Lagged Regression for City Group "C" of Urban Minor Arterial & Collector

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
 Pearson Correlation Coefficient (r) = 0.66700

Figure E6.1: Scatterplot of Change in Observed vs. Change in Predicted AADT from Lagged Model for North Region of Urban Interstate Highways

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
 Pearson Correlation Coefficient (r) = 0.17264

Figure E6.2: Scatterplot of Change in Observed vs. Change in Predicted AADT from
 Table E6.1: See Also Chapter "A" and Section "B" of Urban Prediction, Appendix

Figure E6.3: Scatterplot of Change in Observed vs. Change in Predicted AADT from Lagged Model for City Group "C" of Urban Minor Arterial & Collector

Appendix F

Table F1: ARIMA Model for Vehicle Registrations

County No. Name	Model: ARIMA(p,d,q)	Model Characteristics			Normality [**]	
		P(White- Noise) [*]	$\sqrt{\text{MSE}}$	AIC	W-Value	PROB<W
1 Adams	ARIMA(1,1,0)	0.245-0.737	339.1	352.84	0.9445	0.086
2 Allen	ARIMA(3rd,1, 1st+4th)	0.022-0.083	3950.1	746.37	0.9505	0.158
3 Bartholomew	ARIMA(1,1,0)	0.301-0.824	848.1	622.40	0.9893	0.990
4 Benton	ARIMA(4th,1,0)	0.520-0.950	257.2	532.49	0.9685	0.459
5 Blackford	ARIMA(0,1,1)	0.975-1.000	444.9	573.35	0.8620	<0.01
6 Boone	ARIMA(1,1,0)	0.627-0.960	494.8	581.43	0.9771	0.689
7 Brown	ARIMA(0,1,0)	0.227-0.654	218.4	518.19	0.9382	0.051
8 Carroll	ARIMA(1,1,0)	0.750-0.862	218.0	519.27	0.9552	0.236
9 Cass	ARIMA(0,1,0)	0.358-0.773	818.0	618.55	0.9098	<0.01
10 Clark	ARIMA(1,1,0)	0.102-0.675	1134.5	644.56	0.9333	0.039
11 Clay	ARIMA(0,1,0)	0.863-0.991	469.0	576.28	0.9356	0.044
12 Clinton	ARIMA(0,1,1)	0.381-0.651	333.8	551.89	0.9820	0.838
13 Crawford	ARIMA(0,1,0)	0.315-0.943	119.4	511.26	0.9684	0.457
14 Daviess	ARIMA(1,1,0)	0.183-0.581	320.1	548.32	0.9841	0.902
15 Dearborn	ARIMA(2nd,1,0)	0.668-0.932	433.7	571.49	0.9860	0.934
16 Decatur	ARIMA(0,1,0)	0.730-0.968	387.3	561.73	0.8555	<0.01
17 Dekalb	ARIMA(1,1,0)	0.771-0.936	479.6	579.04	0.9643	0.389
18 Delaware	ARIMA(1,1,0)	0.156-0.246	1552.2	668.32	0.9584	0.291
19 Dubois	ARIMA(1,1,0)	0.174-0.229	443.1	573.20	0.9780	0.715
20 Elkhart	ARIMA(2nd+3rd, 1,0)	0.131-0.414	2040.3	690.42	0.9893	0.990
21 Fayette	ARIMA(0,1,1)	0.277-0.554	375.8	560.66	0.9849	0.915
22 Floyd	ARIMA(0,1,0)	0.272-0.603	818.6	618.04	0.9773	0.693
23 Fountain	ARIMA(0,1,1)	0.958-0.975	308.5	545.54	0.9612	0.337
24 Franklin	ARIMA(0,1,0)	0.714-0.963	353.2	554.71	0.9208	0.015
25 Fulton	ARIMA(0,1,1)	0.672-0.969	308.6	545.83	0.8538	<0.01
26 Gibson	ARIMA(1,1,0)	0.632-0.922	374.1	560.39	0.9844	0.906
27 Grant	ARIMA(0,1,1)	0.088-0.543	1381.7	659.43	0.9843	0.905
28 Greene	ARIMA(0,1,0)	0.440-0.959	510.1	582.66	0.9894	0.990
29 Hamilton	ARIMA(1,1,1)	0.186-0.924	1713.5	676.92	0.9060	<0.01
30 Hancock	ARIMA(1,1,0)	0.241-0.417	687.4	606.44	0.9572	0.270
31 Harrison	ARIMA(0,1,1)	0.183-0.550	348.8	555.03	0.9624	0.356
32 Hendricks	ARIMA(1,1,0)	0.454-0.498	892.1	626.25	0.9561	0.252
33 Henry	ARIMA(0,1,1)	0.354-0.511	724.3	610.45	0.9800	0.776
34 Howard	ARIMA(0,1,1)	0.385-0.729	1441.1	662.76	0.9789	0.742
35 Huntington	ARIMA(0,1,1)	0.668-0.922	367.5	558.94	0.9803	0.786

Table F1, continued

County No. Name	Model: ARIMA(p,d,q)	Model Characteristics			Normality [**]	
		P(White- Noise) [*]	\ MSE	AIC	W-Value	PROB<W
36 Jackson	ARIMA(0,1,0)	0.217-0.415	484.2	578.70	0.9792	0.753
37 Jasper	ARIMA(1,1,0)	0.923-0.986	563.0	591.48	0.9467	0.098
38 Jay	ARIMA(0,1,0)	0.804-0.989	624.7	598.06	0.8447	<0.01
39 Jefferson	ARIMA(0,1,0)	0.597-0.995	547.0	587.96	0.9211	0.016
40 Jennings	ARIMA(0,1,1)	0.549-0.794	250.9	529.97	0.9532	0.203
41 Johnson	ARIMA(1,1,0)	0.301-0.550	947.0	630.86	0.9727	0.553
42 Knox	ARIMA(1,1,0)	0.629-0.812	474.1	578.41	0.9386	0.053
43 Kosciusko	ARIMA(2,1,0)	0.451-0.848	746.9	614.07	0.9675	0.442
44 Lagrange	ARIMA(1,1,0)	0.050-0.107	326.9	549.90	0.9789	0.744
45 Lake	ARIMA(1,1,0)	0.297-0.567	6399.2	776.17	0.9849	0.915
46 Laporte	ARIMA(0,1,0)	0.754-0.902	1717.9	674.94	0.9671	0.435
47 Lawrence	ARIMA(0,1,1)	0.419-0.732	490.4	580.80	0.9700	0.483
48 Madison	ARIMA(0,1,1)	0.388-0.748	1793.4	679.50	0.9738	0.585
49 Marion	ARIMA(0,1,0)	0.120-0.370	9503.1	804.94	0.9818	0.831
50 Marshall	ARIMA(0,1,1)	0.362-0.690	532.7	587.00	0.9849	0.914
51 Martin	ARIMA(0,1,0)	0.268-0.805	202.6	512.48	0.9314	0.036
52 Miami	ARIMA(2nd,1,0)	0.091-0.246	678.6	605.52	0.9578	0.279
53 Monroe	ARIMA(0,1,0)	0.898-0.993	1312.2	654.46	0.9873	0.954
54 Montgomery	ARIMA(1,1,0)	0.540-0.743	418.1	568.61	0.9786	0.735
55 Morgan	ARIMA(0,1,0)	0.599-0.937	791.6	616.05	0.9824	0.850
56 Newton	ARIMA(0,1,2)	0.111-0.222	228.8	524.35	0.9600	0.317
57 Noble	ARIMA(0,1,0)	0.681-0.912	660.2	602.26	0.9820	0.839
58 Ohio	ARIMA(0,1,0)	0.227-0.758	76.5	438.46	0.9684	0.456
59 Orange	ARIMA(1,1,0)	0.444-0.882	178.5	503.98	0.9606	0.326
60 Owen	ARIMA(0,1,0)	0.834-0.959	345.5	553.04	0.9712	0.506
61 Parke	ARIMA(2nd,1,0)	0.301-0.748	330.0	550.78	0.8859	<0.01
62 Perry	ARIMA(0,1,0)	0.212-0.604	429.0	569.50	0.9468	0.099
63 Pike	ARIMA(0,1,0)	0.686-0.828	246.8	527.48	0.9702	0.486
64 Porter	ARIMA(1,1,0)	0.364-0.909	1438.6	662.97	0.9783	0.726
65 Posey	ARIMA(1,1,0)	0.310-0.662	354.3	556.26	0.9903	1.000
66 Pulaski	ARIMA(0,1,0)	0.418-0.679	202.5	512.43	0.9710	0.500
67 Putnam	ARIMA(0,1,0)	0.532-0.946	383.2	560.92	0.9538	0.213
68 Randolph	ARIMA(1,1,0)	0.586-0.951	551.3	589.94	0.8410	<0.01
69 Ripley	ARIMA(0,1,0)	0.658-0.994	375.7	559.41	0.9036	<0.01
70 Rush	ARIMA(0,1,0)	0.640-0.955	412.4	566.50	0.8082	<0.01

Table F1, continued

County No. Name	Model:	Model Characteristics			Normality [**]	
	ARIMA(p,d,q)	P(White- Noise) [*]	\ MSE	AIC	W-Value	PROB<W
71 St. Joseph	ARIMA(0,1,0)	0.053-0.278	2777.7	711.46	0.9811	0.811
72 Scott	ARIMA(0,1,1)	0.664-0.951	271.5	535.78	0.9751	0.628
73 Shelby	ARIMA(1,1,0)	0.505-0.596	494.2	581.39	0.9803	0.786
74 Spencer	ARIMA(0,1,0)	0.695-0.935	367.1	557.66	0.9362	0.046
75 Starke	ARIMA(0,1,0)	0.366-0.664	340.8	552.00	0.9546	0.227
76 Steuben	ARIMA(0,1,0)	0.649-0.971	585.9	593.18	0.8552	<0.01
77 Sullivan	ARIMA(0,1,0)	0.814-0.949	356.2	555.37	0.9125	<0.01
78 Switzerland	ARIMA(0,1,0)	0.503-0.975	102.7	460.84	0.9748	0.618
79 Tippecanoe	ARIMA(1,1,0)	0.592-0.924	995.5	634.62	0.9587	0.295
80 Tipton	ARIMA(0,1,1)	0.169-0.419	279.6	538.13	0.9780	0.716
81 Union	ARIMA(0,1,0)	0.685-0.939	125.1	475.84	0.9443	0.085
82 Vanderburgh	ARIMA(1st+3rd+ 4th,1,0)	0.343-0.733	1883.1	686.97	0.9745	0.609
83 Vermillion	ARIMA(0,1,0)	0.346-0.484	251.6	528.96	0.9771	0.688
84 Vigo	ARIMA(0,1,1)	0.444-0.759	1028.6	637.18	0.9803	0.785
85 Wabash	ARIMA(0,1,0)	0.748-0.886	524.0	584.69	0.9619	0.348
86 Warren	ARIMA(0,1,0)	0.705-0.774	200.4	511.66	0.9579	0.282
87 Warrick	ARIMA(1,1,0)	0.346-0.820	554.8	590.29	0.9639	0.381
88 Washington	ARIMA(1,1,0)	0.709-0.958	272.9	536.23	0.9535	0.208
89 Wayne	ARIMA(0,1,1)	0.627-0.703	1066.9	639.78	0.9731	0.564
90 Wells	ARIMA(0,1,1)	0.338-0.517	283.9	539.60	0.9732	0.569
91 White	ARIMA(1,1,0)	0.771-0.921	314.7	547.15	0.9773	0.694
92 Whitley	ARIMA(1,1,0)	0.502-0.611	378.9	561.11	0.9710	0.500
STATE	ARIMA(0,1,1)	0.322-0.467	59535	945.50	0.9841	0.902

[*] Range of values with autocorrelation lags of 6, 12, 18 and 24.

[**] Number of residuals = 38.

Table F2: Parameter of ARIMA Model for Vehicle Registrations

County No. Name	ARIMA Model: (p,d,q)	Parameter [*]			County No. Name	ARIMA Model: (p,d,q)	Parameter [*]		
		Name	Estimate	t-val.			Name	Estimate	t-val.
1 Adams	(1,1,0)	MU	356.87	3.45	45 Lake	(1,1,0)	MU	5758.41	2.72
		AR1	0.4826	3.34			AR1	0.5252	3.75
2 Allen	(3rd,1, 1st+4th)	MU	4616.62	7.39	46 Laporte	(0,1,0)	MU	1433.34	5.14
		AR3	-0.5594	-3.03					
		MA1	-0.8186	-5.94	47 Lawrence	(0,1,1)	MU	685.03	6.20
		MA4	-0.3433	-2.40			MA1	-0.3998	-2.33
3 Bartho- lomew	(1,1,0)	MU	1186.89	5.51	48 Madison	(0,1,1)	MU	1890.50	4.29
		AR1	0.3723	2.42			MA1	-0.5322	-3.30
4 Benton	(4th,1,0)	MU	145.84	2.64	49 Marion	(0,1,0)	MU	10141.7	6.58
		AR4	0.4560	2.82					
5 Black- ford	(0,1,1)	MU	193.59	3.98	50 Marshall	(0,1,1)	MU	609.47	5.45
		MA1	0.3346	2.10			MA1	-0.3027	-1.76
6 Boone	(1,1,0)	MU	623.80	5.19	51 Martin	(0,1,0)	MU	164.00	4.99
		AR1	0.3417	2.17					
7 Brown	(0,1,0)	MU	275.61	7.78	52 Miami	(2nd,1,0)	MU	522.30	6.19
							AR2	-0.3197	-1.96
8 Carroll	(1,1,0)	MU	271.85	4.10	53 Monroe	(0,1,0)	MU	1437.82	6.75
		AR1	0.4694	3.15					
9 Cass	(0,1,0)	MU	452.50	3.41	54 Montgo- mery	(1,1,0)	MU	452.23	4.55
							AR1	0.3270	2.08
10 Clark	(1,1,0)	MU	1544.37	4.98	55 Morgan	(0,1,0)	MU	1029.53	8.02
		AR1	0.4188	2.79					
11 Clay	(0,1,0)	MU	326.50	4.29	56 Newton	(0,1,2)	MU	181.67	2.45
							MA1	-0.5461	-3.61
							MA2	-0.5097	-3.32

Table F2, continued

County No. Name	ARIMA Model: (p,d,q)	Parameter [*]			County No. Name	ARIMA Model: (p,d,q)	Parameter [*]		
		Name	Estimate	t-val.			Name	Estimate	t-val.
12 Clinton	(0,1,1)	MU	391.69	4.51	57 Noble	(0,1,0)	MU	557.90	5.21
		MA1	-0.6281	-4.03					
13 Crawford	(0,1,0)	MU	153.71	4.75	58 Ohio	(0,1,0)	MU	73.34	5.91
14 Daviess	(1,1,0)	MU	348.96	4.52	59 Orange	(1,1,0)	MU	268.38	5.80
		AR1	0.3373	2.16			AR1	0.3864	2.53
15 Dearborn	(2nd,1,0)	MU	576.97	10.69	60 Owen	(0,1,0)	MU	285.29	5.09
		AR2	-0.3169	-1.97	61 Parke	(2nd,1,0)	MU	182.16	2.28
16 Decatur	(0,1,0)	MU	390.24	6.21			AR2	0.3505	2.17
17 Dekalb	(1,1,0)	MU	511.26	4.43	62 Perry	(0,1,0)	MU	280.18	4.03
		AR1	0.3350	2.12	63 Pike	(0,1,0)	MU	181.95	4.54
18 Delaware	(1,1,0)	MU	1485.74	3.90	64 Porter	(1,1,0)	MU	2305.17	3.61
		AR1	0.3492	2.25			AR1	0.6534	5.16
19 Dubois	(1,1,0)	MU	654.15	4.65	65 Posey	(1,1,0)	MU	419.58	3.50
		AR1	0.5039	3.54			AR1	0.5360	3.86
20 Elkhart	(2nd+3rd, 1,0)	MU	2446.57	11.59	66 Pulaski	(0,1,0)	MU	165.61	5.04
		AR2	-0.2871	-1.74	67 Putnam	(0,1,0)	MU	413.90	6.66
		AR3	-0.3115	-1.88					
21 Fayette	(0,1,1)	MU	361.64	4.03	68 Randolph	(1,1,0)	MU	149.94	0.72
		MA1	-0.4874	-3.12			AR1	0.5873	4.43
22 Floyd	(0,1,0)	MU	939.13	7.12	69 Ripley	(0,1,0)	MU	366.42	6.01

Table F2, continued

County No. Name	ARIMA Model: (p,d,q)	Parameter [*]			County No. Name	ARIMA Model: (p,d,q)	Parameter [*]		
		Name	Estimate	t-val.			Name	Estimate	t-val.
23 Fountain	(0,1,1)	MU	188.86	2.76	70 Rush	(0,1,0)	MU	235.26	3.52
		MA1	-0.3801	-2.39					
24 Franklin	(0,1,0)	MU	304.03	5.31	71 St. Joseph	(0,1,0)	MU	2823.76	6.27
25 Fulton	(0,1,1)	MU	194.82	2.50	72 Scott	(0,1,1)	MU	335.80	5.84
		MA1	-0.5771	-3.53			MA1	-0.3136	-1.82
26 Gibson	(1,1,0)	MU	419.66	3.36	73 Shelby	(1,1,0)	MU	611.39	4.58
		AR1	0.5302	3.76			AR1	0.4114	2.71
27 Grant	(0,1,1)	MU	984.20	3.43	74 Spencer	(0,1,0)	MU	325.55	5.47
		MA1	-0.2864	-1.72					
28 Greene	(0,1,0)	MU	414.90	5.01	75 Starke	(0,1,0)	MU	303.42	5.49
29 Hamilton	(1,1,1)	MU	1968.82	2.92	76 Steuben	(0,1,0)	MU	429.90	4.52
		AR1	0.6683	2.60					
		MA1	0.8758	5.31	77 Sullivan	(0,1,0)	MU	259.61	4.49
30 Hancock	(1,1,0)	MU	891.52	5.06	78 Switzer- land	(0,1,0)	MU	78.71	4.72
		AR1	0.3777	2.44					
31 Harrison	(0,1,1)	MU	555.30	6.59	79 Tippe- canoe	(1,1,0)	MU	1579.00	5.80
		MA1	-0.5062	-3.08			AR1	0.4190	2.78
32 Hend- ricks	(1,1,0)	MU	1659.03	7.29	80 Tipton	(0,1,1)	MU	230.74	3.62
		AR1	0.3751	2.40			MA1	-0.4199	-2.67
33 Henry	(0,1,1)	MU	685.05	4.15	81 Union	(0,1,0)	MU	96.79	4.77
		MA1	-0.4162	-2.54					
34 Howard	(0,1,1)	MU	1281.58	3.84	82 Vander- burgh	(1st+3rd+ 4th,1,0)	MU	1871.02	2.87
		MA1	-0.4413	-2.74			AR1	0.4482	3.12
							AR2	-0.4913	-2.95
							AR4	0.6016	3.71

