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**INFLUENCE OF SPEED LIMITS ON ROADWAY
SAFETY IN INDIANA**

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16. Abstract <p>The influence of speed limits on roadway safety is an extremely important social issue and is subject to an extensive debate in the State of Indiana and nationwide. With roughly 900 fatalities and sixty thousand injuries annually in Indiana, traffic accidents place an incredible social and economic burden on the state. Still, speed limits posted on highways and other roads are routinely exceeded as individual drivers try to balance safety and mobility (speed) as well as risks of penalties from enforcement efforts. This research explores the relationship between speed limits and roadway safety. Specifically, the research focuses on the influence of the posted speed limit on the causation of accidents (the likelihood that unsafe speed would be listed as the primary cause of the accident), the severity of accidents, and speed-limit compliance with an emphasis on speed-limit changes from 65 mph to 70 mph on rural interstates and from 55 mph to 60 mph on select non-freeway multilane rural highways. Data were considered on individual accidents from the Indiana Electronic Vehicle Crash Record System in 2004 and 2006. Data from 2005 were excluded because Indiana raised some interstate and non-interstate speeds in July 1, 2005 – thus making 2005 a transition year as drivers adjusted to new speed limits. With these data, appropriate statistical models were estimated for the causation and severity of different types of accidents on all road classes. The results of the modeling show that higher speed limits did not have a statistically significant effect on the likelihood of unsafe-speed being listed as the primary cause of the accident on interstate highways. For some non-interstate highways, higher speed limits were found to significantly increase the likelihood of unsafe speed being listed as the primary cause of the accident, and for others, the higher speed limits were found to decrease this likelihood. With regard to accident severity, the results show that speed limits did not have a statistically significant effect on the severity of accidents on interstate highways. However, for some non-interstate highways, higher speed limits were found to be associated with higher accident severities – suggesting that future speed limit changes on non-interstates need to be carefully assessed on a case-by-case basis. The findings in this project provide some information to the Indiana Department of Transportation on the potential consequences of future speed-limit policies in the state.</p>			
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TABLE OF CONTENTS

	Page
TABLE OF CONTENTS	ii
LIST OF TABLES	iii
LIST OF FIGURES	iv
CHAPTER 1. INTRODUCTION	1
CHAPTER 2. METHODOLOGY OF STATISTICAL MODELING	10
CHAPTER 3. DATA DESCRIPTION	17
3.1. Accident data for year 2004	18
3.2. Accident data for year 2006	23
CHAPTER 4. ACCIDENT CAUSATION STUDY	27
4.1. Modeling Procedures: accident causation	27
4.2. Results: accident causation models	34
4.2.1. Effect of Speed Limit	35
4.2.2. Effect of Other Explanatory Variables	40
CHAPTER 5. ACCIDENT SEVERITY STUDY	42
5.1. Modeling Procedures: accident severity	42
5.2. Results: accident severity models	44
5.2.1. Effect of Speed Limit	45
5.2.2. Effect of Other Explanatory Variables	51
CHAPTER 6. SPEED LIMITS AND SPEED-LIMIT COMPLIANCE	56
6.1. Effect of Speed Limits on Drivers' Choice of Speed	56
6.2. Data	58
6.3. Methodology	61
6.4. Estimation Results	65
CHAPTER 7. SUMMARY AND CONCLUSIONS	69
LIST OF REFERENCES	74
Appendix A.	78
Appendix B.	81
Appendix C.	108

LIST OF TABLES

Table	Page
Table 4.1 2004 accident causation models: results for speed limit	36
Table 4.2 2006 accident causation models: results for speed limit	37
Table 5.1 2004 accident severity models: results for speed limit	47
Table 5.2 2006 accident severity models: results for speed limit	48
Table 5.3 Speed limit effect on structure of 2004 accident severity models	49
Table 5.4 Speed limit effect on structure of 2006 accident severity models	50
Table 6.1 Survey Questions	60
Table 6.2 Sample statistics (standard deviation in parentheses when appropriate).....	62
Table 6.3 Statistics for variables found to be significant in model estimation	65
Table 6.4 Seemingly unrelated regression equation (SURE) estimation results for the number of miles per hour above the speed limit drivers report as their usual speed (<i>t</i> -statistics in parentheses) ^a	66
Table B.1 Road classes & accident types in 2004 accident causation study	81
Table B.2 Road classes & accident types in 2006 accident causation study	82
Table B.3 Binary logit models for 2004 accident causation	83
Table B.4 Binary logit models for 2006 accident causation	94
Table B.5 Tests of car-SUV separation in 2004 accident causation study	106
Table B.6 Tests of car-SUV separation in 2006 accident causation study	107
Table C.1 Road classes and accident types in 2004 accident severity study..	108
Table C.2 Road classes and accident types in 2006 accident severity study..	109
Table C.3 Speed limit data bins chosen in 2004 accident severity study	110
Table C.4 Speed limit data bins chosen in 2006 accident severity study	111
Table C.5 Multinomial logit models for 2004 accident severity	112
Table C.6 Multinomial logit models for 2006 accident severity	142
Table C.7 Tests of car-SUV separation in 2004 accident severity study	169
Table C.8 Tests of car-SUV separation in 2006 accident severity study	170

LIST OF FIGURES

Figure	Page
Figure 3.1 Percentage distribution of 2004 accidents by road class	19
Figure 3.2 Percentage distribution of 2004 accidents by their type	19
Figure 3.3 Percentage distribution of 2004 accidents by their causation	20
Figure 3.4 Percentage distribution of 2004 accidents by their severity level	21
Figure 3.5 Percentage distributions of 2004 accidents by their causation in four different speed limit data bins.....	21
Figure 3.6 Percentage distributions of 2004 accidents by their severity level in four different speed limit data bins	22
Figure 3.7 Percentage distribution of 2006 accidents by road class	23
Figure 3.8 Percentage distribution of 2006 accidents by their type	24
Figure 3.9 Percentage distribution of 2006 accidents by their causation	24
Figure 3.10 Percentage distribution of 2006 accidents by their severity level ...	25
Figure 3.11 Percentage distributions of 2006 accidents by their causation in four different speed limit data bins.....	25
Figure 3.12 Percentage distributions of 2006 accidents by their severity level in four different speed limit data bins	26
Figure 4.1 Data division by road class and by accident type.....	29
Figure 4.2 Model estimation procedures	31
Figure 4.3 T-ratios of statistically significant speed limit coefficients in 2004 accident causation models	39
Figure 4.4 T-ratios of statistically significant speed limit coefficients in 2006 accident causation models	39
Figure 6.1 The effect of Speed Limits on Driving Speed	57

CHAPTER 1. INTRODUCTION

Speed-limit changes that took effect on July 1, 2005, made Indiana the 30th U.S. state to raise rural interstate speed limits up to 70 mph (for vehicles under 13 tons). The top speed limit value was increased on some portions of the state's interstate highway system from 65 mph to 70 mph. Speed limits were also increased on some non-interstate, non-freeway rural multilane highways from 55 mph to 60 mph. This increase intensified an important debate in the engineering community on the tradeoff between highway mobility (speed) and safety. On one hand, as speed increases, travel times decrease, which reduces transportation costs and leads to an increased productivity and a noticeable positive effect for the national economy. On the other hand, higher speed can possibly have a negative effect on roadway safety.

The relationship between speed limits and roadway safety is not as obvious as it may seem. The reason is that there are several important issues in this relationship. From the basic physics involved, as speed increases, vehicles have higher kinetic energy, travel larger distances during human reaction times, and vehicles are exposed to stronger aerodynamic and centrifugal forces. This tends to increase accident frequency and severity. But there are factors that may work against this. For example, as speed limits increase, the variance of vehicle speeds may decrease, resulting in easier and safer driving conditions. In addition, there are other influences, such as the intensity of police enforcement of posted speed-limit compliance and the engineering design characteristics with relating to roadway design speed. As a result, the overall effect of a speed limit increase on road safety can be ambiguous, and requires

a thorough study. Such a study and a detailed analysis of the relationship between speed limits and safety on Indiana roads will be undertaken in this project.

In general, there are two measures of road safety that are commonly considered:

1. The first measure evaluates accident frequencies on roadway sections. The accident frequency on a road section is obtained by counting the number of accidents occurring on this section during a specified period of time. Then count-data statistical models (e.g. Poisson, negative binomial models and their zero-inflated counterparts) are typically estimated for accident frequencies on different road sections. The explanatory variables used in these models are the road section characteristics (e.g. road section length, curvature, slope, type, etc).
2. The second measure evaluates accident severity outcomes as determined by the injury level sustained by the most severely injured individual (if any) involved into the accident. This evaluation is done by using data on *individual* accidents and estimating discrete outcome statistical models (e.g. ordered probit and multinomial logit models) for the accident severity outcomes. The explanatory variables used in these models are the individual accident characteristics (e.g. time and location of an accident, weather conditions and road characteristics at the accident location, characteristics of the vehicles and drivers involved, etc).

These two measures of road safety are complementary – an accident frequency study gives a statistical model of the probability of an accident occurring on a road section and an accident severity study gives a statistical model of the conditional probability of a severity outcome of an accident, given an accident has occurred.

There are a considerable number of road-safety studies that consider one or both of the two road safety measures described above. Some of the key studies include the following:

- Shankar et al. (1996) used a nested logit model for statistical analysis of accident severity outcomes on rural highways in Washington State. They found that environment conditions, highway design, accident type, driver and vehicle characteristics significantly influence accident severity. They found that overturn accidents, rear-end accidents on wet pavement, fixed-object accidents, and failures to use the restraint belt system lead to higher probabilities of injury or/and fatality accident outcomes, while icy pavement and single-vehicle collisions lead to higher probability of property damage only outcomes.
- Shankar et al. (1997) studied the distinction between safe and unsafe road sections by estimating zero-inflated Poisson and zero-inflated negative binomial models for accident frequencies in Washington State (for these models the zero state corresponds to near zero accident likelihood on safe road sections).
- Duncan et al. (1998) applied an ordered probit model to injury severity outcomes in truck-passenger car rear-end collisions in North Carolina. They found that injury severity is increased by darkness, high speed differentials, high speed limits, wet grades, drunk driving, and being female.
- Karlaftis and Tarko (1998) considered heterogeneous panel data for frequencies of accidents occurred in Indiana over a 6-year period. They developed an improved method of accident frequency modeling in panel data, which is based on a two-step approach: first, heterogeneous data is divided into homogeneous groups by determining (dis)similarities and using cluster analysis; second, negative binomial models are estimated separately for each homogeneous data group. The results obtained by Karlaftis and Tarko clearly indicate that there are significant differences

between the accident frequency models estimated for urban, suburban and rural counties.

- Chang and Mannering (1999) focused on the effects of trucks and vehicle occupancies on accident severities. They estimated nested logit models for severity outcomes of truck-involved and non-truck-involved accidents in Washington State and found that accident injury severity is noticeably worsened if the accident has a truck involved, and that the effects of trucks are more significant for multi-occupant vehicles than for single-occupant vehicles.
- Carson and Mannering (2001) studied the effect of ice warning signs on ice-accident frequencies and severities in Washington State. They modeled accident frequencies and severities by using zero-inflated negative binomial and logit models respectively. They found that the presence of ice warning signs was not a significant factor in reducing ice-accident frequencies and severities.
- Khattak (2001) estimated ordered probit models for severity outcomes of multi-vehicle rear-end accidents in North Carolina. In particular, the results of his research indicate that in two-vehicle collisions the leading driver is more likely to be severely injured, in three-vehicle collisions the driver in the middle is more likely to be severely injured, and being in a newer vehicle protects the driver in rear-end collisions.
- Ulfarsson (2001) and Ulfarsson and Mannering (2004) focused on male and female differences in analysis of accident severity. They used multinomial logit models and accident data from Washington State. They found significant behavioral and physiological differences between genders, and also found that probability of fatal and disabling injuries is higher for females as compared to males.
- Kockelman and Kweon (2002) applied ordered probit models to modeling of driver injury severity outcomes. They used a nationwide accident data

sample and found that pickups and sport utility vehicles are less (more) safe than passenger cars in single-vehicle (two-vehicle) collisions.

- Lee and Mannering (2002) estimated zero-inflated count-data models and nested logit models for frequencies and severities of run-off-roadway accidents in Washington State. They found that run-off-roadway accident frequencies can be reduced by avoiding cut side slopes, decreasing (increasing) the distance from outside shoulder edge to guardrail (light poles), and decreasing the number of isolated trees along roadway. The results of their research also show that run-off-roadway accident severity is increased by alcohol impaired driving, high speeds, and the presence of a guardrail.
- Abdel-Aty (2003) used ordered probit models for analysis of driver injury severity outcomes at different road locations (roadway sections, signalized intersections, toll plazas) in Central Florida. He found higher probabilities of severe accident outcomes for older drivers, male drivers, those not wearing seat belt, drivers who speed, those who drive vehicles struck at the driver's side, those who drive in rural areas, and drivers using electronic toll collection device (E-Pass) at toll plazas.
- Kweon and Kockelman (2003) studied probabilities of accidents and accident severity outcomes for a given fixed driver exposure (which is defined as the total miles driven). They used Poisson and ordered probit models, and considered a nationwide accident data sample. After normalizing accident rates by driver exposure, the results of their study indicate that young drivers are far more crash prone than other drivers, and that sport utility vehicles and pickups are more likely to be involved in rollover accidents.
- Yamamoto and Shankar (2004) applied bivariate ordered probit models to an analysis of driver's and passenger's injury severities in collisions with fixed objects. They considered a 4-year accident data sample from Washington State and found that collisions with leading ends of guardrail

and trees tend to cause more severe injuries, while collisions with sign posts, faces of guardrail, concrete barrier or bridge and fences tend to cause less severe injuries. They also found that proper use of vehicle restraint system strongly decreases the probability of severe injuries and fatalities.

- Khorashadi et al. (2005) explored the differences of driver injury severities in rural and urban accidents involving large trucks. Using 4-years of California accident data and multinomial logit model approach, they found considerable differences between rural and urban accident injury severities. In particular, they found that the probability of severe/fatal injury increases by 26% in rural areas and by 700% in urban areas when a tractor-trailer combination is involved, as opposed to a single-unit truck being involved. They also found that in accidents where alcohol or drug use is identified, the probability of severe/fatal injury is increased by 250% and 800% in rural and urban areas respectively.
- Islam and Mannering (2006) studied driver aging and its effect on male and female single-vehicle accident injuries in Indiana. They employed multinomial logit models and found significant differences between different genders and age groups. Specifically, they found an increase in probabilities of fatality for young and middle-aged male drivers when they have passengers, an increase in probabilities of injury for middle-aged female drivers in vehicles 6 years old or older, and an increase in fatality probabilities for males older than 65 years old.
- Savolainen (2006), Savolainen and Mannering (2006a) and Savolainen and Mannering (2006b) focused on an important topic of motorcycle safety on Indiana roads. He used multinomial and nested logit models and found that poor visibility, unsafe speed, alcohol use, not wearing a helmet, right-angle and head-on collisions, and collisions with fixed objects cause more severe motorcycle-involved accidents.

As far, as the relationship between speed and road safety is concerned two general findings have emerged. First, on all road classes (urban streets, highways, etc) vehicle operating speeds tend to exceed the posted speed limit (Renski et al., 1999; Khan, 2002). Second, there are no sure indications that a reasonable increase in speed limit has a considerable negative impact on traffic safety. For example, O'Donnell and Connor (1996) estimated logit and probit models for injury severity outcomes of accidents in Australia and determined that effects of an increase in vehicle speed from 42 to 100 kilometers per hour (from 26.1 mph to 62.1 mph) are surprisingly small. Shankar et al. (1997) used zero-inflated Poisson and zero-inflated negative binomial models for a study of accident frequencies. They found that a speed limit increase reduced accident frequencies on road sections in the Western part of Washington State, and had no statistically significant effect on accident frequencies in the Eastern part. Very similar results were obtained by Milton and Mannering (1998), who estimated negative binomial models for frequencies of accidents on sections of principal arterials in Washington State in 1992 and 1993 and found a reduction of the frequencies with a speed limit increase. Renski et al. (1999) specifically addressed the effect of speed limit on injury severity outcomes in single-vehicle accidents on interstate highways in North Carolina. They used a paired-comparison analysis and ordered probit modeling. They found that while increasing speed limits from 55 to 60 mph and from 55 to 65 mph increased the probability of sustaining minor and non-incapacitating injuries, increasing speed limits from 65 to 70 mph did not have a significant effect on accident severity. An analysis of speed limit policies for Indiana was recently carried out by Khan (2002). He found that while previous upward changes in speed limits in Indiana during the past two decades did increase speeds observed on roads, there was no statistically significant evidence to indicate that such increases had a negative impact on safety.

In the present study we focus on the relationship between the posted speed limit and road safety. We consider data on individual accidents and use statistical and econometric methodologies to analyze three discrete outcomes. In doing so, our study differs from the previous studies in the analysis of vehicle accident data in that we study both the severity and causation of accidents. We use as a basis for our statistical modeling data compiled from Indiana accident databases for different types of accidents (single-vehicle accidents, car or SUV versus truck accidents, etc) and for all classes of roads (interstate highways, urban streets, US routes, etc).

To statistically assess the effect that speed limits have on roadway safety, we will study the following:

1. **The relationship between speed limits and the primary cause of the accident.** The idea here is to study a relationship between the posted speed limit and the probability of unsafe and/or excessive speed being the primary cause of the accident by the officer at the scene of the accident. This is to be done by estimating of appropriate statistical models for the unsafe-speed-related accident causation. However, considerable caution must be exercised when interpreting the results of this analysis because the determination of the officer at the accident scene as to what constitutes the primary cause is an opinion that may be influenced by a multitude of factors. The consistency of these responses across officers and accidents is likely to be questionable. Still, we provide the analysis with this caveat in mind.
2. **The relationship between speed limits and the injury severity of the accident.** For this we will estimate statistical models for the level of accident severity (determined by the injury level sustained by the most critically injured individual in the accident) which are defined as three discrete outcomes: no-injury, injury and fatality. We will statistically test whether the posted speed limit has any effect on accident severity.

3. **Factors that determine the effect that speed limits have on drivers' speed.** We will study the self reported speeding behavior of drivers on interstate highways by looking at the speed they normally drive on interstate highways with posted speed limits of 55 mph, 65 mph and 70 mph. Although there are obvious limitations in using self-reported data, the statistical assessment of these data will still provide some insights even with these limitations in mind.

To understand the effect of speed limits on safety, while modeling accident causation and severity, we will control for other possible confounding effects, such as road characteristics, weather conditions, driver characteristics, and so on. To increase the predictive power of our models, we will consider accidents separately for each combination of accident type and road class (e.g. single-vehicle accidents on urban streets will be considered separately from car-truck accidents on interstate highways). The use of the above two accident modeling approaches will provide important new insights and sufficient statistical evidence on the effect of the posted speed limit on roadway safety. And, statistically modeling self-reported speed limit compliance will provide some insight into how driver behavior may be changing in response to increased speed limits.

CHAPTER 2. METHODOLOGY OF STATISTICAL MODELING

Our study deals with accident causation and accident severity, both are non-quantitative discrete outcomes of traffic accidents. The most widely used statistical models for non-count data that is composed of discrete outcomes are the multinomial logit model and the ordered probit model. However, there are two potential problems with applying ordered probability models to accident severity outcomes (Savolainen and Mannering 2006b). The first is related to the fact that non-injury accidents are likely to be under-reported in accident data because they are less likely to be reported to authorities. The presence of under-reporting in an ordered probability model can result in biased and inconsistent model coefficient estimates. In contrast, the coefficient estimates of an unordered multinomial logit probability model are consistent except for the constant terms (Washington et. al. 2003, page 279). The second problem is related to undesirable restrictions that ordered probability models place on influences of the explanatory variables (Washington et. al. 2003, page 294). As a result, in our research study we use and estimate binary and multinomial logit models for accident causation and severity.

The multinomial logit model can be introduced as follows. Let there be N available data observations and I possible discrete outcomes in each observation. Then in the multinomial logit model the probability $P_n^{(i)}$ of the i^{th} outcome in the n^{th} observation is specified by equation (Washington et al., 2003, page 263)

$$P_n^{(i)} = \frac{\exp(\beta_i' \mathbf{X}_{in})}{\sum_{j=1}^I \exp(\beta_j' \mathbf{X}_{jn})}, \quad i = 1, 2, 3, \dots, I, \quad n = 1, 2, 3, \dots, N. \quad \text{Eq. 2.1}$$

Here $\mathbf{X}_{in}$ is the vector of explanatory variables for the n^{th} observation and β_i is the vector of model coefficients to be estimated (β_i' is the transpose of β_i). We use a conventional assumption that the first component of vector $\mathbf{X}_{in}$ is equal to unity, and therefore, the first component of vector β_i is the intercept in linear product $\beta_i' \mathbf{X}_{in}$. Note that $P_n^{(i)}$, given by Equation (2.1), is a valid probability set for I discrete outcomes because the necessary and sufficient conditions $P_n^{(i)} \geq 0$ and $\sum_{i=1}^I P_n^{(i)} = 1$ are obviously satisfied¹.

We can multiply the numerator and denominator of the fraction in Equation (2.1) by an arbitrary number without any change of the probabilities. As a result, without any loss of generality we can set one of the intercepts to zero. We choose the first component of vector β_i to be zero in this case. Moreover, if the vector of explanatory variables does not depend on discrete outcomes, i.e. if $\mathbf{X}_{in} \equiv \mathbf{X}_n$, then without any loss of generality we can set one of vectors of model coefficients to zero. We choose vector β_i to be zero in this case.

Because accidents are independent events, the likelihood function L and the log-likelihood function LL for the set of probabilities given in Equation (2.1) are obviously equal to

$$L = \prod_{n=1}^N \prod_{i=1}^I [P_n^{(i)}]^{\delta_{in}}, \quad LL = \sum_{n=1}^N \sum_{i=1}^I \delta_{in} P_n^{(i)}, \quad \text{Eq. 2.2}$$

where δ_{in} is defined to be equal to unity if the i^{th} discrete outcome is observed in the n^{th} observation and to zero otherwise.

¹ Equation (2.1) can formally be derived by using a linear specification $U_{in} \equiv \beta_i' \mathbf{X}_{in} + \tilde{\varepsilon}_{in}$, by defining $P_n^{(i)} = \text{Prob} \left\{ U_{in} \geq \max_{j \neq i} (U_{jn}) \right\}$ and by choosing the Gumbel (Type I) extreme value distribution for the i.i.d. random error terms $\tilde{\varepsilon}_{in}$. For details see Washington et al., 2003.

Now we assume that the explanatory variables vector is independent of the discrete outcomes, $\mathbf{X}_{in} \equiv \mathbf{X}_n$, and consider two simple special cases of the multinomial logit model. First, if there are just two possible discrete outcomes, $I = 2$ and $i = 1, 2$, then in this case the model becomes a binary logit model, and Equation (2.1) simplifies to

$$P_n^{(1)} = \frac{\exp(\beta_1' \mathbf{X}_n)}{\exp(\beta_1' \mathbf{X}_n) + 1}, \quad P_n^{(2)} = \frac{1}{\exp(\beta_1' \mathbf{X}_n) + 1}, \quad \text{Eq. 2.3}$$

where there is only one coefficient vector β_1 to be estimated. Second, if there are three possible discrete outcomes, $I = 3$ and $i = 1, 2, 3$, then in this case Equation (2.1) simplifies to

$$\begin{aligned} P_n^{(1)} &= \frac{\exp(\beta_1' \mathbf{X}_n)}{\exp(\beta_1' \mathbf{X}_n) + \exp(\beta_2' \mathbf{X}_n) + 1}, \\ P_n^{(2)} &= \frac{\exp(\beta_2' \mathbf{X}_n)}{\exp(\beta_1' \mathbf{X}_n) + \exp(\beta_2' \mathbf{X}_n) + 1}, \\ P_n^{(3)} &= \frac{1}{\exp(\beta_1' \mathbf{X}_n) + \exp(\beta_2' \mathbf{X}_n) + 1}, \end{aligned} \quad \text{Eq. 2.4}$$

where there are two coefficient vectors β_1 and β_2 to be estimated. We will use these special-case logit models in the next two chapters.

It is customary to use the maximum likelihood method to estimate unknown vectors of coefficients β_i in the logit models given by Equations (2.1), (2.3) and (2.4). Namely, one finds such values of the unknown coefficients that the likelihood function (and correspondingly the log-likelihood function) given by Equation (2.2) reaches its global maximum. In the present study we use econometric software package LIMDEP for all model estimations by means of the maximum likelihood method². We also use MATLAB software package for initial processing of data.

² LIMDEP can be found at <http://www.limdep.com>, we use Version 7.0 in our study.

In the next chapters we will need to compare several estimated models in order to infer if there are statistically significant differences among these models. As a result, here we would like to demonstrate how model comparisons are done by using a likelihood ratio test. Assume that we have divided a data sample into different data bins. The likelihood ratio test uses the model estimated for the whole data sample and the models separately estimated for each data bin. The test statistic is (Washington et al., 2003, page 244)

$$-2 \left[LL(\boldsymbol{\beta}) - \sum_{m=1}^M LL(\boldsymbol{\beta}_m) \right] \sim \chi^2_{df=(M-1) \times K}, \quad \text{Eq. 2.5}$$

where $LL(\boldsymbol{\beta})$ is the log-likelihood of the model estimated for the whole data sample and $\boldsymbol{\beta}$ is the vector of coefficients estimated for this model; $LL(\boldsymbol{\beta}_m)$ is the log-likelihood of the model estimated for observations in the m^{th} data bin and $\boldsymbol{\beta}_m$ is the vector of coefficients estimated for this model ($m = 1, 2, 3, \dots, M$); M is the number of the data bins; K is the number of coefficients estimated for each model (i.e. K is the length of vectors $\boldsymbol{\beta}$ and $\boldsymbol{\beta}_m$)³; $\chi^2_{df=(M-1) \times K}$ is the chi-squared distribution with $(M-1) \times K$ degrees of freedom (df). The zero-hypothesis for the test statistic given by Equation (2.5) is that the model estimated for the whole data sample and the combination of the M models separately estimated for the data bins, are statistically the same. In other words, for a chosen confidence level π if the left-hand-side of Equation (2.5) is between zero and the $(1-\pi)^{\text{th}}$ percentile of the chi-squared distribution given on the right-hand-side, then we conclude that the division of the data into different bins makes no statistically significant difference for the model estimation. We conclude that there is a difference otherwise.

³ Note that the left-hand-side of Equation (2.5) is always non-negative because a combination of models separately estimated for data bins always provides a fit which is at least as good as the fit for the whole data sample.

At the end of this chapter we describe how the magnitude of the influence of specific explanatory variables on the discrete outcome probabilities can be measured. This is done by elasticity computations (Washington et al., 2003, page 271). Elasticities $E_{X_{jn,k}}^{P_n^{(i)}}$ are computed from the partial derivatives of the outcome probabilities for the n^{th} observation as

$$E_{X_{jn,k}}^{P_n^{(i)}} = \frac{\partial P_n^{(i)}}{\partial X_{jn,k}} \cdot \frac{X_{jn,k}}{P_n^{(i)}}, \quad i, j = 1, \dots, I, \quad n = 1, \dots, N, \quad k = 1, \dots, K. \quad \text{Eq. 2.6}$$

Here $P_n^{(i)}$ is the probability of outcome i given by Equation (2.1), $X_{jn,k}$ is the k^{th} component of the vector of explanatory variables $\mathbf{X}_{jn}$ that enters the formula for the probability of outcome j , and K is the length of this vector. If $j = i$, then the elasticity given by Equation (2.6) is called *direct* elasticity, otherwise, if $j \neq i$, then the elasticity is called *cross* elasticity. The direct elasticity of the outcome probability $P_n^{(i)}$ with respect to variable $X_{in,k}$ measures the percent change in $P_n^{(i)}$ that results from an infinitesimal percentage change in $X_{in,k}$. Note that $X_{in,k}$ directly enters the numerator of the formula for $P_n^{(i)}$, as given by Equation (2.1). The cross elasticity of $P_n^{(i)}$ with respect to variable $X_{jn,k}$ measures the percent change in $P_n^{(i)}$ that results from an infinitesimal percentage change in $X_{jn,k}$. Note that $X_{jn,k}$ enters the numerator of the formula for the probability $P_n^{(j)}$ of the outcome j , which is different from outcome i . Thus, cross elasticities measure indirect effects that arise from the fact that the outcome probabilities must sum to unity, $\sum_{i=1}^I P_n^{(i)} = 1$. If the absolute value of the computed elasticity $E_{X_{jn,k}}^{P_n^{(i)}}$ of explanatory variable $X_{jn,k}$ is less than unity, then this variable is said to be inelastic, and the resulting percentage change in the outcome probability $P_n^{(i)}$ will be less (in its absolute value) than a percentage change in the variable. Otherwise, the variable is said to be elastic.

Using Equation (2.1) and calculating the derivatives in Equation (2.6), we obtain the formulas for the direct and cross elasticities of explanatory variables in the multinomial logit model:

$$\begin{aligned} E_{X_{in,k}}^{P_n^{(i)}} &= [1 - P_n^{(i)}] \cdot \beta_{i,k} X_{in,k} && \text{for direct elasticities;} \\ E_{X_{jn,k}}^{P_n^{(i)}} &= -P_n^{(j)} \cdot \beta_{j,k} X_{jn,k} && \text{for cross elasticities, } j \neq i. \end{aligned} \quad \text{Eq. 2.7}$$

Here $\beta_{i,k}$ is the k^{th} component of the vector of the model estimable coefficients in the formula for the probability $P_n^{(i)}$ of outcome i [refer to Equation (2.1)]. If the explanatory variables vector is independent of the discrete outcomes, $\mathbf{X}_{in} \equiv \mathbf{X}_n$, then Equations (2.7) stay valid with $X_{in,k} \equiv X_{jn,k} \equiv X_{n,k}$.

It is customary to report averaged elasticities, which are the elasticities averaged over all observations (i.e. averaged over $n = 1, 2, 3, \dots, N$). Let us consider the cases of two and three possible discrete outcomes, given by Equations (2.3) and (2.4) respectively, and let us average the elasticities given by Equations 2.7) over all observations. Then we find the averaged direct and cross elasticities. In the case of two discrete outcomes ($i = 1, 2$) we obtain

$$\begin{aligned} \bar{E}_{1;X_k}^{(1)} &= \left\langle E_{X_{1n,k}}^{P_n^{(1)}} \right\rangle_n = \left\langle [1 - P_n^{(1)}] \cdot \beta_{1,k} X_{n,k} \right\rangle_n && \text{averaged direct elasticity;} \\ \bar{E}_{1;X_k}^{(2)} &= \left\langle E_{X_{1n,k}}^{P_n^{(2)}} \right\rangle_n = -\left\langle P_n^{(1)} \cdot \beta_{1,k} X_{n,k} \right\rangle_n && \text{averaged cross elasticity.} \end{aligned} \quad \text{Eq. 2.8}$$

In the case of three discrete outcomes ($i = 1, 2, 3$) we obtain

$$\begin{aligned} \bar{E}_{1;X_k}^{(1)} &= \left\langle E_{X_{1n,k}}^{P_n^{(1)}} \right\rangle_n = \left\langle [1 - P_n^{(1)}] \cdot \beta_{1,k} X_{n,k} \right\rangle_n && \text{averaged direct} \\ \bar{E}_{2;X_k}^{(2)} &= \left\langle E_{X_{2n,k}}^{P_n^{(2)}} \right\rangle_n = \left\langle [1 - P_n^{(2)}] \cdot \beta_{2,k} X_{n,k} \right\rangle_n && \text{elasticities;} \\ \bar{E}_{1;X_k}^{(2)} &= \bar{E}_{1;X_k}^{(3)} = \left\langle E_{X_{1n,k}}^{P_n^{(2,3)}} \right\rangle_n = -\left\langle P_n^{(1)} \cdot \beta_{1,k} X_{n,k} \right\rangle_n && \text{averaged cross} \\ \bar{E}_{2;X_k}^{(1)} &= \bar{E}_{2;X_k}^{(3)} = \left\langle E_{X_{2n,k}}^{P_n^{(1,3)}} \right\rangle_n = -\left\langle P_n^{(2)} \cdot \beta_{2,k} X_{n,k} \right\rangle_n && \text{elasticities.} \end{aligned} \quad \text{Eq. 2.9}$$

Here brackets $\langle \dots \rangle_n$ means averaging over all observations $n = 1, 2, 3, \dots, N$.

All elasticity formulas given above are applicable only when explanatory variable $X_{jn,k}$ used in the outcome probability model is continuous. In the case when $X_{jn,k}$ takes on discrete values, the elasticities given by Equation (2.6) can not be calculated, and they are replaced by *pseudo-elasticities* (for example, see Washington et al., 2003, page 272). The later are given by the following equation, which is an obvious discrete counterpart of Equation (2.6),

$$E_{X_{jn,k}}^{P_n^{(i)}} = \frac{\Delta P_n^{(i)}}{\Delta X_{jn,k}} \cdot \frac{X_{jn,k}}{P_n^{(i)}}, \quad i, j = 1, \dots, I, \quad n = 1, \dots, N, \quad k = 1, \dots, K. \quad \text{Eq. 2.10}$$

Here $\Delta P_n^{(i)}$ denotes the resulting discrete change in the probability of outcome i due to discrete change $\Delta X_{jn,k}$ in variable $X_{jn,k}$. We will neither calculate nor use pseudo-elasticities in the present research study.

CHAPTER 3. DATA DESCRIPTION

The accident data used in the present study is from the Indiana Electronic Vehicle Crash Record System (EVCRS). The EVCRS was launched in 2004 and includes available information on all accidents investigated by Indiana police starting from January 1, 2003.

The information on accidents included into the EVCRS can be divided into three major categories⁴:

1. An Environmental Record – it includes information on circumstances related to an accident. For example, weather, roadway and traffic conditions, number of dead and injured people involved, etc.
2. A Vehicle and Driver Record – it includes information on all vehicles involved into an accident and on all drivers of these vehicles. For example, accident contributing factors by each vehicle, type and model of each vehicle, posted speed limit for each vehicle, driver's injury status, driver's age and gender, driver's name and address, etc.
3. Non-driver Individual Record – it includes information on all people who are involved into an accident but are not drivers. This record includes only the name and address of those people, but it does not include any information on their injuries (if any).

⁴ Note that accident data is subject to missing observations and typos. In addition, there can be misidentification errors on police crash reports due police officers' mistakes and prejudices. We eliminate obvious typos during initial data processing and exclude missing observations, but we do not correct for concealed typos and unobserved misidentification errors. Such correction can be done under the Bayesian statistics and Markov Chain Monte Carlo (MCMC) simulations framework, in which one introduces and estimates auxiliary unobserved state variables that indicate unobserved errors (Tsay, 2002, page 413). This is beyond the scope of our study. We assume that police misidentification errors are sufficiently small not to affect our final results.

In our study we use only information from the first two categories above. These two categories include 127 variables for each accident, which is an abundance of data. However, we do not need to consider all these variables. Indeed, because our study focuses on accident causation and severity, we choose all information and all data variables that can reasonably be related to the subject of our study, and we consider only these variables. For example, we do not consider the name of the road where an accident took place and the license plate numbers of the vehicles involved because we can reasonably expect that these variables do not contribute to the accident cause and severity. The list of all variables that we consider and their explanation is given in Appendix A.

In the present study we use data on 204,382 accidents that occurred in 2004 and 182,922 accidents that occurred in 2006. We do not consider 2005 accidents because in 2005 the top speed limit value was raised on some portions of Indiana interstate highways from 65 to 70 mph, and we would like to separate our research results and conclusions from the effects of drivers' adjustment to new speed limit values.

3.1. Accident data for year 2004

The percentage distributions of 2004 accidents by road class and by accident type are given in Figure 3.1 and Figure 3.2 respectively⁵.

⁵ For convenience, from each of the percentage distribution plot we exclude accidents for which the considered descriptive variable (e.g. road class or accident type) is unknown.

Figure 3.1 Percentage distribution of 2004 accidents by road class

Figure 3.2 Percentage distribution of 2004 accidents by their type

As stated above, the goal of our study is to analyze the effect of speed limit on unsafe-speed-related causation and severity of accidents. As a result, first, we plot the percentage distributions of all 2004 accidents by their causation and severity level in Figure 3.3 and Figure 3.4 respectively. Second, we divide 2004 accidents into four different speed limit data bins, which respectively include accidents that occurred on roads with low (≤ 30 mph), medium-low (> 30 mph but ≤ 50 mph), medium-high (> 50 mph but ≤ 60 mph) and high (> 60 mph) speed limits. Finally, we plot the percentage distributions by accident causation and severity level separately for accidents in each of these chosen speed limit bins. The plots are given in Figure 3.5 and Figure 3.6.

Figure 3.3 Percentage distribution of 2004 accidents by their causation

Figure 3.4 Percentage distribution of 2004 accidents by their severity level

Figure 3.5 Percentage distributions of 2004 accidents by their causation in four different speed limit data bins

Figure 3.6 Percentage distributions of 2004 accidents by their severity level in four different speed limit data bins

We can make some interesting observations by using the plots in Figure 3.5 and Figure 3.6. First, from Figure 3.5 it seems that the probability of unsafe and/or excessive speed being the primary cause of an accident grows with speed limit. Second, from Figure 3.6 it seems that the posted speed limit does not have a clearly pronounced and easily understandable effect on the severity level of an accident. Indeed, the probabilities of fatality and injury appear to decrease for very high speed limit values (> 60 mph). However, we must keep in mind that mathematical relations (or absence of them) inferred from simple descriptive statistics can be spurious. The main reason is that different explanatory variables can be (and usually are) mutually dependent, which greatly complicates the inference problem. Thus, it can well be the case that some other variables impact accident causation and severity, while speed limit simply happens to be correlated with these other variables. As a result, to truly understand the effect of speed limit on accident causation and severity, one has to control for all other relevant variables in making an inference about the effect

of speed limit. This is done by building appropriate statistical models, and this is the main subject of our research, which is presented in the next two Chapters.

3.2. Accident data for year 2006

Now let us describe 2006 accident data that we use. The percentage distributions of 2006 accidents by road class and by accident type are given in Figure 3.7 and Figure 3.8 respectively. The percentage distributions of 2006 accidents by their causation and severity level are plotted in Figure 3.9 and Figure 3.10 respectively. We divide 2006 accidents into four different speed limit data bins the same way as we divided 2004 accidents. The percentage distributions by accident causation and severity level are calculated for 2006 accidents that are inside each of these four speed limit bins and are plotted in Figure 3.11 and Figure 3.12.

Figure 3.7 Percentage distribution of 2006 accidents by road class

Figure 3.8 Percentage distribution of 2006 accidents by their type

Figure 3.9 Percentage distribution of 2006 accidents by their causation

Figure 3.10 Percentage distribution of 2006 accidents by their severity level

Figure 3.11 Percentage distributions of 2006 accidents by their causation in four different speed limit data bins

Figure 3.12 Percentage distributions of 2006 accidents by their severity level in four different speed limit data bins

Using the plots in Figure 3.11 and Figure 3.12, we make the same observations for 2006 accidents as those made for 2004 accidents. First, it again seems that the probability of unsafe and/or excessive speed being the primary cause of an accident grows with speed limit (refer to Figure 3.11). Second, from Figure 3.12 it seems that the posted speed limit does not have a clearly pronounced effect on the severity level of an accident because the probabilities of fatality and injury appear to decrease for very high speed limit values (> 60 mph). However, we again can not make definite inference on the effect of the speed limit from these observations without building appropriate statistical models for accident causation and severity.

CHAPTER 4. ACCIDENT CAUSATION STUDY

In this chapter we study the unsafe-speed-related causation of accidents and its dependence on the posted speed limit and other explanatory variables that characterize accidents. Below, we first explain how we use the available accident data and estimate statistical models for unsafe-speed-related causation. Then, we present the results obtained from the estimation of these models for accidents that happened in Indiana in 2004 and 2006.

4.1. Modeling Procedures: accident causation

There exists one primary cause of each accident, as identified by a police officer in his report on this accident⁶. All possible accident primary causes are classified into three categories:

1. Driver-related contributing circumstances (e.g. unsafe speed, speed too fast for weather conditions, driver illness, improper passing, etc.).
2. Vehicle-related contributing circumstances (e.g. tire failure or defective, brake failure or defective, etc.).
3. Environment-related contributing circumstances (e.g. animal on roadway, roadway surface condition, glare, etc.).

Here we are interested in an unsafe and/or excessive speed being the primary cause of an accident and its dependence on the posted speed limit. As a result, we introduce an indicator (dummy) variable that is equal to unity if the primary cause of an accident is either “unsafe speed” or “speed too fast for weather conditions” and is equal to zero for any other primary cause. We then estimate

⁶ For potential problems with primary cause identification see footnote 4 on page 17.

binary logit models with two possible outcomes that are determined by this indicator variable, refer to equation (2.3).

To uncover the direct influence of the posted speed limit on the accident primary cause, we need to control for other explanatory variables that might also affect accident causation. Examples of these other variables are weather conditions, accident time and date, vehicle and driver characteristics, and so on. All explanatory variables can be divided into two distinct types. First, there are indicator (dummy) variables that are equal to unity if some particular conditions are satisfied, and are equal to zero otherwise. Examples of indicator variables are driver's gender indicator, weekend indicator and precipitation indicator. Second, there are quantitative variables that take on meaningful quantitative values, such as driver's age, speed limit and number of fatalities. In addition, one can easily define derivative indicator variables that are obtained from quantitative variables. For example, one can define a "young driver" indicator as being equal to unity if the driver's age is below 25. When estimating models, we frequently define and use the most useful (as judged by the model likelihood function) new derivative indicator variables that are based on quantitative variables.

Because results of safety analysis vary significantly across different road classes and accident types (Karlaftis and Tarko, 1998; Chang and Mannering, 1999; Khan, 2002; Kweon and Kockelman, 2003; Ulfarsson and Mannering, 2004; Khorashadi et al., 2005), we divide accident data by road class and accident type as shown in Figure 4.1, and we estimate the accident causation models separately for each road-class-accident-type combination. Note that we do not consider accidents with two trucks involved and with more than two vehicles involved (there are less than 12.1% of such accidents, see Figure 3.2 and Figure 3.8). For all two-vehicle accident types other than two-truck accidents, we test whether cars and SUVs can be considered together or must

be considered separately (refer to the additional division shown inside the dotted box in Figure 4.1). This test is done by using the likelihood ratio test, which is explained in CHAPTER 2. The complete list of combinations of different road classes and accident types that we consider in our causation study of 2004 and 2006 accidents can be found in Table B.1 and Table B.2 in Appendix B.

“SUV” means sport utility vehicles, pickups and vans. “Truck” means any possible kind of a truck or a tractor. SUVs and cars are considered together unless their additional division, as shown inside the dotted box, is required by the likelihood ratio test.

Figure 4.1 Data division by road class and by accident type⁷

We check statistical significance of the explanatory variables in all logit models by using 5% significance level for the two-tailed t-test of a large data sample. In other words, coefficients with t-ratios between -1.96 and +1.96 are considered

⁷ We consider US routes and State routes separately even though they have similar design and other properties. The reason is that our final logit models for unsafe-speed-related accident causation on US and State routes turn out to be statistically different from each other. We use the likelihood ratio test to check this difference (but we do not report the test results in this herein).

to be statistically insignificant. Note that the explanatory variables can be mutually dependent (e.g. a quantitative variable and its derivative indicator variable are strongly mutually dependent).

Statistical models are (usually) estimated by maximizing the model's log-likelihood function. However, one can not rely on the log-likelihood maximization alone in order to choose the optimal number of explanatory variables to be included into a statistical model. The reason is that the log-likelihood (LL) function is always maximized when all available explanatory variables are included into the model. This is because a removal of any explanatory variable is equivalent to restricting its value to zero, which always either decreases the maximum of LL or leaves it the same. As a result, in the present study we use the Akaike Information Criterion (AIC), minimization of which ensures an optimal choice of explanatory variables in a model (Tsay, 2002, page 37; Washington et al., 2003, page 212; Wikipedia). The main idea behind the AIC is to examine the complexity of a model together with goodness of its fit to the data sample, and to find a balance between the two. A model with too few explanatory variables will provide a poor fit to the data sample. A model with too many variables will provide a very good fit, but will lack necessary robustness and will perform poorly in out-of-the-sample data. The preferred model with the optimal number of explanatory variables is the model with the lowest AIC value, which is given by equation

$$AIC = -2LL + 2K, \quad \text{Eq. 4.1}$$

where LL is the log-likelihood value of a model, and K is the number of estimable coefficients in the model (one coefficient for each explanatory variable, including the intercepts).

In our research we estimate all logit models by using one of the two procedures A and B shown in Figure 4.2. Procedure A is as follows:

Figure 4.2 Model estimation procedures

A. We start with all explanatory variables initially included into a logit model. Note that, when estimating a model, we have to exclude observations that are missing for any of the included variables. Next, we obtain the final model by using three steps of model estimation. The first step is

1. We remove the least statistically significant explanatory variables (as judged by their t-ratios) one by one if *both* of the following two conditions are satisfied: the removal of a variable decreases the AIC value *and* the removed variable is statistically insignificant (under the 5% confidence level)⁸. Note that while using the Akaike information criterion, we always keep the number of data sample observations constant in order to calculate the changes of the AIC value correctly. Each time when we have removed several (usually four) least significant explanatory variables from a model, we include some of the previously excluded observations back into the data sample because now the model includes fewer variables with missing observations. We keep removing insignificant explanatory variables one by one, periodically including previously excluded observations back into the data sample, until we can not remove any additional variable under the two conditions listed above.

After we removed all variables that we could, we need to check if any of the removed variables can be added back into the model. This is because variables are mutually dependent and “interact” in the model. Therefore, we proceed to the second step of model estimation:

⁸ If the asymptotic normality of maximum likelihood estimates holds, then the AIC value does not change with removal (addition) of a variable whose coefficient has 15.73% p-value for the two-tailed test (15.73% p-value corresponds to $\pm\sqrt{2}$ t-ratio for a normal variate). In this case the 5% confidence level test of the variable is redundant, and the AIC test alone can be used for removal and addition of variables in model estimation steps 1 and 2. Nevertheless, we use both tests to make our estimation procedures more robust in case the normality of maximum likelihood estimates does not hold.

2. We add explanatory variables one by one if *at least one* of the following two conditions is satisfied: *either* the addition of a variable decreases the AIC value *or* the added variable is significant⁹. As usual, the AIC values are compared under the condition that the number of observations is kept constant. As the number of the explanatory variables included into the model grows, the data sample size shrinks because of a larger number of missing observations associated with the included variables. We add explanatory variables one by one until no any additional variable can be added to the model.

Next we return back to the first estimation step given above and remove variables that can be removed. We iterate between steps 1 and 2 until we can neither remove nor add any more variables. At this point we arrive at the model that we call the “AIC optimal model” (refer to Figure 4.2). Next, we proceed to the third and final step of model estimation:

3. To make our final results more robust, we drop from the AIC optimal model all remaining statistically insignificant variables (judged by the 5% significance level for the two-tailed t-test). As a result, we obtain the final model, which is our best model (according to the estimation procedures chosen by us).

Now we describe procedure B:

- B. In this procedure we start with only intercepts (constant terms) initially included into a logit model (refer to Figure 4.2). Next, we proceed in a way very similar to that used in procedure A. We run step 2 of model estimation and add explanatory variables into the model. Then, we iterate between steps 1 and 2 until we can neither remove nor add any more variables, at which point we arrive at the AIC optimal model. Finally, we run step 3 of model estimation and obtain the best final model.

⁹ We first search for and add AIC decreasing variables, and afterwards we add significant variables if there are any.

By default we always use procedure A for model estimation, and only if we can not use it (usually when the available data sample is too small for the initial model estimation with all explanatory variables included), then we resort to procedure B.

4.2. Results: accident causation models

For each of the road-class-accident-type combinations listed in Table B.1 and Table B.2 in Appendix B, we find and estimate the best binary logit model by using either procedure A or procedure B described above. The binary logit models are given in Equation (2.3), where outcome “1” corresponds to the case when the primary cause of an accident is either “unsafe speed” or “speed too fast for weather conditions”, and outcome “2” corresponds to any other primary cause of the accident. The results of the estimation of the best models are given in Table B.3 and Table B.4 for 2004 and 2006 accidents respectively (see Appendix B).

In Table B.5 and Table B.6 in Appendix B we give the results of testing whether, in 2004 and 2006 two-vehicle accidents, cars and SUVs can be considered together or must be considered separately. This testing is done for the best models by using the likelihood ratio test given in Equation (2.5). According to the results shown in Table B.5 and Table B.6, we find that in our unsafe-speed-related accident causation study cars and SUVs can be considered together in all 2004 two-vehicle accidents on all road classes, but they must be considered separately in the case of several road-class-accident-type combinations for 2006 two-vehicle accidents.

Let us now examine the model estimation results, which are given in Table B.3 and Table B.4 for 2004 and 2006 accidents respectively. We will consider the effects of the posted speed limit and other explanatory variables on the

probability of an unsafe and/or excessive speed being the primary cause of an accident. Since our primary interest is the effect of the speed limit, we focus on it first.

4.2.1. Effect of Speed Limit

We assume that the speed limit posted at the location of an accident is known only if it is indicated as known and the same for all vehicles involved into the accident. The speed limit is variable X_{29} in Appendix A. Its coefficients and averaged elasticities in the best final binary logit models for 2004 and 2006 unsafe-speed-related accident causation are given in Table 4.1 and Table 4.2 below. In order to understand the results reported in these tables, please refer to Equations (2.3) and (2.8). These equations give the binary logit model and the corresponding elasticities that we calculate. The outcomes “1” and “2” in the binary models correspond to the “unsafe-speed-related cause” and “any other cause” of an accident. In Table 4.1 and Table 4.2 we report all *statistically significant* coefficients of the speed limit variable (these coefficients are copied from Table B.3 on page 83 and Table B.4 on page 94) and the corresponding elasticities. In addition, in these tables we report all statistically *insignificant* coefficients of the speed limit variable (without elasticities). These insignificant coefficients are shown in the square brackets and are obtained by test-adding the speed limit variable into the AIC optimal logit models (note that this is done only as a test; in Table 4.1, Table 4.2, Table B.3 and Table B.4 all significant coefficients and the corresponding elasticities are reported for the final models, which themselves do not contain any insignificant variables).

We find the following results for the effects of speed limit on accident causation:

Table 4.1 2004 accident causation models: results for speed limit¹⁰

#	Model name		Speed limit coefficient (t-ratio)	Averaged elasticities of speed limit (SL)	
				$\bar{E}_{1,SL}^{(1)}$	$\bar{E}_{1,SL}^{(2)}$
1	County road	rural	(car/SUV)+(car/SUV)	[.00943 (1.67)]	
2		rural	(car/SUV)+(truck)	[-.00555 (-.223)]	
3		rural	one vehicle	.00859 (2.83)	.337
4	County road	urban	(car/SUV)+(car/SUV)	.0368 (2.24)	1.23
5		urban	(car/SUV)+(truck)	[.177 (1.43)]	
6		urban	one vehicle	[.00986 (.827)]	
7	Interstate	rural	(car/SUV)+(car/SUV)	[.0172 (1.27)]	
8		rural	(car/SUV)+(truck)	[-.0127 (-.317)]	
9		rural	one vehicle	[-.0294 (-1.95)]	
10	Interstate	urban	(car/SUV)+(car/SUV)	[.0182 (1.19)]	
11		urban	(car/SUV)+(truck)	[.0539 (1.42)]	
12		urban	one vehicle	[-.00985 (-.873)]	
13	State route	rural	(car/SUV)+(car/SUV)	[-.00230 (-.175)]	
14		rural	(car/SUV)+(truck)	[.00806 (.254)]	
15		rural	one vehicle	[-.0108 (-1.30)]	
16	State route	urban	(car/SUV)+(car/SUV)	.0212 (2.51)	.769
17		urban	(car/SUV)+(truck)	[.0337 (1.05)]	
18		urban	one vehicle	[.000799 (.066)]	
19	City street	rural	(car/SUV)+(car/SUV)	.0225 (2.50)	.773
20		rural	(car/SUV)+(truck)	[.102 (1.25)]	
21		rural	one vehicle	[-.00158 (-.248)]	
22	City street	urban	(car/SUV)+(car/SUV)	[-.00504 (-1.14)]	
23		urban	(car/SUV)+(truck)	[.0113 (.543)]	
24		urban	one vehicle	-.0117 (-3.82)	-.323
25	US route	rural	(car/SUV)+(car/SUV)	[.00721 (.509)]	
26		rural	(car/SUV)+(truck)	[-.0356 (-1.23)]	
27		rural	one vehicle	-.0422 (-3.17)	-2.05
28	US route	urban	(car/SUV)+(car/SUV)	.0181(2.33)	.679
29		urban	(car/SUV)+(truck)	[.0517 (1.50)]	
30		urban	one vehicle	[.00636 (.394)]	

¹⁰ Refer to Equations (2.3) and (2.8), where outcomes “1” and “2” correspond to the “unsafe-speed-related” and “any other” accident causes. We report statistically significant coefficients of the speed limit variable and the corresponding elasticities. In addition, in the square brackets we report statistically insignificant coefficients (obtained by test-adding the speed limit variable into the AIC optimal models). All coefficients are the components of vector β_1 that are multiplied by the speed limit variable in Equation (2.3).

Table 4.2 2006 accident causation models: results for speed limit

#	Model name			Speed limit coefficient (t-ratio)	Averaged elasticities of speed limit (SL)	
					$\bar{E}_{1,SL}^{(1)}$	$\bar{E}_{1,SL}^{(2)}$
1	County road	rural	(car/SUV)+(car/SUV)	[-.0222 (-1.57)]		
2a			(car)+(truck)	[-.115 (-1.36)]		
2b			(SUV)+(truck)	[.246 (.917)]		
3		urban	one vehicle	[.000990 (.155)]		
4			(car/SUV)+(car/SUV)	[-.0101 (-.309)]		
5			(car/SUV)+(truck)	[0.00792 (.113)]		
6		one vehicle	[-.00975 (-.755)]			
7a	Interstate	rural	(car)+(car)	[-.00840 (-.346)]		
7b			(car)+(SUV)	[.0110 (.569)]		
7c			(SUV)+(SUV)	[.0296 (.958)]		
8			(car/SUV)+(truck)	[-.0176 (-.816)]		
9			one vehicle	-.0439 (-5.72)	-2.51	.370
10		urban	(car/SUV)+(car/SUV)	[.0232 (1.85)]		
11a			(car)+(truck)	[-.0479 (-1.49)]		
11b			(SUV)+(truck)	[.113 (1.27)]		
12	one vehicle		[-.0158 (-.811)]			
13	State route	rural	(car/SUV)+(car/SUV)	[.000526 (.0230)]		
14			(car/SUV)+(truck)	[.00874 (.284)]		
15			one vehicle	-.0373 (-5.34)	-1.87	.109
16		urban	(car/SUV)+(car/SUV)	.0277 (3.47)	.999	-.0390
17			(car/SUV)+(truck)	[.0250 (.907)]		
18			one vehicle	[-.0102 (-1.000)]		
19	City street	rural	(car/SUV)+(car/SUV)	[-.00521 (-.241)]		
20a			(car)+(truck)	[.0239 (.381)]		
20b			(SUV)+(truck)	[-.142 (-.634)]		
21			one vehicle	[.00475 (.612)]		
22		urban	(car/SUV)+(car/SUV)	[.00811 (1.010)]		
23a			(car)+(truck)	[.0325 (.889)]		
23b			(SUV)+(truck)	[.118 (1.910)]		
24			one vehicle	[.00226 (.301)]		
25	US route	rural	(car/SUV)+(car/SUV)	[.00969 (.321)]		
26			(car/SUV)+(truck)	[.00144 (.042)]		
27			one vehicle	[-.00537 (-.464)]		
28		urban	(car/SUV)+(car/SUV)	[.0122 (.646)]		
29a			(car)+(truck)	[-.0127 (-.294)]		
29b			(car)+(truck)	[.362 (1.73)]		
30		one vehicle	[-.0101 (-.814)]			

- Speed limit does not have any statistically significant effect on unsafe-speed-related causation of accidents of any types¹¹ on interstate highways (urban and rural), except for the case of 2006 one-vehicle accidents on rural interstates. In this single case the probability of unsafe speed being the primary cause of an accident actually decreases with an increase in the posted speed limit.
- Speed limit does not also have a statistically significant effect on unsafe-speed-related accident causation for the majority of other accident types on the majority of road classes other than the interstate highways.
- There are only ten combinations of different accident types and road classes for which speed limit turns out to have a statistically significant effect on unsafe-speed-related causation of 2004 and 2006 accidents. For convenience, in
- Figure 4.3 and Figure 4.4 we present in graphical form the t-ratios of the speed limit coefficients for these ten combinations. We see that there are mixed effects of the speed limit on unsafe-speed-related accident causation. On one hand, the probability of unsafe speed being the primary cause of an accident rises with an increase in the posted speed limit for 2004 single-vehicle accidents on rural county maintained roads, for 2004 car/SUV-car/SUV accidents on rural city maintained streets, urban US routes and urban county maintained roads, as well as for 2004 & 2006 car/SUV-car/SUV accidents on urban state routes. On the other hand, the probability decreases with an increase in the speed limit for 2004 single-vehicle accidents on rural US routes and urban city maintained streets, and for 2006 single-vehicle accidents on rural state routes and rural interstates.
- The speed limit variable is elastic for only one of the six road-class-accident-type combinations that display a statistically significant increase

¹¹ Note that we consider only single-vehicle accidents and all two-vehicle accidents except those that involve two trucks.

of the unsafe speed accident causation probability with an increase of the posted speed limit (this single combination is 2004 car/SUV-car/SUV accidents on urban county maintained roads).