Table F2, continued

County No. Name	ARIMA Model: (p,d,q)	Parameter [*]			County No. Name	ARIMA Model: (p,d,q)	Parameter [*]		
		Name	Estimate	t-val.			Name	Estimate	t-val.
35 Hunting- ton	(0,1,1)	MU MA1	423.81 -0.4639	4.91 -2.84	83 Vermi- llion	(0,1,0)	MU	211.37	5.18
36 Jackson	(0,1,0)	MU	617.82	7.87	84 Vigo	(0,1,1)	MU MA1	1178.08 -0.4842	4.81 -3.12
37 Jasper	(1,1,0)	MU AR1	355.52 0.3416	2.67 2.03	85 Wabash	(0,1,0)	MU	463.79	5.46
38 Jay	(0,1,0)	MU	227.84	2.25	86 Warren	(0,1,0)	MU	108.74	3.34
39 Jeffer- son	(0,1,0)	MU	390.63	4.40	87 Warrick	(1,1,0)	MU AR1	854.88 0.5048	4.85 3.53
40 Jennings	(0,1,1)	MU MA1	401.37 -0.4876	6.70 -3.10	88 Washing- ton	(1,1,0)	MU AR1	310.82 0.3833	4.41 2.49
41 Johnson	(1,1,0)	MU AR1	1636.07 0.4493	6.01 3.04	89 Wayne	(0,1,1)	MU MA1	786.18 -0.2785	3.58 -1.69
42 Knox	(1,1,0)	MU AR1	427.88 0.5477	2.61 3.96	90 Wells	(0,1,1)	MU MA1	383.81 -0.6392	5.17 -4.08
43 Kosciu- sko	(2,1,0)	MU AR1 AR2	1146.29 0.4937 -0.4388	8.67 3.20 -2.81	91 White	(1,1,0)	MU AR1	343.07 0.4546	3.75 3.03
44 Lagrange	(1,1,0)	MU AR1	360.11 0.3156	4.71 1.98	92 Whitley	(1,1,0)	MU AR1	438.76 0.2790	5.20 1.74
					STATE	(0,1,1)	MU MA1	78722.3 -0.3730	5.98 -2.19

[*] In most cases, Parameters are significant at α -level of 0.05

Table F3: 1989-2015 Vehicle Registration Forecasts by ARIMA Model

County No. Name	Year								
	1989	1990	1991	1992	1993	1994	1995	1996	1997
1 Adams	26698	27075	27442	27804	28163	28521	28878	29235	29592
2 Allen	244579	267100	267018	279068	269026	277490	276021	292638	294105
3 Bartholomew	60632	61871	63077	64272	65461	66649	67836	69023	70210
4 Benton	9312	9194	9064	9105	9059	9030	8996	9040	9044
5 Blackford	13784	13978	14171	14365	14558	14752	14945	15139	15333
6 Boone	35968	36643	37284	37914	38539	39164	39788	40412	41036
7 Brown	13148	13423	13699	13974	14250	14526	14801	15077	15352
8 Carroll	19783	20113	20412	20697	20975	21249	21523	21795	22067
9 Cass	34835	35287	35740	36192	36645	37097	37550	38002	38455
10 Clark	74982	76503	78037	79577	81120	82663	84208	85752	87296
11 Clay	22714	23040	23367	23693	24020	24346	24673	24999	25326
12 Clinton	28524	28916	29308	29700	30091	30483	30875	31266	31658
13 Crawford	9171	9324	9478	9632	9786	9939	10093	10247	10400
14 Daviess	23949	24292	24639	24987	25336	25685	26034	26383	26732
15 Dearborn	33082	33578	34101	34703	35297	35866	36438	37017	37596
16 Decatur	21576	21967	22357	22747	23137	23527	23918	24308	24698
17 Dekalb	33821	34379	34906	35422	35935	36447	36959	37470	37981
18 Delaware	95241	96671	98137	99616	101099	102584	104070	105555	107041
19 Dubois	34655	35310	35964	36618	37273	37927	38581	39235	39889
20 Elkhart	133837	137538	139388	141174	143401	146224	148939	151346	153598
21 Fayette	22841	23202	23564	23926	24287	24649	25011	25372	25734
22 Floyd	52413	53352	54291	55231	56170	57109	58048	58987	59926
23 Fountain	16047	16236	16425	16613	16802	16991	17180	17369	17558
24 Franklin	17580	17884	18188	18492	18796	19100	19404	19708	20012
25 Fulton	18497	18692	18886	19081	19276	19471	19666	19860	20055
26 Gibson	29693	30014	30381	30773	31178	31590	32006	32423	32842
27 Grant	63843	64827	65811	66795	67779	68764	69748	70732	71716
28 Greene	27828	28243	28658	29073	29488	29902	30317	30732	31147
29 Hamilton	93065	95582	98030	100419	102756	105047	107298	109514	111700
30 Hancock	44256	45230	46153	47056	47952	48845	49737	50629	51521

Table F3, continued

County No. Name	Year								
	1989	1990	1991	1992	1993	1994	1995	1996	1997
31 Harrison	28625	29180	29735	30291	30846	31401	31957	32512	33067
32 Hendricks	74488	76287	77998	79677	81343	83005	84665	86325	87984
33 Henry	45604	46289	46974	47659	48344	49029	49714	50399	51084
34 Howard	72690	73971	75253	76534	77816	79098	80379	81661	82942
35 Huntington	31827	32251	32675	33098	33522	33946	34370	34794	35217
36 Jackson	35113	35731	36348	36966	37584	38202	38820	39438	40055
37 Jasper	23084	23468	23852	24236	24620	25004	25388	25772	26156
38 Jay	20377	20605	20833	21060	21288	21516	21744	21972	22200
39 Jefferson	23805	24195	24586	24977	25367	25758	26148	26539	26930
40 Jennings	20797	21198	21600	22001	22402	22804	23205	23607	24008
41 Johnson	74497	76173	77827	79471	81110	82748	84385	86021	87657
42 Knox	34240	34558	34925	35320	35730	36148	36570	36995	37422
43 Kosciusko	60801	62086	62976	63906	65030	66232	67387	68485	69575
44 Lagrange	20959	21347	21717	22079	22440	22801	23161	23521	23881
45 Lake	335361	341383	347279	353110	358907	364685	370454	376218	381979
46 Laporte	84924	86358	87791	89224	90658	92091	93524	94958	96391
47 Lawrence	39190	39875	40560	41245	41930	42615	43300	43985	44671
48 Madison	115980	117871	119761	121652	123542	125433	127323	129214	131104
49 Marion	612979	623120	633262	643404	653546	663687	673829	683971	694113
50 Marshall	38221	38830	39440	40049	40659	41268	41878	42487	43097
51 Martin	9880	10044	10208	10372	10536	10700	10864	11028	11192
52 Miami	34003	34568	34971	35480	36040	36567	37077	37598	38124
53 Monroe	72751	74189	75626	77064	78502	79940	81378	82816	84253
54 Montgomery	32368	32846	33307	33762	34215	34667	35120	35572	36024
55 Morgan	50727	51756	52786	53815	54845	55874	56904	57933	58963
56 Newton	12729	13067	13249	13430	13612	13794	13975	14157	14339
57 Noble	34307	34865	35423	35981	36539	37096	37654	38212	38770
58 Ohio	4662	4736	4809	4882	4956	5029	5102	5176	5249
59 Orange	16492	16761	17030	17298	17566	17835	18103	18372	18640
60 Owen	15986	16272	16557	16842	17127	17413	17698	17983	18269
61 Parke	14008	14213	14326	14517	14675	14860	15033	15217	15396
62 Perry	16658	16938	17219	17499	17779	18059	18339	18620	18900

Table F3, continued

County		Year								
No.	Name	1989	1990	1991	1992	1993	1994	1995	1996	1997
63	Pike	12818	13000	13182	13364	13546	13728	13910	14092	14274
64	Porter	105957	109114	111976	114645	117188	119648	122055	124426	126775
65	Posey	24767	25148	25546	25955	26368	26785	27202	27621	28040
66	Pulaski	13024	13189	13355	13520	13686	13852	14017	14183	14348
67	Putnam	25003	25417	25831	26245	26659	27072	27486	27900	28314
68	Randolph	25893	26088	26265	26430	26589	26745	26898	27049	27200
69	Ripley	22501	22868	23234	23601	23967	24334	24700	25066	25433
70	Rush	16352	16588	16823	17058	17293	17529	17764	17999	18234
71	St. Joseph	191760	194584	197407	200231	203055	205879	208702	211526	214350
72	Scott	17835	18171	18507	18843	19178	19514	19850	20186	20522
73	Shelby	36801	37469	38103	38724	39340	39953	40565	41177	41788
74	Spencer	18647	18972	19298	19623	19949	20274	20600	20925	21251
75	Starke	18980	19284	19587	19891	20194	20498	20801	21104	21408
76	Steuben	25663	26093	26523	26953	27383	27812	28242	28672	29102
77	Sullivan	18453	18712	18972	19231	19491	19751	20010	20270	20529
78	Switzerland	6037	6115	6194	6273	6352	6430	6509	6588	6666
79	Tippecanoe	91093	92767	94386	95982	97568	99150	100730	102309	103889
80	Tipton	16708	16939	17170	17401	17631	17862	18093	18324	18554
81	Union	6786	6883	6979	7076	7173	7270	7367	7463	7560
82	Vanderburgh	134609	139215	138409	139086	138348	142011	143660	145996	145626
83	Vermillion	15916	16128	16339	16551	16762	16973	17185	17396	17607
84	Vigo	82891	84069	85247	86426	87604	88782	89960	91138	92316
85	Wabash	32073	32537	33000	33464	33928	34392	34856	35319	35783
86	Warren	8421	8530	8638	8747	8856	8964	9073	9182	9291
87	Warrick	41652	42594	43493	44370	45236	46096	46954	47810	48666
88	Washington	20479	20814	21134	21448	21761	22072	22383	22694	23005

Table F3, continued

County No. Name	Year								
	1998	1999	2000	2001	2002	2003	2004	2005	2006
1 Adams	29949	30306	30663	31020	31377	31733	32090	32447	32804
2 Allen	303703	298496	305691	306230	318888	321394	329349	327382	333727
3 Bartholomew	71397	72584	73771	74958	76145	77332	78519	79705	80892
4 Benton	9055	9065	9110	9136	9167	9196	9241	9278	9317
5 Blackford	15526	15720	15913	16107	16301	16494	16688	16881	17075
6 Boone	41659	42283	42907	43531	44155	44778	45402	46026	46650
7 Brown	15628	15904	16179	16455	16731	17006	17282	17557	17833
8 Carroll	22339	22611	22883	23155	23427	23699	23970	24242	24514
9 Cass	38907	39360	39812	40265	40717	41170	41622	42075	42527
10 Clark	88840	90385	91929	93474	95018	96562	98107	99651	101195
11 Clay	25652	25979	26305	26632	26958	27285	27611	27938	28264
12 Clinton	32050	32441	32833	33225	33617	34008	34400	34792	35183
13 Crawford	10554	10708	10862	11015	11169	11323	11476	11630	11784
14 Daviess	27081	27430	27779	28128	28477	28825	29174	29523	29872
15 Dearborn	38172	38748	39326	39903	40480	41057	41634	42211	42788
16 Decatur	25088	25479	25869	26259	26649	27040	27430	27820	28210
17 Dekalb	38493	39004	39515	40026	40538	41049	41560	42071	42583
18 Delaware	108527	110012	111498	112984	114470	115955	117441	118927	120413
19 Dubois	40543	41198	41852	42506	43160	43814	44468	45122	45777
20 Elkhart	155973	158487	161015	163464	165867	168287	170745	173213	175665
21 Fayette	26096	26457	26819	27181	27542	27904	28265	28627	28989
22 Floyd	60865	61804	62744	63683	64622	65561	66500	67439	68378
23 Fountain	17747	17936	18124	18313	18502	18691	18880	19069	19258
24 Franklin	20316	20620	20924	21228	21532	21836	22140	22444	22749
25 Fulton	20250	20445	20640	20835	21029	21224	21419	21614	21809
26 Gibson	33261	33680	34100	34519	34939	35358	35778	36198	36617
27 Grant	72700	73685	74669	75653	76637	77621	78606	79590	80574
28 Greene	31562	31977	32392	32807	33222	33636	34051	34466	34881
29 Hamilton	113858	115993	118107	120203	122284	124350	126405	128448	130483
30 Hancock	52412	53304	54195	55087	55978	56870	57761	58653	59544

Table F3, continued

County No. Name	Year								
	1998	1999	2000	2001	2002	2003	2004	2005	2006
31 Harrison	33623	34178	34733	35288	35844	36399	36954	37510	38065
32 Hendricks	89643	91302	92961	94620	96279	97938	99597	101256	102915
33 Henry	51769	52454	53139	53824	54509	55194	55880	56565	57250
34 Howard	84224	85505	86787	88069	89350	90632	91913	93195	94477
35 Huntington	35641	36065	36489	36913	37337	37760	38184	38608	39032
36 Jackson	40673	41291	41909	42527	43144	43762	44380	44998	45616
37 Jasper	26541	26925	27309	27693	28077	28461	28845	29229	29613
38 Jay	22427	22655	22883	23111	23339	23567	23795	24022	24250
39 Jefferson	27320	27711	28102	28492	28883	29274	29664	30055	30445
40 Jennings	24409	24811	25212	25613	26015	26416	26818	27219	27620
41 Johnson	89293	90930	92566	94202	95838	97474	99110	100746	102382
42 Knox	37849	38276	38704	39131	39559	39987	40415	40843	41271
43 Kosciusko	70687	71812	72935	74050	75163	76278	77395	78513	79629
44 Lagrange	24241	24602	24962	25322	25682	26042	26402	26762	27122
45 Lake	387739	393499	399257	405016	410775	416533	422292	428050	433808
46 Laporte	97824	99258	100691	102124	103558	104991	106424	107858	109291
47 Lawrence	45356	46041	46726	47411	48096	48781	49466	50151	50836
48 Madison	132995	134885	136776	138666	140557	142447	144338	146228	148119
49 Marion	704254	714396	724538	734680	744821	754963	765105	775247	785388
50 Marshall	43706	44316	44925	45535	46144	46753	47363	47972	48582
51 Martin	11356	11520	11684	11848	12012	12176	12340	12504	12668
52 Miami	38647	39168	39690	40213	40735	41257	41780	42302	42824
53 Monroe	85691	87129	88567	90005	91442	92880	94318	95756	97194
54 Montgomery	36476	36929	37381	37833	38285	38737	39190	39642	40094
55 Morgan	59992	61022	62051	63081	64110	65140	66169	67199	68229
56 Newton	14520	14702	14884	15066	15247	15429	15611	15792	15974
57 Noble	39328	39886	40444	41002	41560	42117	42675	43233	43791
58 Ohio	5322	5396	5469	5542	5616	5689	5762	5836	5909
59 Orange	18908	19177	19445	19714	19982	20250	20519	20787	21055
60 Owen	18554	18839	19125	19410	19695	19980	20266	20551	20836
61 Parke	15578	15759	15942	16123	16306	16488	16670	16852	17034
62 Perry	19180	19460	19740	20020	20301	20581	20861	21141	21421

Table F3, continued

County No. Name	Year								
	1998	1999	2000	2001	2002	2003	2004	2005	2006
63 Pike	14456	14637	14819	15001	15183	15365	15547	15729	15911
64 Porter	129108	131432	133749	136062	138373	140681	142988	145295	147601
65 Posey	28459	28879	29298	29718	30137	30557	30977	31396	31816
66 Pulaski	14514	14680	14845	15011	15177	15342	15508	15673	15839
67 Putnam	28728	29142	29556	29970	30384	30797	31211	31625	32039
68 Randolph	27351	27501	27651	27802	27952	28102	28251	28401	28551
69 Ripley	25799	26166	26532	26899	27265	27631	27998	28364	28731
70 Rush	18470	18705	18940	19175	19411	19646	19881	20117	20352
71 St. Joseph	217174	219997	222821	225645	228469	231292	234116	236940	239764
72 Scott	20857	21193	21529	21865	22200	22536	22872	23208	23544
73 Shelby	42399	43011	43622	44234	44845	45457	46068	46679	47291
74 Spencer	21577	21902	22228	22553	22879	23204	23530	23855	24181
75 Starke	21711	22015	22318	22622	22925	23228	23532	23835	24139
76 Steuben	29532	29962	30392	30822	31252	31681	32111	32541	32971
77 Sullivan	20789	21049	21308	21568	21828	22087	22347	22606	22866
78 Switzerland	6745	6824	6903	6981	7060	7139	7217	7296	7375
79 Tippecanoe	105468	107047	108626	110205	111784	113363	114942	116521	118100
80 Tipton	18785	19016	19247	19477	19708	19939	20170	20400	20631
81 Union	7657	7754	7850	7947	8044	8141	8238	8334	8431
82 Vanderburgh	147679	149270	152396	153392	155117	156138	158813	160589	162748
83 Vermillion	17819	18030	18241	18453	18664	18876	19087	19298	19510
84 Vigo	93494	94672	95850	97028	98206	99384	100563	101741	102919
85 Wabash	36247	36711	37175	37638	38102	38566	39030	39493	39957
86 Warren	9399	9508	9617	9726	9834	9943	10052	10161	10269
87 Warrick	49521	50376	51231	52086	52941	53796	54651	55506	56361
88 Washington	23316	23626	23937	24248	24559	24870	25181	25491	25802
89 Wayne	65909	66695	67481	68267	69054	69840	70626	71412	72198
90 Wells	29253	29637	30021	30405	30789	31172	31556	31940	32324
91 White	26510	26853	27196	27539	27882	28225	28568	28912	29255
92 Whitley	31263	31701	32140	32579	33018	33456	33895	34334	34773
STATE	5367705	5446427	5525149	5603872	5682594	5761316	5840039	5918761	5997483

Table F3, continued

County No. Name	Year								
	2007	2008	2009	2010	2011	2012	2013	2014	2015
1 Adams	33161	33518	33875	34232	34588	34945	35302	35659	36016
2 Allen	335610	345617	348819	355673	355877	361652	364437	372665	376334
3 Bartholomew	82079	83266	84453	85640	86827	88014	89200	90387	91574
4 Benton	9355	9401	9443	9485	9528	9574	9618	9662	9706
5 Blackford	17269	17462	17656	17849	18043	18237	18430	18624	18817
6 Boone	47274	47897	48521	49145	49769	50393	51016	51640	52264
7 Brown	18109	18384	18660	18935	19211	19487	19762	20038	20313
8 Carroll	24786	25058	25330	25602	25873	26145	26417	26689	26961
9 Cass	42980	43432	43885	44337	44790	45242	45695	46147	46600
10 Clark	102740	104284	105828	107373	108917	110462	112006	113550	115095
11 Clay	28591	28917	29244	29570	29897	30223	30550	30876	31203
12 Clinton	35575	35967	36358	36750	37142	37533	37925	38317	38709
13 Crawford	11938	12091	12245	12399	12552	12706	12860	13014	13167
14 Daviess	30221	30570	30919	31268	31617	31966	32315	32664	33013
15 Dearborn	43365	43942	44519	45095	45672	46249	46826	47403	47980
16 Decatur	28601	28991	29381	29771	30161	30552	30942	31332	31722
17 Dekalb	43094	43605	44117	44628	45139	45650	46162	46673	47184
18 Delaware	121898	123384	124870	126356	127841	129327	130813	132299	133784
19 Dubois	46431	47085	47739	48393	49047	49702	50356	51010	51664
20 Elkhart	178101	180540	182988	185440	187888	190333	192777	195224	197672
21 Fayette	29350	29712	30074	30435	30797	31159	31520	31882	32244
22 Floyd	69318	70257	71196	72135	73074	74013	74952	75891	76831
23 Fountain	19446	19635	19824	20013	20202	20391	20580	20768	20957
24 Franklin	23053	23357	23661	23965	24269	24573	24877	25181	25485
25 Fulton	22003	22198	22393	22588	22783	22978	23172	23367	23562
26 Gibson	37037	37457	37876	38296	38716	39135	39555	39975	40394
27 Grant	81558	82542	83527	84511	85495	86479	87463	88448	89432
28 Greene	35296	35711	36126	36541	36956	37371	37785	38200	38615
29 Hamilton	132509	134528	136541	138549	140551	142550	144544	146536	148525
30 Hancock	60436	61327	62219	63110	64002	64893	65785	66676	67568

Table F3, continued

County No. Name	Year								
	2007	2008	2009	2010	2011	2012	2013	2014	2015
31 Harrison	38620	39175	39731	40286	40841	41397	41952	42507	43063
32 Hendricks	104574	106233	107892	109551	111210	112869	114528	116188	117847
33 Henry	57935	58620	59305	59990	60675	61360	62045	62730	63415
34 Howard	95758	97040	98321	99603	100884	102166	103448	104729	106011
35 Huntington	39456	39879	40303	40727	41151	41575	41998	42422	42846
36 Jackson	46234	46851	47469	48087	48705	49323	49940	50558	51176
37 Jasper	29997	30381	30765	31149	31534	31918	32302	32686	33070
38 Jay	24478	24706	24934	25162	25389	25617	25845	26073	26301
39 Jefferson	30836	31227	31617	32008	32399	32789	33180	33570	33961
40 Jennings	28022	28423	28824	29226	29627	30028	30430	30831	31233
41 Johnson	104018	105654	107290	108926	110562	112198	113835	115471	117107
42 Knox	41698	42126	42554	42982	43410	43838	44266	44694	45121
43 Kosciusko	80745	81861	82977	84094	85210	86326	87443	88559	89675
44 Lagrange	27482	27842	28203	28563	28923	29283	29643	30003	30363
45 Lake	439567	445325	451084	456842	462600	468359	474117	479876	485634
46 Laporte	110724	112158	113591	115025	116458	117891	119325	120758	122191
47 Lawrence	51521	52206	52891	53576	54261	54946	55631	56316	57001
48 Madison	150009	151900	153790	155681	157571	159462	161352	163243	165133
49 Marion	795530	805672	815813	825955	836097	846239	856380	866522	876664
50 Marshall	49191	49801	50410	51020	51629	52239	52848	53458	54067
51 Martin	12832	12996	13160	13324	13488	13652	13816	13980	14144
52 Miami	43347	43869	44391	44913	45436	45958	46480	47003	47525
53 Monroe	98631	100069	101507	102945	104383	105821	107258	108696	110134
54 Montgomery	40546	40999	41451	41903	42355	42807	43260	43712	44164
55 Morgan	69258	70288	71317	72347	73376	74406	75435	76465	77494
56 Newton	16156	16337	16519	16701	16882	17064	17246	17427	17609
57 Noble	44349	44907	45465	46023	46581	47139	47696	48254	48812
58 Ohio	5983	6056	6129	6203	6276	6349	6423	6496	6569
59 Orange	21324	21592	21861	22129	22397	22666	22934	23203	23471
60 Owen	21122	21407	21692	21977	22263	22548	22833	23119	23404
61 Parke	17216	17398	17581	17763	17945	18127	18309	18491	18674
62 Perry	21702	21982	22262	22542	22822	23102	23383	23663	23943

Table F3, continued

County No. Name	Year								
	2007	2008	2009	2010	2011	2012	2013	2014	2015
63 Pike	16093	16275	16457	16639	16821	17003	17185	17367	17549
64 Porter	149907	152213	154518	156823	159129	161434	163739	166044	168349
65 Posey	32235	32655	33074	33494	33914	34333	34753	35172	35592
66 Pulaski	16005	16170	16336	16501	16667	16833	16998	17164	17329
67 Putnam	32453	32867	33281	33695	34109	34523	34936	35350	35764
68 Randolph	28701	28851	29001	29151	29301	29451	29601	29751	29901
69 Ripley	29097	29463	29830	30196	30563	30929	31296	31662	32028
70 Rush	20587	20822	21058	21293	21528	21763	21999	22234	22469
71 St. Joseph	242587	245411	248235	251059	253883	256706	259530	262354	265178
72 Scott	23879	24215	24551	24887	25223	25558	25894	26230	26566
73 Shelby	47902	48513	49125	49736	50348	50959	51570	52182	52793
74 Spencer	24507	24832	25158	25483	25809	26134	26460	26785	27111
75 Starke	24442	24745	25049	25352	25656	25959	26263	26566	26869
76 Steuben	33401	33831	34261	34691	35121	35551	35980	36410	36840
77 Sullivan	23126	23385	23645	23904	24164	24424	24683	24943	25202
78 Switzerland	7454	7532	7611	7690	7768	7847	7926	8004	8083
79 Tippecanoe	119679	121258	122837	124416	125995	127574	129153	130732	132311
80 Tipton	20862	21093	21323	21554	21785	22015	22246	22477	22708
81 Union	8528	8625	8722	8818	8915	9012	9109	9206	9302
82 Vanderburgh	163842	165895	167649	170022	171562	173451	175013	177211	179020
83 Vermillion	19721	19932	20144	20355	20567	20778	20989	21201	21412
84 Vigo	104097	105275	106453	107631	108809	109987	111165	112343	113521
85 Wabash	40421	40885	41349	41812	42276	42740	43204	43668	44131
86 Warren	10378	10487	10596	10704	10813	10922	11030	11139	11248
87 Warrick	57215	58070	58925	59780	60635	61490	62345	63200	64055
88 Washington	26113	26424	26735	27045	27356	27667	27978	28289	28600
89 Wayne	72984	73771	74557	75343	76129	76915	77701	78488	79274
90 Wells	32708	33091	33475	33859	34243	34627	35010	35394	35778
91 White	29598	29941	30284	30627	30970	31313	31656	31999	32342
92 Whitley	35211	35650	36089	36528	36966	37405	37844	38283	38721
STATE	6076206	6154928	6233650	6312373	6391095	6469817	6548539	6627262	6705984

Table F4: Autoregression Model for Vehicle Registrations

County No. Name	D-W (d) [*]		Model Characteristics			Normality [**]	
	OLS	AUTOREG	R ²	\ MSE	AIC	W-Value	PROB<W
1 Adams	0.170	1.114	99.48	381.4	579.22	0.9503	0.140
2 Allen	0.329	1.889	99.16	5797.3	790.81	0.9396	0.054
3 Bartholomew	0.197	1.176	99.66	900.9	645.95	0.9776	0.703
4 Benton	0.229	1.831	97.36	283.2	555.88	0.9646	0.388
5 Blackford	0.663	2.154	97.51	438.3	588.65	0.8622	<0.01
6 Boone	0.186	1.281	99.59	520.6	603.27	0.9590	0.291
7 Brown	0.144	1.598	99.64	220.5	536.73	0.9588	0.288
8 Carroll	0.156	1.080	99.60	243.5	544.22	0.9815	0.824
9 Cass	0.398	1.766	98.43	805.8	636.70	0.9350	0.040
10 Clark	0.131	1.093	99.66	1247.7	671.82	0.9178	0.011
11 Clay	0.295	1.785	98.99	463.6	593.78	0.9589	0.289
12 Clinton	0.212	1.167	99.43	378.2	578.12	0.9838	0.895
13 Crawford	0.220	1.866	98.97	199.1	528.11	0.9691	0.466
14 Daviess	0.168	1.252	99.55	338.2	569.86	0.9742	0.598
15 Dearborn	0.278	1.628	99.59	448.7	591.31	0.9691	0.467
16 Decatur	0.367	1.669	99.35	377.6	577.48	0.8723	<0.01
17 Dekalb	0.203	1.373	99.47	503.3	600.75	0.9568	0.253
18 Delaware	0.120	1.234	99.38	1658.2	694.25	0.9623	0.348
19 Dubois	0.112	0.952	99.66	514.6	602.84	0.9644	0.385
20 Elkhart	0.438	1.580	99.50	2154.2	713.17	0.9575	0.265
21 Fayette	0.178	1.084	99.26	410.3	584.63	0.9255	0.018
22 Floyd	0.190	1.753	99.58	813.6	638.10	0.9633	0.367
23 Fountain	0.249	1.273	98.60	324.1	566.07	0.9868	0.947
24 Franklin	0.282	1.925	99.10	347.6	571.22	0.9466	0.092
25 Fulton	0.205	1.288	98.92	352.4	573.04	0.9425	0.070
26 Gibson	0.138	0.936	99.55	437.9	590.17	0.9609	0.325
27 Grant	0.177	1.363	98.94	1432.7	682.41	0.9772	0.691
28 Greene	0.231	1.828	99.24	508.2	601.18	0.9879	0.963
29 Hamilton	0.088	1.343	99.51	1831.7	702.25	0.9419	0.066
30 Hancock	0.130	1.181	99.61	738.9	630.89	0.9468	0.094
31 Harrison	0.075	1.059	99.69	398.1	583.29	0.9153	<0.01
32 Hendricks	0.125	1.171	99.79	957.2	651.13	0.9488	0.114
33 Henry	0.165	1.088	99.28	791.1	635.93	0.9658	0.409
34 Howard	0.138	1.094	99.31	1591.2	690.91	0.9715	0.516
35 Huntington	0.191	1.106	99.50	406.8	583.98	0.9744	0.603

Table F4, continued

County No. Name	D-W (d) [*]		Model Characteristics			Normality [**]	
	OLS	AUTOREG	R ²	\ MSE	AIC	W-Value	PROB<W
36 Jackson	0.248	1.402	99.65	482.2	597.06	0.9922	1.000
37 Jasper	0.207	1.879	98.90	585.1	612.22	0.9656	0.406
38 Jay	0.426	2.020	96.61	604.8	614.11	0.8910	<0.01
39 Jefferson	0.415	1.966	99.06	538.2	605.21	0.9616	0.337
40 Jennings	0.117	1.051	99.69	283.7	556.43	0.9394	0.052
41 Johnson	0.095	1.039	99.74	1059.3	659.21	0.9737	0.583
42 Knox	0.156	0.846	99.30	569.9	610.94	0.9511	0.153
43 Kosciusko	0.219	1.301	99.63	860.3	642.39	0.9241	0.017
44 Lagrange	0.139	1.355	99.51	342.5	570.95	0.9542	0.207
45 Lake	0.103	0.919	99.06	7580.1	813.01	0.9561	0.240
46 Laporte	0.251	1.823	99.42	1709.8	695.74	0.9524	0.177
47 Lawrence	0.241	1.165	99.64	519.4	602.76	0.9876	0.959
48 Madison	0.135	0.994	99.37	2078.9	711.61	0.9834	0.882
49 Marion	0.264	1.517	99.47	9466.5	829.23	0.9802	0.782
50 Marshall	0.179	1.372	99.53	550.5	607.63	0.9637	0.372
51 Martin	0.251	1.760	99.28	202.3	529.40	0.9401	0.056
52 Miami	0.370	1.464	99.03	694.7	625.19	0.9590	0.291
53 Monroe	0.321	2.113	99.54	1299.2	674.16	0.9902	0.990
54 Montgomery	0.222	1.292	99.52	436.5	589.44	0.9676	0.441
55 Morgan	0.182	1.671	99.66	794.9	636.40	0.9812	0.813
56 Newton	0.173	1.129	99.11	258.6	548.83	0.9795	0.760
57 Noble	0.535	1.891	99.17	629.4	617.00	0.9806	0.795
58 Ohio	0.177	1.655	99.36	77.1	454.54	0.9854	0.923
59 Orange	0.222	1.139	99.70	190.9	524.79	0.9801	0.780
60 Owen	0.249	1.835	99.40	345.7	571.15	0.9582	0.278
61 Parke	0.238	2.076	98.54	346.9	571.39	0.9413	0.063
62 Perry	0.297	1.709	98.88	424.9	587.02	0.9395	0.053
63 Pike	0.202	1.567	99.06	245.6	544.48	0.9715	0.517
64 Porter	0.104	0.684	99.65	1896.4	704.64	0.9441	0.079
65 Posey	0.114	0.868	99.52	421.3	587.23	0.9630	0.362
66 Pulaski	0.209	1.578	99.25	201.9	529.24	0.9836	0.889
67 Putnam	0.295	1.866	99.54	380.6	578.48	0.9589	0.290
68 Randolph	0.326	1.528	98.25	602.9	614.72	0.8547	<0.01
69 Ripley	0.324	2.313	99.41	371.9	576.56	0.9578	0.271
70 Rush	0.347	1.913	97.91	411.9	584.63	0.8764	<0.01

Table F4, continued

County No. Name	D-W (d) [*]		Model Characteristics			Normality [**]	
	OLS	AUTOREG	R ²	\ MSE	AIC	W-Value	PROB<W
71 St. Joseph	0.468	1.660	99.44	2679.7	730.15	0.9886	0.974
72 Scott	0.175	1.362	99.59	279.7	554.76	0.9739	0.589
73 Shelby	0.194	1.108	99.59	537.3	605.75	0.9844	0.907
74 Spencer	0.207	1.757	99.34	367.0	575.92	0.9201	0.013
75 Starke	0.194	1.551	99.32	339.5	569.78	0.9795	0.760
76 Steuben	0.249	1.884	98.84	586.0	612.30	0.8276	<0.01
77 Sullivan	0.310	1.653	98.84	355.7	573.26	0.9404	0.058
78 Switzerland	0.297	1.726	99.14	101.9	475.68	0.9700	0.483
79 Tippecanoe	0.197	1.214	99.76	1079.9	660.40	0.9661	0.415
80 Tipton	0.261	1.360	99.19	294.0	558.47	0.9778	0.708
81 Union	0.325	1.618	99.15	123.4	490.48	0.9486	0.110
82 Vanderburgh	0.204	1.434	99.40	2294.4	719.12	0.9566	0.250
83 Vermillion	0.208	1.430	99.22	250.2	545.87	0.9936	1.000
84 Vigo	0.146	1.158	99.49	1140.6	665.02	0.9606	0.319
85 Wabash	0.263	1.492	99.29	518.5	602.56	0.9686	0.458
86 Warren	0.363	1.772	98.38	196.4	526.58	0.9658	0.409
87 Warrick	0.068	0.965	99.68	645.8	620.95	0.9290	0.025
88 Washington	0.170	1.507	99.58	287.8	557.41	0.9506	0.146
89 Wayne	0.223	1.398	99.01	1092.6	660.98	0.9813	0.816
90 Wells	0.131	0.861	99.55	352.4	573.14	0.9734	0.575
91 White	0.186	1.077	99.51	348.7	572.17	0.9799	0.775
92 Whitley	0.158	1.379	99.53	390.9	581.01	0.9591	0.293
STATE	0.192	1.201	99.63	63553	978.04	0.9461	0.090

[*] i. [$\alpha=0.01$] OLS: (d_L, d_U)=(1.24, 1.34); AUTOREG: (d_L, d_U)=(1.19, 1.39)

ii. [$\alpha=0.05$] OLS: (d_L, d_U)=(1.43, 1.54); AUTOREG: (d_L, d_U)=(1.38, 1.60)

[**] Number of residuals = 39

Table F5: Parameter of Autoregression Model for Vehicle Registrations

County No. Name	Parameter Estimate			t-value [*]		
	Const.	Year	AR1	Const.	Year	AR1
1 Adams	-744337	387.62	-0.9329	-10.05	10.30	-17.95
2 Allen	-9441216	4879.86	-0.8637	-11.09	11.28	-9.55
3 Bartholomew	-2338426	1206.65	-0.9074	-14.91	15.15	-13.60
4 Benton	-186007	98.63	-0.9239	-3.01	3.14	-12.92
5 Blackford	-424032	220.58	-0.6823	-12.43	12.73	-5.18
6 Boone	-1240895	641.71	-0.9161	-13.36	13.61	-15.08
7 Brown	-545474	280.70	-0.9473	-10.71	10.85	-19.10
8 Carroll	-545635	284.26	-0.9339	-11.42	11.72	-18.09
9 Cass	-950196	496.28	-0.8320	-8.85	9.09	-7.63
10 Clark	-3087642	1590.91	-0.9428	-11.28	11.44	-18.49
11 Clay	-677403	352.32	-0.8640	-10.40	10.64	-10.39
12 Clinton	-751287	392.11	-0.8929	-12.34	12.68	-12.33
13 Crawford	-302985	156.79	-0.8981	-9.04	9.21	-12.40
14 Daviess	-703513	365.95	-0.9343	-10.19	10.44	-17.20
15 Dearborn	-1119860	579.23	-0.8750	-16.68	16.99	-10.81
16 Decatur	-761928	394.20	-0.8121	-17.71	18.04	-8.23
17 Dekalb	-1028573	533.78	-0.9261	-10.63	10.86	-15.73
18 Delaware	-2943407	1529.71	-0.9554	-5.74	5.86	-16.17
19 Dubois	-1302953	672.28	-0.9487	-11.46	11.64	-20.91
20 Elkhart	-4870840	2516.70	-0.7827	-22.38	22.76	-7.68
21 Fayette	-699004	363.05	-0.9092	-9.70	9.92	-13.79
22 Floyd	-1885282	974.19	-0.9163	-13.14	13.37	-15.46
23 Fountain	-384655	201.78	-0.8938	-6.69	6.90	-10.67
24 Franklin	-590108	305.33	-0.8511	-12.92	13.16	-9.95
25 Fulton	-423269	222.00	-0.9321	-6.22	6.42	-17.82
26 Gibson	-888260	461.79	-0.9443	-9.55	9.78	-20.01
27 Grant	-1951923	1014.92	-0.9303	-5.70	5.83	-12.83
28 Greene	-848351	440.65	-0.8962	-10.49	10.73	-13.21
29 Hamilton	-3967982	2039.70	-0.9655	-6.99	7.06	-21.24
30 Hancock	-1757857	905.69	-0.9387	-11.65	11.82	-18.70
31 Harrison	-1073732	553.71	-0.9684	-8.95	9.08	-24.24
32 Hendricks	-3231128	1661.33	-0.9419	-15.96	16.15	-18.98
33 Henry	-1339820	696.89	-0.9180	-9.05	9.27	-14.50
34 Howard	-2541022	1315.35	-0.9496	-6.04	6.15	-16.88
35 Huntington	-843817	440.27	-0.9126	-11.89	12.21	-14.74