Figure 4.3 T-ratios of statistically significant speed limit coefficients in 2004 accident causation models

Figure 4.4 T-ratios of statistically significant speed limit coefficients in 2006 accident causation models

We postpone a discussion of the above findings until the last chapter, which discusses our results for both accident causation and accident severity.

4.2.2. Effect of Other Explanatory Variables

Now we use model estimation results given in Table B.3 and Table B.4 in Appendix B to study the influence of explanatory variables other than the posted speed limit on unsafe-speed-related causation of 2004 and 2006 accidents. We limit our consideration to several of the most important variables, which are statistically significant not just in a few but in many models for different road classes and accident types¹².

- **Variable “wint” (see pages 84 and 95):** We find that the probability of unsafe-speed-related cause of an accident increases during winter season. This seasonal effect is very strong. It is reasonable because driving conditions in Indiana worsen during winters, while some drivers apparently fail to adjust their driving speeds accordingly.
- **Variables “precip”, “snow” and “dry” (see pages 86 and 97):** We find that the probability of unsafe-speed-related cause of an accident increases when precipitation and/or snow is observed at the accident location, and it decreases when the road surface is dry. This is a very strong effect on all road classes, and it can clearly be explained by drivers not being adjusting their speed appropriately when the weather conditions are less safe for driving.
- **Variable “nojun” (see pages 87 and 98):** The absence or presence of a road junction at the accident location has a mixed effect on the probability of unsafe-speed-related cause of an accident. The probability of an unsafe-speed-related accident with only one vehicle involved decreases when no junction is present on the road, but the probability increases when two vehicles are involved. This can be explained by two concurrent effects. On one hand, the road is safer in the absence of

¹² One of the reasons for this limitation is that the number of available accident observations in our data sample is relatively small for several road-class-accident-type combinations, refer to Table B.1 and Table B.2.

junctions. On the other hand, drivers might have a habit of slowing down a bit when they approach a junction and see another vehicle(s) on or near the junction¹³.

- **Variables "curve" (see pages 88 and 99):** We find an expected result that the probability of unsafe-speed-related cause of an accident decreases when the road is straight and increases when the road is at curve. Clearly curved roads are less safe because of centrifugal forces acting onto moving vehicles in the rotating coordinate frame of reference.
- **Variable "heavy" (see pages 89 and 101):** We find that heavy trucks and tractors are less likely to cause unsafe-speed-related accidents than other vehicles are. The reason can be that drivers of trucks and tractors are more professional and are less likely to speed.
- **Variables "stopsig" (see pages 92 and 103):** We find that the presence of a stop sign generally reduces the probability of unsafe-speed-related accidents, which can be due to effectiveness of stop signs in controlling traffic flows on streets and minor roads.
- **Variable "X₃₄" (see pages 93 and 104):** We find that the probability of unsafe-speed-related cause of an accident decreases with the age of the driver at fault. This is a very strong effect on all road classes. Apparently older drivers are more experienced, more careful and much less likely to exceed safe driving speed.

¹³ Note that police officer's misidentification errors can be stronger for a single-vehicle accident because in this case the officer has to rely on testimonies of occupants of the single vehicle involved into the accident. See footnote 4 on page 17 for discussion of misidentification errors.

CHAPTER 5. ACCIDENT SEVERITY STUDY

In this chapter our goal is to reveal and study the impact of the posted speed limit on the severity level of an accident. Similar to the previous chapter, we first describe the procedures of accident severity statistical modeling that we use, and second, we present and discuss the results that we obtain for 2004 and 2006 accidents. In our analysis, we will compare the cross-sectional effect of speed limits in each accident year. We do not restrict our analysis to the change in accident severity only roadway segments that had increased speed limits. If he had done so, the natural variation in accidents over time during the two-year period (driving behavior, vehicle safety features, etc) would have masked the effect of speed limits. Instead, by using a cross-sectional analysis and controlling for all characteristics of accidents (driver characteristics, weather conditions, roadway geometrics, urban/rural location, etc.) we are able to isolate the effects of speed-limit variations in a given accident year.

5.1. Modeling Procedures: accident severity

For each accident, the severity level is determined by the injury level sustained by the most injured individual (if any) involved into the accident. By using the available individual accident data, we are able to distinguish between three levels of accident severity. Listed in increasing order, these are

1. no-injury or property damage only (PDO),
2. injury,
3. fatality,

refer to Figure 3.4 and Figure 3.10. As a result, for the statistical modeling of accident severity we use a multinomial logit model with three possible outcomes that correspond to these three levels of accident severity. This multinomial logit model is given by Equation (2.4), where the outcomes “1”, “2” and “3” correspond to “fatality”, “injury” and “PDO” levels of accident severity respectively.

We estimate multinomial logit models for accident severity in a way similar to the estimation of binary logit models for accident causation considered in the previous chapter. Namely, we again consider different road classes and accident types separately, as shown in Figure 4.1. The list of all combinations of different road classes and accident types that we consider in our accident severity study can be found in Table C.1 and Table C.2 for 2004 and 2006 accidents respectively (see Appendix C). We again use 5% significance level for the two-tailed t-test of a large data sample in order to make inference on statistical significance of all indicator and quantitative explanatory variables in the accident severity logit models. We also use the same AIC-based procedures (A and B) for all severity model estimations, as described in CHAPTER 4 on pages 32 and 33 and in Figure 4.2.

Thus, to study the impact of speed limit on the resulting accident severity, for each road-class-accident-type combination we proceed as follows:

1. First, using the data on accidents that constitute the considered road-class-accident-type combination and the procedures described above, we find the best multinomial logit model with three possible accident severity outcomes (fatality, injury, PDO). From this model we can immediately see whether there is any statistically significant effect of the posted speed limit on the resulting accident severity level.

2. Second, we divide the accident data into separate speed limit data bins, according to the posted speed limit at the place of an accident¹⁴. The speed limit bins chosen by us for 2004 and 2006 accidents are given in Table C.3 and Table C.4 in Appendix C.
3. Third, we take the best logit model obtained in the first step¹⁵ and re-estimate it separately for each of the speed-limit data bins chosen in the second step. Then we test to see if there are statistically significant differences among the models estimated for the different speed-limit bins. This is done by using the likelihood ratio test, which is given by Equation (2.5) and explained in the end of CHAPTER 2. We use 5% confidence level for the likelihood ratio test statistic in Equation (2.5) to make inference on whether the collection of models estimated separately for the speed-limit data bins is statistically the same as the model estimated for the whole data sample which includes all speed limits together. In other words, if the left-hand-side of Equation (2.5) is between zero and the 95th percentile of the chi-squared distribution given on the right-hand-side, then we conclude that the posted speed limit makes no statistically significant difference for the structure of accident severity models in the case of the considered road-class-accident-type combination. We conclude that there is a difference otherwise.

5.2. Results: accident severity models

For each of the road-class-accident-type combinations listed in Table C.1 and Table C.2 in Appendix C, we find and estimate the best multinomial logit model, as given in Equation (2.3) with the outcomes “1”, “2” and “3” corresponding to

¹⁴ We disregard accidents with more than one posted speed limit at the accident location.

¹⁵ In the third step we first remove the speed limit variable (if any) from the best final model because the speed limit is usually constant inside the speed limit data bins. In some cases of the 2004 accident severity models we have to remove additional explanatory variables that are constant inside some of the speed limit bins. For specific cases of the removal see Table 5.3.

“fatality”, “injury” and “PDO” accident severity levels respectively. Table C.5 and Table C.6 in Appendix C give the estimation results for the best models in the cases of 2004 and 2006 accidents.

In Table C.7 and Table C.8 we show the results of testing whether in two-vehicle accidents cars and SUVs can be considered together or must be considered separately in our accident severity study. This testing is done by using the likelihood ratio test in exactly the same way as done in the accident causation study. If the likelihood ratio test indicates that cars and SUVs should be considered separately, then we apply the additional division shown inside the dotted box in Figure 3.2 and find the best model separately for each of the sub-categories obtained by this additional division. For example, from the test results given in Table C.7 we see that the 2004 “car/SUV-truck accidents on rural interstates” category has to be divided into sub-categories 8a (car-truck accidents) and 8b (SUV-truck accidents).

5.2.1. Effect of Speed Limit

To judge whether speed limit makes any statistically significant difference for the resulting accident severity outcomes, we first study the severity model estimation results for the speed limit variable and its elasticities reported in Table 5.1 and Table 5.2 for 2004 and 2006 accidents respectively. In order to understand the results presented in these tables, refer to Equations (2.4) and (2.9), where outcomes “1”, “2” and “3” correspond to “fatality”, “injury” and “PDO” accident severity outcomes respectively. In Table 5.1 and Table 5.2 the elasticities are reported only for statistically significant coefficients of the speed limit variable (which are copied from Table C.5 on page 112 and Table C.6 on page 142). In Table 5.1 and Table 5.2 we also report all statistically insignificant coefficients of the speed limit variable, which are shown in the square brackets and are obtained by test-adding the speed limit variable into the AIC optimal

models (note that this is done only as a test; in Table 5.1, Table 5.2, Table C.5 and Table C.6 all significant coefficients and the corresponding elasticities are reported for the final models, which themselves do not contain any insignificant variables).

We find that

- Speed limit did not have any statistically significant effect on severity of 2004 and 2006 accidents of any type¹⁶ on interstate highways (both urban and rural). This indicates that the speed-limit increases in 2005 did not affect the relative severity of accidents on interstates with different speed limits.
- Higher speed limit values did generally lead to higher probabilities of more severe accidents (fatality and injury) on road classes other than interstate highways. This effect is especially strong for 2004 and 2006 accidents on rural country roads, urban city maintained streets and urban U.S. routes.
- The speed limit variable seems to be inelastic for some of the road-class-accident-type combinations that display a statistically significant relationship between speed limit and accident severity. For others, especially in the case of fatal accident outcomes, elasticities of the speed limit can be quite high.

¹⁶ Remember that we consider only single- and two-vehicle accidents (except for two-truck accidents).

Table 5.1 2004 accident severity models: results for speed limit¹⁷

#	Model name*			Speed limit coefficient (t-ratio)		Averaged elasticities of speed limit (SL)			
				fatality [β_1]	injury [β_2]	$\bar{E}_{1,SL}^{(1)}$	$\bar{E}_{1,SL}^{(2)} = \bar{E}_{1,SL}^{(3)}$	$\bar{E}_{2,SL}^{(2)}$	$\bar{E}_{2,SL}^{(1)} = \bar{E}_{2,SL}^{(3)}$
1	County road	rural	(C/S)+(C/S)	.108 (3.61)	.0255 (5.15)	4.49	-.042	.776	-.297
2			(C/S)+(T)	[.337 (1.34)]	.0414 (3.42)			1.35	-.405
3			one vehicle	.0382 (3.47)	[-.00315 (-1.03)]	1.75	-.022		
4		urban	(C/S)+(C/S)	.0323 (3.75)	.0323 (3.75)	1.19	-.001	.927	-.259
5			(C/S)+(T)	[-.00511 (.000)]	[.0536 (1.08)]				
6			one vehicle	[-.0974 (-.853)]	[.00469 (.354)]				
7	Interstate	rural	(C/S)+(C/S)	[.000351 (.000)]	[.0116 (.646)]				
8a			(C)+(T)	[.00133 (.000)]	[.00870 (.358)]				
8b			(S)+(T)	[.0272 (.000)]	[.0374 (1.33)]				
9			one vehicle	[-.0186 (-1.49)]	[-.0186 (-1.49)]				
10		urban	(C/S)+(C/S)	[.0171 (1.41)]	[.0171 (1.41)]				
11			(C/S)+(T)	[.0798 (.518)]	[.000717 (.026)]				
12			one vehicle	[.0366 (.938)]	[-.00262 (-.240)]				
13	State route	rural	(C/S)+(C/S)	[.0628 (1.43)]	.0306 (3.90)			1.03	-.505
14			(C/S)+(T)	[.168 (1.88)]	[.0239 (1.36)]				
15			one vehicle	[.0313 (1.09)]	[-.00313 (-.422)]				
16a		urban	(C)+(C)	.0340 (5.14)	.0340 (5.14)	1.27	-.001	.949	-.319
16b			(C)+(S)	.0225 (4.36)	.0225 (4.36)	.853	-.001	.652	-.201
16c			(S)+(S)	.0315 (3.39)	.0315 (3.39)	1.21	-.005	.951	-.265
17			(C/S)+(T)	.0418 (2.89)	.0418 (2.89)	1.64	-.010	1.29	-.363
18			one vehicle	[.0448 (1.19)]	[.00242 (.306)]				
19	City street	rural	(C/S)+(C/S)	.114 (2.53)	.0273 (5.40)	4.23	-.009	.775	-.240
20			(C/S)+(T)	[-.0733 (-.667)]	.0676 (3.17)			2.11	-.597
21			one vehicle	[-.0218 (-.800)]	[-.00128 (-.244)]				
22		urban	(C/S)+(C/S)	.0938 (2.76)	.0304 (11.8)	3.14	-.003	.785	-.232
23a			(C)+(T)	.0469 (3.99)	.0469 (3.99)	1.58	-.003	1.30	-.290
23b			(S)+(T)	.0640 (4.41)	.0640 (4.41)	2.15	-.005	1.82	-.329
24			one vehicle	[.0132 (.789)]	[-.000526(-.136)]				
25	US route	rural	(C/S)+(C/S)	.340 (2.48)	.0409 (4.54)	17.0	-.212	1.39	-.685
26			(C/S)+(T)	[-.00980(-.271)]	.0720 (3.02)			2.37	-1.38
27			one vehicle	[-.00249(-.075)]	[.00304 (.275)]				
28		urban	(C/S)+(C/S)	.0263 (5.76)	.0263 (5.76)	1.04	-.001	.779	-.265
29			(C/S)+(T)	.0307 (2.52)	.0307 (2.52)	1.26	-.002	.986	-.278
30			one vehicle	[.00230 (.055)]	[-.0139 (-1.37)]				

* "C", "S" and "T" mean car, SUV and truck respectively.

¹⁷ Refer to Equations (2.4) and (2.9), where outcomes "1", "2", "3" correspond to "fatality", "injury", "PDO". We report statistically significant coefficients of the speed limit variable and the corresponding elasticities. In the square brackets we report insignificant coefficients (obtained by test-adding the speed limit variable into the AIC optimal models). All coefficients are the components of vectors β_1 and β_2 , multiplied by the speed limit variable in Equation (2.4).

Table 5.2 2006 accident severity models: results for speed limit

#	Model name*			Speed limit coefficient (t-ratio)		Averaged elasticities of speed limit (SL)			
				fatality [β_1]	injury [β_2]	$\bar{E}_{1,SL}^{(1)}$	$\bar{E}_{1,SL}^{(2)} = \bar{E}_{1,SL}^{(3)}$	$\bar{E}_{2,SL}^{(2)}$	$\bar{E}_{2,SL}^{(1)} = \bar{E}_{2,SL}^{(3)}$
1	County road	rural	(C/S)+(C/S)	.0396(5.48)	.0396(5.48)	1.61	-.016	1.20	-.429
2			(C/S)+(T)	.0648(3.06)	.0648(3.06)	2.77	-.032	2.35	-.453
3			one vehicle	.00506(2.04)	.00506(2.04)	.235	-.002	.185	-.052
4a		urban	(C)+(C)	[.00689(.000)]	[.00507(.321)]				
4b			(C)+(S)	[.0231(.000)]	.0613(2.43)			1.80	-.405
4c			(S)+(S)	[.0110(.000)]	[.0269(.843)]				
5	(C/S)+(T)		[-.5454(-.518)]	[-.0288(-.301)]					
6	one vehicle	[-.0852(-1.23)]	[.000725(.069)]						
7	Interstate	rural	(C/S)+(C/S)	[.103(1.28)]	[.00872(.884)]				
8			(C/S)+(T)	[.150(.908)]	[.00133(.063)]				
9			one vehicle	[-.0237(-1.55)]	[-.0237(-1.55)]				
10		urban	(C/S)+(C/S)	[11.04(.000)]	[-.00108(-.135)]				
11			(C/S)+(T)	[-.00188(-.011)]	[.0120(.519)]				
12			one vehicle	[.00776(.197)]	[.00384(.476)]				
13	State route	rural	(C/S)+(C/S)	.248(3.48)	.0416(3.25)	11.9	-.495	1.32	-.759
14			(C/S)+(T)	.127(2.50)	.127(2.50)	5.79	-.541	5.36	-.970
15			one vehicle	0.0636(2.34)	[.0127(2.25)]	3.34	-.029		
16		urban	(C/S)+(C/S)	.251(3.35)	.0290(7.95)	9.40	-.015	.835	-.253
17			(C/S)+(T)	[5.60(.000)]	[.452(1.73)]				
18			one vehicle	[.0268(.418)]	[-.0115(-.827)]				
19	City street	rural	(C/S)+(C/S)	.0414(6.13)	.0414(6.13)	1.46	-.001	1.12	-.349
20			(C/S)+(T)	[.0185(.000)]	[.540(1.43)]				
21			one vehicle	[-.0800(-1.46)]	[-.00409(-.381)]				
22a		urban	(C)+(C)	.0251(6.33)	.0251(6.33)	.810	.000	.626	-.184
22b			(C)+(S)	.0218(4.65)	.0218(4.65)	.727	-.001	.560	-.167
22c			(S)+(S)	.0343(4.20)	.0343(4.20)	1.14	-.001	.865	-.279
23	(C/S)+(T)		.0284(2.34)	.0284(2.34)	.937	-.001	.831	-.107	
24	one vehicle	[.00968(.382)]	[-.00128(-.240)]						
25	US route	rural	(C/S)+(C/S)	[.0644(1.32)]	[.0272(1.84)]				
26			(C/S)+(T)	.0608(3.07)	.0608(3.07)	3.12	-.078	2.28	-.912
27			one vehicle	[.0137(1.56)]	[.0137(1.56)]				
28		urban	(C/S)+(C/S)	.0154(2.14)	.0154(2.14)	.613	-.001	.443	-.171
29			(C/S)+(T)	.0586(3.60)	.0586(3.60)	2.33	-.027	2.02	-.337
30			one vehicle	[.0327(.450)]	[.0134(.878)]				

* "C", "S" and "T" mean car, SUV and truck respectively.

Table 5.3 Speed limit effect on structure of 2004 accident severity models¹⁸

#	Model name			M	K	LL(β _m)	Σ LL(β _m)	df	p-value	conclusion*	
1	County road	rural	(car/SUV)+(car/SUV)	6	15	-1656.7	-1588.2	75	1.7e-5	SL effect	
2			(car/SUV)+(truck)	5	8	-256.74	-235.02	32	0.085		
3			one vehicle	7	20	-5066.7	-4990.7	120	0.026	SL effect	
4		urban	(car/SUV)+(car/SUV)	7	9	-691.21	-657.69	54	0.11		
5			(car/SUV)+(truck)	3	5	-90.86	-86.40	10	0.54		
6			one vehicle	4	8	-332.07	-320.00	24	0.45		
7	Interstate	rural	(car/SUV)+(car/SUV)	4	5	-414.78	-404.68	15	0.16		
8a**			(car)+(truck)	3	5	-84.02	-79.32	10	0.49		
8b			(SUV)+(truck)	2	8	-49.65	-45.94	8	0.49		
9			one vehicle	4	11	-1346.2	-1324.2	33	0.17		
10		urban	(car/SUV)+(car/SUV)	3	13	-684.32	-666.77	26	0.11		
11			(car/SUV)+(truck)	2	6	-299.29	-296.98	6	0.60		
12	one vehicle		5	12	-761.47	-738.41	48	0.55			
13	State route	rural	(car/SUV)+(car/SUV)	2	11	-1310.1	-1293.1	11	3.8e-4	SL effect	
14***			(car/SUV)+(truck)	4	10	-381.87	-368.11	30	0.60		
15			one vehicle	6	13	-2153.5	-2117.0	65	0.23		
16a		urban	(car)+(car)	8	7	-1129.5	-1094.6	49	0.026	SL effect	
16b			(car)+(SUV)	7	10	-1557.2	-1512.4	60	7.8e-3	SL effect	
16c			(SUV)+(SUV)	3	8	-497.85	-485.13	16	0.063		
17	urban	(car/SUV)+(truck)	6	4	-177.67	-162.33	20	0.059			
18		one vehicle	7	10	-618.56	-569.55	60	1.4e-3	SL effect		
19		City street	rural	(car/SUV)+(car/SUV)	10	10	-1376.0	-1313.4	90	8.3e-3	SL effect
20	(car/SUV)+(truck)			4	8	-73.63	-63.33	24	0.66		
21	one vehicle			6	13	-946.00	-905.80	65	0.095		
22	urban		(car/SUV)+(car/SUV)	10	20	-14620	-14435	180	3.3e-14	SL effect	
23a			(car)+(truck)	4	12	-534.10	-509.25	36	0.064		
23b			(SUV)+(truck)	6	6	-354.56	-323.86	30	6.2e-4	SL effect	
24	US route	rural	one vehicle	5	22	-3627.5	-3560.3	88	1.0e-3	SL effect	
25			urban	(car/SUV)+(car/SUV)	6	8	-996.60	-969.57	40	0.068	
26				(car/SUV)+(truck)	2	11	-275.63	-262.02	11	4.3e-3	SL effect
27		one vehicle		5	10	-1236.7	-1219.5	40	0.72		
28		(car/SUV)+(car/SUV)		5	11	-2361.9	-2326.9	44	7.6e-3	SL effect	
29		(car/SUV)+(truck)		7	8	-314.86	-287.88	48	0.26		
30	one vehicle	7	10	-493.83	-458.36	60	0.16				

* – For models with “SL effect” conclusion speed limit is statistically significant for the structure of accident severity models, it is not significant otherwise.

** – Variables X33f and X15 are constant inside speed limit bins and have been removed from the best final logit model before carrying out the test.

*** – Variable X33f is constant and has been removed from the best final logit model.

¹⁸ The tests of the effect are done by using the likelihood ratio, refer to paragraph 3 on page 44.

Table 5.4 Speed limit effect on structure of 2006 accident severity models

#	Model name			M	K	$LL(\beta_m)$	$\sum LL(\beta_m)$	df	p-value	conclusion*
1	County road	rural	(car/SUV)+(car/SUV)	4	9	-847.91	-813.01	27	1.2e-4	SL effect
2			(car/SUV)+(truck)	5	7	-119.31	-100.96	28	0.13	
3			one vehicle	5	19	-7154.2	-7106.0	76	0.058	
4a		urban	(car)+(car)	7	4	-303.42	-291.38	24	0.46	
4b			(car)+(SUV)	4	3	-235.35	-226.24	9	0.033	SL effect
4c			(SUV)+(SUV)	4	5	-161.81	-151.13	15	0.13	
5			(car/SUV)+(truck)	3	4	-15.658	-98.097	8	0.17	
6			one vehicle	5	8	-342.22	-330.11	32	0.84	
7	Interstate	rural	(car/SUV)+(car/SUV)	4	9	-451.87	-438.45	27	0.47	
8			(car/SUV)+(truck)	2	6	-98.695	-97.460	6	0.87	
9			one vehicle	5	12	-1474.1	-1465.6	48	0.53	
10		urban	(car/SUV)+(car/SUV)	8	9	-836.55	-811.72	63	0.89	
11			(car/SUV)+(truck)	2	9	-221.17	-215.30	9	0.23	
12			one vehicle	5	11	-882.75	-862.84	44	0.65	
13	State route	rural	(car/SUV)+(car/SUV)	2	9	-575.69	-559.57	9	1.8e-4	SL effect
14			(car/SUV)+(truck)	2	4	-76.769	-72.761	4	0.091	
15			one vehicle	5	16	-3707.8	-3657.2	64	0.00204	SL effect
16		urban	(car/SUV)+(car/SUV)	8	10	-3268.3	-3203.0	70	1.5e-4	SL effect
17			(car/SUV)+(truck)	5	5	-153.32	-146.63	20	0.86	
18			one vehicle	6	8	-747.88	-715.34	40	7.4e-3	SL effect
19	City street	rural	(car/SUV)+(car/SUV)	7	7	-1088.1	-1046.1	42	1.3e-3	SL effect
20			(car/SUV)+(truck)	3	2	-2851.8	-2834.5	4	5.3e-6	SL effect
21			one vehicle	2	11	-288.38	-283.71	11	0.59	
22a		urban	(car)+(car)	6	15	-6848.4	-6782.1	75	4.8e-4	SL effect
22b			(car)+(SUV)	6	14	-4300.4	-4247.2	70	3.3e-2	SL effect
22c			(SUV)+(SUV)	2	10	-1350.6	-1338.5	10	7.4e-2	SL effect
23			(car/SUV)+(truck)	6	11	-523.35	-498.99	55	0.71	
24			one vehicle	4	20	-2432.0	-2393.4	60	0.065	
25	US route	rural	(car/SUV)+(car/SUV)	4	9	-329.22	-311.62	27	0.13	
26			(car/SUV)+(truck)	3	7	-243.30	-233.82	14	0.17	
27			one vehicle	2	14	-1484.2	1472.3	14	0.049	SL effect
28		urban	(car/SUV)+(car/SUV)	2	7	-969.51	-961.10	7	0.019	SL effect
29			(car/SUV)+(truck)	2	6	-192.74	-184.75	6	0.014	SL effect
30			one vehicle	3	9	-173.27	-166.32	18	0.74	

* – For models with “SL effect” conclusion speed limit is statistically significant for the structure of accident severity models, it is not significant otherwise.

Next let us refer to Table 5.3 and Table 5.4, which are related to 2004 and 2006 accident data respectively. These tables give the results for the log-likelihood ratio tests of statistically significant differences among the models estimated for different speed-limit bins for each of the considered road-class-accident-type combination (the bins themselves are given in Table C.3 and Table C.4 in Appendix C). We find the following results:

- Speed limit does not have any statistically significant effect on the structure of severity models for 2004 and 2006 accidents on interstate highways (both urban and rural).
- Speed limit has a statistically significant effect on the structure of severity models for accidents on all other road classes (with the exception of 2004 accidents on urban county maintained roads, for which speed limit has no any statistically significant effect on the severity model structure).

5.2.2. Effect of Other Explanatory Variables

Now we use model estimation results given in Table C.5 and Table C.6 in Appendix C and consider the influence of explanatory variables other than the posted speed limit on severity of 2004 and 2006 accidents. Similar to the accident causation study, we again limit our consideration to several of the most important and most statistically significant variables.

- **Variables “wint” and “sum” (see pages 113 and 143):** We find that the probability of higher severity of an accident generally decreases during winters and increases during summers (this effect was stronger in year 2004). This result appears to be an unexpected result. However, it can be explained. First, drivers do take some extra precautions during bad winter weather. Although these precautions are not sufficient to keep the drivers safe (refer to accident causation study results in Section 4.2.2), they can reduce probabilities of very severe accident outcomes.

Second, it is very likely that the number of minor (PDO) accidents sharply increases during winters due to less safe weather and roadway conditions. This increase shifts the outcome probabilities (conditioned on the fact that an accident occurred and observed) toward less severe accident outcomes. In other words, the number of serious accidents (e.g. fatalities) might increase during winters, but the number of minor accidents is likely to increase much more. The summer seasonal effect is the opposite of the winter seasonal effect.

- **Variables “dark” and “darklamp” (see pages 118, 119, 148 and 149):** We find that the probability of higher severity of an accident generally increases when the road is dark, even if there are street lights. The explanation can be that during night time drivers have harder time controlling their vehicles and holding the road. Thus, drivers become more likely to be involved into serious accidents (such as head-on collisions, collisions with stationary objects, and rollovers).
- **Variables “nojun” and “way4” (see pages 123, 153 and 154):** We find that accidents are generally more likely to be more severe if they occur at road junctions, and especially at 4-way intersections. This effect mainly concerns two-vehicle accidents and it can be explained as follows. On one hand, two-vehicle collisions in which one vehicle hits a side of the other vehicle are most likely to occur at road junctions. On the other hand, side impacts are highly dangerous due to high driver and passenger vulnerability during such impacts.
- **Variables “driver” and “env” (see pages 127, 128 and 155):** We find that the probability of higher severity of an accident generally increases when the primary cause of the accident is driver-related, while the probability decreases when the primary cause is environment-related. This is a relatively strong effect. It is due to human mistakes being especially dangerous because they are totally unpredictable, while

environment (e.g. weather-related) factors are observable and can be accounted for by taking additional precautions.

- **Variables “hl5”, “hl10” and “hl20” (see pages 128, 129, 156 & 157):** Depending on the road class and accident type, we find that an accident has higher probability of a severe outcome if help arrives more quickly. This effect can be due to a data selection bias because help is not needed at all in the case of minor accidents.
- **Variable “moto” (see pages 130 and 157):** Accidents involving a motorcycle are typically more severe. This is a strong effect. It is explained by very high vulnerability of motorcycle riders.
- **Variable “vage” and “voldo” (see pages 132, 140, 158 and 165):** We find that the probability of higher severity of an accident increases with the age of a vehicle involved into the accident. This may be an outgrowth of older vehicles being generally less safe than newer vehicles.
- **Variable “X₂₇” and “maxpass” (see pages 133, 140, 159 and 166):** We find that the probability of higher severity of an accident typically increases with the number of occupants in vehicles involved into the accident. This effect is expected for three reasons. First, the likelihoods of at least one death and at least one injury increase when there are more occupants in a colliding vehicle. Second, occupants’ bodies hit each other during a collision. Third, a more heavily occupied vehicle has higher mass and higher kinetic energy to dissipate during a collision.
- **Variable “priv” (see pages 135 and 160):** We find that accidents occurred in private drives are typically less severe. Such accidents are minor because vehicles generally travel at low speeds in private drives.
- **Variable “X₃₃” (see pages 137 and 163):** We find that the probability of higher severity of an accident considerably increases when at least one of the vehicles involved in the accident caught fire. This is a very strong effect. Obviously, fire is very dangerous for drivers and passengers involved into an accident.

- **Variables “X₃₅”, “ff” and “mm” (see pages 139, 141, 165 and 168):**

We find that generally the probability of higher severity of an accident increases when the driver at fault is female. In addition, when two female drivers are involved in a two-vehicle accident, then this accident is more likely to be reported as severe, as compared to the case when two male drivers are involved. This could be the result of physical and behavioral difference between genders.

The previous analysis is based on cross-sectional data comparing the effect of different speed limits on a class of roadways for a single year. This is an important consideration because it controls for possible changes in vehicle safety features, enforcement levels and driver behavior that may change from one year to the next. Still, it may also be of interest to compare 2004 and 2006 accident-severity models to see if the 2005 speed-limit increase (and the other factors that may have varied over this time period) significantly changed the estimated parameters in the accident severity models. To address this possibility, we consider; 1) interstates that remained had the same 55 mph speed limits in 2004 and 2006 (which are in urban areas), and 2) interstates that were 65 mph in 2004 and increased to 70 mph in 2006 (which are in rural areas). The appropriate statistical test is (Washington et. al, 2003),

$$-2 \left[LL(\beta_{all}) - LL(\beta_{2004}) - LL(\beta_{2006}) \right] \sim \chi^2_{df = K}, \quad \text{Eq. 5.1}$$

where $LL(\beta_{all})$ is the log-likelihood at converged values of β for the model estimated 2004 and 2006 data for the accident type being considered; $LL(\beta_{2004})$ is the log-likelihood of the model estimated for 2004 observations; $LL(\beta_{2006})$ is the log-likelihood of the model estimated for 2006 observations; and K is the number of parameters estimated for each model.

The estimation results show that the accident severity parameter estimates (for single and multivehicle crashes) did not significantly change from 2004 to 2006

on Interstates that remained at 55 mph. This indicates that the "halo effect" of the increased speed limits (from 65 mph to 70 mph in rural areas) did not significantly affect those interstates that remained at 55 mph. Temporal stability tests also showed that accident severity parameter estimates (for single and multivehicle crashes) did not significantly change from 2004 to 2006 on Interstates that were 65mph in 2004 and either 65 or 70mph in 2006. The temporal stability of these models adds further evidence to support the cross-sectional finding that the higher range of speed limits in effect on Indiana interstates in 2006 has not significantly affected the severity of accidents.

CHAPTER 6. SPEED LIMITS AND SPEED-LIMIT COMPLIANCE

In this chapter we will not focus on the accident-generating outcomes of increased speed limits, but instead try to provide insight into the factors that determine drivers' usual speed selection when faced with specific speed limits under low traffic-volume conditions (free-flow conditions as defined by the Transportation Research Board, 2000, see also Mannering et. al., 2005). To be sure, previous studies have looked at factors that affect usual driving speeds (Kweon and Kockelman, 2003). However, this chapter differs from previous work in that it considers normally selected driving speeds under a range of speed limits that concurrently exist on interstate highways in the study area. By considering such a range of speed limits on drivers' normally selected speed, it is hoped that some additional insight can be provided with regard to the trade-offs drivers make with regard to speed, safety and the adherence to speed-limit laws.

6.1. Effect of Speed Limits on Drivers' Choice of Speed

To understand the effects that speed limits have on drivers' speed choice, some of the principles developed in previous literature relating to risk selection are used (Peltzman, 1975; Viscusi and Carvallo, 1995; Winston et. al., 2006). In so doing, drivers are assumed to maximize their utility from driving by trading off driving speed and safety. Figure 6.1 shows how speed limits can affect the tradeoff between drivers' choice of driving speed and safety. For illustrative purposes, consider safety as the probability of avoiding an accident. Following Winston, Maheshri and Mannering (2006) in Figure 6.1, the marginal rate of

transformation between safety S and driving speed s is shown by the slope of line Ss (linearity is assumed for simplicity). Given this marginal rate of transformation between safety and speed, and the absence of a speed limit, the driver maximizes utility at equilibrium A (reflecting the tangency of an indifference curve U_0), with S^* and s^* chosen as the optimal levels of safety and driving speed. In the presence of a speed limit below A that is strictly followed, the trade-off between accident likelihood and speed will move to B . However, since B is below drivers' optimal speed selection, drivers will tend toward their optimal speed/safety equilibrium (point A). They trade off the additional utility of driving faster against the risk of detection by law enforcement, their respect for the law, and so on, resulting in a new equilibrium at point C , which is likely to be somewhere between points A and B for most drivers.

Figure 6.1 The effect of Speed Limits on Driving Speed

One could also imagine a case where the speed limit is set above point *A* (this may be the case for some older drivers, for example, that might have lower speed equilibrium points). For these drivers, point *D* would be too risky. While one would expect these drivers to still choose point *A*, it is possible that they may try to maintain a higher speed and end up at some point to the left of *A* (such as point *E*).

Given the range of driver abilities, values of time (utility of speed) and acceptance of risk, for any given section of highway and traffic flow conditions there will be a distribution of point *A*'s that will determine the variance of traffic speed. Depending on traffic conditions and driver populations, the imposition of a speed limit will result in new equilibrium points that could increase or decrease this variance.

Please note in the above examples, for purposes of exposition, it is assumed that the slope of *Ss* will remain constant. In fact, the speed selection choices of other drivers in the presence of speed limits may alter risks and change the slope of *Ss*.

6.2. Data

Given the discussion relating to Figure 6.1, the empirical question becomes one of identifying the factors that determine individual drivers' choice of point *C* (or point *E* if speed limits are too high). To study this, a survey was developed and administered to Indiana residents in the late fall of 2005 on the campus of Purdue University. The timing of the survey was particularly relevant since Indiana raised the speed limits on its rural interstates from 65 mph to 70 mph on July 1, 2005. Thus survey respondents had current experience with interstate speed limits set at 55 mph (urban areas), 65 mph (some suburban areas that were not increased to 70 mph) and 70 mph (rural areas).

The survey questions are presented in Table 6.1. To avoid the interactions of traffic flow and speed, the speed-related questions (Questions 2, 3 and 4) focused on self-reported normal driving speeds on interstate highways (of specified speed limit) with little traffic. As can be seen from Table 6.1, a broad range of socioeconomic and opinion data were gathered.

The survey was administered to a sample of licensed drivers who indicated they regularly drove on Indiana freeways. The sample consisted of undergraduate and graduate students at Purdue, primarily from engineering disciplines. Because our study is exploratory in nature, no attempt was made to acquire a random sample of Purdue University students (or Indiana drivers). The implication of this will be discussed later in the chapter. In all, 250 surveys were administered (most in a classroom environment), and 204 surveys were returned with complete information. Of these 204 respondents, 194 reported normally driving above a 55 mph speed limit, 190 reported normally driving above a 65 mph speed limit, and 178 reported normally driving above a 70 mph speed limit. This would suggest that for the majority of drivers in the survey, the speed limit is to the left of their point A (see Figure 6.1). However, there is also evidence that a small number of survey respondents view the speed limit as being set above their point A. Of the 204 respondents, 1 person normally drove below the 55 mph speed limit (9 reported they drive at the 55 mph speed limit), 3 people normally drove below the 65 mph speed limit (11 reported they drive at the 65 mph speed limit), and 6 people drove below the 70 mph speed limit (20 reported they drive at the 70 mph speed limit).

Summary statistics for the sample are presented in Table 6.2. This table shows that the reported average normal driving speed was nearly 66 mph on interstates posted with 55 mph speed limits, about 74 mph on interstates posted at 65 mph and almost 78 mph on interstates that are posted at 70 mph.

Table 6.1 Survey Questions

-
1. Indiana recently raised the speed limit on some of its interstate highways from 65mph to 70mph. Do you think this is:

☐ too fast
☐ about right
☐ still too slow
 2. On an interstate with a 55 mph speed limit and little traffic, about how fast do you normally drive? _____mph
 3. On an interstate with a 65 mph speed limit and little traffic, about how fast do you normally drive? _____mph
 4. On an interstate with a 70 mph speed limit and little traffic, about how fast do you normally drive? _____mph
 5. How would you rate the quality of pavements on Indiana interstates?

☐ poor
☐ fair
☐ good
☐ very good
☐ don't know
 6. Compared to adjacent states (Ohio, Illinois, Michigan and Kentucky), how would you rate the quality of pavements on Indiana interstates?

☐ worse than adjacent states
☐ about the same

☐ better than adjacent states
☐ don't know
 7. Which one of these luxury car brands do you believe has the most prestige?
(select one)

☐ Acura
☐ Audi
☐ BMW
☐ Cadillac
☐ Infiniti

☐ Jaguar
☐ Lexus
☐ Lincoln
☐ Mercedes
 8. Which one of these of these vehicle brands do you believe provides the best value for the money? **(select one)**

☐ Chevrolet
☐ Dodge
☐ Ford
☐ Honda
☐ Hyundai

☐ Kia
☐ Mazda
☐ Nissan
☐ Toyota
 9. Are you? ☐ female ☐ male
 10. Are you? ☐ married ☐ single ☐ separated

☐ divorced
☐ other
 11. What is your age? _____
 12. What is your highest completed level of education?

☐ some high school
☐ technical college degree

☐ post graduate degree
☐ high school diploma
☐ college degree
 13. What is the approximate annual household income of the household you consider home?

☐ no income
☐ under \$10,000
☐ \$10,000-\$19,999

☐ \$20,000-\$29,999
☐ \$30,000-\$39,999
☐ \$40,000-\$49,999

☐ \$50,000-\$74,999
☐ \$75,000-\$100,000
☐ Over \$100,000
 14. Including yourself, how many people live in the household you consider home?

 15. How many children, in the household you consider home, are under age 6?

 16. How many children, in the household you consider home, are aged 6 to 16?

 17. How many people living, in the household you consider home, work outside the home?

 18. How many licensed and operable motor vehicles does your "home" household have?

 19. How many years have you had a driver's license?

-

Kockelman and Bottom (2006) found, with observed speed data from Austin, Texas, that a 5 mph increase in the speed limit was associated with a 3.2 mph increase in average speeds. In the current sample, the observed 3.83 mph increase in normal speeds between 65 mph and 70 mph posted interstates is close to this.

The data indicate that the amount driven above the speed limit declines with higher speed limits (presumably as the speed limit approaches point A in Figure 6.1). In terms of the standard deviations of normal driving speeds, the greatest reported variance is at the 55 mph speed limit (6.24 mph), and the variances at 65 mph and 70 mph speed limits are roughly the same (5.03 mph and 5.24 mph, respectively). Although the variance differences among the three speed limits are small, which is consistent with the findings of Kockelman and Bottom (2006), there is a higher variance with the 55 mph speed limit. While the sample is small and traffic-related effects are not accounted for (recall that only low-volume conditions are considered), in this sample it appears that a 55 mph speed limit may be too slow to achieve minimum speed variance.

Table 6.2 shows that the values of other variables in the sample, particularly those relating to socioeconomic variables, reflect those of the Purdue University community – with an average age of only 25, 25% being married, 18% having children under 6 years of age, and so on.

6.3. Methodology

As indicated in Table 6.1 and Table 6.2, the survey contains three questions relating to normal driving speed under various speed limits; 1) normal driving speed on an interstate with a 70 mph speed limit and little traffic, 2) normal driving speed on an interstate with a 65 mph speed limit and little traffic, and 3) normal driving speed on an interstate with a 55 mph speed limit and little traffic.

Table 6.2 Sample statistics (standard deviation in parentheses when appropriate)

Variable	Values
Percent believing Indiana's recently raised the speed limits from 65mph to 70mph is: too fast/about right/still too slow	2/72/26
Average normal driving speed on an interstate with a 55 mph speed limit and little traffic	65.92 (6.24)
Average normal driving speed on an interstate with a 65 mph speed limit and little traffic	74.05 (5.03)
Average normal driving speed on an interstate with a 70 mph speed limit and little traffic	77.88 (5.24)
Percent rating the quality of pavements on Indiana interstates as: poor/fair/good/very good/don't know	11/30/44/9/6
Percent rating the quality of pavements on Indiana interstates as: worse than adjacent states/about the same/better than adjacent states/don't know	12/45/16/27
Percent believing the following luxury car brands provide the most prestige: Acura/ Audi/BMW/Cadillac/Infiniti/Jaguar/Lexus/Lincoln/Mercedes Benz	1/6/23/4/2/19/10/2/33
Percent believing the following vehicle brands provide the best value for the money: Chevrolet/Dodge/Ford/Honda/Hyundai/Kia/Mazda/Nissan/Toyota	8/2/11/37/6/2/2/7/25
Percent: female/male	26/74
Percent: married/single/separated/divorced/other	25/71/0/0/4
Average age	25.00 (6.46)
Percent with highest completed level of education: some high school/ high school diploma/technical college degree/college degree /post graduate degree	1/48/4/29/18
Percent with annual household income as: no income/ under \$10,000/\$10,000-\$19,999/ \$20,000-\$29,999/\$30,000-\$39,999/\$40,000-\$49,999/\$50,000-\$74,999/\$75,000-\$100,000/Over \$100,000	4/1/16/8/6/5/17/16/27
Average number of people living in household	3.52 (1.52)
Average number of children in household that are under age 6	0.18 (0.50)
Average number of children in household that are aged 6 to 16	0.26 (0.60)
Average number of people in household that work outside the home	1.91 (1.17)
Average number of licensed motor vehicles in household	2.82 (1.41)
Average number of years licensed	7.04 (6.11)

To develop a statistical model for each of these three questions, the use of ordinary least squares regressions is an obvious choice. Under standard linear regression assumptions, that includes the assumption that the model has all of the information relating to the regression equation and variables, estimated regression coefficients for the three equations are unbiased and efficient (Washington et. al., 2003). However, if some information is not taken into account, the properties relating to the unbiasedness and efficiency of estimated coefficients cannot be determined. A classic example of potentially missing information is the knowledge that the disturbance term in one regression equation is correlated with the disturbance term in another. This will be the case for the three equations relating to normal driving speed at different speed limits since the unobserved factors that determine driving speed for each speed limit will likely be highly correlated.

For model formulation, the speed variables are transformed by subtracting the speed limit from the reported normal driving speed – giving the number of miles per hour normally driven above the speed limit. This is formalized in the following equation system:

$$Speed_{70} = \beta_{70}Z + \alpha_{70}X + \varepsilon_{70} \quad \text{Eq. 6.1}$$

$$Speed_{65} = \beta_{65}Z + \alpha_{65}X + \varepsilon_{65} \quad \text{Eq. 6.2}$$

$$Speed_{55} = \beta_{55}Z + \alpha_{55}X + \varepsilon_{55} \quad \text{Eq. 6.3}$$

In these equations, $Speed_{70}$, $Speed_{65}$ and $Speed_{55}$ are the number of miles per hour respondents normally drive above the speed limit (with little traffic) for 70, 65, and 55 mph speed limits, respectively. These variables can take on positive values if respondents normally drive above the speed limit and negative values if they normally drive below it. Also in these equations, Z is a vector of driver and driver-household characteristics, X is a vector of vector of driver

preferences and opinions, β 's, α 's, are vectors of estimable coefficients, and ε 's are disturbance terms. Note that Equations 6.1, 6.2 and 6.3 do not directly interact with each other. That is, $Speed_{70}$, does not directly determine $Speed_{65}$, $Speed_{65}$ does not directly affect $Speed_{55}$, and so on, as one would expect in a classic simultaneous equation system (see, for example, Shankar and Mannering, 1998). However, because all three responses represented by Equations 6.1, 6.2 and 6.3 are from the same driver, these equations are likely to share unobserved characteristics. In this case, the equations are seemingly unrelated but there will be contemporaneous (cross-equation) correlation of error terms. If Equations 6.1, 6.2 and 6.3 are estimated separately by ordinary least squares, the coefficient estimates are consistent but not efficient. Efficient coefficient estimates are obtained by considering the contemporaneous correlation of disturbances ε_1 , ε_2 and ε_3 . Considering contemporaneous correlation in seemingly unrelated equations was first considered by Zellner (1962). Estimation of seemingly unrelated equations is accomplished using generalized least squares. Recall that under ordinary least squares assumptions the disturbance terms have equal variances and are not correlated, resulting in coefficients being estimated as,

$$\hat{\beta} = (X^T X)^{-1} X^T Y \quad \text{Eq. 6.4}$$

where $\hat{\beta}$ is a $p \times 1$ column vector (where p is the number of coefficients), X is an $n \times p$ matrix of data (where n is the number of observations), X^T is the transpose of X , and Y is an $n \times 1$ column vector. Generalized least squares generalizes this expression by using a matrix that considers for correlation among equation error terms (Ω), Equation 6.4 is rewritten as,

$$\hat{\beta} = (X^T \Omega^{-1} X)^{-1} X^T \Omega^{-1} Y \quad \text{Eq. 6.5}$$

The most difficult aspect of generalized least squares estimation is obtaining an estimate of the Ω matrix. In seemingly unrelated regression estimation, Ω is

estimated from initial ordinary least squares estimates of individual equations (Washington et. al. 2003).

6.4. Estimation Results

Table 6.3 presents the sample statistics for the variables found to be significant in the speed models. Excluding respondents with missing data, there were 195 valid observations. Following the numbers presented earlier in Table 6.2, with regard to the dependent variables, the table shows that drivers reported that they normally drove an average of nearly 11 mph faster than the speed limit on interstates posted 55 mph, about 9 mph faster than the speed limit on interstates posted at 65 mph, and nearly 8 mph faster than the speed limit on interstates posted at 70 mph. The standard deviation of normal driving speeds above the posted speed limit was 6.21 mph for 55 mph speed limits, 5.10 mph for 65 mph speed limits and 5.35 mph for 70 mph speed limits.

Seemingly unrelated regression estimation results are presented in Table 6.4. In general, the models fit the data well (especially considering the variance in the data) and the coefficient estimates are of plausible sign and generally good statistical reliability. It should be noted that these same models were run as separate regressions using ordinary least squares. The ordinary least squares regression coefficients had noticeably higher standard errors resulting in lower t -statistics (in fact, three variables included in the models presented in Table 6.4 had t -statistics less than one). Thus, the efficiency gains from using seemingly unrelated regression estimation are considerable in this case.

The results in Table 6.4 show that men normally drive faster than the speed limit on interstates posted 65 mph. However, this coefficient estimate was not highly significant and the male indicator variable was not statistically significant (p -values less than 0.10) on interstates posted 55 mph and 65 mph.

As expected, increasing driver age generally had a negative effect on the miles per hour normally driven above the speed limit. The age variable was significant for interstates posted 65 mph and 70 mph, resulting in about a tenth of a mile per hour reduction for each year older the driver becomes. However, age was found to be statistically insignificant for interstates with 55 mph speed limits.

Drivers from high-income households (\$75,000 per year or greater) were found to be more likely to normally drive faster under all three speed-limit postings considered. Having a higher income resulted in about 2 mph higher normal speeds for 55 mph and 65 mph speed limits and a little over 1 mph higher speed for interstates with 70 mph speed limits. This could be reflecting their higher value of time or perhaps higher vehicle quality.

Drivers from lower-income households (\$30,000 per year or greater) were found to be more likely to normally drive slower on interstates with 55 mph speed limits. However, this variable was not highly significant (p -value of 0.12) and the effect on normal speed was less than 1 mph. Again, this could be a result of value of time and vehicle quality.

The number of children less than six years of age in the household caused normal driving speeds to be lower for all three speed-limit models. The effect was to lower normal driver speeds about 1 mph. This may be a result of higher safety awareness among drivers with younger children.

Table 6.3 Statistics for variables found to be significant in model estimation

Variable	Mean	Standard deviation	Minimum/Maximum
<u>Dependent variables</u>			
Miles per hour normally driven above a 55 mph speed limit	10.96	6.21	-5/35
Miles per hour normally driven above a 65 mph speed limit	9.06	5.10	-5/25
Miles per hour normally driven above a 70 mph speed limit	7.88	5.35	-10/20
<u>Driver/household attributes</u>			
Male indicator (1 if driver is male, 0 otherwise)	0.742	0.439	0/1
Driver age (years)	25.21	6.58	17/51
High income indicator (1 if household's total annual income is \$75,000 or greater, 0 otherwise)	0.268	0.444	0/1
Low income indicator (1 if household's total annual income is less than \$30,000, 0 otherwise)	0.289	0.454	0/1
Number of children under the age of 6 years old in the household	0.196	0.522	0/3
Late license indicator (1 if driver was first licensed at age 17 or greater, 0 otherwise)	0.361	0.481	0/1
<u>Driver opinions</u>			
Good pavement indicator (1 if driver believes pavement quality on Indiana interstates is good or very good, 0 otherwise)	0.531	0.500	0/1
German prestige indicator (1 if driver believes if German-brand vehicles are the most prestigious, 0 otherwise)	0.634	0.483	0/1
Japanese prestige indicator (1 if driver believes if Japanese-brand vehicles are the most prestigious, 0 otherwise)	0.119	0.324	0/1

Table 6.4 Seemingly unrelated regression equation (SURE) estimation results for the number of miles per hour above the speed limit drivers report as their usual speed (*t*-statistics in parentheses)^a

Variable	Estimated Coefficient (55 mph SL)	Estimated Coefficient (65 mph SL)	Estimated Coefficient (70 mph SL)
Constant	11.11 (12.37)**	10.88 (10.27)**	10.86 (8.44)**
<u>Driver/household attributes</u>			
Male indicator (1 if driver is male, 0 otherwise)	—	0.470 (1.37)*	—
Driver age (years)	—	-0.088 (-2.47)**	-0.129 (-2.83)**
High income indicator (1 if household's total annual income is \$75,000 or greater, 0 otherwise)	1.958 (2.06)**	2.099 (2.71)**	1.255 (1.52)*
Low income indicator (1 if household's total annual income is less than \$30,000, 0 otherwise)	-0.763 (-1.17)	—	—
Number of children under the age of 6 years old in the household	-1.207 (-1.54)*	-0.993 (-1.48)*	-1.359 (-1.87)**
Late license indicator (1 if driver was first licensed at age 17 or greater, 0 otherwise)	-3.851 (-4.38)**	-2.148 (-3.00)**	-1.919 (-2.50)**
<u>Driver opinions</u>			
Good pavement indicator (1 if driver believes pavement quality on Indiana interstates is good or very good, 0 o.w.)	1.160 (1.46)*	1.067 (1.62)*	1.006 (1.43)*
German prestige indicator (1 if driver believes if German-brand vehicles are the most prestigious, 0 otherwise)	1.137 (1.85)**	—	0.582 (1.35)*
Japanese prestige indicator (1 if driver believes if Japanese-brand vehicles are the most prestigious, 0 o.w.)	-1.348 (-1.25)	-0.814 (-1.35)*	—
R ²	0.226	0.200	0.170
Number of observations		195	
Equation system R ²		0.202	

^a One-tailed *t*-test results: ** significantly different from zero at more than 95% confidence, * significantly diff. from zero at > 90% conf.

Individuals that were licensed at age 17 or later had normal driving speeds that were significantly slower under all three speed-limit postings (official licensing age is 16 years in Indiana). The magnitude of this slow down ranged from nearly 4 mph on interstates with 55 mph speed limits to about 2 mph on interstates with 65 mph or 70 mph speed limits. This variable was also found to be significant in some previous safety-related research. For example, using a sample of Washington State drivers, Mannering (1993) found that the number of years after age 16 (the official licensing age in Washington) that women were licensed significantly increased the frequency of their roadway accidents. This variable may be capturing a self-selection process where individuals that are risk adverse or have poorer innate driving skills may wait longer to be licensed and drive more slowly.

Three preference/opinion variables were also found to influence normal driving speed. Those drivers that subjectively rated Indiana interstates as having pavements that were good or very good in quality were more likely to drive faster for all three speed limits considered (about 1 mph faster). This could reflect the impression that high quality pavements are quieter and safer which allows individuals to drive faster while maintaining the same risk/ergonomic comfort levels.

Two variables relating to drivers' impressions of vehicle prestige also played a role in the choice of normal interstate speed under various speed limits. Individuals believing that German manufacturers (Mercedes Benz, BMW and Audi) made the most prestigious cars were more likely to drive faster than the speed limit on interstates posted 55 mph and 70 mph. It is likely that this variable is capturing unobserved heterogeneity in the data (that is correlated with vehicle manufacturer perceptions) relating to drivers' perceptions of risk, the utility derived from higher speed driving, and so on. In a similar vein, those drivers believing that Japanese manufacturers made the most prestigious

vehicles drove slower (less above the speed limit) on interstates posted 55 mph and 65 mph.

Given these estimation results, and the observation that drivers' reported speeds are generally well above the speed limit, what does this say about how speed limits should be set? And, what does this say about enforcement of posted speed limits? The results of this study cannot answer these question directly, but it seems clear that drivers do not believe that driving above the speed limit significantly threatens their safety. In fact, a recent survey of 988 Indiana drivers from Bureau of Motor Vehicle offices in Tippecanoe County indicated that 35% did not believe their safety was threatened until they were driving 20 mph over the speed limit, and an additional 3% thought that speed was snot a threat to their safety at all (Mannering, 2007). It appears as though setting speed limits that will be respected requires a complex assessment of society's desire for safety and individual drivers' perception of the speed-safety relationship and the trade-offs they are willing to make – which includes the effect of enforcement.

CHAPTER 7. SUMMARY AND CONCLUSIONS

The findings of our study are drawn from three statistical models. First we develop a binary model to study the probability that unsafe speed will be determined to be the primary cause of the accident (as reported by the officer). Second, we develop a series of models to study accident severity defined by the injury level of the most severely injured person in the accident. The alternatives are no-injury, injury and fatality. And third, we develop a model to predict normal interstate driving speeds reported by Indiana drivers on interstate highways that are posted 55 mph, 65 mph and 70 mph under low traffic conditions (level of service A).

For interstate highways, we find that speed limits had no statistically significant effect on the probability that unsafe speed will be listed as the primary cause of the accident except with 2006 data on one vehicle accidents on rural interstates. In this case higher speed limits actually reduced the likelihood that unsafe speed was listed as the primary cause of the accident. As mentioned earlier, some caution should be exercised in interpreting these results because the determination of the officer at the accident scene as to what constitutes the primary cause is an opinion that may be influenced by a multitude of factors (including the posted speed limit itself).

With regard to the effect of speed limits on the severity of vehicle accidents on interstate highways, we find that, for both 2004 and 2006 accident data, speed limits have an insignificant effect on accident severity on interstate highways. This is an important finding because the July 1, 2005 increase in maximum

interstate speeds from 65 mph to 70 mph has been the focus of considerable media attention. Thus, our analysis covers data from the 70 mph maximum speed limit era (2006) as well as the 65 mph maximum speed limit era (2004). We exclude 2005 data because it is a transition year with speed limits being raised in mid year.