Table F5, continued

County No. Name	Parameter Estimate			t-value [*]		
	Const.	Year	AR1	Const.	Year	AR1
36 Jackson	-1246589	644.61	-0.8936	-16.30	16.60	-12.77
37 Jasper	-791974	409.91	-0.9001	-8.35	8.51	-13.60
38 Jay	-479596	251.88	-0.7863	-7.59	7.85	-7.39
39 Jefferson	-831320	430.13	-0.8302	-12.95	13.19	-9.30
40 Jennings	-776283	400.45	-0.9503	-11.68	11.86	-20.03
41 Johnson	-3170493	1630.82	-0.9514	-12.99	13.15	-21.03
42 Knox	-873033	456.90	-0.9551	-5.01	5.16	-16.22
43 Kosciusko	-2178096	1124.92	-0.9102	-14.59	14.84	-14.29
44 Lagrange	-715954	370.26	-0.9421	-9.76	9.94	-18.65
45 Lake	-10961179	5688.15	-0.9645	-3.84	3.92	-16.67
46 Laporte	-2902492	1503.78	-0.8873	-10.12	10.32	-10.60
47 Lawrence	-1342928	694.91	-0.8802	-17.42	17.74	-11.77
48 Madison	-3686988	1913.32	-0.9422	-7.46	7.61	-15.98
49 Marion	-20181695	10466.0	-0.8864	-12.33	12.58	-9.96
50 Marshall	-1203659	624.18	-0.9165	-12.37	12.63	-15.41
51 Martin	-339700	175.86	-0.9031	-10.02	10.21	-13.48
52 Miami	-1053834	547.49	-0.8429	-11.30	11.55	-8.60
53 Monroe	-2949154	1519.77	-0.8649	-16.49	16.73	-10.95
54 Montgomery	-917211	477.57	-0.9076	-12.30	12.61	-14.03
55 Morgan	-2055788	1058.82	-0.9256	-13.73	13.92	-16.41
56 Newton	-364943	190.05	-0.9275	-7.19	7.37	-15.93
57 Noble	-1112325	576.34	-0.7282	-20.74	21.15	-6.52
58 Ohio	-144617	74.99	-0.9355	-8.58	8.75	-15.95
59 Orange	-535957	277.84	-0.8946	-17.56	17.92	-12.79
60 Owen	-555160	286.79	-0.8991	-8.93	9.07	-11.14
61 Parke	-392342	204.70	-0.8947	-6.75	6.94	-11.85
62 Perry	-587331	304.06	-0.8690	-9.35	9.53	-10.15
63 Pike	-368800	191.98	-0.8970	-9.26	9.50	-12.97
64 Porter	-4533899	2331.86	-0.9520	-10.87	11.00	-22.71
65 Posey	-843173	436.43	-0.9476	-9.39	9.57	-21.36
66 Pulaski	-335261	175.18	-0.9023	-10.05	10.34	-13.63
67 Putnam	-845258	437.71	-0.8787	-15.08	15.37	-11.68
68 Randolph	-529541	279.38	-0.9157	-4.99	5.18	-15.30
69 Ripley	-745074	385.87	-0.8605	-14.92	15.21	-10.83
70 Rush	-450685	235.33	-0.8759	-6.52	6.70	-9.03

Table F5, continued

County No. Name	Parameter Estimate			t-value [*]		
	Const.	Year	AR1	Const.	Year	AR1
71 St. Joseph	-5699940	2964.41	-0.7701	-21.51	22.03	-7.01
72 Scott	-664563	343.02	-0.9115	-13.84	14.07	-14.88
73 Shelby	-1226955	635.57	-0.9171	-12.61	12.86	-14.97
74 Spencer	-660711	341.54	-0.9089	-10.63	10.82	-14.55
75 Starke	-611637	317.22	-0.9014	-10.85	11.08	-13.33
76 Steuben	-847531	438.48	-0.8988	-8.42	8.58	-11.68
77 Sullivan	-510186	266.26	-0.8833	-7.94	8.15	-8.94
78 Switzerland	-161669	84.32	-0.8737	-11.15	11.46	-11.63
79 Tippecanoe	-3215587	1662.88	-0.9329	-14.98	15.25	-17.40
80 Tipton	-471442	245.67	-0.8929	-9.52	9.76	-11.41
81 Union	-200286	104.16	-0.8536	-12.37	12.66	-10.32
82 Vanderburgh	-4164783	2164.85	-0.9509	-7.88	8.06	-13.21
83 Vermillion	-422693	220.68	-0.8928	-10.49	10.78	-12.28
84 Vigo	-2265143	1181.79	-0.9530	-6.11	6.27	-14.51
85 Wabash	-935622	486.93	-0.8714	-12.31	12.61	-10.63
86 Warren	-228129	119.11	-0.8282	-9.43	9.69	-8.48
87 Warrick	-1680322	865.23	-0.9658	-9.73	9.86	-25.74
88 Washington	-640686	332.23	-0.9427	-10.27	10.48	-18.73
89 Wayne	-1564114	817.00	-0.9052	-7.60	7.81	-11.60
90 Wells	-749552	389.68	-0.9391	-10.54	10.79	-19.28
91 White	-696346	361.93	-0.9281	-10.19	10.43	-16.19
92 Whitley	-864279	448.04	-0.9226	-11.85	12.09	-15.80
STATE	-155807093	80712.4	-0.9169	-12.94	13.20	-13.93

[*] In most cases, parameters are significant at α -level of 0.0001

Table F6: 1989-2015 Vehicle Registration Forecasts by
AutoRegressive Procedure

County No. Name	Year								
	1989	1990	1991	1992	1993	1994	1995	1996	1997
1 Adams	26684	27068	27452	27837	28221	28606	28991	29376	29762
2 Allen	254786	261034	267095	272996	278757	284399	289936	295384	300755
3 Bartholomew	60612	61910	63200	64482	65757	67025	68288	69546	70799
4 Benton	9612	9753	9892	10027	10159	10289	10416	10542	10665
5 Blackford	14080	14496	14850	15162	15445	15708	15958	16198	16432
6 Boone	35805	36418	37033	37651	38271	38893	39516	40141	40767
7 Brown	13136	13401	13667	13934	14201	14469	14738	15007	15277
8 Carroll	19678	19968	20258	20547	20836	21124	21412	21700	21988
9 Cass	35220	36000	36732	37425	38085	38717	39327	39917	40492
10 Clark	75177	76853	78525	80192	81855	83513	85168	86819	88467
11 Clay	22825	23251	23667	24075	24475	24868	25256	25639	26018
12 Clinton	28196	28632	29064	29492	29915	30336	30753	31167	31580
13 Crawford	9144	9273	9406	9541	9678	9817	9958	10101	10245
14 Daviess	24009	24398	24786	25172	25557	25941	26324	26705	27086
15 Dearborn	32827	33331	33844	34365	34894	35429	35969	36515	37064
16 Decatur	21686	22166	22629	23080	23520	23952	24376	24795	25209
17 Dekalb	33660	34154	34651	35150	35652	36156	36662	37171	37681
18 Delaware	95612	97301	98982	100657	102325	103987	105643	107294	108939
19 Dubois	34649	35299	35950	36603	37256	37910	38565	39222	39878
20 Elkhart	133366	136212	138987	141705	144380	147020	149634	152226	154802
21 Fayette	22657	23061	23461	23857	24250	24641	25029	25415	25799
22 Floyd	52443	53412	54381	55351	56322	57292	58263	59235	60206
23 Fountain	16046	16315	16577	16832	17082	17327	17567	17803	18035
24 Franklin	17522	17778	18040	18309	18584	18863	19146	19432	19721
25 Fulton	18293	18516	18738	18960	19182	19404	19627	19849	20071
26 Gibson	29938	30417	30894	31370	31846	32321	32795	33268	33741
27 Grant	63700	64928	66142	67342	68529	69703	70867	72021	73164
28 Greene	27879	28343	28804	29263	29720	30175	30629	31082	31533
29 Hamilton	92389	94312	96238	98169	100103	102041	103982	105927	107875
30 Hancock	44023	44900	45780	46660	47543	48427	49312	50198	51086

Table F6, continued

County No. Name	Year								
	1989	1990	1991	1992	1993	1994	1995	1996	1997
31 Harrison	28260	28793	29327	29861	30396	30932	31468	32004	32542
32 Hendricks	74067	75681	77297	78916	80538	82162	83788	85416	87046
33 Henry	45321	46098	46868	47632	48391	49145	49894	50639	51379
34 Howard	72201	73669	75128	76581	78026	79465	80898	82325	83746
35 Huntington	31639	32101	32560	33018	33474	33929	34383	34835	35287
36 Jackson	35182	35865	36544	37219	37891	38560	39226	39890	40552
37 Jasper	23130	23560	23988	24414	24839	25262	25684	26104	26524
38 Jay	20613	21031	21414	21769	22102	22418	22720	23011	23294
39 Jefferson	23907	24390	24864	25330	25790	26245	26696	27143	27587
40 Jennings	20575	20958	21341	21726	22111	22497	22883	23271	23659
41 Johnson	74346	75922	77500	79081	80665	82250	83838	85428	87020
42 Knox	34527	35038	35547	36053	36558	37060	37560	38058	38554
43 Kosciusko	60037	61102	62173	63248	64328	65412	66500	67590	68684
44 Lagrange	20856	21206	21556	21908	22261	22615	22970	23326	23682
45 Lake	335420	341716	347991	354244	360478	366693	372888	379066	385226
46 Laporte	85393	87250	89067	90849	92600	94322	96020	97696	99353
47 Lawrence	38855	39596	40331	41062	41789	42511	43231	43947	44661
48 Madison	114919	117045	119159	121261	123352	125433	127504	129566	131620
49 Marion	615790	628459	640879	653076	665077	676903	688574	700108	711521
50 Marshall	37964	38576	39190	39804	40419	41035	41652	42269	42887
51 Martin	9911	10104	10295	10485	10673	10861	11047	11232	11416
52 Miami	33887	34628	35339	36024	36688	37333	37963	38580	39186
53 Monroe	72946	74564	76168	77761	79344	80919	82486	84046	85602
54 Montgomery	32347	32855	33361	33863	34364	34862	35358	35853	36346
55 Morgan	50716	51737	52761	53788	54818	55849	56883	57918	58955
56 Newton	12768	12979	13188	13396	13603	13808	14013	14216	14419
57 Noble	34240	34753	35284	35827	36380	36938	37502	38069	38639
58 Ohio	4656	4723	4791	4859	4928	4997	5066	5136	5206
59 Orange	16517	16811	17104	17395	17684	17973	18260	18546	18831
60 Owen	15914	16135	16363	16596	16835	17079	17327	17579	17834
61 Parke	14288	14546	14799	15047	15290	15529	15765	15997	16226
62 Perry	16781	17170	17549	17917	18278	18631	18977	19318	19654

Table F6, continued

County No. Name	Year								
	1989	1990	1991	1992	1993	1994	1995	1996	1997
63 Pike	12852	13065	13276	13485	13692	13898	14102	14305	14507
64 Porter	104656	106965	109275	111586	113898	116211	118525	120840	123156
65 Posey	24859	25297	25734	26172	26610	27047	27485	27922	28359
66 Pulaski	13047	13235	13421	13607	13791	13975	14157	14339	14520
67 Putnam	25065	25536	26004	26467	26928	27386	27841	28294	28746
68 Randolph	25963	26258	26551	26844	27135	27426	27715	28004	28292
69 Ripley	22508	22882	23258	23635	24014	24393	24774	25155	25537
70 Rush	16481	16829	17163	17484	17795	18097	18390	18676	18956
71 St. Joseph	192908	196648	200209	203634	206953	210190	213364	216490	219579
72 Scott	17701	18044	18388	18731	19074	19418	19761	20104	20448
73 Shelby	36729	37402	38073	38741	39406	40069	40730	41388	42045
74 Spencer	18657	18994	19331	19668	20006	20344	20682	21021	21360
75 Starke	19026	19372	19715	20055	20394	20730	21064	21396	21728
76 Steuben	25563	25904	26254	26614	26981	27356	27737	28124	28517
77 Sullivan	18569	18932	19284	19626	19959	20284	20602	20915	21221
78 Switzerland	6043	6128	6213	6298	6382	6467	6552	6636	6721
79 Tippecanoe	91012	92734	94452	96166	97877	99584	101289	102990	104690
80 Tipton	16711	17008	17299	17586	17868	18146	18421	18692	18961
81 Union	6806	6921	7035	7147	7258	7368	7477	7585	7693
82 Vanderburgh	136462	138947	141411	143854	146277	148683	151073	153446	155806
83 Vermillion	15959	16210	16457	16702	16943	17183	17421	17657	17891
84 Vigo	82817	84122	85421	86714	88003	89286	90565	91839	93108
85 Wabash	32196	32770	33332	33885	34430	34967	35498	36023	36543
86 Warren	8491	8660	8821	8974	9122	9264	9403	9538	9671
87 Warrick	41460	42296	43134	43973	44812	45653	46494	47336	48179
88 Washington	20418	20732	21048	21364	21682	22000	22319	22639	22959
89 Wayne	58824	59837	60832	61809	62772	63720	64657	65582	66496
90 Wells	25521	25910	26299	26689	27078	27467	27856	28246	28635
91 White	23161	23549	23935	24320	24703	25084	25464	25843	26220
92 Whitley	27196	27619	28044	28471	28900	29330	29761	30194	30628
STATE	4639362	4727592	4815197	4902229	4988736	5074761	5160344	5245522	5330329

Table F6, continued

County No. Name	1998	1999	2000	2001	Year 2002	2003	2004	2005	2006
1 Adams	30147	30533	30919	31305	31691	32077	32463	32850	33236
2 Allen	306058	311304	316500	321653	326769	331852	336908	341940	346951
3 Bartholomew	72048	73293	74534	75772	77008	78240	79470	80698	81924
4 Benton	10786	10906	11024	11141	11256	11370	11482	11594	11705
5 Blackford	16662	16889	17114	17337	17560	17782	18003	18224	18445
6 Boone	41395	42023	42653	43284	43916	44548	45182	45816	46450
7 Brown	15548	15819	16091	16363	16635	16908	17182	17455	17730
8 Carroll	22275	22563	22850	23137	23423	23710	23996	24283	24569
9 Cass	41053	41604	42145	42679	43207	43729	44247	44761	45272
10 Clark	90111	91753	93391	95027	96660	98291	99919	101545	103170
11 Clay	26393	26765	27135	27502	27867	28230	28592	28953	29312
12 Clinton	31990	32398	32804	33209	33613	34015	34416	34816	35216
13 Crawford	10390	10537	10684	10833	10982	11132	11283	11434	11586
14 Daviess	27465	27844	28222	28599	28975	29351	29726	30100	30474
15 Dearborn	37617	38174	38733	39295	39859	40425	40993	41562	42132
16 Decatur	25619	26027	26432	26835	27236	27636	28035	28433	28830
17 Dekalb	38193	38707	39222	39738	40256	40775	41295	41816	42338
18 Delaware	110579	112214	113845	115471	117092	118710	120324	121934	123540
19 Dubois	40536	41195	41854	42514	43174	43835	44497	45159	45822
20 Elkhart	157365	159919	162464	165003	167537	170067	172594	175120	177643
21 Fayette	26180	26561	26939	27316	27692	28067	28441	28813	29185
22 Floyd	61178	62150	63122	64094	65066	66039	67012	67984	68957
23 Fountain	18264	18491	18714	18936	19155	19372	19588	19802	20015
24 Franklin	20013	20306	20602	20898	21196	21496	21796	22097	22398
25 Fulton	20293	20515	20737	20959	21181	21404	21626	21848	22070
26 Gibson	34213	34685	35156	35627	36097	36566	37036	37504	37973
27 Grant	74299	75425	76544	77655	78760	79858	80951	82038	83120
28 Greene	31983	32432	32880	33328	33775	34221	34666	35112	35556
29 Hamilton	109827	111781	113738	115698	117661	119626	121594	123565	125538
30 Hancock	51975	52864	53755	54647	55539	56433	57327	58221	59117

Table F6, continued

County No. Name	Year								
	1998	1999	2000	2001	2002	2003	2004	2005	2006
31 Harrison	33079	33618	34156	34695	35235	35775	36316	36856	37398
32 Hendricks	88678	90312	91947	93584	95222	96861	98502	100144	101787
33 Henry	52117	52850	53581	54309	55035	55758	56479	57198	57915
34 Howard	85162	86573	87979	89380	90777	92170	93559	94944	96326
35 Huntington	35737	36187	36635	37083	37531	37977	38424	38869	39314
36 Jackson	41212	41871	42528	43183	43838	44491	45144	45795	46446
37 Jasper	26942	27360	27777	28193	28609	29024	29438	29852	30266
38 Jay	23570	23841	24108	24372	24633	24892	25150	25406	25662
39 Jefferson	28029	28469	28908	29344	29780	30215	30649	31082	31515
40 Jennings	24048	24437	24827	25217	25608	25999	26391	26783	27176
41 Johnson	88614	90210	91807	93406	95007	96609	98212	99817	101423
42 Knox	39049	39542	40033	40523	41011	41498	41983	42467	42950
43 Kosciusko	69781	70881	71982	73086	74191	75299	76408	77518	78630
44 Lagrange	24039	24398	24756	25116	25476	25837	26198	26560	26922
45 Lake	391370	397497	403609	409706	415788	421856	427911	433953	439982
46 Laporte	100993	102617	104227	105826	107414	108992	110562	112125	113680
47 Lawrence	45373	46082	46790	47496	48201	48905	49607	50309	51010
48 Madison	133665	135703	137734	139758	141775	143787	145792	147793	149788
49 Marion	722827	734037	745162	756212	767196	778121	788994	799821	810606
50 Marshall	43506	44125	44744	45364	45984	46604	47225	47846	48467
51 Martin	11600	11782	11964	12146	12327	12507	12687	12867	13046
52 Miami	39783	40372	40954	41532	42104	42672	43238	43800	44360
53 Monroe	87152	88698	90241	91781	93317	94852	96385	97916	99445
54 Montgomery	36838	37328	37817	38305	38792	39278	39764	40248	40733
55 Morgan	59994	61034	62076	63119	64163	65208	66254	67301	68349
56 Newton	14620	14821	15021	15220	15418	15616	15814	16011	16207
57 Noble	39210	39783	40356	40931	41506	42081	42657	43233	43808
58 Ohio	5277	5348	5419	5490	5561	5633	5705	5777	5850
59 Orange	19116	19400	19683	19966	20248	20530	20811	21092	21372
60 Owen	18093	18354	18618	18885	19153	19423	19695	19969	20243
61 Parke	16453	16678	16900	17121	17339	17557	17773	17988	18201
62 Perry	19986	20314	20639	20962	21282	21599	21915	22230	22543

Table F6, continued

County No. Name	Year								
	1998	1999	2000	2001	2002	2003	2004	2005	2006
63 Pike	14707	14907	15107	15305	15503	15700	15896	16092	16288
64 Porter	125472	127789	130107	132426	134745	137065	139385	141706	144028
65 Posey	28797	29234	29671	30108	30546	30983	31420	31857	32294
66 Pulaski	14701	14881	15061	15240	15419	15597	15776	15953	16131
67 Putnam	29195	29644	30090	30536	30981	31425	31868	32311	32753
68 Randolph	28579	28866	29152	29437	29722	30006	30290	30574	30857
69 Ripley	25919	26302	26686	27069	27453	27838	28222	28607	28991
70 Rush	19230	19500	19765	20027	20285	20540	20793	21044	21293
71 St. Joseph	222640	225678	228699	231708	234706	237696	240681	243660	246637
72 Scott	20791	21134	21477	21821	22164	22507	22850	23193	23536
73 Shelby	42699	43353	44004	44655	45304	45952	46599	47245	47890
74 Spencer	21699	22039	22378	22718	23058	23398	23738	24079	24419
75 Starke	22057	22386	22713	23039	23365	23689	24013	24337	24659
76 Steuben	28913	29315	29719	30128	30539	30953	31370	31788	32209
77 Sullivan	21524	21822	22116	22407	22695	22980	23264	23545	23825
78 Switzerland	6805	6890	6974	7059	7143	7228	7312	7396	7481
79 Tippecanoe	106386	108081	109773	111463	113152	114838	116524	118207	119890
80 Tipton	19228	19492	19754	20014	20273	20531	20787	21042	21296
81 Union	7800	7907	8013	8119	8225	8331	8436	8541	8646
82 Vanderburgh	158151	160485	162806	165117	167418	169710	171992	174267	176534
83 Vermillion	18123	18355	18585	18814	19043	19270	19497	19723	19949
84 Vigo	94374	95635	96893	98147	99398	100646	101890	103132	104371
85 Wabash	37059	37571	38080	38586	39089	39591	40090	40588	41085
86 Warren	9801	9929	10056	10181	10305	10429	10551	10674	10795
87 Warrick	49022	49867	50712	51558	52404	53251	54099	54947	55796
88 Washington	23281	23602	23925	24248	24571	24895	25220	25545	25870
89 Wayne	67402	68299	69188	70071	70947	71818	72683	73544	74401
90 Wells	29024	29414	29803	30192	30582	30971	31361	31750	32140
91 White	26596	26972	27346	27719	28092	28464	28835	29205	29575
92 Whitley	31063	31499	31936	32373	32812	33251	33691	34132	34573
STATE	5414795	5498950	5582818	5666424	5749789	5832933	5915876	5998633	6081220