The finding that the speed-safety relationship on interstate highways is not statistically significant, at least in the ranges we consider (maximum of 65 mph in 2004 and 70 mph in 2006), can be the result of a number of factors. First, drivers seem to have a tendency to compensate for posted speed limits. Based on the survey of Indiana drivers conducted in the Fall of 2005, compliance with speed limits improves from 55 mph to 65 mph interstates and 65 mph to 70 mph interstates. Our survey indicated that average driving speeds under free flow conditions were nearly 66 mph on interstates posted 55 mph, 74 mph on interstates posted 65mph, and almost 78 mph on interstates posted 70 mph. Our survey also shows that the higher speed limits of 65 and 70 mph have a lower variance of speeds. The reduction in speed variance as the posted speed limit increases has been discussed in the literature by many including Renski et al., 1999. The "speed variance reduction effect" can be explained by an analysis of Figure 6.1 (Chapter 6) – drivers have an optimal speed under specific traffic conditions and tend towards that speed while weighing the probability of being detected by law enforcement.

Countering this reduction in speed variance is the fact that at higher speeds, vehicles travel larger distances during driver reaction times. Thus, drivers have less time to react to changing conditions on the road (such as weather conditions or an object on the roadway surface), resulting in an increase in the frequency and severity of unsafe-speed-related accidents. In addition, a vehicle generally loses stability and roadway traction with an increase in speed because of increased aerodynamic and centripetal forces acting on the vehicle. Also, the

average kinetic energy of vehicles increases with their speeds. Because this energy must be dissipated during an accident, collisions tend to become more severe as speeds increase.

Another factor that could be playing a role in our interstate speed limit finding is that the high design standards of interstate highways (full access control, high design speeds, median design, shoulders, etc.) may act to mitigate the physics associated with higher speeds. However, with current interstates designed for 70 mph speeds, it is unclear if this finding would hold for maximum speed limits of 75 mph or more. Also, the level of enforcement could be playing a role.

The finding that higher speed limits do not significantly affect the severity of accidents on interstates suggests that the reduction in speed variance, the fact that average speeds do not seem to change that much (average speeds only go up about 3.8 mph between interstates posted 65 mph and 70 mph) and the high design standards of interstate highways are enough to offset the physics associated with higher speed travel. It also suggests that increasing speed limits on rural interstates from 65 mph to 70 mph (for vehicles under 13 tons gross weight) did not adversely affect the relative severity of accidents on lower and higher speed-limit interstate segments.

For non-interstate highways, the results are quite different. In 2004, for the probability that unsafe speed being listed as the primary cause of the accident, higher speed limits increase this probability for one-vehicle accidents on rural county-maintained roads and for multivehicle accidents on a number of roadway classes. Interestingly, higher speed limits decrease the likelihood of unsafe speed being listed as the primary cause for one-vehicle accidents on rural US routes and urban streets. In 2006, higher speed limits were found to increase this probability for multivehicle accidents on urban state routes but to decrease it for single-vehicle accidents on rural state routes. The conclusion that can be

drawn from these findings is that the effect of speed limits on the probability of unsafe speed being reported as the primary cause of the accident varies by roadway type and also varies by accident year, suggesting that the increase in speed limits in 2005 has had an effect on the speed-limit causality of accidents and/or officer reporting tendencies.

In terms of accident severities on non-interstate highways, both 2004 and 2006 accident data show that higher speed limits are associated with a greater likelihood of injury and/or fatality on some (but not all) roadway types (county, state, city and US routes) and accident types (single and multivehicle). The data also show that the speed-limit effects on accident severity vary from 2004 to 2006, suggesting that drivers may still be adjusting their speed behavior in response to the new speed limits and/or this may be reflecting a natural evolution of driver behavior over time.

This study's findings have a number of implications for speed limit policies in the State of Indiana. Our findings suggest that the effect of speed limits on the probability of unsafe speed being listed as the primary cause of the accident and on accident severity are not significant for the speed-limit ranges that we have studied (55mph, 65mph, 70mph). Whether this finding would hold true if speed limits were increased further to 75mph or 80mph remains an open question. To be sure, the additional speed would increase stopping distances and the energy that would need to be dissipated in the accident. Also, at some point, higher speed limits may start increasing the variance in driver speeds as some drivers continue to drive at or above the speed limit while others drive below the speed limit because the speed limit may have been raised above their "optimum" speed. And, increasing the speed limit above 70 mph would mean increasing it above the roadway's design speed, which could have additional implications. With these factors considered (along with other factors that may come into play such as drivers' variations in driver behavior in response to

speed limits), we speculate that there will be a point beyond which higher speed limits will significantly increase the severity of accidents on interstates. This is because at some speed-limit level the "traffic calming" effects of higher speed limits will likely become insufficient to offset the physics involved as they now seem to be doing.

With regard to speed limit policies on roadways other than interstate highways, our results suggest that considerable caution should be exercised. The findings show that, on some non-interstate roadway and accident type combinations, higher speed limits significantly increase likelihood that unsafe speed will be listed as the primary cause of the accident and also on some non-interstate roadway and accident type combinations significantly increase the likelihood that accidents will result in injuries and fatalities. Thus, changing speed limits on non-interstate highways should be done on a case-by-case basis taking into account past accident history as well as the specific geometrics and access control of the facility, as these factors can vary widely even within the same class of highways (non-interstate).

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Appendix A.

List of explanatory variables:

- X₃ – Collision date
- X₄ – Day of the week
- X₅ – Collision time
- X₁₃ – Construction
(no; yes; buck-up of traffic outside of but due to construction zone)
- X₁₄ – Light condition
(daylight; dawn / dusk; dark with street lights on; dark with no lights)
- X₁₅ – Weather condition
(clear; cloudy; sleet/hail / freezing rain; fog / smoke / smog; rain; snow; severe cross wind)
- X₁₆ – Surface condition
(dry; wet; muddy; snow / slush; ice; loose material on roadway; water)
- X₁₇ – Type of median
(drivable; curbed; barrier wall; none)
- X₁₈ – Type of roadway junction
(no junction involved; four-way intersection; ramp T-intersection; Y-intersection; traffic circle / roundabout; five point or more; interchange)
- X₁₉ – Road character
(straight / level; straight / grade; straight / hillcrest; curve / level; curve / grade; curve / hillcrest; non roadway crash)
- X₂₀ – Primary contributing circumstance
(alcoholic beverages; illegal drugs; driver asleep or fatigue; prescription drugs; driver illness; **unsafe speed**; failure to yield right of way; disregard signal / red signal; left of center; improper passing; improper turning; improper lane usage; following too closely; unsafe backing; overcorrecting / oversteering; ran off road right; ran off road left; wrong way on one way; pedestrian action; passenger distraction; violation of license restriction; jackknifing; cell phone usage; other telematics in use; other (explain in narrative); driver distracted [explain in narrative]; **speed too fast for weather conditions**; engine failure or defective; accelerator failure or defective; brake failure or defective; tire failure or defective;

headlight defective or not on; other lights defective; steering failure; window / windshield defective; oversize / overweight load; insecure / leaky load; tow hitch failure; other explained in narrative; glare; roadway surface condition; holes / ruts in surface; shoulder defective; road under construction; severe crosswinds; obstruction not marked; lane marking obscured; view obstructed; animal on roadway; traffic control problem; other [explained in narrative]; utility work)

X₂₂ – Time when help arrived

X₂₅ – Vehicle type, considered for the vehicle at fault, i.e. for the vehicle that contributed to the primary cause of an accident
(passenger car / station wagon; pickup; van; sport utility vehicle; truck [single 2 axle, 6 tires]; truck [single 3 or more axles]; truck / trailer [not semi]; tractor / one semi trailer; tractor / double trailer; tractor / triple trailer tractor [cab only, no trailer]; motor home / recreational vehicle; motorcycle; bus/seats 9-15 persons with driver; bus / seats 15+ persons with driver; school bus; unknown type; farm vehicle; combination vehicle; pedestrian; bicycle)

X₂₆ – Vehicle year, considered for all vehicles involved

X₂₇ – Number of occupants, considered for all vehicles involved

X₂₈ – Vehicle license state, considered for the vehicle at fault, i.e. for the vehicle that contributed to the primary cause of an accident
(Indiana; Indiana's neighboring states [IL, KY, OH, MI]; other US states; Canada / Mexico / U.S. Territories; other foreign countries)

X₂₉ – Speed limit, considered only if known and the same speed limit value for all vehicles involved

X₃₀ – Road type, considered for the vehicle at fault, i.e. for the vehicle contributed to the primary cause of an accident
(one lane [one way]; two lanes [one way]; multi-lanes [one way]; two lanes [two way]; multi-lane undivided [two way]; multi-lane undivided 2-way left [two way]; multi-lane divided 3 or more lanes [two way]; alley; private drive)

X₃₁ – Traffic control, considered for the vehicle at fault, i.e. for the vehicle contributed to the primary cause of an accident
(officer / crossing guard / flagman; RR crossing gate / flagman; RR crossing flashing signal; RR crossing sign; traffic control signal; flashing signal; stop sign; yield sign; lane control; no passing zone; other regulatory sign / marking; none)

- X_{33} – Fire, considered for all vehicles involved
(*no*; *yes*)
- X_{34} – Driver age, considered for all drivers involved
- X_{35} – Driver gender, considered for all drivers involved

Appendix B.

Table B.1 Road classes & accident types in 2004 accident causation study

#	Road-class-accident-type combination			Number of observations			
				all	available for the models*		
					total	unsafe-speed-related	other causes
1	County road	rural	(car/SUV**)+(car/SUV)	7249	5198	518	4680
2			(car/SUV)+(truck***)	647	617	28	589
3			one vehicle	18045	11998	1877	10121
4		urban	(car/SUV)+(car/SUV)	1854	1490	97	1393
5			(car/SUV)+(truck)	143	121	7	114
6			one vehicle	972	689	142	547
7	Interstate	rural	(car/SUV)+(car/SUV)	1041	995	168	827
8			(car/SUV)+(truck)	811	338	77	311
9			one vehicle	3347	1617	430	1187
10		urban	(car/SUV)+(car/SUV)	2227	1386	131	1255
11			(car/SUV)+(truck)	3306	922	84	838
12			one vehicle	1605	1442	463	979
13	State route	rural	(car/SUV)+(car/SUV)	4774	2311	170	2141
14			(car/SUV)+(truck)	682	665	41	624
15			one vehicle	9775	6432	540	5892
16		urban	(car/SUV)+(car/SUV)	7999	4698	191	4507
17			(car/SUV)+(truck)	636	633	16	617
18			one vehicle	1488	1004	99	905
19	City street	rural	(car/SUV)+(car/SUV)	3778	2648	155	2493
20			(car/SUV)+(truck)	261	261	9	252
21			one vehicle	2387	2187	265	1922
22		urban	(car/SUV)+(car/SUV)	62701	50180	1901	48279
23			(car/SUV)+(truck)	3574	3105	85	3200
24			one vehicle	12205	7988	1134	6854
25	US route	rural	(car/SUV)+(car/SUV)	2588	2005	152	1853
26			(car/SUV)+(truck)	566	563	52	511
27			one vehicle	4202	2667	247	2420
28		urban	(car/SUV)+(car/SUV)	6895	6462	328	6134
29			(car/SUV)+(truck)	750	734	37	697
30			one vehicle	1061	988	97	891

* – observations available for the best estimated statistical models after exclusion of all missing observations

** – “SUV” includes sport utility vehicles, pickups and vans

*** – “truck” includes any possible kind of truck or tractor

Table B.2 Road classes & accident types in 2006 accident causation study

#	Road-class-accident-type combination			Number of observations			
				all	available for the models*		
					total	unsafe-speed-related	other causes
1	County road	rural	(car/SUV**)+(car/SUV)	5956	1698	111	1587
2a			(car)+(truck***)	194	194	6	188
2b			(SUV)+(truck***)	150	126	2	124
3		one vehicle	16132	3518	500	3018	
4		urban	(car/SUV)+(car/SUV)	1485	1483	66	1417
5			(car/SUV)+(truck)	83	79	5	74
6	one vehicle		797	752	103	649	
7a	Interstate	rural	(car)+(car)	395	354	37	317
7b			(car)+(SUV)	518	476	59	417
7c			(SUV)+(SUV)	210	209	26	183
8			(car/SUV)+(truck)	757	742	97	645
9			one vehicle	3730	3637	489	3148
10		urban	(car/SUV)+(car/SUV)	2392	2203	172	2031
11a			(car)+(truck)	627	541	47	494
11b			(SUV)+(truck)	220	209	20	189
12			one vehicle	1883	303	75	228
13	State route	rural	(car/SUV)+(car/SUV)	4577	4377	217	4160
14			(car/SUV)+(truck)	522	511	30	481
15			one vehicle	10155	9421	546	8875
16		urban	(car/SUV)+(car/SUV)	7461	6241	220	6021
17			(car/SUV)+(truck)	509	508	23	485
18			one vehicle	1700	1603	126	1477
19	City street	rural	(car/SUV)+(car/SUV)	3778	1294	55	1239
20a			(car)+(truck)	97	97	4	93
20b			(SUV)+(truck)	57	57	3	54
21			one vehicle	2104	1929	225	1704
22		urban	(car/SUV)+(car/SUV)	50034	20704	563	20141
23a			(car)+(truck)	1526	945	25	920
23b			(SUV)+(truck)	788	481	8	473
24			one vehicle	110682	9011	945	8066
25	US route	rural	(car/SUV)+(car/SUV)	2478	2353	129	2224
26			(car/SUV)+(truck)	474	457	27	430
27			one vehicle	4204	4151	262	3889
28		urban	(car/SUV)+(car/SUV)	6925	6140	206	5934
29a			(car)+(truck)	346	342	12	330
29b			(SUV)+(truck)	226	226	2	224
30			one vehicle	1209	1148	90	1058

* – observations available for the best estimated statistical models after exclusion of all missing observations

** – “SUV” includes sport utility vehicles, pickups and vans

*** – “truck” includes any possible kind of truck or tractor

Table B.3 Binary logit models for 2004 accident causation¹⁹

#	Model name			Log-likelihood		R^2	Coefficient (t-ratio)	
				model	restricted*		X_{29}	constant
1	County road	rural	(car/SUV)+(car/SUV)	-1426.7	-1685.9	.154		-1.14(-6.71)
2			(car/SUV)+(truck)	-87.04	-113.95	.236		
3			one vehicle	-4468.1	-5203.8	.141	.00859(2.83)	-.743(-3.30)
4		urban	(car/SUV)+(car/SUV)	-246.94	-307.15	.196	.0368(2.24)	-1.42(-2.12)
5**			(car/SUV)+(truck)	-16.14	-26.74	.396		-2.57(-2.00)
6			one vehicle	-305.79	-350.52	.128		
7	Interstate	rural	(car/SUV)+(car/SUV)	-327.44	-451.78	.275		.985(-2.40)
8			(car/SUV)+(truck)	-128.79	-193.32	.334		
9			one vehicle	-564.03	-936.51	.398		
10		urban	(car/SUV)+(car/SUV)	-339.99	-436.39	.221		-1.52(-4.83)
11			(car/SUV)+(truck)	-203.66	-306.50	.336		-.928(-2.92)
12			one vehicle	-700.30	-942.58	.257		
13	State route	rural	(car/SUV)+(car/SUV)	-537.67	-607.23	.115		-1.72(-6.68)
14			(car/SUV)+(truck)	-128.69	-153.94	.164		-2.08(-6.50)
15			one vehicle	-1452.8	-1854.5	.217		
16		urban	(car/SUV)+(car/SUV)	-716.67	-798.76	.103	.0212(2.51)	-2.77(-7.83)
17			(car/SUV)+(truck)	-57.96	-74.64	.224		-4.05(-8.74)
18			one vehicle	-274.39	-323.30	.103		-1.03(-2.08)
19	City street	rural	(car/SUV)+(car/SUV)	-525.56	-586.00	.094	.0225(2.50)	-2.87(-5.48)
20			(car/SUV)+(truck)	-35.71	-39.15	.088		-3.69(-8.93)
21			one vehicle	-681.68	-807.55	.156		
22		urban	(car/SUV)+(car/SUV)	-6259.1	-7117.7	.121		-2.43(-20.9)
23			(car/SUV)+(truck)	-323.90	-389.67	.169		-.983(-2.22)
24			one vehicle	-2776.2	-3263.2	.149	-.0117(-3.82)	
25	US route	rural	(car/SUV)+(car/SUV)	-404.95	-475.98	.149		-2.14(-8.87)
26			(car/SUV)+(truck)	-147.16	-173.39	.151		-.822(-3.51)
27			one vehicle	-593.93	-822.88	.278	-.0422(-3.17)	3.48(4.66)
28		urban	(car/SUV)+(car/SUV)	-1088.6	-1200.4	.093	.0181(2.33)	-2.32(-6.06)
29			(car/SUV)+(truck)	-117.72	-146.59	.197		
30			one vehicle	-206.07	-255.30	.193		-.916(-2.15)

.... – positive coefficient

.... – negative coefficient

* – restricted log-likelihood found by setting all coefficients except intercepts to zero

** – models are estimated by using procedure A on page 32, except the models marked by bold numbers and estimated by using procedure B on page 33

" X_{29} " – "posted speed limit (if the same for all vehicles involved)" quantitative variable
 "constant" – "constant term (intercept)" quantitative variable

¹⁹ Refer to Equation (2.3), where outcomes "1" and "2" correspond to "unsafe-speed-related cause" and "any other cause". Only statistically significant coefficients, which are components of vector β_1 in Equation (2.3), are given in the table.

Table B.3 (Continued)

#	Coefficient (t-ratio)					
	wint [X ₃]	mon [X ₄]	tues [X ₄]	wed [X ₄]	fr [X ₄]	sat [X ₄]
1		.382(2.91)				
2						
3	.370(6.32)					
4						
5						
6						
7	.916(4.40)					
8						
9	1.34(8.52)					
10						
11	.630(4.44)					
12	.662(4.59)					
13	.613(3.57)					
14						
15	.562(5.60)					-.291(-2.00)
16						
17	1.59(2.39)					
18						
19						
20						
21	.426(2.94)			-.608(-2.23)		
22	.425(7.71)					
23						
24	.262(3.57)					
25						
26						
27	.514(3.13)				-.639(-2.75)	
28	.431(3.52)					
29						
30						

.... – positive coefficient
 – negative coefficient

"wint" – "winter season" indicator variable
 "mon" – "Monday" indicator variable
 "tues" – "Tuesday" indicator variable
 "wed" – "Wednesday" indicator variable
 "fr" – "Friday" indicator variable
 "sat" – "Saturday" indicator variable

Table B.3 (Continued)

#	Coefficient (t-ratio)						
	sund [X ₄]	wday [X ₄]	jobend [X ₅]	peak [X ₅]	nigh [X ₅]	nocons [X ₁₃]	light [X ₁₄]
1							
2							
3							.416(7.64)
4							-.515(-2.28)
5							
6				.535(2.27)			
7							-.509(-2.35)
8	1.14(2.29)						
9							
10		-.660(-2.90)					
11							
12		-.333(-2.51)				.962(4.98)	
13							
14							
15							.693(7.26)
16					1.64(3.67)		
17							
18							.745(2.50)
19	.597(2.39)		.382(2.07)				
20							
21							
22							
23		.677(-2.25)					
24							
25							
26							
27							
28		-.280(-2.03)					
29		-1.08(-3.42)					
30							

.... – positive coefficient
 – negative coefficient

"sund" – "Sunday" indicator variable
 "wday" – "weekday (Monday through Friday)" indicator variable
 "jobend" – "evening rush hours: from 16:00 to 19:00" indicator variable²⁰
 "peak" – "rush hours: 7:00 to 9:00 OR 17:00 to 19:00" indicator variable
 "nigh" – "late night hours: 1:00 to 5:00" indicator variable
 "nocons" – "no construction at the accident location" indicator variable
 "light" – "daylight time OR street lights lit up during dark time" indicator variable

²⁰ We use military 24-hour time everywhere in our research.

Table B.3 (Continued)

#	Coefficient (t-ratio)					
	dark [X ₁₄]	day [X ₁₄]	precip [X ₁₅]	snow [X ₁₅]	dry [X ₁₆]	slush [X ₁₆]
1					-1.90(-17.7)	
2					-2.32(-5.00)	
3					-1.20(-20.0)	
4					-1.91(-7.22)	
5					-4.40(-2.44)	
6					-1.25(-6.25)	
7					-2.08(-9.83)	
8					-2.57(-7.55)	
9	-.627(-4.10)		.466(3.04)		-2.88(-11.5)	
10				1.66(5.37)	-1.72(-7.58)	
11		-.599(-2.28)			-2.46(-8.85)	
12			.947(5.24)		-1.38(-7.94)	
13					-1.21(-7.05)	
14				1.50(2.88)	-1.39(-3.66)	
15			.317(2.66)		-1.55(-12.0)	
16					-1.61(-10.5)	
17						1.49(2.29)
18			.670(.318)		-.941(-2.83)	
19					-1.28(-7.36)	
20		.562(4.11)	.376(2.22)		-1.01(-6.33)	2.30(3.00)
21						
22			.468(6.69)		-1.30(-17.5)	
23					-1.70(-7.20)	
24			.241(2.68)		-1.01(-11.5)	
25					-1.74(-8.98)	
26	-1.58(-2.54)				-1.90(-6.04)	
27	-1.01(-6.32)				-2.06(-10.7)	
28					-1.31(-11.1)	
29		.752(-2.06)			-1.21(-3.35)	
30					-1.93(-6.62)	

.... – positive coefficient
 – negative coefficient

"dark" – "dark time with no street lights" indicator variable
 "day" – "daylight time" indicator variable
 "precip" – "precipitation: rain OR snow OR sleet OR hail OR freezing rain" indicator variable
 "snow" – "snowing weather" indicator variable
 "dry" – "roadway surface is dry" indicator variable
 "slush" – "roadway surface is covered by snow/slush" indicator variable

Table B.3 (Continued)

#	Coefficient (t-ratio)					
	driv [X ₁₇]	wall [X ₁₇]	nojun [X ₁₈]	ramp [X ₁₈]	way4 [X ₁₈]	T [X ₁₈]
1			.482(4.03)			
2						
3			-.300(-3.83)			
4						
5						
6						
7			.976(3.15)			
8				-1.90(-2.27)		
9						
10						
11						
12	-.698(-3.66)		-.533(-3.03)			
13			.465(2.62)			
14						.905(2.19)
15			-.540(-4.09)			
16					-.462(-2.76)	
17						
18			-.560(-2.31)			
19	-.542(-2.99)					
20						
21						
22					-.210(-3.76)	
23		1.47(3.75)				
24				1.22(5.13)		
25			.691(3.49)			
26						
27		1.31(5.24)				
28			.383(3.17)			
29					-1.30(-2.85)	
30						

.... – positive coefficient
 – negative coefficient

"driv" – "road median is a drivable" indicator variable
 "wall" – "road median is a barrier wall" indicator variable
 "nojun" – "no road junction at the accident location" indicator variable
 "ramp" – "accident location is near or on a ramp" indicator variable
 "way4" – "accident location is at a 4-way intersection" indicator variable
 "T" – "accident location is at a T-intersection" indicator variable

Table B.3 (Continued)

#	Coefficient (t-ratio)					
	curve [X ₁₉]	sg [X ₁₉]	sl [X ₁₉]	str [X ₁₉]	cl [X ₁₉]	hl5 [X ₂₂]
1						
2						
3	.892(14.9)					
4			-1.08(-4.10)			
5						
6					.892(3.42)	
7						.499(2.13)
8						
9			-.482(-3.26)			.421(2.24)
10						
11						
12				-.983(-5.73)		
13						
14						
15				-.959(-9.56)		
16						
17						-1.92(-2.49)
18	.582(2.18)					
19	.865(3.47)					
20			-1.14(-8.21)			
21						
22	.884(9.43)					
23						
24	.896(11.5)					
25						-.463(-2.05)
26						-.856(-2.00)
27				-1.35(-7.54)		
28		.608(3.18)				-.283(-2.32)
29						
30	.981(3.22)					

.... – positive coefficient
 – negative coefficient

"curve" – "road is at curve" indicator variable
 "sg" – "road is straight AND at grade" indicator variable
 "sl" – "road is straight AND level" indicator variable
 "str" – "road is straight" indicator variable
 "cl" – "road is at-curve AND level" indicator variable
 "hl5" – "help arrived in 5 minutes or less after the crash" indicator variable

Table B.3 (Continued)

#	Coefficient (t-ratio)					
	hl10 [X ₂₂]	hg30 [X ₂₂]	hg60 [X ₂₂]	car [X ₂₅]	heavy [X ₂₅]	moto [X ₂₅]
1						
2						
3	.141(2.41)			.220(3.87)		
4						
5						
6						
7						
8					-2.32(-5.44)	
9						
10		-.736(-2.16)				
11					-1.86(-5.15)	
12		-.393(-2.12)				
13						
14						
15						
16						
17						
18						
19						
20						
21						
22						
23					-.936(-3.74)	
24					-1.44(-4.96)	
25				.411(2.06)		
26						
27			-.657(-2.03)			
28						
29					-1.18(-2.88)	
30						2.49(5.38)

.... – positive coefficient
 – negative coefficient

"hl10" – "help arrived in 10 minutes or less after the crash" indicator variable
 "hg30" – "help arrived in more than 30 minutes after the crash" indicator variable
 "hg60" – "help arrived in more than 1 hour after the crash" indicator variable
 "car" – "the vehicle at fault is a car" indicator variable
 "heavy" – "the vehicle at fault is a truck or a tractor" indicator variable
 "moto" – "the vehicle at fault is a motorcycle" indicator variable

Table B.3 (Continued)

#	Coefficient (t-ratio)					
	pickup [X ₂₅]	vage [X ₂₆]	voldg [X ₂₆]	v7g [X ₂₆]	X ₂₇	Ind [X ₂₈]
1						
2						
3			.256(4.66)		.131(4.84)	-.353(-2.79)
4						
5					-2.47(-2.15)	
6						
7						-.667(-3.22)
8					-.586(-3.35)	
9						
10						
11					.273(2.08)	
12						
13						
14	.942(2.34)					
15		.0411(4.64)				
16						
17						
18						
19						
20						
21						
22		.0255(5.39)				
23		0.0629(3.29)				
24						
25					-.302(-2.24)	
26						
27						
28						
29						
30				-.724(-2.38)	.320(2.34)	

.... – positive coefficient
 – negative coefficient

"pickup" – "the vehicle at fault is a pickup" indicator variable
 "vage" – "age (in years) of the vehicle at fault" quantitative variable
 "voldg" – "the vehicle at fault is more than 7 years old" indicator variable
 "v7g" – "age of the vehicle at fault is > 3 and ≤ 7 years" indicator variable
 "X₂₇" – "number of occupants in the vehicle at fault" quantitative variable
 "Ind" – "license state of the vehicle at fault is Indiana" indicator variable

Table B.3 (Continued)

#	Coefficient (t-ratio)						
	othUS [X ₂₈]	neighs [X ₂₈]	w2 [X ₃₀]	ln2 [X ₃₀]	r22 [X ₃₀]	rmu2 [X ₃₀]	rmu22 [X ₃₀]
1							
2							
3							
4							
5						2.34(2.11)	
6						2.28(3.65)	
7							
8							
9							
10							
11							
12							
13							
14							
15					-.420(-3.41)		
16							-2.07(-2.89)
17							
18							
19	.929(1.97)		.720(2.27)				
20							
21							
22				.312(5.83)			
23							
24							
25							
26							
27							
28		.653(3.66)				.357(2.61)	
29							
30							

.... – positive coefficient
 – negative coefficient

-
- "othUS" – "license state of the vehicle at fault is a U.S. state except Indiana and its neighboring states (IL, KY, OH, MI)" indicator variable
- "neighs" – "license state of the vehicle at fault is an Indiana's neighboring state (IL, KY, OH, MI)" indicator variable
- "w2" – "road traveled by the vehicle at fault is two-way" indicator variable
- "ln2" – "road traveled by the vehicle at fault is two-lane" indicator variable
- "r22" – "road traveled by the vehicle at fault is two-lane AND two-way" indicator variable
- "rmu2" – "road traveled by the vehicle at fault is multi-lane AND undivided two-way" indicator variable
- "rmu22" – "road traveled by the vehicle at fault is multi-lane AND undivided two-way left" indicator variable

Table B.3 (Continued)