Table F6, continued

County No. Name	Year								
	2007	2008	2009	2010	2011	2012	2013	2014	2015
1 Adams	33622	34009	34396	34782	35169	35556	35943	36330	36717
2 Allen	351944	356922	361887	366840	371782	376717	381644	386564	391479
3 Bartholomew	83149	84371	85592	86812	88031	89248	90464	91680	92895
4 Benton	11815	11924	12032	12139	12246	12352	12458	12563	12667
5 Blackford	18666	18887	19108	19328	19549	19770	19990	20211	20431
6 Boone	47086	47722	48358	48995	49632	50269	50907	51546	52184
7 Brown	18004	18279	18554	18829	19105	19381	19657	19934	20210
8 Carroll	24855	25141	25426	25712	25998	26283	26569	26854	27139
9 Cass	45781	46288	46793	47296	47798	48300	48800	49300	49799
10 Clark	104792	106413	108032	109649	111265	112879	114492	116104	117714
11 Clay	29671	30028	30385	30742	31097	31453	31808	32162	32516
12 Clinton	35614	36012	36409	36806	37202	37598	37993	38388	38783
13 Crawford	11739	11892	12045	12199	12353	12507	12661	12816	12971
14 Daviess	30847	31220	31592	31964	32336	32707	33078	33449	33819
15 Dearborn	42703	43276	43849	44423	44998	45573	46149	46725	47301
16 Decatur	29227	29623	30019	30414	30809	31205	31599	31994	32389
17 Dekalb	42861	43385	43909	44434	44960	45486	46013	46541	47069
18 Delaware	125143	126742	128339	129932	131523	133111	134697	136279	137860
19 Dubois	46485	47149	47813	48478	49142	49808	50473	51139	51806
20 Elkhart	180165	182685	185205	187724	190243	192761	195279	197797	200314
21 Fayette	29556	29927	30296	30665	31034	31402	31770	32137	32503
22 Floyd	69930	70904	71877	72850	73824	74797	75771	76744	77718
23 Fountain	20227	20438	20647	20856	21064	21272	21479	21685	21891
24 Franklin	22700	23003	23306	23609	23913	24217	24521	24825	25129
25 Fulton	22292	22514	22736	22958	23180	23402	23624	23846	24068
26 Gibson	38441	38908	39376	39843	40309	40776	41242	41708	42174
27 Grant	84198	85271	86340	87405	88467	89525	90581	91633	92683
28 Greene	36000	36444	36888	37331	37774	38216	38659	39101	39543
29 Hamilton	127513	129490	131470	133451	135435	137420	139408	141397	143388
30 Hancock	60013	60910	61807	62705	63603	64502	65401	66300	67200

Table F6, continued

County No. Name	Year								
	2007	2008	2009	2010	2011	2012	2013	2014	2015
31 Harrison	37939	38482	39024	39567	40110	40653	41197	41741	42286
32 Hendricks	103431	105076	106722	108369	110017	111666	113315	114965	116616
33 Henry	58631	59345	60058	60769	61479	62188	62896	63603	64310
34 Howard	97705	99080	100452	101822	103188	104552	105914	107273	108630
35 Huntington	39759	40203	40647	41091	41534	41977	42420	42863	43305
36 Jackson	47097	47746	48395	49044	49692	50340	50987	51635	52282
37 Jasper	30679	31092	31505	31917	32329	32741	33153	33564	33976
38 Jay	25917	26171	26424	26678	26930	27183	27436	27688	27940
39 Jefferson	31948	32380	32811	33243	33674	34105	34536	34966	35397
40 Jennings	27569	27962	28356	28750	29144	29539	29934	30329	30724
41 Johnson	103030	104639	106248	107859	109470	111082	112696	114310	115925
42 Knox	43432	43913	44392	44871	45348	45825	46301	46776	47250
43 Kosciusko	79742	80856	81971	83087	84204	85321	86439	87558	88677
44 Lagrange	27285	27648	28011	28375	28740	29104	29469	29835	30200
45 Lake	445999	452004	457998	463982	469954	475917	481870	487813	493748
46 Laporte	115230	116775	118315	119852	121384	122913	124439	125963	127485
47 Lawrence	51710	52410	53109	53807	54505	55203	55900	56598	57294
48 Madison	151779	153765	155747	157725	159700	161670	163638	165602	167563
49 Marion	821356	832073	842761	853425	864065	874686	885290	895877	906451
50 Marshall	49089	49711	50333	50955	51577	52199	52822	53445	54068
51 Martin	13225	13403	13582	13760	13938	14115	14293	14470	14647
52 Miami	44918	45475	46030	46583	47136	47688	48240	48790	49341
53 Monroe	100973	102500	104026	105551	107075	108599	110123	111645	113168
54 Montgomery	41216	41699	42181	42663	43145	43626	44107	44587	45068
55 Morgan	69398	70447	71498	72549	73600	74652	75705	76758	77811
56 Newton	16403	16598	16793	16988	17182	17376	17570	17764	17957
57 Noble	44385	44961	45537	46113	46689	47266	47842	48418	48995
58 Ohio	5922	5995	6068	6141	6214	6287	6360	6434	6507
59 Orange	21653	21933	22213	22492	22772	23051	23330	23609	23888
60 Owen	20519	20796	21074	21353	21633	21914	22195	22476	22758
61 Parke	18414	18626	18837	19048	19258	19467	19676	19884	20092
62 Perry	22855	23166	23476	23785	24094	24402	24709	25016	25323

Table F6, continued

County No. Name	Year								
	2007	2008	2009	2010	2011	2012	2013	2014	2015
63 Pike	16483	16678	16873	17068	17262	17456	17649	17843	18036
64 Porter	146350	148672	150995	153318	155642	157966	160291	162615	164941
65 Posey	32731	33168	33605	34041	34478	34915	35352	35789	36226
66 Pulaski	16308	16486	16663	16839	17016	17192	17369	17545	17721
67 Putnam	33194	33635	34076	34516	34956	35396	35835	36274	36713
68 Randolph	31140	31422	31705	31987	32269	32550	32832	33113	33394
69 Ripley	29376	29762	30147	30532	30917	31303	31688	32074	32460
70 Rush	21540	21786	22030	22273	22516	22757	22998	23238	23477
71 St. Joseph	249610	252582	255552	258520	261488	264455	267421	270387	273352
72 Scott	23879	24223	24566	24909	25252	25595	25938	26281	26624
73 Shelby	48535	49178	49821	50464	51105	51747	52387	53028	53668
74 Spencer	24759	25100	25441	25782	26123	26463	26804	27145	27487
75 Starke	24981	25303	25624	25945	26266	26586	26906	27225	27544
76 Steuben	32632	33056	33482	33908	34337	34766	35196	35627	36058
77 Sullivan	24103	24379	24655	24929	25202	25475	25747	26018	26289
78 Switzerland	7565	7650	7734	7818	7903	7987	8071	8156	8240
79 Tippecanoe	121571	123250	124929	126606	128283	129959	131634	133308	134981
80 Tipton	21549	21801	22053	22304	22554	22804	23054	23303	23551
81 Union	8751	8856	8961	9065	9170	9274	9379	9483	9587
82 Vanderburgh	178794	181047	183294	185536	187772	190003	192230	194453	196671
83 Vermillion	20174	20398	20623	20846	21070	21293	21516	21738	21961
84 Vigo	105607	106840	108071	109300	110527	111751	112974	114194	115413
85 Wabash	41580	42074	42567	43060	43552	44043	44533	45024	45513
86 Warren	10916	11037	11158	11278	11398	11518	11638	11757	11877
87 Warrick	56645	57495	58346	59197	60048	60900	61753	62605	63459
88 Washington	26196	26522	26848	27175	27502	27830	28157	28485	28813
89 Wayne	75254	76104	76950	77794	78635	79474	80311	81146	81979
90 Wells	32529	32919	33308	33698	34087	34477	34866	35256	35645
91 White	29944	30313	30681	31049	31417	31784	32150	32517	32883
92 Whitley	35015	35457	35900	36343	36786	37230	37674	38119	38563
STATE	6163651	6245939	6328097	6410134	6492061	6573887	6655620	6737269	6818839

Table F7: 1989-2015 Vehicle Registration Forecasts (Combined)

County No. Name	Year								
	1989	1990	1991	1992	1993	1994	1995	1996	1997
1 Adams	26691	27072	27447	27820	28192	28563	28935	29306	29677
2 Allen	249683	264067	267057	276032	273892	280945	282979	294011	297430
3 Bartholomew	60622	61890	63139	64377	65609	66837	68062	69285	70505
4 Benton	9462	9474	9478	9566	9609	9660	9706	9791	9854
5 Blackford	13932	14237	14511	14763	15002	15230	15452	15669	15882
6 Boone	35886	36530	37159	37782	38405	39028	39652	40276	40901
7 Brown	13142	13412	13683	13954	14226	14497	14770	15042	15315
8 Carroll	19731	20041	20335	20622	20905	21187	21467	21748	22028
9 Cass	35027	35643	36236	36809	37365	37907	38438	38960	39473
10 Clark	75080	76678	78281	79885	81488	83088	84688	86286	87882
11 Clay	22769	23146	23517	23884	24247	24607	24964	25319	25672
12 Clinton	28360	28774	29186	29596	30003	30409	30814	31217	31619
13 Crawford	9157	9299	9442	9586	9732	9878	10026	10174	10323
14 Daviess	23979	24345	24713	25080	25447	25813	26179	26544	26909
15 Dearborn	32954	33454	33972	34534	35096	35647	36203	36766	37330
16 Decatur	21631	22066	22493	22913	23329	23739	24147	24551	24954
17 Dekalb	33741	34266	34778	35286	35794	36302	36810	37320	37831
18 Delaware	95427	96986	98560	100137	101712	103286	104857	106425	107990
19 Dubois	34652	35304	35957	36610	37264	37918	38573	39228	39884
20 Elkhart	133602	136875	139188	141440	143891	146622	149287	151786	154200
21 Fayette	22749	23132	23512	23891	24269	24645	25020	25394	25766
22 Floyd	52428	53382	54336	55291	56246	57201	58156	59111	60066
23 Fountain	16046	16275	16501	16723	16942	17159	17373	17586	17797
24 Franklin	17551	17831	18114	18401	18690	18981	19275	19570	19867
25 Fulton	18395	18604	18812	19021	19229	19438	19646	19855	20063
26 Gibson	29816	30215	30638	31072	31512	31955	32400	32846	33291
27 Grant	63771	64877	65976	67068	68154	69233	70307	71376	72440
28 Greene	27854	28293	28731	29168	29604	30039	30473	30907	31340
29 Hamilton	92727	94947	97134	99294	101430	103544	105640	107721	109788
30 Hancock	44140	45065	45966	46858	47747	48636	49525	50414	51303

Table F7, continued

County No.	Name	Year								
		1989	1990	1991	1992	1993	1994	1995	1996	1997
31	Harrison	28443	28987	29531	30076	30621	31167	31712	32258	32804
32	Hendricks	74278	75984	77648	79297	80941	82584	84227	85871	87515
33	Henry	45462	46193	46921	47646	48368	49087	49804	50519	51232
34	Howard	72446	73820	75191	76558	77921	79282	80639	81993	83344
35	Huntington	31733	32176	32617	33058	33498	33938	34376	34814	35252
36	Jackson	35148	35798	36446	37093	37737	38381	39023	39664	40304
37	Jasper	23107	23514	23920	24325	24730	25133	25536	25938	26340
38	Jay	20495	20818	21123	21415	21695	21967	22232	22491	22747
39	Jefferson	23856	24293	24725	25153	25579	26001	26422	26841	27259
40	Jennings	20686	21078	21470	21863	22257	22650	23044	23439	23833
41	Johnson	74422	76048	77664	79276	80888	82499	84112	85725	87339
42	Knox	34383	34798	35236	35687	36144	36604	37065	37527	37988
43	Kosciusko	60419	61594	62574	63577	64679	65822	66943	68038	69130
44	Lagrange	20907	21277	21636	21994	22351	22708	23065	23423	23782
45	Lake	335391	341550	347635	353677	359693	365689	371671	377642	383603
46	Laporte	85159	86804	88429	90037	91629	93207	94772	96327	97872
47	Lawrence	39022	39735	40446	41154	41859	42563	43266	43966	44666
48	Madison	115450	117458	119460	121457	123447	125433	127414	129390	131362
49	Marion	614385	625790	637071	648240	659312	670295	681202	692040	702817
50	Marshall	38092	38703	39315	39927	40539	41152	41765	42378	42992
51	Martin	9895	10074	10252	10428	10605	10780	10955	11130	11304
52	Miami	33945	34598	35155	35752	36364	36950	37520	38089	38655
53	Monroe	72849	74377	75897	77413	78923	80430	81932	83431	84928
54	Montgomery	32357	32851	33334	33812	34289	34765	35239	35712	36185
55	Morgan	50721	51747	52774	53802	54831	55862	56893	57926	58959
56	Newton	12748	13023	13218	13413	13608	13801	13994	14187	14379
57	Noble	34273	34809	35353	35904	36459	37017	37578	38141	38704
58	Ohio	4659	4729	4800	4871	4942	5013	5084	5156	5228
59	Orange	16504	16786	17067	17346	17625	17904	18182	18459	18736
60	Owen	15950	16203	16460	16719	16981	17246	17512	17781	18051
61	Parke	14148	14380	14563	14782	14982	15194	15399	15607	15811
62	Perry	16719	17054	17384	17708	18028	18345	18658	18969	19277

Table F7, continued

County No. Name	Year								
	1989	1990	1991	1992	1993	1994	1995	1996	1997
63 Pike	12835	13032	13229	13424	13619	13813	14006	14198	14390
64 Porter	105307	108040	110626	113116	115543	117930	120290	122633	124966
65 Posey	24813	25222	25640	26063	26489	26916	27343	27771	28200
66 Pulaski	13035	13212	13388	13564	13739	13913	14087	14261	14434
67 Putnam	25034	25477	25917	26356	26793	27229	27664	28097	28530
68 Randolph	25928	26173	26408	26637	26862	27085	27307	27527	27746
69 Ripley	22504	22875	23246	23618	23990	24363	24737	25111	25485
70 Rush	16417	16708	16993	17271	17544	17813	18077	18338	18595
71 St. Joseph	192334	195616	198808	201933	205004	208035	211033	214008	216965
72 Scott	17768	18108	18447	18787	19126	19466	19805	20145	20485
73 Shelby	36765	37436	38088	38733	39373	40011	40647	41282	41916
74 Spencer	18652	18983	19314	19646	19977	20309	20641	20973	21305
75 Starke	19003	19328	19651	19973	20294	20614	20932	21250	21568
76 Steuben	25613	25998	26389	26783	27182	27584	27990	28398	28809
77 Sullivan	18511	18822	19128	19429	19725	20017	20306	20592	20875
78 Switzerland	6040	6122	6203	6285	6367	6449	6530	6612	6694
79 Tippecanoe	91053	92751	94419	96074	97723	99367	101010	102650	104290
80 Tipton	16710	16974	17235	17493	17750	18004	18257	18508	18758
81 Union	6796	6902	7007	7111	7215	7319	7422	7524	7626
82 Vanderburgh	135536	139081	139910	141470	142313	145347	147367	149721	150716
83 Vermillion	15938	16169	16398	16626	16853	17078	17303	17526	17749
84 Vigo	82854	84096	85334	86570	87804	89034	90263	91489	92712
85 Wabash	32134	32653	33166	33675	34179	34679	35177	35671	36163
86 Warren	8456	8595	8730	8861	8989	9114	9238	9360	9481
87 Warrick	41556	42445	43313	44171	45024	45874	46724	47573	48422
88 Washington	20448	20773	21091	21406	21721	22036	22351	22666	22982
89 Wayne	58828	59728	60619	61500	62375	63242	64103	64959	65809
90 Wells	25660	26046	26433	26819	27206	27593	27979	28366	28752
91 White	23222	23625	24008	24379	24746	25110	25472	25833	26193
92 Whitley	27241	27682	28117	28550	28984	29419	29854	30289	30726
STATE	4649283	4732759	4815923	4898800	4981415	5063789	5145941	5227891	5309656

Table F7, continued

County No. Name	Year								
	1998	1999	2000	2001	2002	2003	2004	2005	2006
1 Adams	30048	30419	30791	31162	31534	31905	32277	32648	33020
2 Allen	304881	304900	311096	313942	322829	326623	333129	334661	340339
3 Bartholomew	71723	72938	74153	75365	76576	77786	78994	80202	81408
4 Benton	9921	9985	10067	10138	10211	10283	10362	10436	10511
5 Blackford	16094	16304	16514	16722	16930	17138	17345	17553	17760
6 Boone	41527	42153	42780	43407	44035	44663	45292	45921	46550
7 Brown	15588	15861	16135	16409	16683	16957	17232	17506	17781
8 Carroll	22307	22587	22866	23146	23425	23704	23983	24262	24541
9 Cass	39980	40482	40979	41472	41962	42449	42934	43418	43900
10 Clark	89476	91069	92660	94251	95839	97427	99013	100598	102183
11 Clay	26023	26372	26720	27067	27413	27757	28102	28445	28788
12 Clinton	32020	32420	32819	33217	33615	34012	34408	34804	35199
13 Crawford	10472	10622	10773	10924	11076	11227	11380	11532	11685
14 Daviess	27273	27637	28000	28363	28726	29088	29450	29812	30173
15 Dearborn	37895	38461	39030	39599	40169	40741	41313	41886	42460
16 Decatur	25354	25753	26150	26547	26943	27338	27732	28126	28520
17 Dekalb	38343	38855	39368	39882	40397	40912	41428	41944	42460
18 Delaware	109553	111113	112672	114228	115781	117333	118883	120431	121977
19 Dubois	40540	41196	41853	42510	43167	43825	44483	45141	45799
20 Elkhart	156669	159203	161740	164234	166702	169177	171670	174167	176654
21 Fayette	26138	26509	26879	27248	27617	27985	28353	28720	29087
22 Floyd	61021	61977	62933	63888	64844	65800	66756	67712	68668
23 Fountain	18006	18213	18419	18624	18828	19032	19234	19435	19636
24 Franklin	20164	20463	20763	21063	21364	21666	21968	22271	22573
25 Fulton	20272	20480	20688	20897	21105	21314	21522	21731	21939
26 Gibson	33737	34183	34628	35073	35518	35962	36407	36851	37295
27 Grant	73500	74555	75606	76654	77699	78740	79778	80814	81847
28 Greene	31772	32204	32636	33067	33498	33929	34359	34789	35219
29 Hamilton	111843	113887	115923	117951	119973	121988	124000	126007	128011
30 Hancock	52193	53084	53975	54867	55759	56651	57544	58437	59331