#	Coefficient (t-ratio)					
	priv [X ₃₀]	stopsig [X ₃₁]	nosig [X ₃₁]	nopass [X ₃₁]	Incontr [X ₃₁]	sign [X ₃₁]
1		-.441(-2.98)				
2						
3			-.519(-9.34)			
4				1.55(4.73)		
5						
6				.613(2.25)		
7						
8						1.30(3.88)
9			-.600(-2.97)			
10					.674(2.72)	
11						
12						
13		-1.54(-3.25)				
14						
15		.996(2.67)				
16		-1.32(-2.58)				
17						
18			-.665(-2.63)			
19						
20						
21						
22		-.619(-7.36)				
23						
24	-.599(-2.09)					.175(2.51)
25		-1.66(-2.75)				
26						
27			-.351(-2.04)			
28						
29						
30						

.... – positive coefficient
 – negative coefficient

"priv" – "road traveled by the vehicle at fault is a private drive" indicator variable
 "stopsig" – "traffic control device for the vehicle at fault is a «stop sign»" indicator variable
 "nosig" – "no any traffic control device for the vehicle at fault" indicator variable
 "nopass" – "traffic control device for the vehicle at fault is a «no passing zone»" indicator variable
 "Incontr" – "traffic control device for the vehicle at fault is a «lane control»" indicator variable
 "sign" – "traffic control device for the vehicle at fault is any traffic sign" indicator Variable

Table B.3 (Continued)

#	Coefficient (t-ratio)					
	X ₃₃	X ₃₄	age4 [X ₃₄]	X ₃₅	maxpass [X ₂₇]	mm [X ₃₅]
1			-.0183(-5.71)		.132(3.13)	
2		-.0581(-8.00)				
3		-.0293(-13.1)		-.248(-4.29)		
4		-.0321(-3.45)				
5					2.15(2.61)	
6		-.0381(-8.19)				
7						
8						
9		-.0157(-4.01)				
10						.569(2.72)
11						
12						
13	2.74(3.85)	-.0143(-2.75)				
14			-1.84(-2.84)			
15		-.0307(-9.37)				
16						
17						
18		-.0313(3.78)				
19		-.0201(-3.52)				
20		-.358(-7.93)		-.563(-3.69)		
21						
22		-.0241(-9.43)		-.211(-3.99)		
23		-.0335(-3.79)				
24		-.0367(-14.3)		-.422(-5.70)		
25						.498(2.58)
26						
27		-.0263(-4.90)		.333(-2.01)		
28		-.0179(-4.69)				
29						
30		-.0203(-2.25)				

.... – positive coefficient
 – negative coefficient

"X₃₃" – "at least one of the vehicles involved was on fire" indicator variable
 "X₃₄" – "age (in years) of the driver at fault" quantitative variable
 "age4" – "age of the driver at fault is ≥ 40 and < 50" indicator variable
 "X₃₅" – "gender of the driver at fault: 1 – female, 0 – male" indicator variable
 "maxpass" – "the largest number of occupants in all vehicles involved" indicator variable
 "mm" – "two male drivers involved into a two-vehicle accident" indicator variable

Table B.4 Binary logit models for 2006 accident causation

#	Model name			Log-likelihood		R^2	Coefficient (t-ratio)	
				model	restricted*		X ₂₉	constant
1**	County road	rural	(car/SUV)+(car/SUV)	-342.72	-41.06	.164		
2a			(car)+(truck)	-18.849	-26.763	.296		-5.12(-5.10)
2b			(SUV)+(truck)	-5.0592	-10.270	.507		
3		urban	one vehicle	-1204.3	-1438.2	.163		
4			(car/SUV)+(car/SUV)	-227.21	-269.91	.158		-2.63(-12.2)
5			(car/SUV)+(truck)	-15.788	-18.893	.164		-3.54(-4.94)
6	one vehicle	-256.10	-300.36	.147				
7a	Interstate	rural	(car)+(car)	-85.811	-118.56	.276		-1.50(-3.53)
7b			(car)+(SUV)	-127.43	-178.37	.286		-2.14(-3.06)
7c			(SUV)+(SUV)	-50.205	-78.501	.360		-1.98(-4.10)
8			(car/SUV)+(truck)	-222.35	-287.72	.227		-1.08(-2.67)
9			one vehicle	-918.40	-1435.7	.360	-.0439(-5.72)	3.59(6.96)
10		urban	(car/SUV)+(car/SUV)	-508.16	-603.72	.158		-2.77(-6.43)
11a			(car)+(truck)	-116.08	-159.73	.273		-1.31(-3.03)
11b			(SUV)+(truck)	-32.424	-65.943	.508		-4.48(-3.00)
12			one vehicle	-136.07	-169.56	.198		-1.04(-2.03)
13			State route	(car/SUV)+(car/SUV)	-774.29	-863.45	.103	
14	(car/SUV)+(truck)	-92.951		-114.16	.186		-2.63(-6.19)	
15	one vehicle	-1616.3		-2084.9	.225	-.0373(-5.34)	1.07(2.68)	
16	urban	(car/SUV)+(car/SUV)		-850.84	-952.04	.106	.0277(3.47)	-2.50(-6.45)
17		(car/SUV)+(truck)		-81.158	-93.656	.133		-3.76(-11.3)
18		one vehicle	-358.35	-441.38	.188		.615(2.03)	
19	City street	rural	(car/SUV)+(car/SUV)	-211.60	-227.51	.070		-3.41(-18.0)
20a			(car)+(truck)	-13.637	-16.670	.182		-4.34(-4.32)
20b			(SUV)+(truck)	-11.753	-11.753	.000		-2.89(-4.87)
21			one vehicle	-597.08	-694.78	.141		-1.63(-6.62)
22		urban	(car/SUV)+(car/SUV)	-2265.6	-2584.8	.123		-3.02(-12.6)
23a			(car)+(truck)	-93.362	-115.47	.191		-5.49(-10.0)
23b			(SUV)+(truck)	-29.107	-40.704	.285		-6.80(-6.78)
24			one vehicle	-2597.7	-3024.6	.141		-.556(-4.78)
25	US route	rural	(car/SUV)+(car/SUV)	-456.42	-499.97	.087		
26			(car/SUV)+(truck)	-80.524	-102.56	.215		-4.55(-8.95)
27			one vehicle	-708.44	-977.40	.275		-1.60(-5.96)
28		urban	(car/SUV)+(car/SUV)	-834.94	-901.81	.074		-1.68(-6.19)
29a			(car)+(truck)	-46.549	-51.986	.105		-3.60(-10.6)
29b			(SUV)+(truck)	-11.446	-11.446	.000		-4.72(-6.64)
30			one vehicle	-250.31	-315.51	.207		-1.71(-5.00)

.... – positive coefficient

.... – negative coefficient

* – restricted log-likelihood found by setting all coefficients except intercepts to zero

** – models are estimated by using procedure A on page 32, except the models marked by bold numbers and estimated by using procedure B on page 33

“ X_{29} ” – “posted speed limit (if the same for all vehicles involved)” quantitative variable

“constant” – “constant term (intercept)” quantitative variable

Table B.4 (Continued)

#	Coefficient (t-ratio)					
	wint [X ₃]	fall [X ₃]	tues [X ₄]	wed[X ₄]	thday [X ₄]	peak [X ₅]
1**						
2a						
2b						
3	.460(4.29)					
4	.747(2.74)		.932(3.21)			
5						
6						
7a						
7b	.772(2.05)					
7c					1.56(2.61)	
8						
9	.590(4.59)			.345(2.22)		
10						-.775(-4.11)
11a						
11b						
12						
13						
14					-1.66(-2.18)	
15	.540(5.17)					
16						
17				1.08(2.32)		
18			.729(3.00)			
19						
20a	2.67(2.25)					
20b						
21		-.432(-2.34)				
22	.229(2.39)					
23a						
23b	2.38(3.01)					
24	.178(2.15)					
25						
26						
27	.650(4.32)					
28						
29a						
29b						
30		-.727(-2.23)				

... – positive coefficient

... – negative coefficient.

"wint" – "winter season" indicator variable

"fall" – "fall season" indicator variable

"tues" – "Tuesday" indicator variable

"wed" – "Wednesday" indicator variable

"thday" – "Thursday" indicator variable

"peak" – "rush hours: 7:00 to 9:00 OR 17:00 to 19:00" indicator variable

Table B.4 (Continued)

#	Coefficient (t-ratio)					
	nigh [X ₅]	dayt [X ₅]	lunch [X ₅]	light [X ₁₄]	dark [X ₁₄]	day [X ₁₄]
1**						
2a						
2b						
3						.368(3.59)
4						
5						
6						
7a						
7b						
7c						
8						
9	-.825(-4.07)					
10						-.381(-2.15)
11a	1.48(2.73)					
11b						-2.64(-3.47)
12						
13						
14			1.06(2.36)			
15				.792(8.08)		
16	1.41(3.56)					
17						
18		.511(2.37)				
19						
20a						
20b						
21				.527(3.37)		
22		-.216(-2.45)				
23a						
23b						
24						
25						
26						
27					-.721(-4.92)	
28				-.609(-2.91)		
29a						
29b						
30						

.... – positive coefficient

.... – negative coefficient.

- "nigh" – "late night hours: from 1:00 to 5:00" indicator variable
"dayt" – "day hours: from 9:00 to 17:00" indicator variable
"lunch" – "lunch hours: 11:00 to 14:00" indicator variable
"light" – "daylight time OR street lights lit up during dark time" indicator variable
"dark" – "dark time with no street lights" indicator variable
"day" – "daylight time" indicator variable

Table B.4 (Continued)

#	Coefficient (t-ratio)					
	darklamp [X ₁₄]	precip [X ₁₅]	snow [X ₁₅]	dry [X ₁₆]	slush [X ₁₆]	ice [X ₁₆]
1**				-1.88(-8.85)		
2a		3.68(3.29)				
2b						
3				-1.28(-12.6)		
4				-1.90(-6.62)		
5						
6			1.34(2.95)	-7.30(-3.18)		
7a				-2.77(-6.39)		
7b	1.42(3.10)			-2.34(-7.03)		
7c			3.49(3.00)	-2.09(-3.70)		
8		1.02(2.34)		-1.37(-3.04)		
9		.753(4.35)		-2.57(-12.4)		
10		.718(2.30)		-1.21(-3.91)		
11a				-2.34(-6.59)		
11b			6.96(4.53)			
12		1.96(5.97)				
13				-1.70(-11.7)		
14				-1.44(-3.39)		
15		.342(2.56)		-1.39(-10.2)		
16				-1.62(-11.4)		
17						4.24(3.41)
18				-1.46(-7.22)		
19		1.13(3.93)				
20a						
20b						
21			.904(2.42)		1.22(3.29)	
22		.305(2.44)		-1.58(-12.0)		
23a						
23b						
24				-.985(-13.3)		
25				-1.57(-8.64)		
26		2.44(5.48)				
27		.468(2.48)		-1.87(-8.86)		
28				-1.41(-9.68)		
29a					2.76(2.62)	
29b						
30		1.99(8.17)				

... – positive coefficient

.... – negative coefficient.

- "darklamp" – "dark time with street lights on" indicator variable
 "precip" – "precipitation: rain OR snow OR sleet OR hail OR freezing rain" indicator variable
 "snow" – "snowing weather" indicator variable
 "dry" – "roadway surface is dry" indicator variable
 "slush" – "roadway surface is covered by snow/slush" indicator variable
 "ice" – "roadway surface is icy" indicator variable

Table B.4 (Continued)

#	Coefficient (t-ratio)					
	driv [X ₁₇]	wall [X ₁₇]	nojun [X ₁₈]	ramp [X ₁₈]	way4 [X ₁₈]	T [X ₁₈]
1**					-.786(-2.54)	
2a						
2b						
3		1.64(2.35)	-.639(-5.53)			
4						
5						
6		2.33(2.29)				.729(-3.18)
7a						
7b			1.66(2.82)			
7c						
8						
9		.302(2.18)	-1.20(-5.30)			
10		.637(2.64)				
11a						
11b		3.16(2.10)				
12						
13			.357(2.40)			
14	1.17(2.45)					
15				.990(2.36)		
16						
17						
18						
19						
20a						
20b						
21				1.25(2.10)		
22	.180(2.01)				-.234(-2.52)	
23a						1.31(2.72)
23b						
24						.401(4.14)
25						
26						
27	-.765(-3.56)					
28			.307(2.13)			
29a						
29b						
30						

... – positive coefficient

... – negative coefficient.

"driv" – "road median is a drivable" indicator variable

"wall" – "road median is a barrier wall" indicator variable

"nojun" – "no road junction at the accident location" indicator variable

"ramp" – "accident location is near or on a ramp" indicator variable

"way4" – "accident location is at a 4-way intersection" indicator variable

"T" – "accident location is at a T-intersection" indicator variable

Table B.4 (Continued)

#	Coefficient (t-ratio)					
	Y [X ₁₈]	int [X ₁₈]	curve [X ₁₉]	sg [X ₁₉]	sl [X ₁₉]	str [X ₁₉]
1**						
2a						
2b						
3			1.05(9.61)			
4						
5						
6						-0.857(-3.73)
7a						
7b						
7c						
8						
9					-0.418(-3.33)	
10						
11a						
11b						
12						-1.62(-4.84)
13						
14	3.27(3.48)			1.17(2.71)		
15						-1.05(-10.6)
16						
17						
18						-1.18(-5.70)
19			1.34(3.18)			
20a						
20b						
21			1.15(7.43)			
22			.898(5.40)			
23a			1.90(2.84)			
23b						
24			1.11(13.9)			
25						-0.640(-2.84)
26						
27	2.15(3.85)		1.00(6.70)			
28						
29a						
29b						
30		1.45(2.24)	.813(2.91)			

... – positive coefficient

... – negative coefficient.

- "Y" – "accident location is at a Y-intersection" indicator variable
 "int" – "accident location is near or on an interchange" indicator variable
 "curve" – "road is at curve" indicator variable
 "sg" – "road is straight AND at grade" indicator variable
 "sl" – "road is straight AND level" indicator variable
 "str" – "road is straight" indicator variable

Table B.4 (Continued)

#	Coefficient (t-ratio)					
	cl [X ₁₉]	cg [X ₁₉]	lev [X ₁₉]	grd [X ₁₉]	hl5 [X ₂₂]	hl10 [X ₂₂]
1**						
2a						
2b						
3						
4	1.32(3.09)					
5						
6						
7a	1.39(2.17)					
7b	1.61(2.93)					
7c						
8						
9					.324(2.06)	
10						
11a						
11b						
12						
13		.937(3.86)				
14						
15						
16			-.490(-2.92)			
17				1.11(2.28)		
18						
19						
20a						
20b						
21						.403(2.61)
22						
23a						
23b						
24						
25						
26						.957(2.04)
27						.630(4.39)
28						
29a						
29b						
30						

... – positive coefficient

... – negative coefficient.

- "cl" – "road is at-curve AND level" indicator variable
 "cg" – "road is at-curve AND grade" indicator variable
 "lev" – "road is 'at-curve or straight' AND level" indicator variable
 "grd" – "road is 'at-curve or straight' AND grade" indicator variable
 "hl5" – "help arrived in 5 minutes or less after the crash" indicator variable
 "hl10" – "help arrived in 10 minutes or less after the crash" indicator variable

Table B.4 (Continued)

#	Coefficient (t-ratio)					
	car [X ₂₅]	heavy [X ₂₅]	van [X ₂₅]	truck3 [X ₂₅]	trac1 [X ₂₅]	vage [X ₂₆]
1**						
2a						
2b						
3						
4						
5			2.85(2.01)			
6						
7a						
7b						
7c						
8		-1.18(-4.12)				
9		-.509(-2.61)				
10						
11a					-1.28(-2.77)	
11b						
12						
13						
14				1.33(1.98)		
15			-.733(-2.65)			.0184(2.03)
16						
17						
18						
19						
20a						
20b						
21						
22						.0277(3.44)
23a	1.71(3.17)					
23b						
24		-1.17(-3.74)				
25						
26						
27					1.04(3.77)	
28						
29a						
29b						
30						

... – positive coefficient

... – negative coefficient.

- "car" – "the vehicle at fault is a car" indicator variable
 "heavy" – "the vehicle at fault is a truck or a tractor" indicator variable
 "van" – "the vehicle at fault is a van" indicator variable
 "track3" – "the vehicle at fault is a truck (single 3 or more axes)" indicator variable
 "trac1" – "the vehicle at fault is a tractor/one semi trailer" indicator variable
 "vage" – "age (in years) of the vehicle at fault" quantitative variable

Table B.4 (Continued)

#	Coefficient (t-ratio)					
	voldg [X ₂₆]	X ₂₇	Ind [X ₂₈]	neighs [X ₂₈]	neighc [X ₂₈]	w2 [X ₃₀]
1**						
2a						
2b				4.40(2.10)		
3						
4						
5						
6	.522(2.49)					
7a						
7b		-.527(-2.07)				
7c	1.33(2.42)					
8						
9						
10						
11a			.910(2.08)			
11b						
12						
13						
14						
15						
16						
17						
18						
19						
20a						
20b						
21						
22						.601(3.57)
23a						
23b						
24		.0805(3.26)				
25			-.734(-3.35)			
26						
27						
28						
29a						
29b						
30				.959(2.98)		

... – positive coefficient

... – negative coefficient.

"voldg" – "the vehicle at fault is more than 7 years old" indicator variable

"X₂₇" – "number of occupants in the vehicle at fault" quantitative variable

"Ind" – "license state of the vehicle at fault is Indiana" indicator variable

"neighs" – "license state of the vehicle at fault is Indiana's neighboring state (IL, KY, OH, MI)" indicator variable

"neighc" – "license state of the vehicle at fault is from Canada, Mexico, or US territories" indicator variable

"w2" – "road traveled by the vehicle at fault is two-way" indicator variable

Table B.4 (Continued)

#	Coefficient (t-ratio)					
	r11 [X ₃₀]	r21 [X ₃₀]	rmd2 [X ₃₀]	priv [X ₃₀]	w1 [X ₃₀]	stopsig [X ₃₁]
1**						-.658(-2.23)
2a						
2b						
3						
4						
5						
6						
7a					-2.67(-2.49)	
7b						
7c						
8					-1.63(-2.59)	
9						
10			.664(2.31)			
11a						
11b	4.12(2.51)					
12						
13						
14						
15						
16						
17						
18						
19						-1.64(-2.26)
20a						
20b						
21						
22						-.458(-3.12)
23a						
23b						
24				-.611(-3.14)		
25						
26						
27						
28						
29a		2.22(2.22)				
29b						
30						

.... – positive coefficient

.... – negative coefficient.

- "r11" – "road traveled by the vehicle at fault is one-lane & one-way" indicator var.
 "r21" – "road traveled by the veh. at fault is two-lanes AND one-way" indic. var.
 "rmd2" – "road traveled by the vehicle at fault is multy-lane divided 3 or more AND two-way" indicator variable
 "priv" – "road traveled by the vehicle at fault is private drive" indicator variable
 "w1" – "road traveled by the vehicle at fault is one-way" indicator variable
 "stopsig" – "traffic control device for the vehicle at fault is «stop sign»" indicator var.

Table B.4 (Continued)

#	Coefficient (t-ratio)					
	nopass [X ₃₁]	Incontr [X ₃₁]	fl [X ₃₁]	X ₃₃	X ₃₄	age1 [X ₃₄]
1**					-.0213(-4.20)	
2a						
2b						
3	.501(3.69)				-.0391(-11.3)	
4						
5						
6					-.448(-5.98)	
7a						
7b						
7c						
8						
9					-.0182(-4.10)	
10						
11a						
11b						
12		1.09(3.01)			-.0229(-2.07)	
13						
14						
15					-.0346(-9.64)	
16					-.0201(-4.56)	
17						
18					-.0525(-6.49)	
19						
20a						
20b						
21					-.0393(-6.33)	
22				1.38(3.29)	-.0169(-5.86)	
23a			4.18(4.23)			1.05(2.24)
23b		1.56(2.01)				
24					-.0400(-13.1)	
25						
26						1.08(2.19)
27					-.0195(-3.99)	
28				2.06(3.21)	-.0149(-3.42)	
29a						
29b						
30					-.0481(-5.01)	

.... – positive coefficient

.... – negative coefficient.

"nopass" – "traffic control device for the vehicle at fault is a «no passing zone»" indicator variable

"Incontr" – "traffic control device for the vehicle at fault is a «lane control»" indicator variable

"fl" – "traffic control device for the vehicle at fault is flashing signal" indicator

"X₃₃" – "at least one of the vehicles involved was on fire" indicator variable

"X₃₄" – "age (in years) of the driver at fault" quantitative variable

Table B.4 (Continued)

#	Coefficient (t-ratio)					
	X ₃₅	maxpass [X ₂₇]	youngdrv [X ₃₄]	olddrv [X ₃₄]	mm [X ₃₅]	
1**		-.383(-3.91)				
2a						
2b				-1.32(-3.34)		
3	-.305(-2.74)					
4						
5	2.29(2.13)					
6						
7a		.496(2.78)				
7b	.818(2.46)					
7c						
8						
9						
10		.189(2.82)				
11a						
11b						
12						
13			-.0186(-2.88)			
14						
15						
16					.457(3.14)	
17						
18						
19						
20a						
20b						
21	-.322(-1.97)					
22					.254(2.72)	
23a						
23b	2.66(3.08)					
24	-.456(-5.71)					
25			-.0218(-3.14)			
26						
27						
28					.493(3.33)	
29a						
29b						
30						

... – positive coefficient

... – negative coefficient.

- "X₃₅" – "gender of the driver at fault: 1 – female, 0 – male" indicator variable
- "maxpass" – "the largest number of occupants in all vehicles involved" indicator variable
- "youngdrv" – "the driver at fault is younger than the other driver involved" indicator variable
- "olddrv" – "the driver at fault is older than the other driver involved" indicator var.
- "mm" – "two male drivers involved into a two-vehicle accident" indicator var.

Table B.5 Tests of car-SUV separation in 2004 accident causation study²¹

#	Model name			M	K	$LL(\beta_m)$	$\sum LL(\beta_m)$	df	p-value	conclusion*
1	County road	rural	(car/SUV)+(car/SUV)	3	7	-1426.61	-1418.48	14	0.30	Car = SUV
2			(car/SUV)+(truck)	2	2	-87.04	-86.24	2	0.45	Car = SUV
4		urban	(car/SUV)+(car/SUV)	3	6	-246.94	-240.33	12	0.35	Car = SUV
5			(car/SUV)+(truck)	2	5	-16.14	-15.11	5	0.84	Car = SUV
7	Interstate	rural	(car/SUV)+(car/SUV)	3	7	-327.44	-317.43	14	0.13	Car = SUV
8			(car/SUV)+(truck)	2	6	-128.79	-127.07	6	0.75	Car = SUV
10		urban	(car/SUV)+(car/SUV)	3	7	-339.99	-333.09	14	0.46	Car = SUV
11			(car/SUV)+(truck)	2	7	-203.66	-201.12	7	0.65	Car = SUV
13	State route	rural	(car/SUV)+(car/SUV)	3	7	-537.67	-530.30	14	0.40	Car = SUV
14			(car/SUV)+(truck)	2	6	-128.69	-123.18	6	0.88	Car = SUV
16		urban	(car/SUV)+(car/SUV)	3	7	-716.67	-707.19	14	0.17	Car = SUV
17			(car/SUV)+(truck)	2	4	-57.96	-57.47	4	0.91	Car = SUV
19	City street	rural	(car/SUV)+(car/SUV)	3	11	-525.56	-519.80	22	0.97	Car = SUV
20			(car/SUV)+(truck)	2	2	-35.71	-35.33	2	0.68	Car = SUV
22		urban	(car/SUV)+(car/SUV)	3	12	-6259.14	-6246.99	24	0.44	Car = SUV
23			(car/SUV)+(truck)	2	7	-323.90	-322.02	7	0.81	Car = SUV
25	US route	rural	(car/SUV)+(car/SUV)	3	7	-404.95	-399.41	14	0.68	Car = SUV
26			(car/-SUV)+(truck)	2	5	-147.16	-143.83	5	0.25	Car = SUV
28		urban	(car/SUV)+(car/SUV)	3	11	-1088.61	-1081.30	22	0.88	Car = SUV
29			(car/SUV)+(truck)	2	5	-117.72	-115.99	5	0.63	Car = SUV

* For all models 1–29 we find that “Car = SUV”, which means that in 2004 unsafe-speed-related accident causation study cars and SUVs can be considered together.

²¹ These tests are intended for testing whether in two-vehicle accidents cars and SUVs can be considered together or must be considered separately. The testing is done for all two-vehicle accident best final models by using the likelihood ratio test given in Equation (2.5). Please refer to Equation (2.5) for explanation of the quantities reported in the table. The p-values given in the next to last column are the probability values of the test statistic under the zero hypothesis (which is that cars and SUVs can be considered together).

Table B.6 Tests of car-SUV separation in 2006 accident causation study

#	Model name			M	K	$LL(\beta_m)$	$\sum LL(\beta_m)$	df	p-value	conclusion*
1	County road	rural	(car/SUV)+(car/SUV)	3	5	-342.72	-335.58	10	0.16	Car = SUV
2		urban	(car/SUV)+(truck)	2	4	-191.86	-131.52	4	0.02	Car ≠ SUV
4	County road	rural	(car/SUV)+(car/SUV)	3	5	-227.21	-223.57	10	0.70	Car = SUV
5		urban	(car/SUV)+(truck)	2	3	-157.00	-154.17	3	0.90	Car = SUV
7	Interstate	rural	(car/SUV)+(car/SUV)	3	3	-50.625	-44.218	6	0.05	Car ≠ SUV
8		urban	(car/SUV)+(truck)	2	5	-222.35	-219.80	5	0.40	Car = SUV
10	Interstate	rural	(car/SUV)+(car/SUV)	3	8	-508.16	-501.60	16	0.66	Car = SUV
11		urban	(car/SUV)+(truck)	2	6	-137.34	-129.39	6	0.01	Car ≠ SUV
13	State route	rural	(car/SUV)+(car/SUV)	3	5	-774.29	-770.94	10	0.75	Car = SUV
14		urban	(car/SUV)+(truck)	2	8	-92.951	-89.165	8	0.48	Car = SUV
16	State route	rural	(car/SUV)+(car/SUV)	3	6	-850.84	-841.88	12	0.12	Car = SUV
17		urban	(car/SUV)+(truck)	2	4	-81.158	-79.467	4	0.50	Car = SUV
19	City street	rural	(car/SUV)+(car/SUV)	3	4	-211.60	-209.63	8	0.86	Car = SUV
20		urban	(car/SUV)+(truck)	2	3	-20.366	-16.153	3	0.04	Car ≠ SUV
22	City street	rural	(car/SUV)+(car/SUV)	3	14	-2265.6	-2246.7	28	0.102	Car = SUV
23		urban	(car/SUV)+(truck)	2	6	-143.81	-137.52	6	0.05	Car ≠ SUV
25	US route	rural	(car/SUV)+(car/SUV)	3	4	-456.42	-454.21	8	0.82	Car = SUV
26		urban	(car/SUV)+(truck)	2	5	-80.524	-77.449	5	0.29	Car = SUV
28	US route	rural	(car/SUV)+(car/SUV)	3	7	-834.94	-829.20	14	0.65	Car = SUV
29		urban	(car/SUV)+(truck)	2	4	-56.753	-51.514	4	0.03	Car ≠ SUV

* For all models 2, 7, 11, 20, 23 and 29 we find that “Car ≠ SUV”, which means that for these models cars and SUVs must be considered separately in 2006 accident causation study. For all other models we find that “Car = SUV”, which means that cars and SUVs can be considered together.

Appendix C.