Table F7, continued

County No. Name	Year								
	1998	1999	2000	2001	2002	2003	2004	2005	2006
31 Harrison	33351	33898	34445	34992	35539	36087	36635	37183	37731
32 Hendricks	89161	90807	92454	94102	95751	97400	99050	100700	102351
33 Henry	51943	52652	53360	54067	54772	55476	56179	56881	57583
34 Howard	84693	86039	87383	88725	90064	91401	92736	94070	95402
35 Huntington	35689	36126	36562	36998	37434	37869	38304	38739	39173
36 Jackson	40943	41581	42218	42855	43491	44127	44762	45397	46031
37 Jasper	26741	27142	27543	27943	28343	28742	29142	29541	29940
38 Jay	22999	23248	23496	23741	23986	24230	24472	24714	24956
39 Jefferson	27675	28090	28505	28918	29332	29744	30157	30569	30980
40 Jennings	24228	24624	25019	25415	25811	26208	26604	27001	27398
41 Johnson	88954	90570	92187	93804	95423	97042	98661	100282	101903
42 Knox	38449	38909	39368	39827	40285	40742	41199	41655	42110
43 Kosciusko	70234	71346	72458	73568	74677	75789	76902	78015	79129
44 Lagrange	24140	24500	24859	25219	25579	25939	26300	26661	27022
45 Lake	389555	395498	401433	407361	413282	419195	425102	431002	436895
46 Laporte	99409	100938	102459	103975	105486	106992	108493	109992	111486
47 Lawrence	45364	46061	46758	47453	48148	48843	49537	50230	50923
48 Madison	133330	135294	137255	139212	141166	143117	145065	147011	148954
49 Marion	713541	724217	734850	745446	756009	766542	777050	787534	797997
50 Marshall	43606	44220	44834	45449	46064	46679	47294	47909	48525
51 Martin	11478	11651	11824	11997	12169	12342	12513	12685	12857
52 Miami	39215	39770	40322	40872	41420	41965	42509	43051	43592
53 Monroe	86422	87914	89404	90893	92380	93866	95352	96836	98320
54 Montgomery	36657	37128	37599	38069	38539	39008	39477	39945	40413
55 Morgan	59993	61028	62063	63100	64137	65174	66212	67250	68289
56 Newton	14570	14761	14952	15143	15333	15523	15712	15901	16090
57 Noble	39269	39834	40400	40966	41533	42099	42666	43233	43800
58 Ohio	5300	5372	5444	5516	5589	5661	5734	5807	5879
59 Orange	19012	19288	19564	19840	20115	20390	20665	20939	21214
60 Owen	18323	18597	18871	19147	19424	19702	19980	20260	20540
61 Parke	16016	16218	16421	16622	16822	17022	17221	17420	17618
62 Perry	19583	19887	20190	20491	20791	21090	21388	21686	21982

Table F7, continued

County No. Name	Year								
	1998	1999	2000	2001	2002	2003	2004	2005	2006
63 Pike	14581	14772	14963	15153	15343	15532	15722	15911	16100
64 Porter	127290	129611	131928	134244	136559	138873	141187	143501	145815
65 Posey	28628	29056	29485	29913	30341	30770	31198	31626	32055
66 Pulaski	14608	14780	14953	15126	15298	15470	15642	15813	15985
67 Putnam	28962	29393	29823	30253	30682	31111	31540	31968	32396
68 Randolph	27965	28183	28401	28619	28837	29054	29271	29488	29704
69 Ripley	25859	26234	26609	26984	27359	27734	28110	28485	28861
70 Rush	18850	19102	19353	19601	19848	20093	20337	20580	20822
71 St. Joseph	219907	222838	225760	228677	231588	234494	237399	240300	243201
72 Scott	20824	21164	21503	21843	22182	22522	22861	23200	23540
73 Shelby	42549	43182	43813	44444	45074	45704	46333	46962	47590
74 Spencer	21638	21970	22303	22636	22968	23301	23634	23967	24300
75 Starke	21884	22200	22516	22830	23145	23459	23773	24086	24399
76 Steuben	29223	29638	30056	30475	30895	31317	31741	32165	32590
77 Sullivan	21156	21435	21712	21987	22261	22534	22805	23076	23345
78 Switzerland	6775	6857	6938	7020	7102	7183	7265	7346	7428
79 Tippecanoe	105927	107564	109200	110834	112468	114101	115733	117364	118995
80 Tipton	19006	19254	19500	19746	19991	20235	20478	20721	20963
81 Union	7728	7830	7932	8033	8135	8236	8337	8438	8539
82 Vanderburgh	152915	154878	157601	159255	161268	162924	165403	167428	169641
83 Vermillion	17971	18193	18413	18634	18854	19073	19292	19511	19729
84 Vigo	93934	95154	96372	97588	98802	100015	101227	102437	103645
85 Wabash	36653	37141	37627	38112	38596	39078	39560	40041	40521
86 Warren	9600	9719	9836	9953	10070	10186	10302	10417	10532
87 Warrick	49272	50121	50971	51822	52672	53523	54375	55226	56078
88 Washington	23298	23614	23931	24248	24565	24882	25200	25518	25836
89 Wayne	66655	67497	68335	69169	70000	70829	71655	72478	73300
90 Wells	29139	29525	29912	30299	30685	31072	31458	31845	32232
91 White	26553	26912	27271	27629	27987	28345	28702	29058	29415
92 Whitley	31163	31600	32038	32476	32915	33354	33793	34233	34673
STATE	5391250	5472689	5553984	5635148	5716192	5797125	5877958	5958697	6039352

Table F7, continued

County No. Name	Year								
	2007	2008	2009	2010	2011	2012	2013	2014	2015
1 Adams	33392	33763	34135	34507	34879	35251	35622	35994	36366
2 Allen	343777	351270	355353	361257	363830	369185	373041	379615	383907
3 Bartholomew	82614	83819	85023	86226	87429	88631	89832	91034	92234
4 Benton	10585	10662	10737	10812	10887	10963	11038	11112	11187
5 Blackford	17967	18175	18382	18589	18796	19003	19210	19417	19624
6 Boone	47180	47809	48440	49070	49700	50331	50962	51593	52224
7 Brown	18056	18331	18607	18882	19158	19434	19710	19986	20262
8 Carroll	24820	25099	25378	25657	25935	26214	26493	26771	27050
9 Cass	44380	44860	45339	45817	46294	46771	47247	47723	48199
10 Clark	103766	105349	106930	108511	110091	111671	113249	114827	116405
11 Clay	29131	29473	29814	30156	30497	30838	31179	31519	31859
12 Clinton	35595	35989	36384	36778	37172	37566	37959	38353	38746
13 Crawford	11838	11991	12145	12299	12452	12606	12761	12915	13069
14 Daviess	30534	30895	31256	31616	31977	32337	32696	33056	33416
15 Dearborn	43034	43609	44184	44759	45335	45911	46488	47064	47641
16 Decatur	28914	29307	29700	30093	30485	30878	31271	31663	32056
17 Dekalb	42977	43495	44013	44531	45050	45568	46087	46607	47126
18 Delaware	123521	125063	126605	128144	129682	131219	132755	134289	135822
19 Dubois	46458	47117	47776	48435	49095	49755	50415	51075	51735
20 Elkhart	179133	181613	184097	186582	189066	191547	194028	196511	198993
21 Fayette	29453	29819	30185	30550	30915	31280	31645	32009	32373
22 Floyd	69624	70580	71536	72493	73449	74405	75361	76318	77274
23 Fountain	19837	20036	20236	20435	20633	20831	21029	21227	21424
24 Franklin	22876	23180	23483	23787	24091	24395	24699	25003	25307
25 Fulton	22148	22356	22565	22773	22981	23190	23398	23607	23815
26 Gibson	37739	38182	38626	39069	39512	39956	40398	40841	41284
27 Grant	82878	83906	84933	85958	86981	88002	89022	90040	91057
28 Greene	35648	36078	36507	36936	37365	37793	38222	38651	39079
29 Hamilton	130011	132009	134006	136000	137993	139985	141976	143967	145957
30 Hancock	60224	61118	62013	62907	63802	64698	65593	66488	67384

Table F7, continued

County No. Name	Year								
	2007	2008	2009	2010	2011	2012	2013	2014	2015
31 Harrison	38280	38828	39377	39926	40476	41025	41575	42124	42674
32 Hendricks	104003	105655	107307	108960	110614	112268	113922	115577	117232
33 Henry	58283	58982	59681	60379	61077	61774	62471	63167	63862
34 Howard	96732	98060	99387	100713	102036	103359	104681	106001	107321
35 Huntington	39607	40041	40475	40909	41343	41776	42209	42643	43076
36 Jackson	46665	47299	47932	48565	49198	49831	50464	51096	51729
37 Jasper	30338	30737	31135	31533	31931	32329	32727	33125	33523
38 Jay	25197	25438	25679	25920	26160	26400	26640	26881	27121
39 Jefferson	31392	31803	32214	32625	33036	33447	33858	34268	34679
40 Jennings	27795	28192	28590	28988	29386	29784	30182	30580	30978
41 Johnson	103524	105147	106769	108393	110016	111640	113266	114891	116516
42 Knox	42565	43019	43473	43926	44379	44831	45283	45735	46186
43 Kosciusko	80244	81359	82474	83590	84707	85824	86941	88058	89176
44 Lagrange	27383	27745	28107	28469	28831	29194	29556	29919	30282
45 Lake	442783	448665	454541	460412	466277	472138	477994	483845	489691
46 Laporte	112977	114467	115953	117439	118921	120402	121882	123361	124838
47 Lawrence	51616	52308	53000	53692	54383	55075	55766	56457	57148
48 Madison	150894	152833	154769	156703	158636	160566	162495	164423	166348
49 Marion	808443	818873	829287	839690	850081	860463	870835	881200	891558
50 Marshall	49140	49756	50371	50987	51603	52219	52835	53451	54067
51 Martin	13028	13200	13371	13542	13713	13884	14054	14225	14396
52 Miami	44132	44672	45210	45748	46286	46823	47360	47896	48433
53 Monroe	99802	101285	102767	104248	105729	107210	108691	110171	111651
54 Montgomery	40881	41349	41816	42283	42750	43217	43683	44150	44616
55 Morgan	69328	70367	71407	72448	73488	74529	75570	76611	77653
56 Newton	16279	16468	16656	16844	17032	17220	17408	17595	17783
57 Noble	44367	44934	45501	46068	46635	47202	47769	48336	48903
58 Ohio	5952	6025	6098	6172	6245	6318	6391	6465	6538
59 Orange	21488	21762	22037	22311	22584	22858	23132	23406	23679
60 Owen	20820	21102	21383	21665	21948	22231	22514	22797	23081
61 Parke	17815	18012	18209	18405	18601	18797	18993	19188	19383
62 Perry	22278	22574	22869	23164	23458	23752	24046	24339	24633

Table F7, continued

County No. Name	Year								
	2007	2008	2009	2010	2011	2012	2013	2014	2015
63 Pike	16288	16477	16665	16853	17041	17229	17417	17605	17792
64 Porter	148129	150443	152757	155071	157386	159700	162015	164330	166645
65 Posey	32483	32911	33340	33768	34196	34624	35052	35481	35909
66 Pulaski	16156	16328	16499	16670	16841	17012	17183	17354	17525
67 Putnam	32824	33251	33678	34105	34532	34959	35386	35812	36239
68 Randolph	29921	30137	30353	30569	30785	31001	31216	31432	31647
69 Ripley	29237	29612	29988	30364	30740	31116	31492	31868	32244
70 Rush	21064	21304	21544	21783	22022	22260	22498	22736	22973
71 St. Joseph	246099	248997	251894	254790	257686	260581	263476	266371	269265
72 Scott	23879	24219	24558	24898	25237	25577	25916	26256	26595
73 Shelby	48218	48846	49473	50100	50726	51353	51979	52605	53231
74 Spencer	24633	24966	25299	25632	25966	26299	26632	26965	27299
75 Starke	24712	25024	25337	25649	25961	26272	26584	26896	27207
76 Steuben	33016	33443	33871	34300	34729	35158	35588	36019	36449
77 Sullivan	23614	23882	24150	24417	24683	24949	25215	25480	25745
78 Switzerland	7509	7591	7672	7754	7835	7917	7999	8080	8162
79 Tippecanoe	120625	122254	123883	125511	127139	128767	130394	132020	133646
80 Tipton	21205	21447	21688	21929	22169	22410	22650	22890	23129
81 Union	8640	8740	8841	8942	9042	9143	9244	9344	9445
82 Vanderburgh	171318	173471	175472	177779	179667	181727	183622	185832	187846
83 Vermillion	19947	20165	20383	20601	20818	21035	21252	21470	21686
84 Vigo	104852	106058	107262	108466	109668	110869	112070	113269	114467
85 Wabash	41000	41480	41958	42436	42914	43391	43869	44346	44822
86 Warren	10647	10762	10877	10991	11105	11220	11334	11448	11562
87 Warrick	56930	57783	58635	59488	60342	61195	62049	62903	63757
88 Washington	26154	26473	26792	27110	27429	27748	28068	28387	28706
89 Wayne	74119	74937	75753	76568	77382	78195	79006	79817	80626
90 Wells	32618	33005	33392	33778	34165	34552	34938	35325	35712
91 White	29771	30127	30483	30838	31193	31548	31903	32258	32612
92 Whitley	35113	35554	35994	36435	36876	37318	37759	38201	38642
STATE	6119929	6200434	6280874	6361254	6441578	6521852	6602080	6682266	6762412

Table F8: Surrounding County and Township for Cities of Indiana

City Rank(*)	City Name	County No. Name	Surrounding Township(s) or County(ies)	1980 City Pop.
74	ALEXANDRIA	48 Madison	Monroe	6028
8	ANDERSON	48 Madison	(**)	64695
79	ANGOLA	76 Steuben	Pleasant	5486
62	AUBURN	17 DeKalb	Jackson, Union	8122
40	BEDFORD	47 Lawrence	Shawswick	14410
44	BEECH GROVE	49 Marion	Franklin, Perry	13196
91	BICKNELL	42 Knox	Vigo	4713
10	BLOOMINGTON	53 Monroe	(**)	52044
58	BLUFFTON	90 Wells	Harrison, Lancaster	8705
72	BOONVILLE	87 Warrick	Boon	6300
63	BRAZIL	11 Clay	Brazil	7852
32	CARMEL	29 Hamilton	Clay	18272
78	CHARLESTOWN	10 Clark	Charlestown	5596
82	CLINTON	83 Vermillion	Clinton	5267
84	COLUMBIA CITY	92 Whitley	Columbia	5091
20	COLUMBUS	3 Bartholomew	(**)	30614
34	CONNERSVILLE	21 Fayette	Conersville, Harrison	17023
43	CRAWFORDSVILLE	54 Montgomery	Union	13325
35	CROWN POINT	45 Lake	Center	16455
60	DECATUR	1 Adams	Root, Washington	8649
16	EAST CHICAGO	45 Lake	North	39786
14	ELKHART	20 Elkhart	Baugo, Cleveland, Concord, Osolo	41305
53	ELWOOD	48 Madison	Pipe-Creek	10867
4	EVANSVILLE	82 Vanderburgh	(**)	130496
2	FORT WAYNE	2 Allen	(**)	172391
37	FRANKFORT	12 Clinton	Center	15168
48	FRANKLIN	41 Johnson	Franklin, Needham	11563
89	GARRETT	17 DeKalb	Keyser	4874
3	GARY	45 Lake	(**)	151968
70	GAS CITY	27 Grant	Mill	6370
30	GOSHEN	20 Elkhart	Elkhart, Jefferson	19665
61	GREENCASTLE	67 Putnam	Greencastle	8403
50	GREENFIELD	30 Hancock	Center	11304
55	GREENSBURG	16 Decatur	Washington	9254
31	GREENWOOD	41 Johnson	Pleasant, White-River	20175

Table F8, continued

City Rank(*)	Name	County No. Name	Surrounding Township(s) or County(ies)	1980 City Pop.
6	HAMMOND	45 Lake	(**)	93714
66	HARTFORD CITY	5 Blackford	Licking, Washington	7622
23	HOBART	45 Lake	Hobart	22987
80	HUNTINGBURG	19 Dubois	Patoka	5376
36	HUNTINGTON	35 Huntington	Huntington	16202
1	INDIANAPOLIS	49 Marion	(***)	700807
56	JASPER	19 Dubois	Bainbridge	9097
27	JEFFERSONVILLE	10 Clark	Jeffersonville	22033
67	KENDALLVILLE	57 Noble	Allen, Wayne	7299
11	KOKOMO	34 Howard	(**)	47808
12	LAFAYETTE	79 Tippecanoe	Fairfield, Wea	43011
41	LAKE STATION	45 Lake	Center, Hanover	15083
25	LAPORTE	46 LaPorte	Center, Kankakee, Pleasant, Scipio	21796
22	LAWRENCE	49 Marion	Lawrence	25591
94	LAWRENCEBURG	15 Dearborn	Lawrenceburg	4403
49	LEBANON	6 Boone	Center	11456
71	LINTON	28 Greene	Grant, Stockton	6315
33	LOGANSPOUT	9 Cass	Eel	17731
46	MADISON	39 Jefferson	Madison	12472
19	MARION	27 Grant	Center, Franklin, Pleasant, Washington	35874
52	MARTINSVILLE	55 Morgan	Washington	11311
18	MICHIGAN CITY	46 LaPorte	CoolSpring, Michigan	36850
15	MISHAWAKA	71 St. Joseph	Penn	40201
93	MITCHELL	47 Lawrence	Marion	4641
83	MONTICELLO	91 White	Union	5162
65	MT. VERNON	65 Posey	Black	7656
7	MUNCIE	18 Delaware	(**)	77216
92	NAPPANEE	20 Elkhart	Locke, Union	4694
17	NEW ALBANY	22 Floyd	New-Albany	37103
29	NEW CASTLE	33 Henry	Henry	20056
69	NEW HAVEN	2 Allen	Adams	7105
47	NOBLESVILLE	29 Hamilton	Noblesville	12253
75	NORTH VERNON	40 Jennings	Center, Vernon	5768

Table F8, continued

City Rank(*)	Name	County No. Name	Surrounding Township(s) or County(ies)	1980 City Pop.
42	PERU	52 Miami	Peru, Washington	13764
64	PLYMOUTH	50 Marshall	Center	7693
21	PORTAGE	64 Porter	Portage	27409
68	PORTLAND	38 Jay	Wayne	7074
57	PRINCETON	26 Gibson	Patoka	8976
88	RENSSELAER	37 Jasper	Marion	4994
13	RICHMOND	89 Wayne	Center, Wayne	41349
86	ROCHESTER	25 Fulton	Rochester	5050
73	RUSHVILLE	70 Rush	Rushville	6113
81	SALEM	88 Washington	Washington	5290
85	SCOTTSBURG	72 Scott	Vienna	5068
38	SEYMOUR	36 Jackson	Jackson, Redding	15050
39	SHELBYVILLE	73 Shelby	Addison	15003
5	SOUTH BEND	71 St. Joseph	(**)	109727
90	SULLIVAN	77 Sullivan	Hamilton	4774
59	TELL CITY	62 Perry	Troy	8704
9	TERRE HAUTE	84 Vigo	(**)	61125
87	TIPTON	80 Tipton	Cicero	5004
24	VALPARAISO	64 Porter	Center, Washington	22247
28	VINCENNES	42 Knox	Vincennes	20857
45	WABASH	85 Wabash	Noble	12985
54	WARSAW	43 Kosciusko	Wayne	10647
51	WASHINGTON	14 Daviess	Washington	11325
26	WEST LAFAYETTE	79 Tippecanoe	Wabash	21247
77	WHITING	45 Lake	North	5630
76	WINCHESTER	68 Randolph	White-River	5659

(*) Based on 1980 City Population

(**) County in Second Column

(***) 49-Marion, 29-Hamilton, 32-Hendricks, 55-Morgan,
41-Johnson, 73-Shelby, 30-Hancock, 6-Boone

Table F9: City Population Forecasts by Ratio Method

City Rank(*)	Name	YEAR							
		1985	1990	1995	2000	2005	2010	2015	2020
74	ALEXANDRIA	6145	6262	6351	6390	6406	6412	6412	6390
8	ANDERSON	64147	64003	63934	63827	63729	63613	63479	63232
79	ANGOLA	5825	6111	6327	6479	6584	6660	6719	6725
62	AUBURN	8427	8724	8993	9254	9523	9741	9937	10096
40	BEDFORD	14592	14767	14900	14984	14991	14956	14907	14816
44	BEECH GROVE	13521	13905	14158	14269	14320	14363	14427	14455
91	BICKNELL	4627	4619	4550	4465	4422	4397	4431	4439
10	BLOOMINGTON	52297	53651	55568	57186	58682	60352	62559	65336
58	BLUFFTON	8988	9284	9554	9811	10055	10266	10443	10568
72	BOONVILLE	6603	6901	7188	7447	7663	7894	8109	8280
63	BRAZIL	7815	7777	7749	7721	7759	7815	7871	7936
32	CARMEL	21471	24379	26968	29232	31042	32045	32342	32202
78	CHARLESTOWN	5888	6162	6387	6551	6667	6721	6709	6642
82	CLINTON	5402	5504	5585	5633	5660	5666	5622	5563
84	COLUMBIA CITY	5263	5442	5607	5760	5892	5991	6058	6124
20	COLUMBUS	31621	32585	33365	33939	34240	34217	33944	33469
34	CONNERSVILLE	17245	17512	17772	18024	18291	18482	18628	18734
43	CRAWFORDSVILLE	13531	13664	13749	13761	13755	13701	13610	13446
35	CROWN POINT	16791	17167	17435	17578	17709	17942	18284	18702
60	DECATUR	9096	9569	10047	10558	11093	11635	12208	12800
16	EAST CHICAGO	37695	36181	35104	34495	34380	34662	35217	35845
14	ELKHART	42042	42905	43794	44626	45442	46216	46932	47523
53	ELWOOD	10662	10557	10465	10387	10324	10282	10275	10261
4	EVANSVILLE	130262	130099	129226	127879	126585	125705	125004	124202
2	FORT WAYNE	176204	180696	184790	188228	191473	194712	197898	200527
37	FRANKFORT	14964	14880	14862	14899	14992	15103	15205	15307
48	FRANKLIN	11620	11825	12017	12173	12378	12619	12832	12995
89	GARRETT	4858	4890	4937	5017	5104	5191	5278	5342
3	GARY	147391	145052	143733	143445	144578	146746	149518	152215
70	GAS CITY	6306	6280	6242	6184	6109	6056	6019	5961
30	GOSHEN	20645	21610	22459	23226	23936	24536	25033	25435
61	GREENCASTLE	8365	8143	8013	7921	7944	7944	7860	7776
50	GREENFIELD	11843	12411	12915	13314	13594	13755	13874	13895
55	GREENSBURG	9303	9409	9515	9629	9784	9931	10077	10208
31	GREENWOOD	22593	24899	26867	28454	29553	30007	30124	29990

Table F9, continued

Rank(*)	City Name	YEAR							
		1985	1990	1995	2000	2005	2010	2015	2020
6	HAMMOND	90892	89449	88636	88458	89157	90494	92203	93866
66	HARTFORD CITY	7352	7161	7040	6919	6820	6777	6728	6671
23	HOBART	23030	23041	22998	23009	23160	23495	23911	24305
80	HUNTINGBURG	5559	5774	5981	6149	6276	6387	6491	6579
36	HUNTINGTON	16251	16348	16461	16631	16873	17189	17496	17715
1	INDIANAPOLIS	711536	726248	738125	747442	756381	763025	767152	767849
56	JASPER	9384	9724	10019	10261	10434	10623	10820	10971
27	JEFFERSONVILLE	23217	24263	25111	25747	26189	26382	26339	26141
67	KENDALLVILLE	7662	8031	8371	8678	8952	9181	9354	9499
11	KOKOMO	48034	48567	49167	49657	50025	50317	50537	50630
12	LAFAYETTE	42538	42748	43875	44747	45454	46333	47430	48693
41	LAKE STATION	15388	15708	15921	16033	16144	16353	16668	17046
25	LAPORTE	21724	21822	21966	22090	22221	22378	22528	22639
22	LAWRENCE	26920	28020	28691	28981	29204	29302	29241	28975
94	LAWRENCEBURG	4549	4695	4823	4951	5069	5183	5293	5384
49	LEBANON	12077	12683	13264	13774	14244	14643	14945	15145
71	LINTON	6483	6637	6764	6851	6905	6938	6952	6965
33	LOGANSPOUT	17065	16642	16332	16192	16145	16229	16379	16530
46	MADISON	12749	13087	13402	13609	13794	13924	13963	13947
19	MARION	34212	33154	32334	31723	31334	31089	30917	30722
52	MARTINSVILLE	11882	12475	13008	13468	13839	14120	14313	14432
18	MICHIGAN CITY	36865	37022	37209	37350	37507	37649	37754	37784
15	MISHAWAKA	40906	41639	42052	42173	42159	42230	42401	42614
93	MITCHELL	4855	5032	5162	5256	5297	5292	5276	5224
83	MONTICELLO	5383	5581	5725	5824	5890	5956	5973	5995
65	MT. VERNON	7884	8118	8317	8478	8603	8720	8852	8955
7	MUNCIE	75102	74592	74778	74970	75246	75727	76543	77768
92	NAPPANEE	4893	5087	5257	5415	5567	5702	5807	5889
17	NEW ALBANY	36773	36654	36629	36638	36705	36891	37069	37171
29	NEW CASTLE	19373	18953	18645	18390	18203	18075	17948	17798
69	NEW HAVEN	7101	7158	7230	7290	7328	7377	7444	7515
47	NOBLESVILLE	13648	14932	16099	17131	18000	18584	18941	19116
75	NORTH VERNON	6025	6294	6516	6674	6797	6878	6902	6931

Table F9, continued

Rank(*)	City Name	YEAR							
		1985	1990	1995	2000	2005	2010	2015	2020
42	PERU	13592	13639	13733	13897	14123	14419	14771	15106
64	PLYMOUTH	7943	8193	8423	8619	8815	8991	9167	9302
21	PORTAGE	30641	33701	36306	38346	39821	40621	40938	40855
68	PORTLAND	7082	7090	7156	7189	7230	7328	7426	7508
57	PRINCETON	9185	9395	9559	9679	9769	9859	9904	9926
88	RENSSELAER	5183	5357	5532	5706	5881	6077	6265	6426
13	RICHMOND	40038	39159	38545	38098	37886	37749	37711	37620
86	ROCHESTER	5234	5412	5541	5635	5708	5775	5830	5875
73	RUSHVILLE	5829	5665	5608	5566	5544	5559	5573	5608
81	SALEM	5463	5647	5820	5963	6112	6231	6344	6422
85	SCOTTSBURG	5299	5529	5727	5892	6010	6083	6122	6122
38	SEYMOUR	15673	16250	16719	17142	17457	17749	17957	18103
39	SHELBYVILLE	14726	14605	14579	14579	14648	14700	14752	14795
5	SOUTH BEND	108428	107897	107429	106961	106707	106780	107116	107493
90	SULLIVAN	4829	4884	4918	4966	5001	5021	5021	5028
59	TELL CITY	8641	8616	8629	8648	8691	8773	8842	8954
9	TERRE HAUTE	59412	58210	57340	56709	56323	55969	55708	55485
87	TIPTON	4986	4992	5010	5016	5016	5022	5034	5022
24	VALPARAISO	23912	25513	27017	28339	29478	30416	31080	31500
28	VINCENNES	20564	20314	20013	19804	19720	19586	19511	19419
45	WABASH	12812	12812	12790	12760	12745	12722	12782	12782
54	WARSAW	11683	12657	13495	14213	14822	15328	15739	16072
51	WASHINGTON	11504	11735	11891	11995	12092	12256	12412	12576
26	WEST LAFAYETTE	21468	21780	21737	21895	22231	22533	22783	22989
77	WHITING	5334	5120	4967	4881	4865	4905	4983	5072
76	WINCHESTER	5666	5719	5780	5840	5881	5928	5968	5961

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
P-value: 0.015

Figure F1.1: Normal Probability Plot of Residuals from ARIMA(0,1,0)
Forecast of Franklin County Vehicle Registration

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
P-value: 0.295

Figure F1.2: Normal Probability Plot of Residuals from ARIMA(1,1,0)

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
P-value: 0.694

Figure F1.3: Normal Probability Plot of Residuals from ARIMA(1,1,0)

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
P-value: 0.092

Figure F1.4: Normal Probability Plot of Residuals from Autoregressive Forecasts of Franklin County Vehicle Registration

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
P-value: 0.415

Figure F1.5: Normal Probability Plot of Residuals from Autoregressive Forecasts of Tippecanoe County Vehicle Registration

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
P-value: 0.775

Figure F1.6: Normal Probability Plot of Residuals from Autoregressive Forecasts of White County Vehicle Registration

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
STD DEV: 353

Figure F2.1: Residual Plot against Time from ARIMA(0,1,0) Forecasts

Figure F2.2: Residual Plot against Time from ARIMA(1,1,0) Forecasts

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
STD DEV: 312

Figure F2.3: Residual Plot against Time from ARIMA(1,1,0) Forecasts of White County Vehicle Registration

Figure F2.4: Residual Plot against Time from Autoregressive Forecasts of Franklin County Vehicle Registration

Figure F2.5: Residual Plot against Time from Autoregressive Forecasts of Tippecanoe County Vehicle Registration

Figure F2.6: Residual Plot against Time from Autoregressive Forecasts of White County Vehicle Registration

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
 Pearson Correlation Coefficient (r) = 0.99537

Figure F3.1: Plot of Observed values against Autoregressive Forecasts of Franklin County Vehicle Registration

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
 Pearson Correlation Coefficient (r) = 0.99492

Figure F3.2: Plot of Observed values against Box-Jenkin Forecasts of Franklin County Vehicle Registration

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
 Pearson Correlation Coefficient (r) = 0.99524

Figure F3.3: Plot of Observed values against Combined Forecasts of Franklin County Vehicle Registration

Figure F3.4: Plot of Observed values against Autoregressive Forecasts of Tippecanoe County Vehicle Registration

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
 Pearson Correlation Coefficient (r) = 0.99889

Figure F3.5: Plot of Observed values against Box-Jenkin Forecasts of Tippecanoe County Vehicle Registration

LEGEND: A = 1 OBS, B = 2 OBS, ETC.
 Pearson Correlation Coefficient (r) = 0.99889

Figure F3.6: Plot of Observed values against Combined Forecasts of Tippecanoe County Vehicle Registration

SYMBOL: r = Observed Value; a = Autoregressive Forecast

Figure F4.1: Observed values and Autoregressive Forecasts of Franklin County Vehicle Registration

Note: One symbol before 1988 means that both forecast and observed value are superimposed in plot.

SYMBOL: r = Observed Value; a = Autoregressive Forecast

Figure F4.2: Observed values and Autoregressive Forecasts of Tippecanoe County Vehicle Registration

Note: One symbol before 1988 means that both forecast and observed value are superimposed in plot.

SYMBOL: r = Observed Value; b = Box-Jenkin Forecast

Figure F4.3: Observed values and Box-Jenkin Forecasts of Franklin County Vehicle Registration

Note: One symbol before 1988 means that both forecast and observed value are superimposed in plot.

Figure F4.5: Observed values and Combined Forecasts of Franklin County Vehicle Registration

Note: One symbol before 1988 means that both forecast and observed value are superimposed in plot.

Figure F4.6: Observed values and Combined Forecasts of Tippecanoe County Vehicle Registration

Note: One symbol before 1988 means that both forecast and observed value are superimposed in plot.

Appendix G

Table G1: 90-Percent Confidence Limits of Forecast Measures
for Models of Interstate Highways

Region	Model	MAE		MAPE		RMSPE		$\overline{O}$	
		L90	U90	L90	U90	L90	U90	L90	U90
Interstate Highways (Rural & Urban)									
North	Elasticity	1611	2346	5.05	8.35	6.08	12.17	1.06	1.10
	Lag-AADT	3326	5193	8.71	13.19	9.45	18.18	1.10	1.16
	Combined	2549	3639	6.97	10.53	7.55	14.46	1.08	1.12
Central	Elasticity	2584	3362	6.60	8.70	7.52	11.52	1.08	1.10
	Lag-AADT	2739	3735	7.16	9.44	8.20	12.46	1.09	1.11
	Combined	2491	3216	6.44	8.38	7.27	10.90	1.07	1.09
South	Elasticity	1504	2471	6.59	9.51	6.88	12.45	1.07	1.11
	Lag-AADT	1432	2220	6.98	8.98	6.66	10.88	1.08	1.10
	Combined	1091	1800	5.69	8.23	6.07	10.68	1.06	1.10
Rural Interstate Highways									
ALL	Elasticity	1639	2083	7.78	10.68	9.39	15.25	1.09	1.13
	Lag-AADT	1865	2535	7.98	10.36	8.98	13.72	1.09	1.13
	Combined	1290	1746	6.06	8.20	7.25	11.41	1.07	1.09
North	Elasticity	1964	3185	8.33	14.37	7.74	19.10	1.09	1.15
	Lag-AADT	1893	4036	7.84	14.86	7.19	20.96	1.09	1.19
	Combined	1474	2789	6.11	11.49	5.60	16.13	1.06	1.14
Central	Elasticity	1605	2232	5.65	8.11	5.85	10.94	1.06	1.10
	Lag-AADT	2126	2864	7.96	11.20	8.36	14.60	1.09	1.13
	Combined	1451	2071	5.60	8.30	6.27	11.19	1.06	1.10
South	Elasticity	955	1811	6.86	10.38	6.85	13.35	1.08	1.12
	Lag-AADT	826	1620	6.03	8.83	5.74	11.30	1.06	1.10
	Combined	830	1650	6.16	9.26	6.19	11.81	1.07	1.11

Table G1, continued

Region	Model	MAE		MAPE		RMSPE		$\bar{Q}$	
		L90	U90	L90	U90	L90	U90	L90	U90
Urban Interstate Highways									
ALL	Elasticity	2315	2918	4.26	5.82	4.83	8.01	1.04	1.06
	Lag-AADT	3408	4618	6.20	8.40	7.14	11.25	1.07	1.09
	Combined	2415	3229	4.49	6.03	5.07	8.06	1.05	1.07
North	Elasticity	3345	4994	5.72	10.60	5.60	15.49	1.07	1.13
	Lag-AADT	3864	6762	7.15	12.75	7.24	17.88	1.08	1.16
	Combined	3647	5800	6.46	11.56	6.30	16.46	1.07	1.15
Central	Elasticity	2390	3104	4.28	7.02	4.70	10.32	1.04	1.08
	Lag-AADT	3207	4553	5.63	8.57	6.01	11.71	1.06	1.10
	Combined	2729	3627	4.91	7.47	5.26	10.17	1.05	1.09
South	Elasticity	1147	2689	2.22	7.34	1.96	11.47	1.02	1.08
	Lag-AADT	2332	5025	5.04	11.26	4.15	15.80	1.05	1.13
	Combined	1495	3150	2.90	8.22	2.21	12.61	1.03	1.09

Note: L90 = Lower limit of 90% confidence limit, and
 U90 = Upper limit of 90% confidence limit.

Table G2: 95-Percent Confidence Limits of Forecast Measures
for Models of Interstate Highways

Region	Model	MAE		MAPE		RMSPE		$\bar{Q}$	
		L95	U95	L95	U95	L95	U95	L95	U95
Interstate Highways (Rural & Urban)									
North	Elasticity	1537	2419	4.72	8.68	5.47	12.78	1.05	1.11
	Lag-AADT	3139	5380	8.26	13.64	8.58	19.05	1.09	1.17
	Combined	2440	3748	6.62	10.88	6.86	15.15	1.07	1.13
Central	Elasticity	2507	3438	6.40	8.90	7.13	11.91	1.07	1.11
	Lag-AADT	2641	3833	6.94	9.66	7.78	12.87	1.08	1.12
	Combined	2421	3286	6.25	8.57	6.91	11.26	1.07	1.09
South	Elasticity	1407	2568	6.29	9.81	6.32	13.01	1.07	1.11
	Lag-AADT	1353	2299	6.78	9.18	6.24	11.31	1.08	1.10
	Combined	1020	1871	5.43	8.49	6.04	10.71	1.06	1.10
Rural Interstate Highways									
ALL	Elasticity	1596	2127	7.50	10.96	8.82	15.82	1.08	1.14
	Lag-AADT	1799	2600	7.75	10.59	8.52	14.18	1.09	1.13
	Combined	1245	1791	5.85	8.41	6.84	11.82	1.06	1.10
North	Elasticity	1834	3315	7.68	15.02	6.53	20.31	1.08	1.16
	Lag-AADT	1666	4264	7.09	15.61	5.72	22.43	1.08	1.20
	Combined	1334	2929	5.54	12.06	4.48	17.25	1.06	1.14
Central	Elasticity	1542	2295	5.40	8.36	5.34	11.45	1.06	1.10
	Lag-AADT	2052	2938	7.64	11.52	7.73	15.22	1.09	1.13
	Combined	1389	2134	5.33	8.57	5.77	11.69	1.06	1.10
South	Elasticity	867	1899	6.50	10.74	6.18	14.02	1.08	1.12
	Lag-AADT	744	1701	5.74	9.12	5.17	11.87	1.06	1.10
	Combined	746	1734	5.84	9.58	5.62	12.38	1.07	1.11

Table G2, continued

Region	Model	MAE		MAPE		RMSPE		$\bar{Q}$	
		L95	U95	L95	U95	L95	U95	L95	U95
Urban Interstate Highways									
ALL	Elasticity	2255	2977	4.11	5.97	4.52	8.32	1.04	1.06
	Lag-AADT	3289	4736	5.98	8.62	6.73	11.66	1.06	1.10
	Combined	2335	3308	4.33	6.19	4.78	8.36	1.05	1.07
North	Elasticity	3173	5166	5.21	11.11	4.57	16.52	1.06	1.14
	Lag-AADT	3563	7064	6.56	13.34	6.14	18.98	1.07	1.17
	Combined	3423	6024	5.94	12.08	5.24	17.51	1.07	1.15
Central	Elasticity	2318	3175	4.00	7.30	4.14	10.88	1.04	1.08
	Lag-AADT	3072	4688	5.33	8.87	5.44	12.28	1.06	1.10
	Combined	2640	3716	4.66	7.72	4.77	10.66	1.05	1.09
South	Elasticity	974	2862	1.65	7.91	0.89	12.54	1.01	1.09
	Lag-AADT	2028	5328	4.34	11.96	2.84	17.11	1.05	1.13
	Combined	1308	3337	2.30	8.82	1.04	13.79	1.02	1.10

Note: L95 = Lower limit of 95% confidence limit, and
 U95 = Upper limit of 95% confidence limit.