Table C.1 Road classes and accident types in 2004 accident severity study

#	Road-class-accident-type combination			Number of observations				
				all	available for the models*			
					total	fatal	injury	PDO
1	County road	rural	(car/SUV**)+(car/SUV)	7260	2788	22	741	2025
2			(car/SUV)+(truck***)	649	615	5	143	467
3			one vehicle	18121	9433	115	2289	7029
4		urban	(car/SUV)+(car/SUV)	1861	1400	1	293	1106
5			(car/SUV)+(truck)	143	120	0	21	99
6			one vehicle	980	713	3	165	545
7	Interstate	rural	(car/SUV)+(car/SUV)	1044	955	3	157	795
8a			(car)+(truck)	516	470	6	78	386
8b			(SUV)+(truck)	295	244	1	58	185
9			one vehicle	3351	3284	23	510	2751
10		urban	(car/SUV)+(car/SUV)	2234	1698	4	258	1436
11			(car/SUV)+(truck)	1085	756	5	122	629
12			one vehicle	1614	1526	14	345	1167
13		State route	rural	(car/SUV)+(car/SUV)	4788	1979	23	638
14	(car/SUV)+(truck)			683	653	22	195	436
15	one vehicle			9798	6368	50	1200	5118
16a	urban		(car)+(car)	2701	2318	2	581	1735
16b			(car)+(SUV)	3872	3344	4	783	2557
16c			(SUV)+(SUV)	1473	1084	6	231	847
17			(car/SUV)+(truck)	641	339	2	69	268
18			one vehicle	1502	1381	9	308	1064
19	City street	rural	(car/SUV)+(car/SUV)	3820	2610	4	591	2015
20			(car/SUV)+(truck)	263	175	1	35	739
21			one vehicle	2412	2033	13	495	1525
22		urban	(car/SUV)+(car/SUV)	63367	33141	28	7290	25823
23a			(car)+(truck)	2321	1421	3	236	1182
23b			(SUV)+(truck)	1273	990	3	145	842
24			one vehicle	12549	6431	64	2249	4118
25			US route	rural	(car/SUV)+(car/SUV)	2592	1499	17
26	(car/SUV)+(truck)	566			413	21	154	238
27	one vehicle	4211			2982	24	508	2450
28	urban	(car/SUV)+(car/SUV)		6931	4839	6	1219	3614
29		(car/SUV)+(truck)		752	704	3	163	538
30		one vehicle		1073	1063	13	292	758

* – observations available for the best final estimated statistical models after exclusion of all missing observations

** – “SUV” includes sport utility vehicles, pickups and vans

*** – “truck” includes any possible kind of truck or tractor

Table C.2 Road classes and accident types in 2006 accident severity study

#	Road-class-accident-type combination			Number of observations				
				all	available for the models*			
					total	fatal	injury	PDO
1	County road	rural	(car/SUV**)+(car/SUV)	5966	4323	14	369	3940
2			(car/SUV)+(truck***)	345	286	3	42	241
3			one vehicle	16165	14733	143	3313	11277
4a		urban	(car)+(car)	536	489	0	107	275
4b			(car)+(SUV)	691	232	0	40	192
4c			(SUV)+(SUV)	261	225	0	37	188
5			(car/SUV)+(truck)	80	80	1	5	74
6		one vehicle	800	745	2	174	569	
7	Interstate	rural	(car/SUV)+(car/SUV)	1124	994	6	167	821
8			(car/SUV)+(truck)	758	649	11	79	559
9			one vehicle	3736	3676	22	571	3083
10		urban	(car/SUV)+(car/SUV)	2395	2178	1	303	1874
11			(car/SUV)+(truck)	850	692	2	89	601
12			one vehicle	1884	1834	13	397	1424
13	State route	rural	(car/SUV)+(car/SUV)	4582	763	28	274	461
14			(car/SUV)+(truck)	524	125	10	18	97
15			one vehicle	10172	9611	81	1659	7871
16		urban	(car/SUV)+(car/SUV)	7483	6224	7	1398	4819
17			(car/SUV)+(truck)	510	482	2	65	415
18			one vehicle	1715	1579	16	404	1159
19	City street	rural	(car/SUV)+(car/SUV)	2926	2103	1	473	1629
20			(car/SUV)+(truck)	155	84	0	9	75
21			one vehicle	2115	624	4	164	456
22a		urban	(car)+(car)	20109	13499	2	2983	10514
22b			(car)+(SUV)	23000	8282	8	1866	6408
22c			(SUV)+(SUV)	7216	2544	3	601	1940
23			(car/SUV)+(truck)	2323	1570	2	175	1393
24		one vehicle	10869	4152	40	1561	2551	
25	US route	rural	(car/SUV)+(car/SUV)	2481	541	16	185	340
26			(car/SUV)+(truck)	566	386	9	108	269
27			one vehicle	4257	4019	26	642	3351
28		urban	(car/SUV)+(car/SUV)	6941	1680	2	463	1215
29			(car/SUV)+(truck)	572	467	5	62	400
30			one vehicle	1211	285	4	98	183

* – observations available for the best final estimated statistical models after exclusion of all missing observations

** – “SUV” includes sport utility vehicles, pickups and vans

*** – “truck” includes any possible kind of truck or tractor

Table C.3 Speed limit data bins chosen in 2004 accident severity study

#	Road type	Speed limit intervals (in mph)												
		[5,10)*	[10,15)	[15,20)	[20,25)	[25,30)	[30,35)	[35,40)	[40,45)	[45,50)	[50,55)	[55,60)	[60,65)	≥65
1	County road	533**					305	623	576	156	604	-	-	
2		109					56	78	140	134	-	-	-	
3		129				856	794	1345	1584	603	4122	-	-	
4		101				376	242	323	280	33	45	-	-	
5		40					33	34	-	-	-	-	-	
6		200					87	284	99	-	-	-	-	
7	Interstate	57							111	205	549	-	-	
8a		57								64	81	-	-	
8b		65										52	-	
9		164								340	318	2444	-	
10		470									959	215	-	
11		643										45	-	
12	State route	62							173	90	929	261	-	
13		603								1376	-	-	-	
14		65								82	55	376	-	
15		81						51	146	581	607	4792	-	
16a		35			132	473	545	332	306	109	136	-	-	
16b		230				659	751	401	486	196	235	-	-	
16c	City street	261					370	328	-	-	-	-	-	
17		26				58	83	41	82	49	-	-	-	
18		67				214	165	162	242	125	323	-	-	
19		74	70	129	579	486	717	241	710	194	49	-	-	
20		68							46	30	31	-	-	
21		38	53	60	516	598	606	-	-	-	-	-	-	
22	US route	242	319	574	2022	9862	8379	5219	1464	163	179	-	-	
23a		560						345	287	36	-	-	-	
23b		93				333	225	133	54	22	-	-	-	
24		965				2271	1256	1053	197	-	-	-	-	
25		42					59	76	206	153	963	-	-	
26		97									276	-	-	
27	US route	30						66	149	159	2553	-	-	
28		919						949	1825	358	272	-	-	
29		-	30	87	120	75	187	65	70	-	-	-	-	
30		53				73	135	86	258	120	242	-	-	

* – Interval [5,10) includes speed limits larger or equal to 5 mph and smaller than 10 mph. All other intervals are similarly defined.

** – Numbers printed on top the speed limit data bins inside the table, give data sample sizes in the corresponding bins.

Table C.4 Speed limit data bins chosen in 2006 accident severity study

#	Road type	Speed limit intervals (in mph)														
		[5,10)*	[10,15)	[15,20)	[20,25)	[25,30)	[30,35)	[35,40)	[40,45)	[45,50)	[50,55)	[55,60)	[60,65)	[65,70)	[70,75)	≥75
1	County road	807**								345	98	223		-		
2		45						35	54	70		82	-			
3		1127						3233		2993	1021	6359			-	
4a		26					83	72	110	111	9	11	-			
4b		84						51	44	53			-			
4c		63						43	47	47			-			
5		21						25		16			-			
6		44					143	128	108	295			-			
7	Interstate	173										225		177	336	-
8		56										265				-
9		75								74		433	1019	2054	-	
10		53					50	74	93	146	206	1165	331	-		
11		121										511				-
12		102								207		1131	259	119	-	
13	State route	252									511				-	
14		57										68				-
15		365								935	748	7267	296		-	
16		147				339	1470	1508	970	981	367	442		-		
17		212							580	71	46	45		-		
18		277						205	172	282	143	368		-		
19	City street	140				100	523	438	577	208	117				-	
20		1665							660	381		-				
21		338								228						-
22a		850				985	5440	3629	1928	667		-				
22b		335				572	2901	2313	1620	541				-		
22c		1211						1333							-	
23		86				134	561	442	227	120				-		
24		593					1598	818	723							-
25	US route	68								121	244	34	-			
26		84									240		62	-		
27		3134											869		-	
28		943								737					-	
29		391									76				-	
30		100								116		61			-	

* – Interval [5,10) includes speed limits larger or equal to 5 mph and smaller than 10 mph. All other intervals are similarly defined.

** – Numbers printed on top the speed limit data bins inside the table, give data sample sizes in the corresponding bins.

Table C.5 Multinomial logit models for 2004 accident severity²²

#	Model name			Log-likelihood		R^2	Coefficient (t-ratio)	
				model	restricted*		X_{29}	
							fatality [β_1]	injury [β_2]
1	County road	rural	(car/SUV)+(car/SUV)	-1636.3	-1735.9	.057	.108 (3.61)	.0255 (5.15)
2			(car/SUV)+(truck)	-250.47	-287.90	.130		.0414 (3.42)
3			one vehicle	-5060.1	-5816.0	.130	.0382 (3.47)	
4		urban	(car/SUV)+(car/SUV)	-683.95	-726.22	.058	.0323 (3.75)	.0323 (3.75)
5**			(car/SUV)+(truck)	-104.80	-131.83	.205		
6			one vehicle	-359.79	-404.07	.110		
7	Interstate	rural	(car/SUV)+(car/SUV)	-456.77	-473.11	.035		
8a			(car)+(truck)	-198.37	-219.34	.095		
8b			(SUV)+(truck)	-114.91	-140.04	.179		
9		urban	one vehicle	-1360.9	-1550.4	.122		
10			(car/SUV)+(car/SUV)	-710.09	-751.00	.054		
11			(car/SUV)+(truck)	-336.87	-363.30	.073		
12	State route	rural	one vehicle	-772.32	-887.87	.130		
13			(car/SUV)+(car/SUV)	-1302.1	-1360.4	.043		.0306 (3.90)
14			(car/SUV)+(truck)	-362.86	-405.25	.105		
15		urban	one vehicle	-2188.0	-2714.2	.194		
16a			(car)+(car)	-1116.2	-1157.9	.036	.0340 (5.14)	.0340 (5.14)
16b			(car)+(SUV)	-1547.8	-1608.4	.038	.0225 (4.36)	.0225 (4.36)
16c	urban	(SUV)+(SUV)	-492.07	-517.33	.049	.0315 (3.39)	.0315 (3.39)	
17		(car/SUV)+(truck)	-173.40	-183.09	.053	.0418 (2.89)	.0418 (2.89)	
18		one vehicle	-677.08	-784.90	.137			
19	City street	rural	(car/SUV)+(car/SUV)	-1358.7	-1425.1	.047	.114 (2.53)	.0273 (5.40)
20			(car/SUV)+(truck)	-68.07	-93.51	.272		.0676 (3.17)
21			one vehicle	-1025.6	-1203.4	.148		
22		urban	(car/SUV)+(car/SUV)	-14547	-15236	.045	.0938 (2.76)	.0304 (11.8)
23a			(car)+(truck)	-526.00	-580.96	.095	.0469 (3.99)	.0469 (3.99)
23b			(SUV)+(truck)	-344.88	-366.77	.060	.0640 (4.41)	.0640 (4.41)
24	US route	rural	one vehicle	-4004.8	-4493.6	.109		
25			(car/SUV)+(car/SUV)	-978.44	-1029.3	.049	.340 (2.48)	.0409 (4.54)
26			(car/SUV)+(truck)	-270.09	-309.90	.128		.0720 (3.02)
27		urban	one vehicle	-1251.3	-1496.3	.164		
28			(car/SUV)+(car/SUV)	-2345.1	-2457.6	.046	.0263 (5.76)	.0263 (5.76)
29			(car/SUV)+(truck)	-311.62	-336.81	.075	.0307 (2.52)	.0307 (2.52)
30			one vehicle	-549.94	-639.11	.140		

... – positive coefficient

... – negative coefficient

* – restricted log-likelihood found by setting all coefficients except intercepts to zero (with the exception of model 5, in case of which intercepts are also set to zero)

** – models are estimated by using procedure A on page 32, except the models marked by bold numbers and estimated by using procedure B on page 33

 X_{29} – “posted speed limit (if the same for all vehicles involved)” quantitative variable

²² See Equation (2.4), where outcomes “1”, “2”, “3” correspond to “fatality”, “injury”, “PDO”. Only statistically significant coefficients, which are components of vectors β_1 and β_2 , are given.

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	constant		wint [X ₃]		sum [X ₃]	
	fatality	injury	fatality	injury	fatality	injury
1	-12.0 (-6.27)	-3.30 (-12.4)	-.260 (-2.61)	-.260 (-2.61)		
2	-7.41 (-5.59)	-4.07 (-6.90)				
3	-6.43 (-10.7)	-1.45 (-13.7)			.232 (3.51)	.232 (3.51)
4	-9.13 (-8.46)	-3.57 (-8.23)				
5		-2.78 (-3.72)				
6	-6.90 (-9.19)	-2.50 (-9.49)				
7	-6.25 (-10.2)	-2.33 (-10.7)				
8a	-5.97 (-5.85)	-1.87 (-7.79)				
8b	-6.76 (-5.65)	-3.35 (-4.72)				
9	-4.84 (-20.4)	-3.04 (-12.7)				
10	-8.01 (-8.12)	-2.40 (-11.2)				
11	-6.23 (-10.0)	-2.53 (-10.4)				
12	-5.88 (-12.5)	-3.25 (-9.55)			1.13 (2.09)	
13	-5.24 (-13.2)	-3.47 (-7.44)				
14	-4.30 (-9.91)	-2.88 (-7.34)	-.619 (-2.58)	-.619 (-2.58)		
15	-4.31 (-16.9)	-1.64 (-11.7)				
16a	-9.26 (-8.86)	-3.02 (-3.09)				
16b	-8.88 (-11.6)	-3.14 (-10.3)				
16c	-7.13 (-8.91)	-3.22 (-7.13)				.412 (2.37)
17	-7.42 (-6.33)	-3.22 (-5.16)				
18	-6.31 (-10.7)	-1.60 (-11.3)			1.96 (2.76)	
19	-11.3 (-5.04)	-2.25 (-8.63)	-.276 (-2.34)	-.276 (-2.34)		
20	-6.22 (-5.18)	-5.50 (-4.69)				
21	-5.62 (-17.1)	-3.16 (-14.6)	-.317 (-2.24)	-.317 (-2.24)		
22	-14.0 (-8.80)	-2.93 (-26.5)		-.0872 (-2.45)		
23a	-9.67 (-8.74)	-3.87 (-8.47)				
23b	-8.24 (-9.27)	-4.38 (-7.74)				
24	-7.38 (-16.7)	-4.30 (-13.9)	-1.09 (-2.65)	-.410 (-5.95)		
25	-22.6 (-3.00)	-3.11 (-6.50)	-.287 (-2.12)	-.287 (-2.12)		
26	-4.73 (-6.79)	-5.49 (-4.06)				
27	-5.56 (-22.6)	-1.86 (-11.2)				
28	-8.57 (-15.6)	-3.12 (-9.77)				
29	-8.67 (-7.46)	-4.01 (-6.27)				
30	-5.20 (-10.1)	-1.61 (-9.51)			.429 (2.43)	.429 (2.43)

.... – positive coefficient
 – negative coefficient

"constant" – "constant term (intercept)" quantitative variable
 "wint" – "winter season" indicator variable
 "sum" – "summer season" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	fall [X ₃]		mon [X ₄]		tues [X ₄]	
	fatality	injury	fatality	injury	fatality	injury
1						
2			2.67 (2.11)	.933 (3.29)		
3						
4	-.445 (-2.68)	-.445 (-2.68)				
5						
6						
7						
8a						
8b						1.10 (2.57)
9		-.264 (-2.04)				
10					-.457 (-2.14)	-.457 (-2.14)
11						
12						
13						
14				.524 (1.99)		
15						
16a						
16b						
16c						
17					.823 (2.50)	.823 (2.50)
18						
19						
20						
21			-.374 (-2.09)	-.374 (-2.09)		
22					1.03 (2.23)	
23a						
23b						
24						
25						
26	1.08 (2.04)					
27						
28						
29		-.679 (-2.54)				
30						

.... – positive coefficient
 – negative coefficient

"fall" – "fall season" indicator variable
 "mon" – "Monday" indicator variable
 "tues" – "Tuesday" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	sund [X ₄]		sat [X ₄]		wed [X ₄]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4						
5						
6						
7						
8a						
8b						
9						
10						
11						
12						
13	1.20 (2.50)					
14						
15						
16a						
16b						
16c						
17						
18						
19						
20			2.08 (2.64)	2.08 (2.64)		
21						
22						
23a						
23b						
24						
25						
26						
27					-.397 (-2.21)	-.397 (-2.21)
28						
29						
30						

.... – positive coefficient
 – negative coefficient

"sund" – "Sunday" indicator variable
 "sat" – "Saturday" indicator variable
 "wed" – "Wednesday" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	thday [X ₄]		nigh [X ₅]		morn [X ₅]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4						
5						
6						
7						
8a						
8b						
9						
10					-.414 (-2.33)	-.414 (-2.33)
11						
12	-.517 (-2.56)	-.517 (-2.56)				
13						
14						
15						
16a						
16b						
16c						
17						
18						
19						
20						
21						
22						
23a			3.30 (2.30)			
23b						
24						
25						
26						
27						
28						
29						
30	1.73 (2.71)					

.... – positive coefficient
 – negative coefficient

"thday" – "Thursday" indicator variable
 "nigh" – "late night hours: 1:00 to 5:00" indicator variable²³
 "morn" – "morning hours: 5:00 to 9:00" indicator variable

²³ We use military 24-hour time everywhere in our research.

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	dayt [X ₅]		nocons [X ₁₃]		cons [X ₁₃]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4						
5						
6						
7						
8a						
8b						
9						
10						
11						
12			.510 (2.19)	.510 (2.19)		
13						
14						
15						
16a	-.228 (-2.15)	-.228 (-2.15)				
16b						
16c					2.58 (2.09)	
17						
18	.324 (2.21)	.324 (2.21)				
19						
20						
21						
22						
23a						
23b						
24			.672 (2.73)	.672 (2.73)		
25						
26						
27	.282 (2.40)	.282 (2.40)				
28						
29						
30						

.... – positive coefficient
 – negative coefficient

"dayt" – "day hours: 9:00 to 17:00" indicator variable
 "nocons" – "no construction at the accident location" indicator variable
 "cons" – "construction at the accident location" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	light [X ₁₄]		dark [X ₁₄]		day [X ₁₄]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						.199 (3.74)
4						
5						
6						
7			.845 (4.25)	.845 (4.25)		
8a						
8b			1.22 (3.07)	1.22 (3.07)		
9						
10						
11						
12						
13			1.06 (2.35)			
14			1.24 (2.44)			
15		.261 (3.10)				
16a						
16b						
16c						
17						
18						
19						-.297 (-2.75)
20						
21						
22						
23a						
23b						
24					-.824 (-3.15)	
25			1.29 (2.55)			
26						
27						
28						
29						
30						.642 (4.04)

.... – positive coefficient
.... – negative coefficient

"light" – "daylight time OR street lights lit up during dark time" indicator variable
 "dark" – "dark time with no street lights" indicator variable
 "day" – "daylight time" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	dawn [X ₁₄]		darklamp [X ₁₄]		precip [X ₁₅]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4						
5						1.46 (2.39)
6						
7						
8a						
8b						
9						
10						
11						
12					-1.02 (-6.41)	-1.02 (-6.41)
13						
14						
15						
16a						
16b						
16c						
17						
18						
19						
20		2.78 (2.53)				
21						
22			.188 (4.76)	.188 (4.76)		
23a			.545 (2.55)	.545 (2.55)		
23b			.641 (2.00)			
24						
25						
26						
27						
28						
29			.643 (2.17)	.643 (2.17)		
30						

.... – positive coefficient
.... – negative coefficient

"dawn" – "dawn OR dusk" indicator variable
 "darklamp" – "dark AND street lights on" indicator variable
 "precip" – "precipitation: rain OR snow OR sleet OR hail OR freezing rain" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	snow [X ₁₅]		clear [X ₁₅]		clo [X ₁₅]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4						
5						
6						
7						
8a						
8b						
9		-1.14 (-6.01)				
10						
11						
12						
13						
14						
15						
16a						
16b						
16c						
17						
18	-.779 (-2.39)	-.779 (-2.39)				
19						
20						
21						
22						
23a						
23b						
24						
25						
26					1.64 (2.99)	
27						
28		-1.01 (-2.82)				
29			.615 (2.88)	.615 (2.88)		
30						

.... – positive coefficient
 – negative coefficient

"snow" – "snowing weather" indicator variable
 "clear" – "clear weather" indicator variable
 "clo" – "cloudy weather" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	rain [X ₁₅]		soil [X ₁₅]		dry [X ₁₆]	
	fatality	injury	fatality	injury	fatality	injury
1						
2	3.23 (2.57)					
3						
4						
5						
6						
7		.644 (2.58)				
8a			1.89 (1.99)	1.89 (1.99)		
8b						
9						
10						
11						
12						
13						
14						
15						
16a						
16b						
16c						
17						
18						
19						
20						
21						
22						
23a						
23b						
24					.861 (2.52)	.324 (5.05)
25						
26						
27						
28						
29						
30						

.... – positive coefficient
.... – negative coefficient

"rain" – "rainy weather" indicator variable
 "soil" – "blowing sand OR soil OR snow" indicator variable
 "dry" – "roadway surface is dry" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	slush [X ₁₆]		driv [X ₁₇]		nomed [X ₁₇]	
	fatality	injury	fatality	injury	fatality	injury
1						.304 (2.60)
2						
3	-1.46 (-2.48)	-.430 (-4.63)				
4						
5						
6						
7						
8a	2.70 (2.18)					
8b						
9						
10						
11						
12						
13						
14						
15						
16a				-.387 (-3.09)		
16b						
16c						
17						
18						
19						
20			-1.14 (-2.38)	-1.14 (-2.38)		
21	-.713 (-2.67)	-.713 (-2.67)				
22	-.236 (-2.84)	-.236 (-2.84)				-.112 (-3.54)
23a						
23b						
24			.361 (6.27)	.361 (6.27)		
25			-1.66 (-2.19)			
26						
27						
28		-.870 (-2.97)				
29						
30	-.779 (-2.16)	-.779 (-2.16)			-1.62 (-2.03)	

.... – positive coefficient
.... – negative coefficient

"slush" – "roadway surface is covered by snow/slush" indicator variable
 "driv" – "road median is a drivable" indicator variable
 "nomed" – "no median" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	curb [X ₁₇]		nojun [X ₁₈]		way4 [X ₁₈]	
	fatality	injury	fatality	injury	fatality	injury
1						.240 (2.29)
2						.699 (2.81)
3						
4					.542 (3.93)	.542 (3.93)
5						
6						
7			.498 (2.11)	.498 (2.11)		
8a						
8b						
9				-.367 (-2.09)		
10						
11						
12						
13						
14						
15						
16a						
16b	.407 (2.67)	.407 (2.67)				
16c						
17						
18						
19			-.278 (-2.82)			
20						
21	-1.21 (-3.07)	-1.21 (-3.07)				
22			-.371 (-11.3)	-.371 (-11.3)		
23a			-.472 (-2.75)			
23b						
24					.298 (3.41)	.298 (3.41)
25						
26					.517 (2.16)	.517 (2.16)
27						
28			-.182 (-2.44)	-.182 (-2.44)		
29					.441 (2.17)	.441 (2.17)
30						

.... – positive coefficient
 – negative coefficient

"curb" – "road median is curbed" indicator variable
 "nojun" – "no road junction at the accident location" indicator variable
 "way4" – "accident location is at a 4-way intersection" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	T [X ₁₈]		ramp [X ₁₈]		curve [X ₁₉]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4						
5						
6						
7						
8a						
8b						
9						
10			-0.394 (-2.28)	-0.394 (-2.28)		
11						
12						
13						
14						
15						
16a						
16b						
16c						
17						
18						
19						
20		1.82 (2.83)				
21					0.311 (2.30)	0.311 (2.30)
22						
23a						
23b						
24						
25						
26						
27						0.278 (2.01)
28						
29						
30						

.... – positive coefficient
.... – negative coefficient

"T" – "accident location is at a T-intersection" indicator variable
 "ramp" – "accident location is near or on a ramp" indicator variable
 "curve" – "road is at curve" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	sg [X ₁₉]		sl [X ₁₉]		str [X ₁₉]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3					-.176 (-2.93)	-.176 (-2.93)
4						
5						
6						
7						
8a						
8b	-1.39 (-2.36)	-1.39 (-2.36)				
9			-.256 (-2.33)	-.256 (-2.33)		
10						
11						
12						
13						
14						
15					-1.20 (-4.13)	-.291 (-3.12)
16a						
16b						
16c						
17						
18						
19						
20						
21						
22						
23a						
23b						
24			.173 (2.68)	.173 (2.68)		
25						
26						
27						
28						
29						
30						

.... – positive coefficient
.... – negative coefficient

"sg" – "road is straight AND at grade" indicator variable
 "sl" – "road is straight AND level" indicator variable
 "str" – "road is straight" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	cl [X ₁₉]		sh [X ₁₉]		cg [X ₁₉]	
	fatality	injury	fatality	injury	fatality	injury
1			.329 (2.05)	.329 (2.05)		
2						
3						
4						
5						
6						
7						
8a						
8b						
9						
10						
11					.999 (2.40)	.999 (2.40)
12						
13						
14						
15						
16a						
16b						
16c						
17						
18						
19						
20						
21						
22						
23a						
23b						
24						
25						
26	1.62 (2.39)					
27						
28						
29						
30	2.73 (4.20)					

.... – positive coefficient
 – negative coefficient

"cl" – "road is at-curve AND level" indicator variable
 "sh" – "road is straight AND hillcrest" indicator variable
 "cg" – "road is at-curve AND at grade" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	lev [X ₁₉]		driver [X ₂₀]		veh [X ₂₀]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4						
5						
6			1.27 (4.94)	1.27 (4.94)		
7						
8a						
8b			1.96 (2.89)	1.96 (2.89)		
9				1.46 (11.6)		
10						
11						
12		-.397 (-2.76)		1.44 (6.83)		
13			.573 (2.66)	.573 (2.66)		
14					-1.58 (-2.32)	-1.58 (-2.32)
15						
16a						
16b						
16c						
17						
18						
19						
20						
21				1.45 (9.71)		
22						
23a						
23b						
24			1.04 (10.5)	1.04 (10.5)		
25						
26			1.01 (2.30)	1.01 (2.30)		
27						
28			.569 (2.37)	.569 (2.37)		
29						
30						

.... – positive coefficient
.... – negative coefficient

"lev" – "road is at level" indicator variable
 "driver" – "primary cause of accident is driver-related" indicator variable
 "veh" – "primary cause of accident is vehicle-related" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	env [X ₂₀]		hl5 [X ₂₂]		hl10 [X ₂₂]	
	fatality	injury	fatality	injury	fatality	injury
1						
2					1.16 (5.04)	1.16 (5.04)
3	-2.90 (-6.30)	-1.27 (-19.7)				
4						
5						
6					.804 (4.26)	.804 (4.26)
7						
8a						
8b						1.10 (3.20)
9						
10						
11						
12						
13					.631 (6.37)	.631 (6.37)
14						
15		-1.78 (-18.5)				
16a			.700 (6.33)	.700 (6.33)		
16b			.662 (7.07)	.662 (7.07)		
16c				.442 (2.64)		
17						
18		-1.62 (-7.63)	.887 (6.27)	.887 (6.27)		
19					.742 (7.20)	.742 (7.20)
20						
21						
22					1.47 (2.35)	.777 (22.8)
23a			.969 (6.00)	.969 (6.00)		
23b				.629 (3.08)		
24					.872 (13.6)	.872 (13.6)
25					.647 (5.65)	
26						
27		-1.59 (-12.7)				
28			.690 (9.24)	.690 (9.24)		
29			.974 (4.62)	.974 (4.62)		
30		-1.34 (-6.07)	.965 (6.09)			

.... – positive coefficient
 – negative coefficient

"env" – "primary cause of accident is environment-related" indicator variable
 "hl5" – "help arrived in 5 minutes or less after the crash" indicator variable
 "hl10" – "help arrived in 10 minutes or less after the crash" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	hl20 [X ₂₂]		hg30 [X ₂₂]		car [X ₂₅]	
	fatality	injury	fatality	injury	fatality	injury
1	2.27 (2.21)	.740 (6.37)				
2						
3	1.38 (5.19)	.705 (12.3)				
4	.758 (3.78)	.758 (3.78)				
5						
6						
7						
8a						
8b						
9		1.06 (7.99)				
10	.886 (4.97)	.886 (4.97)				
11	1.27 (4.82)	1.27 (4.82)				
12	.938 (5.52)	.938 (5.52)				
13						
14	1.55 (5.23)	1.55 (5.23)				
15	.872 (9.39)	.872 (9.39)				
16a						
16b						
16c						
17						
18						
19						
20	1.88 (2.80)	1.88 (2.80)				
21	.881 (6.04)	.881 (6.04)				
22						
23a					.575 (2.87)	.575 (2.87)
23b						
24						
25						
26			-2.40 (-3.22)	-2.40 (-3.22)		
27	.851 (6.24)	.851 (6.24)				
28						
29						
30						