Table G3: 90-Percent Confidence Limits of Forecast Measures
for Models of Urban Principal Arterial

Region	Model	MAE		MAPE		RMSPE		$\bar{Q}$	
		L90	U90	L90	U90	L90	U90	L90	U90
City Group "A"									
North	Elasticity	683	946	5.12	7.10	5.62	9.56	1.05	1.07
	Lag-AADT	1002	1460	7.24	9.58	7.73	12.19	1.08	1.10
	Combined	710	998	5.22	6.88	5.52	8.76	1.05	1.07
Central	Elasticity	1033	1306	7.86	10.60	8.22	13.79	1.08	1.10
	Lag-AADT	833	1275	5.63	7.75	6.24	10.52	1.07	1.09
	Combined	624	950	4.73	6.93	5.53	9.60	1.05	1.07
South	Elasticity	1057	1639	9.27	15.33	7.42	19.86	1.09	1.15
	Lag-AADT	417	1067	4.12	12.68	3.95	19.68	1.05	1.13
	Combined	531	919	4.71	11.01	3.33	16.59	1.05	1.11
City Group "B"									
North	Elasticity	791	1176	6.01	8.99	5.83	11.99	1.06	1.10
	Lag-AADT	841	1456	6.35	9.83	6.53	13.17	1.07	1.11
	Combined	787	1231	5.97	8.49	5.80	10.79	1.06	1.10
Central	Elasticity	588	1046	4.19	6.99	4.00	9.13	1.04	1.08
	Lag-AADT	962	1857	6.55	11.37	6.27	15.18	1.07	1.13
	Combined	749	1399	5.35	8.81	4.88	11.62	1.06	1.10
South	Elasticity	-41	722	-0.40	3.46	-0.96	5.14	1.00	1.04
	Lag-AADT	1117	1542	4.22	6.44	1.72	9.06	1.04	1.06
	Combined	607	1059	1.96	4.90	0.06	7.14	1.02	1.04

Table G3, continued

Region	Model	MAE		MAPE		RMSPE		$\overline{Q}$	
		L90	U90	L90	U90	L90	U90	L90	U90
City Group "C"									
North	Elasticity	811	1116	6.88	8.92	6.97	11.02	1.07	1.09
	Lag-AADT	889	1282	7.82	10.72	8.23	13.96	1.08	1.12
	Combined	642	957	5.58	7.90	6.16	10.50	1.06	1.08
Central	Elasticity	908	1199	7.29	9.53	7.52	12.26	1.08	1.10
	Lag-AADT	1075	1609	8.00	10.86	8.67	14.40	1.09	1.13
	Combined	771	1106	5.90	8.32	6.56	11.55	1.07	1.09
South	Elasticity	368	1373	3.33	10.03	1.94	14.36	1.04	1.10
	Lag-AADT	343	1700	3.40	9.94	2.79	13.36	1.07	1.59
	Combined	239	1457	2.03	9.03	2.10	12.65	1.02	1.10
City Group "D"									
North	Elasticity	1020	1889	10.20	17.76	10.03	23.80	1.13	1.23
	Lag-AADT	1271	2451	10.20	31.74	11.28	57.34	1.12	1.34
	Combined	1050	1893	10.02	18.64	8.86	27.11	1.12	1.22
Central	Elasticity	566	934	6.78	11.24	6.08	15.16	1.07	1.11
	Lag-AADT	450	879	5.23	8.83	4.88	11.87	1.06	1.10
	Combined	312	709	3.85	7.71	4.15	10.96	1.04	1.08
South	Elasticity	764	1100	6.71	9.55	6.91	12.30	1.07	1.11
	Lag-AADT	1107	1736	9.20	13.38	9.53	17.60	1.11	1.17
	Combined	854	1327	7.17	10.43	7.58	13.57	1.08	1.12

Note: L90 = Lower limit of 90% confidence limit, and
 U90 = Upper limit of 90% confidence limit.

Table G4: 95-Percent Confidence Limits of Forecast Measures
for Models of Urban Principal Arterial

Region	Model	MAE		MAPE		RMSPE		$\bar{Q}$	
		L95	U95	L95	U95	L95	U95	L95	U95
City Group "A"									
North	Elasticity	657	972	4.92	7.30	5.23	9.95	1.05	1.07
	Lag-AADT	957	1506	7.01	9.81	7.30	12.63	1.07	1.11
	Combined	681	1027	5.05	7.05	5.20	9.08	1.05	1.07
Central	Elasticity	1007	1333	7.59	10.87	7.67	14.33	1.07	1.11
	Lag-AADT	789	1319	5.42	7.96	5.81	10.94	1.06	1.10
	Combined	592	982	4.52	7.14	5.12	10.00	1.05	1.07
South	Elasticity	992	1703	8.59	16.01	6.03	21.25	1.08	1.16
	Lag-AADT	344	1140	3.17	13.63	2.20	21.43	1.04	1.14
	Combined	487	962	4.00	11.72	1.85	18.07	1.04	1.12
City Group "B"									
North	Elasticity	752	1215	5.71	9.29	5.20	12.61	1.06	1.10
	Lag-AADT	778	1519	6.00	10.18	5.85	13.85	1.06	1.12
	Combined	742	1276	5.72	8.74	5.29	11.29	1.06	1.10
Central	Elasticity	540	1095	3.89	7.29	3.45	9.67	1.04	1.08
	Lag-AADT	867	1951	6.04	11.88	5.33	16.12	1.06	1.14
	Combined	680	1468	4.98	9.18	4.17	12.33	1.06	1.10
South	Elasticity	-176	857	-1.08	4.14	-2.04	6.22	0.99	1.05
	Lag-AADT	1042	1617	3.83	6.83	0.43	10.35	1.03	1.07
	Combined	528	1139	1.44	5.42	-1.19	8.39	1.01	1.05

Table G4, continued

Region	Model	MAE		MAPE		RMSPE		$\bar{Q}$	
		L95	U95	L95	U95	L95	U95	L95	U95
City Group "C"									
North	Elasticity	780	1146	6.68	9.12	6.57	11.42	1.07	1.09
	Lag-AADT	850	1321	7.54	11.00	7.67	14.53	1.08	1.12
	Combined	611	989	5.35	8.13	5.73	10.93	1.05	1.09
Central	Elasticity	879	1227	7.07	9.75	7.06	12.73	1.07	1.11
	Lag-AADT	1023	1661	7.71	11.15	8.11	14.97	1.09	1.13
	Combined	738	1139	5.66	8.56	6.07	12.04	1.06	1.10
South	Elasticity	243	1497	2.50	10.86	0.40	15.90	1.03	1.11
	Lag-AADT	174	1868	2.59	10.75	1.48	14.67	1.07	1.59
	Combined	88	1608	1.17	9.89	0.79	13.96	1.01	1.11
City Group "D"									
North	Elasticity	929	1981	9.41	18.55	8.58	25.25	1.11	1.25
	Lag-AADT	1147	2575	7.93	34.01	6.43	62.19	1.10	1.36
	Combined	962	1981	9.11	19.55	6.94	29.03	1.11	1.23
Central	Elasticity	528	973	6.31	11.71	5.13	16.12	1.06	1.12
	Lag-AADT	405	924	4.85	9.21	4.15	12.60	1.05	1.11
	Combined	270	751	3.44	8.12	3.44	11.68	1.03	1.09
South	Elasticity	730	1134	6.43	9.83	6.37	12.84	1.07	1.11
	Lag-AADT	1044	1799	8.78	13.80	8.72	18.41	1.11	1.17
	Combined	806	1375	6.84	10.76	6.98	14.17	1.08	1.12

Note: L95 = Lower limit of 95% confidence limit, and
U95 = Upper limit of 95% confidence limit.

Table G5: 90-Percent Confidence Limits of Forecast Measures
for Models of Urban Minor Arterial & Collector

City Group	Model	MAE		MAPE		RMSPE		$\bar{Q}$	
		L90	U90	L90	U90	L90	U90	L90	U90
A	Elasticity	1370	3979	12.41	27.99	10.93	38.69	1.12	1.28
	Lag-AADT	746	1826	6.71	16.23	7.37	21.54	1.07	1.17
	Combined	764	2152	5.02	17.28	5.63	22.38	1.06	1.16
B	Elasticity	849	1781	14.82	36.50	14.94	52.75	1.16	1.38
	Lag-AADT	168	1095	3.36	11.52	3.46	18.82	1.03	1.15
	Combined	461	1310	9.17	20.65	8.83	29.06	1.09	1.23
C	Elasticity	486	1024	4.31	14.57	4.29	26.51	1.05	1.15
	Lag-AADT	494	1024	4.28	14.42	4.27	26.19	1.05	1.15
	Combined	487	1021	4.23	14.45	4.26	26.34	1.05	1.15
D	Elasticity	743	1284	9.49	14.93	10.45	19.99	1.10	1.16
	Lag-AADT	500	928	6.86	10.68	7.16	14.51	1.08	1.12
	Combined	401	688	5.27	8.71	5.73	12.35	1.05	1.09

Note: L90 = Lower limit of 90% confidence limit, and
U90 = Upper limit of 90% confidence limit.

Table G6: 95-Percent Confidence Limits of Forecast Measures
for Models of Urban Minor Arterial & Collector

City Group	Model	MAE		MAPE		RMSPE		$\bar{Q}$	
		L95	U95	L95	U95	L95	U95	L95	U95
A	Elasticity	1076	4274	10.65	29.75	7.80	41.82	1.10	1.30
	Lag-AADT	624	1948	5.63	17.31	5.77	23.14	1.06	1.18
	Combined	607	2309	3.64	18.66	3.74	24.27	1.05	1.17
B	Elasticity	746	1884	12.43	38.89	10.79	56.90	1.14	1.40
	Lag-AADT	66	1197	2.47	12.41	1.78	20.51	1.02	1.16
	Combined	368	1404	7.91	21.91	6.61	31.28	1.08	1.24
C	Elasticity	429	1082	3.21	15.67	1.92	28.88	1.04	1.16
	Lag-AADT	438	1080	3.20	15.50	1.94	28.52	1.04	1.16
	Combined	430	1078	3.14	15.54	1.91	28.68	1.04	1.16
D	Elasticity	689	1338	8.94	15.48	9.48	20.95	1.09	1.17
	Lag-AADT	457	972	6.48	11.06	6.42	15.25	1.07	1.13
	Combined	373	716	4.93	9.05	5.06	13.01	1.05	1.09

Note: L95 = Lower limit of 95% confidence limit, and
U95 = Upper limit of 95% confidence limit.

VITA

VITA

Sunil K. Saha was born on June 30, 1957 in Bangladesh. He received his Bachelor of Science in Civil Engineering from the Bangladesh University of Engineering and Technology (BUET), Dhaka in March 1980. He served as a Lecturer in Civil Engineering from April 1980 to June 1983 and as an Assistant Professor of Civil Engineering from July 1983 to August 1984 at BUET, Dhaka, Bangladesh. He came to Purdue University, Indiana in August 1984 for graduate study. He received his Master of Science in Civil Engineering in August 1986, with an emphasis in Transportation Engineering. Since then, he has been working in the Ph.D. program in the area of Transportation Engineering at Purdue University. He expects to receive his Doctor of Philosophy in Civil Engineering in December 1990. Since August 1984, he has worked as a Graduate Instructor in the School of Civil Engineering at Purdue University. He was a teaching assistant for several courses, including highway transportation characteristics and traffic engineering.

He is a member of the Institute of Transportation Engineers, Transportation Research Board, American Society of Civil Engineers, and Omega Rho honor society. Sunil is married to Puspa R. Saha and they have a son, Sudip K. Saha (Mital), who was born in 1984.

IMPLEMENTATION REPORT

THE DEVELOPMENT OF A PROCEDURE TO FORECAST TRAFFIC VOLUMES ON URBAN SEGMENTS OF THE STATE AND INTERSTATE HIGHWAY SYSTEMS

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Purdue University

In Cooperation with the
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and the
U.S. Department of Transportation
Federal Highway Administration

The contents of this report reflect the views of the author who is responsible for the facts and accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the Federal Highway Administration. This report does not constitute a standard, specifications or regulations.

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IMPLEMENTATION REPORT

The implementation of the results of this study will be accomplished in several ways:

1. By following the step-by-step procedure outlined in this Implementation Report.
2. By using a computer program specially developed to carry out the calculations that are part of that step-by-step procedure.
3. By applying the forecast monitoring procedure outlined in Section 10.4 of the Final Report.

Implementation Guidelines

One purpose of this research was to prepare guidelines for the use of the models developed in this study. The work elements undertaken to accomplish that purpose included review of the related literature, preparation of the data bases, testing different data bases and their formats and stratification, analysis and development of different types of traffic models, forecasts of input variables for which no outside source is available,

evaluation of different models, and development of a monitoring procedure to determine the need for model recalibration. Figures 11.1, 11.2 and 11.3 (extracted from the Final Report) present the process for implementation of the models to forecast traffic on interstate highways, urban principal arterials, and urban minor arterials & collectors, respectively.

The steps that are recommended for the implementation of the elasticity and lag-AADT models to predict the future traffic for urban segment of the state highways and interstate highways of Indiana are listed below.

1. Find the exact location (i.e., city and county) of the roadway for which the forecast is needed.
2. Select the traffic models that will be used to predict traffic.
 - a. Determine the functional class of roadway.

This will determine which models are applicable to the project site. To determine the functional class, the functional classification system map -- prepared by Program Development Division of INDOT -- and the road inventory file of INDOT, will be the two best guides. Moreover, the definitions provided in Table 4.1 of the Final Report would be helpful to find the appropriate highway class. The project site

Figure 11.1: Process for Implementation of the Model on Interstate Highways

Figure 11.2: Process for Implementation of the Model on Urban Principal Arterial

Figure 11.3: Process for Implementation of the Model on Urban Minor Arterial & Collector

will be classified into one of the four categories of highways listed in Table 4.1. If the classification is not clear-cut, then personal judgment should be used, and documentation provided.

b. Examine the area type.

Check if the project site is rural or urban in nature. If the project site is in a rural area for noninterstate highways, then the models developed in the rural phase of this study (Fricker and Saha, 1987) will be applicable to that site. Otherwise, the procedures described in this section will be applied. Suburban segments can be identified as urban segments, because data from suburban segments were included with urban segments in the model building process.

c. Find the geographical region.

Consult Figure 4.2 (taken from the Final Report) to determine the geographical region (north, central and south) of the project site. This finding will be used to select the appropriate model for urban principal arterial models and the regional model of interstate highways.

d. Determine the city group.

Figure 4.2: Suggested Geographical Boundaries of State of Indiana

Find the city group (A, B, C or D) based on the size of the city population. Section 4.6.1 of the Final Report introduced the city group based on 1980 city population, as summarized below.

CTYGR	1980 City Population (1000)
A	30 - 50
B	20 - 30
C	10 - 20
D	5 - 10

In using the forecasting models, population in the base year can be used to determine the city group. For interstate highways, an additional group, A+, was designated for cities with more than 50,000 population in 1980. If the population is not known, a population estimate from the closest census year population to the base year either by ratio method (Section 9.3.1 of the Final Report) or by linear interpolation or extrapolation from city population forecasts in Table F9 in Appendix F. The city group information will be used by the computer program to select models for noninterstate urban highways.

e. Select appropriate models.

The information from steps 2a to 2d are used by the computer program to find the appropriate model(s). Steps 2a and 2b are used to determine

highway class and its area type.

- i. Interstate Highways: The computer program will find the appropriate elasticity models from Final Report Table 6.26, by using the the information obtained on area type (step 2b) and geographical region (2c). For each project site, three alternative models -- regional interstate model, statewide rural or urban interstate model, and regional rural or urban interstate model -- will be identified in this table. Figure 11.1 shows those appropriate models for each case. For instance, if the project site is identified as being in the northern region and in a rural area, then the models A1, B and C1 from Table 6.26 will be the selected for that project site. Similarly, three alternative lag-AADT models will be selected from Final Report Table 8.4.
- ii. Urban Principal Arterial: The information on geographical region (step 2c) and on city group (step 2d) of the project site will be used to find the appropriate elasticity model from Final Report Table 6.27. Similarly, the lag-AADT will be used identified from Final Report Table 8.5.

iii. Urban Minor Arterial & Collector: The city group (step 2d) is the only basis for selecting the appropriate model for this highway category, if the area type (step 2b) and the functional class (step 2a) had identified the project site as "Urban Minor Arterial & Collector". The appropriate elasticity and lag-AADT models will be identified from Final Report Tables 6.28 and 8.6, respectively.

3. Collect the base year AADT ($AADT_b$) and the lag year AADT (LAADT).

The base or lag year may be different from the present/current year, but it is the year for which most recent data needed by the are available. $AADT_b$ (required by the elasticity model) or LAADT (required by the lag-AADT model) for a project site can be one value for a small project (e.g., intersections) or a series of estimates for roadway sections for a larger project (e.g., lane widening). The primary source of data is the Highway Department's Traffic Volume Book. If this source fails to provide such information, then it could be determined from short-term counts at the project site, using the procedures described in Final Report Section 2.7.

4. Collect the base and future year data for the predictor variables used in the elasticity models.

The description of the predictor variables in Section 4.6.3 of the Final Report is a guide to the sources of the required predictor variables. Except vehicle registration and city population forecasts, the forecasts of the predictor variables used in the models are available from outside sources. The combined vehicle registration forecasts developed by time series analysis and presented in Final Report Appendix Table F7 will serve as future year values for vehicle registration at the county and state level. The ratio method of making city population forecasts presented in Appendix Table F9 can be used as required by any model. The lag-AADT models need only the estimate of city population in the base year (if required) to select the appropriate model for noninterstate highways. They do not need any other information for the predictor variables, to forecast traffic.

5. Estimate the future year AADT.

- a. Calculate the future year AADT by using the appropriate elasticity model(s) (Final Report Tables 6.26-6.28), as determined in step 2e, with the values found in steps 3 and 4. Denote the future ("f"-year) AADT estimate from the elasticity (E) model as $AADT_f^E$.

For each interstate highway segment, the average forecasts from the three alternative models will be designated as $AADT_f^E$. Only one forecast will be computed for each noninterstate highway segment.

- b. Calculate the future year AADT by using appropriate lag-AADT model(s) (Final Report Tables 8.4-8.6), as determined in step 2e with the values found in steps 3 and 4. Denote the AADT estimate from the lag-AADT (or "L") model as $AADT_f^L$.
- c. Find the average of the two AADT estimates found in steps 5a and 5b.

$$AADT_f = \left| AADT_f^E + AADT_f^L \right| * 0.5 \quad (11.1)$$

where,

$AADT_f$ = Future year AADT estimate,

$AADT_f^E$ = Future year AADT estimate by Elasticity model(s),

$AADT_f^L$ = Future year AADT estimate by Lag-AADT model(s).

The AADT forecast ($AADT_f$) from Equation (11.1) will be used as the "future year AADT" for the project site. The user may give different weight to the AADT values found in step 5a or step 5b, based on model performance. Equation (11.1) would then be modified to be

$$AADT_f^W = w * AADT_f^E + (1 - w) * AADT_f^L \quad (11.2)$$

where,

$AADT_f^W$ = Weighted AADT estimate,

w = Weight given to AADT estimate from
Elasticity model, $0 < w < 1.00$,

and other terms as defined in Equation (11.1).

In the future, the performance of the models can be used to determine the weight "w" in Equation (11.2). But, based on comparable values of the forecasting measuring criteria (MAE, MAPE, RMSPE and $\bar{Q}$) for the elasticity and lag-AADT models, and improved performance of the combined forecasts, a simple average, shown in Equation (11.1), is recommended at present.

6. Adjust the estimated future year AADT.

If necessary, the forecast from step 5 can be adjusted by using information on changes in fuel price, fuel supply (energy crisis), fleet fuel efficiency (miles per gallon), household size, inflation rate, etc., which have not been included in model formulation because of insufficient information and future uncertainty about those factors. Empirical results can be useful in incorporating such adjustments, if the user has a "feel" for any of these factors. This step is completely optional and it is left to the user to decide whether to modify the forecast values

obtained in step 5. Because of its optional nature, this step was not shown in the process for implementation in Figures 11.1 to 11.3.