.... – positive coefficient
 – negative coefficient

"hl20" – "help arrived in 20 minutes or less after the crash" indicator variable
 "hg30" – "help arrived in more than 30 minutes after the crash" indicator variable
 "car" – "the vehicle at fault is a car" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	SUV [X ₂₅]		heavy [X ₂₅]		moto [X ₂₅]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3					2.93 (12.2)	2.93 (12.2)
4						
5						
6					2.32 (3.69)	2.32 (3.69)
7						
8a						
8b						
9						
10						
11						
12					2.86 (4.51)	2.86 (4.51)
13						
14			-1.19 (-2.07)	-1.19 (-2.07)		
15					3.09 (9.82)	3.09 (9.82)
16a						
16b						
16c						
17						
18					1.94 (4.97)	1.94 (4.97)
19						
20						
21						3.46 (8.00)
22						
23a						
23b						
24					2.31 (11.5)	2.31 (11.5)
25		-.550 (-2.78)				
26						
27					4.19 (5.67)	4.19 (5.67)
28						
29						
30						

.... – positive coefficient
.... – negative coefficient

"SUV" – "the vehicle at fault is a SUV" indicator variable
 "heavy" – "the vehicle at fault is a truck or a tractor" indicator variable
 "moto" – "the vehicle at fault is a motorcycle" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	pickup [X ₂₅]		van [X ₂₅]		trac1 [X ₂₅]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4						
5						
6						
7						
8a						
8b						
9						
10						
11						
12						
13						
14						
15						
16a						
16b			.300 (2.08)	.300 (2.08)		
16c		-.351 (-2.11)				
17						
18						
19			-.428 (-2.20)	-.428 (-2.20)		
20						
21						
22						
23a						
23b					-.905 (-2.71)	-.905 (-2.71)
24						
25						
26						
27						
28		-.291 (-2.83)				
29						
30						

.... – positive coefficient
 – negative coefficient

"pickup" – "the vehicle at fault is a pickup" indicator variable

"van" – "the vehicle at fault is a van" indicator variable

"trac1" – "the vehicle at fault is a tractor OR one semi-trailer" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	vage [X ₂₆]		voldg [X ₂₆]		v7g [X ₂₆]	
	fatality	injury	fatality	injury	fatality	injury
1	.128 (3.91)					
2						
3	.0311 (6.59)	.0311 (6.59)				
4		.0420 (3.14)				
5			-1.25 (-3.74)	-1.25 (-3.74)		
6					-.532 (-2.47)	-.532 (-2.47)
7						
8a					-.797 (-2.55)	-.797 (-2.55)
8b						
9				.228 (2.04)		
10						
11						
12						
13						
14	.0601 (3.35)	.0601 (3.35)				
15	.0332 (4.37)	.0332 (4.37)				
16a						
16b						
16c						
17						
18						
19						
20						
21	.0216 (2.02)	.0216 (2.02)				
22			1.40 (2.74)	.110 (3.72)		
23a						
23b						
24				.315 (5.53)		
25						
26						
27	.0329 (3.27)	.0329 (3.27)				
28						
29						
30						

.... – positive coefficient
 – negative coefficient

"vage" – "age (in years) of the vehicle at fault" quantitative variable
 "voldg" – "the vehicle at fault is more than 7 years old" indicator variable
 "v7g" – "age of the vehicle at fault is ≥ 3 and ≤ 7 years" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	v3g [X ₂₆]		X ₂₇		Ind [X ₂₈]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3			.0382 (3.47)	.0382 (3.47)		
4						
5						
6						
7						
8a			.303 (2.37)	.303 (2.37)		
8b						
9			.110 (2.60)	.110 (2.60)		
10						
11						
12						
13						
14						
15						
16a						
16b	-.406 (-2.71)	-.406 (-2.71)	-.142 (-2.15)	-.142 (-2.15)	.404 (2.04)	.404 (2.04)
16c						
17						
18						
19			-.238 (-3.14)	-.238 (-3.14)		
20						
21			.133 (2.26)	.133 (2.26)		
22			-.0628 (-2.89)	-.0628 (-2.89)		
23a						
23b						
24			.0817 (3.11)	.0817 (3.11)	.477 (4.10)	.477 (4.10)
25						
26						
27						
28						
29						
30						

.... – positive coefficient
 – negative coefficient

"v3g" – "age of the vehicle at fault is > 1 and ≤ 3 years" indicator variable
 "X₂₇" – "number of occupants in the vehicle at fault" quantitative variable
 "Ind" – "license state of the vehicle at fault is Indiana" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	othUS [X ₂₈]		Inm [X ₃₀]		r22 [X ₃₀]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4						
5						
6	3.60 (2.82)	3.60 (2.82)				
7						
8a						
8b						
9						
10	-.970 (-2.20)	-.970 (-2.20)				
11	-.695 (-2.28)	-.695 (-2.28)				
12						
13						.369 (3.18)
14						
15						
16a						
16b						
16c						
17						
18	-1.12 (-2.26)	-1.12 (-2.26)	.414 (2.85)	.414 (2.85)		
19						
20						
21						
22						
23a						
23b						
24						
25						
26						
27						
28						
29						
30						

.... – positive coefficient
 – negative coefficient

"othUS" – "license state of the vehicle at fault is a U.S. state except Indiana and its neighboring states (IL, KY, OH, MI)" indicator variable
 "Inm" – "road traveled by the vehicle at fault is multi-lane" indicator variable
 "r22" – "road traveled by the vehicle at fault is two-lane AND two-way" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	rmu22 [X ₃₀]		rmd2 [X ₃₀]		priv [X ₃₀]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4						
5				2.06 (2.99)		
6						
7						
8a						
8b						
9						
10	3.89 (3.15)					
11						
12						
13						
14						
15						
16a						
16b						
16c						
17						
18						
19						
20						
21					-1.14 (-3.10)	-1.14 (-3.10)
22					-.489 (-3.05)	-.489 (-3.05)
23a			.374 (1.98)	.374 (1.98)		
23b						
24						-.490 (-4.09)
25						
26						
27						
28						
29						
30						

.... – positive coefficient
.... – negative coefficient

"rmu22" – "road traveled by the vehicle at fault is multi-lane AND undivided two-way left" indicator variable

"rmd2" – "road traveled by the vehicle at fault is multi-lane AND divided three or more" indicator variable

"priv" – "road traveled by the vehicle at fault is a private drive" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	stopsig [X ₃₁]		nosig [X ₃₁]		nopass [X ₃₁]	
	fatality	injury	fatality	injury	fatality	injury
1	.260 (2.50)	.260 (2.50)				
2						
3						
4						
5						
6						
7						
8a						
8b						
9						
10						
11						
12						
13	1.24 (2.48)	.444 (3.02)				
14						
15					.198 (2.02)	.198 (2.02)
16a						
16b						
16c						
17					3.51 (2.41)	
18						
19						
20						
21						
22			-.106 (-2.71)	-.106 (-2.71)		
23a						
23b						
24						
25	.505 (2.82)	.505 (2.82)				
26						
27				-.286 (-2.45)		
28						
29						
30						

.... – positive coefficient
 – negative coefficient

"stopsig" – "traffic control device for the vehicle at fault is a «stop sign»" indicator variable
 "nosig" – "no any traffic control device for the vehicle at fault" indicator variable
 "nopass" – "traffic control device for the vehicle at fault is a «no passing zone»" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	sig [X ₃₁]		other [X ₃₁]		X ₃₃	
	fatality	injury	fatality	injury	fatality	injury
1					2.36 (1.99)	1.85 (3.11)
2						
3			1.56 (2.85)	.631 (2.52)	2.24 (5.03)	1.00 (3.88)
4						
5						
6					2.81 (2.36)	2.81 (2.36)
7						
8a					6.11 (4.48)	
8b						
9						
10					1.78 (2.03)	1.78 (2.03)
11					4.51 (4.33)	
12						
13					2.62 (2.82)	
14					2.81 (2.74)	
15					1.96 (3.13)	
16a						
16b						
16c					5.07 (3.73)	
17						
18						
19						
20						
21						
22					1.95 (8.94)	1.95 (8.94)
23a						2.67 (3.01)
23b						
24	.268 (2.44)	.268 (2.44)			1.16 (4.19)	1.16 (4.19)
25						
26					3.21 (3.57)	
27						
28					1.91 (3.60)	1.91 (3.60)
29						
30						

.... – positive coefficient
.... – negative coefficient

"sig" – "traffic control device for the vehicle at fault is a signal" indicator variable
 "other" – "traffic control device for the vehicle at fault is an «other regulatory sign or marking»" indicator variable
 "X₃₃" – "at least one of the vehicles involved was on fire" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	X ₃₄		age2 [X ₃₄]		age3 [X ₃₄]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3	-.0071 (3.93)					
4						
5						
6						
7						
8a						
8b						
9			-.576 (-3.67)	-.576 (-3.67)		
10					-.377 (-2.09)	-.377 (-2.09)
11						
12						
13						
14						
15						
16a						
16b						
16c						
17						
18						
19						
20						
21						
22	.0346 (3.54)	.00180 (2.20)				
23a						
23b						
24		.381 (2.20)				
25						
26						
27						
28						
29						
30						

.... – positive coefficient
.... – negative coefficient

"X₃₄" – "age (in years) of the driver at fault" quantitative variable
 "age2" – "age of the driver at fault is ≥ 24 and < 30" indicator variable
 "age3" – "age of the driver at fault is ≥ 30 and < 40" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	age5 [X ₃₄]		X ₃₅		oldvage [X ₂₆]	
	fatality	injury	fatality	injury	fatality	injury
1	1.09 (2.37)					
2				.540 (2.11)		
3				.290 (5.39)		
4			-.403 (-2.51)	-.403 (-2.51)		
5						
6						
7						
8a						
8b						
9			.365 (3.44)	.365 (3.44)		
10						
11						
12				.533 (3.94)		
13			-2.02 (-2.69)			
14						
15			-.900 (-2.42)	.229 (2.74)		
16a						
16b						
16c						.0428 (2.73)
17						
18						
19						
20		-1.33 (-2.11)				
21						
22						
23a		-.556 (-2.82)		-.600 (-2.47)		
23b						
24				.412 (7.07)		
25						
26						
27						
28						
29						
30						

.... – positive coefficient
 – negative coefficient

"age5" – "age of the driver at fault is ≥ 50 years" indicator variable
 "X₃₅" – "gender of the driver at fault: 1 – female, 0 – male" indicator variable
 "oldvage" – "age (in years) of the oldest vehicle involved" quantitative variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	voldo [X ₂₆]		maxpass [X ₂₇]		age5y [X ₃₄]	
	fatality	injury	fatality	injury	fatality	injury
1			-.691 (-1.99)	.133 (3.60)		
2						
3						
4			.186 (2.71)	.186 (2.71)		
5				.863 (2.60)		
6						
7						
8a						
8b					-1.50 (-3.39)	-1.50 (-3.39)
9						
10			.600 (2.64)	.141 (2.42)		
11						
12						
13						
14				.282 (2.34)		
15						
16a			.182 (3.32)	.182 (3.32)		
16b			.207 (4.04)	.207 (4.04)		
16c						
17						
18						
19			.198 (3.40)	.198 (3.40)		
20						
21						
22			.190 (10.8)	.190 (10.8)		
23a						
23b	.415 (2.07)	.415 (2.07)				
24						
25						
26	.592 (2.60)	.592 (2.60)				
27						
28			.132 (4.10)	.132 (4.10)		
29				.244 (2.10)		
30						

.... – positive coefficient
 – negative coefficient

"voldo" – "age of the oldest vehicle involved is > 7 years" indicator variable
 "maxpass" – "the largest number of occupants in all vehicles involved" quantitative variable
 "age5y" – "age of the youngest driver is ≥ 50 years" indicator variable

Table C.5 (Continued)

#	Coefficient (t-ratio)					
	ff [X ₃₅]		mm [X ₃₅]		mf [X ₃₅]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4				-.676 (-3.68)		
5						
6						
7						
8a						
8b						
9						
10	.448 (2.66)	.448 (2.66)				
11						
12						
13						
14						
15						
16a		.280 (2.53)				
16b		.462 (4.21)				
16c						
17						
18						
19			-.245 (-2.27)	-.245 (-2.27)		
20						
21						
22				-.262 (-7.73)		
23a					.473 (2.49)	.473 (2.49)
23b						
24						
25						
26					-1.97 (-2.50)	
27						
28			-.306 (-3.73)	-.306 (-3.73)		
29						
30						

.... – positive coefficient
 – negative coefficient

"ff" – "two female drivers involved into a two-vehicle accident" indicator variable
 "mm" – "two male drivers involved into a two-vehicle accident" indicator variable
 "mf" – "male and female drivers involved into a two-vehicle accident" indicator variable

Table C.6 Multinomial logit models for 2006 accident severity

#	Model name			Log-likelihood		R^2	Coefficient (t-ratio)	
							X_{29}	
	model	restricted*	fatality [β_1]	injury [β_2]				
1	County road	rural	(car/SUV)+(car/SUV)	-2345.1	-2457.6	.046	.0396 (5.48)	.0396 (5.48)
2			(car/SUV)+(truck)	-113.99	-135.50	.159	.0648 (3.06)	.0648 (3.06)
3			one vehicle	-7152.1	-8621.2	.170	.00506 (2.04)	.00506 (2.04)
4a		urban	(car)+(car)	-356.34	-256.92	.387		
4b			(car)+(SUV)	-232.26	-106.65	n/a		.0613 (2.43)
4c			(SUV)+(SUV)	-183.12	-100.57	.821		
5	(car/SUV)+(truck)		-16.716	-24.014	.304			
6	one vehicle	-367.48	-418.24	.121				
7	Interstate	rural	(car/SUV)+(car/SUV)	-459.31	-485.53	.054		
8			(car/SUV)+(truck)	-271.78	-294.68	.078		
9			one vehicle	-1491.0	-1718.3	.132		
10		urban	(car/SUV)+(car/SUV)	-853.29	-887.05	.038		
11			(car/SUV)+(truck)	-252.55	-278.96	.097		
12			one vehicle	-900.79	-1032.2	.127		
13	State route	rural	(car/SUV)+(car/SUV)	-560.40	-605.43	.074	.248 (3.48)	.0416 (3.25)
14			(car/SUV)+(truck)	-72.403	-84.740	.146	.127 (2.50)	.127 (2.50)
15			one vehicle	-3704.3	-4873.2	.240	.0636 (2.34)	
16		urban	(car/SUV)+(car/SUV)	-3225.9	-3368.2	.042	.252 (3.35)	.0290 (7.95)
17			(car/SUV)+(truck)	-192.97	-203.31	.051		
18			one vehicle	-899.36	-982.58	.085		
19	City street	rural	(car/SUV)+(car/SUV)	-1068.42	-1129.4	.054	.0414 (6.13)	.0414 (6.13)
20			(car/SUV)+(truck)	-77.136	-28.602	n/a		
21			one vehicle	-317.09	-382.38	.171		
22a		urban	(car)+(car)	-6828.1	-7148.6	.045	.0251 (6.33)	.0251 (6.33)
22b			(car)+(SUV)	-4289.5	-4480.3	.043	.0218 (4.65)	.0218 (4.65)
22c			(SUV)+(SUV)	-1341.6	-1413.2	.051	.0343 (4.20)	.0343 (4.20)
23	(car/SUV)+(truck)		-520.63	-563.91	.077	.0284 (2.34)	.0284 (2.34)	
24	one vehicle	-2681.6	-2955.4	.093				
25	US route	rural	(car/SUV)+(car/SUV)	-380.51	-412.77	.078		
26			(car/SUV)+(truck)	-237.97	-268.53	.113	.0608 (3.07)	.0608 (3.07)
27			one vehicle	-1491.0	-1917.7	.223		
28		urban	(car/SUV)+(car/SUV)	-967.22	-1003.9	.037	.0154 (2.14)	.0154 (2.14)
29			(car/SUV)+(truck)	-185.87	-209.82	.114	.0586 (3.60)	.0586 (3.60)
30			one vehicle	-176.49	-202.75	.129		

.... – positive coefficient

.... – negative coefficient

* – restricted log-likelihood found by setting all coefficients except intercepts to zero

** – models are estimated by using procedure A on page 32, except the models marked by bold numbers and estimated by using procedure B on page 33

X_{29} – “posted speed limit (if the same for all vehicles involved)” quantitative variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	constant		wint [X ₃]		sum [X ₃]	
	fatality	injury	fatality	injury	fatality	injury
1	-9.88 (-8.23)	-3.45 (-10.0)				
2	-6.57 (-4.36)	-5.00 (-4.82)				
3	-5.31 (-21.2)	-2.25 (-14.9)				
4a		.954 (5.64)				
4b		-4.09 (-3.78)				
4c						
5	-8.86 (-4.10)	-7.25 (-3.69)				
6	-7.00 (-9.20)	-2.54 (-8.65)				
7	-6.27 (-11.2)	-2.89 (-10.2)				
8	-5.01 (-10.8)	-3.24 (-8.56)				
9	-10.2 (-7.26)	-3.76 (-22.9)				
10	-8.42 (-8.23)	-2.90 (-12.5)				
11	-6.05 (-8.32)	-2.70 (-10.9)				
12	-6.62 (-15.0)	-3.84 (-15.8)		-.414 (-2.69)		
13	-18.5 (-4.74)	-5.00 (-5.88)				
14	-9.24 (-3.42)	-8.38 (-3.12)				
15	-7.83 (-5.28)	-1.78 (-16.9)			.198 (2.71)	.198 (2.71)
16	-19.1 (-4.58)	-2.77 (-16.6)				
17	-3.43 (-3.37)	-2.22 (-12.6)				
18	-4.93 (-14.3)	-1.99 (-8.01)				
19	-9.35 (-9.03)	-3.58 (-11.8)				
20		-2.08 (-4.04)				
21	-4.65 (-8.25)	-1.07 (-3.87)			.582 (2.55)	.582 (2.55)
22a	-9.47 (-13.1)	-2.58 (-15.9)				
22b	-8.25 (-15.5)	-2.27 (-11.9)				
22c	-8.34 (-12.6)	-3.04 (-9.33)				
23	-8.69 (-7.93)	-4.19 (-8.75)				
24	-5.63 (-21.9)	-3.42 (-15.1)		-.207 (-2.48)		
25	-4.44 (-9.52)	-2.04 (4.11)				
26	-7.48 (-6.35)	-4.32 (-3.99)				
27	-4.93 (-10.5)	-1.24 (-3.40)				
28	-8.27 (-7.86)	-2.13 (-6.45)				
29	-11.4 (-4.75)	-3.56 (-5.04)				
30	-5.39 (-7.12)	-2.32 (-4.48)

– positive coefficient
– negative coefficient

“constant” – “constant term (intercept)” quantitative variable

“wint” – “winter season” indicator variable

“sum” – “summer season” indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	fall [X ₃]		mon [X ₄]		sund [X ₄]	
	fatality	injury	fatality	injury	fatality	injury
1	2.28 (4.01)					
2						
3						
4a						
4b						
4c						
5			3.49 (2.53)			
6						
7						
8						
9						
10						
11	-1.18 (-3.64)	-1.18 (-3.64)				
12						
13						
14						
15						
16						
17						
18						
19						
20						
21						
22a						
22b			1.79 (2.52)			
22c						
23					.876 (2.19)	.876 (2.19)
24						
25	2.14 (4.11)					
26		-1.49 (-3.92)			2.99 (4.08)	
27						
28						
29	-.714 (-2.00)	-.714 (-2.00)				
30						

.... – positive coefficient
 – negative coefficient

"fall" – "fall season" indicator variable
 "mon" – "Monday" indicator variable
 "sund" – "Sunday" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	wday [X ₄]		wed [X ₄]		jobend [X ₅]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3	-.159 (-3.41)	-.159 (-3.41)				
4a						
4b						
4c						
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						
16						
17	-2.81 (-1.97)					
18						
19						
20						
21						
22a						
22b						
22c						
23						
24				-.264 (-2.58)	.214 (2.45)	.214 (2.45)
25						
26						
27						
28						
29						
30						

.... – positive coefficient
.... – negative coefficient

"wday" – "any weekday except Saturday and Sunday" indicator variable
 "wed" – "Wednesday" indicator variable
 "jobend" – "end of job hours: from 16:00 to 19:00" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	peak [X ₅]		nigh [X ₅]		dayt [X ₅]	
	fatality	injury	fatality	injury	fatality	injury
1			2.15 (2.32)			
2						
3						
4a						
4b						
4c						
5						
6						
7			1.06 (2.27)	1.06 (2.27)		
8					-.641 (-2.62)	-.641 (-2.62)
9						.252 (2.46)
10						
11						
12						
13						
14						
15						.178 (2.59)
16						
17						
18						
19						
20						
21						.477 (2.11)
22a	-.117 (-2.39)	-.117 (-2.39)				
22b		-.137 (-2.20)				
22c						
23						
24						
25						
26						
27						
28						
29						
30						

.... – positive coefficient
.... – negative coefficient

"peak" – "rush hours: 7:00 to 9:00 OR 17:00 to 19:00" indicator variable
 "nigh" – "late night hours: from 1:00 to 5:00" indicator variable
 "dayt" – "day hours: from 9:00 to 17:00" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	lunch [X ₅]		even [X ₅]		nocons [X ₁₃]	
	fatality	injury	fatality	injury	fatality	injury
1						
2	-1.25 (-2.44)	-1.25 (-2.44)				
3						
4a						
4b						
4c			-3.10 (-5.13)	-3.10 (-5.13)		
5						
6						
7						
8						
9						
10	.581 (3.23)	.581 (3.23)				
11						
12						
13						
14						
15						
16						
17						
18						
19						
20						
21						
22a						
22b						
22c						
23						
24						
25						
26						
27					-.677 (-2.06)	-.677 (-2.06)
28						
29						
30						

.... – positive coefficient
.... – negative coefficient

“lunch” – “lunch hours: 11:00 to 14:00” indicator variable
 “even” – “evening hours: 17:00 to 22:00” indicator variable
 “nocons” – “no construction at the accident location” indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	cons [X ₁₃]		dark [X ₁₄]		day [X ₁₄]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3					-.738 (-4.06)	
4a						
4b						
4c						
5						
6						
7			.482 (2.12)	.482 (2.12)		
8						
9						
10					-.425 (-2.95)	-.425 (-2.95)
11						
12			1.40 (2.33)	1.40 (2.33)		
13			1.24 (2.85)			
14						
15					-.931 (-3.80)	
16						
17				1.52 (3.16)		
18					.529 (4.35)	.529 (4.35)
19	-1.51 (-2.06)	-1.51 (-2.06)				
20						
21						
22a						
22b					-.150 (-2.26)	-.150 (-2.26)
22c						
23						
24					-1.20 (-3.37)	
25						
26						
27					.235 (2.33)	.235 (2.33)
28						
29						
30

– positive coefficient
– negative coefficient

"cons" – "construction at the accident location" indicator variable
 "dark" – "dark time with no street lights" indicator variable
 "day" – "daylight time" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	dawn [X ₁₄]		darklamp [X ₁₄]		precip [X ₁₅]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4a						
4b						
4c						
5						
6						
7						
8						
9						
10						
11			.722 (2.45)	.722 (2.45)		
12						
13						
14			2.97 (2.42)	2.97 (2.42)		
15					-1.09 (-2.56)	
16						
17						
18						
19						
20						
21						
22a						
22b						
22c						
23	3.14 (2.21)					
24						
25						
26						
27						
28						
29						
30						

.... – positive coefficient
 – negative coefficient

"dawn" – "dawn OR dusk" indicator variable
 "darklamp" – "dark AND street lights on" indicator variable
 "precip" – "precipitation: rain OR snow OR sleet OR hail OR freezing rain" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	snow [X ₁₅]		clear [X ₁₅]		dry [X ₁₆]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3				.0929 (2.11)		
4a						
4b						
4c						
5						
6						
7						
8						
9						
10						
11						
12					.574 (4.44)	.574 (4.44)
13						
14						
15						
16						
17						
18						
19						
20						
21			.518 (2.46)	.518 (2.46)		
22a				-.143 (-3.36)		
22b						
22c						
23						
24	-.651 (-3.07)	-.651 (-3.07)			.385 (4.78)	.385 (4.78)
25						
26						
27						
28						
29						
30						

.... – positive coefficient
.... – negative coefficient

"snow" – "snowing weather" indicator variable
 "clear" – "clear weather" indicator variable
 "dry" – "roadway surface is dry" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	wet [X ₁₆]		ice [X ₁₆]		lose [X ₁₆]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3					.428 (3.30)	.428 (3.30)
4a						
4b						
4c						
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						
16						
17						
18						
19						
20						
21			-2.16 (-2.10)	-2.16 (-2.10)		
22a						
22b						
22c						
23	.584 (3.01)	.584 (3.01)				
24						
25						
26						
27						
28						
29						
30

– positive coefficient
– negative coefficient

"wet" – "roadway surface is wet" indicator variable
 "ice" – "roadway surface is icy" indicator variable
 "lose" – "roadway surface has loose material on it" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	water [X ₁₆]		driv [X ₁₇]		wall [X ₁₇]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4a						
4b						
4c			-1.13 (-2.41)			
5						
6						
7			.467 (2.55)	.467 (2.55)		
8						
9						
10			.439 (2.44)	.439 (2.44)		
11		2.30 (2.40)				
12						
13						
14						
15						
16						
17						
18						
19						
20						
21						
22a						
22b						
22c						
23						
24			.281 (3.83)	.281 (3.83)		
25						
26					-2.10 (-1.97)	
27						
28						
29						
30						

.... – positive coefficient
.... – negative coefficient

"water" – "roadway surface has water on it" indicator variable
 "driv" – "road median is a drivable" indicator variable
 "wall" – "road median is a wall" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	nomed [X ₁₇]		curb [X ₁₇]		nojun [X ₁₈]	
	fatality	injury	fatality	injury	fatality	injury
1						
2	-2.73 (-2.10)					
3			-1.71 (-2.57)		.167 (2.35)	.167 (2.35)
4a						
4b						
4c						
5						
6						
7					.591 (2.19)	.591 (2.19)
8						
9						
10					.536 (3.73)	.536 (3.73)
11						
12						
13						
14						
15						
16					-.367 (-5.86)	-.367 (-5.86)
17						
18					-.548 (-4.14)	-.548 (-4.14)
19		-.236 (-2.13)				
20						
21						
22a		-.112 (-2.37)			-.389 (-8.68)	-.389 (-8.68)
22b					-.252 (-4.18)	-.252 (-4.18)
22c						
23						
24						
25			-1.21 (-2.38)	-1.21 (-2.38)		
26						
27						
28						
29						
30

– positive coefficient
– negative coefficient

"nomed" – "no median" indicator variable
 "curb" – "road median is curbed" indicator variable
 "nojun" – "no road junction at the accident location" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	way4 [X ₁₈]		T [X ₁₈]		str [X ₁₉]	
	fatality	injury	fatality	injury	fatality	injury
1						
2	1.13 (3.18)	1.13 (3.18)				
3					-.194 (-3.95)	-.194 (-3.95)
4a						
4b						
4c						
5						
6						
7						
8			3.37 (2.65)			
9						
10						
11						
12						
13						
14						
15					-.322 (-4.80)	-.322 (-4.80)
16						
17						
18						
19	.328 (2.95)	.328 (2.95)				
20						
21						
22a						
22b						
22c						
23		.682 (4.11)				
24						
25		.436 (2.03)				
26						
27					-.227 (-2.02)	-.227 (-2.02)
28						
29						
30						

.... – positive coefficient
.... – negative coefficient

"way4" – "accident location is at a 4-way intersection" indicator variable
 "T" – "accident location is at a T-intersection" indicator variable
 "str" – "road is straight" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	hill [X ₁₉]		driver [X ₂₀]		env [X ₂₀]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3					-3.70 (-7.24)	-1.75 (-30.4)
4a						
4b						
4c						
5						
6					-1.01 (-4.10)	-1.01 (-4.10)
7						
8						
9			3.64 (3.12)	1.67 (14.5)		
10						
11		1.25 (2.18)				
12				1.52 (8.49)		
13			1.08 (2.43)	1.08 (2.43)		
14						
15					-4.07 (-7.81)	-2.04 (-27.3)
16			-2.50 (-2.76)			
17						
18						
19						
20						
21					-1.39 (-3.55)	-1.39 (-3.55)
22a						
22b						
22c						
23						
24				1.01 (7.15)		
25						
26						
27					-3.91 (-3.79)	-1.98 (-17.1)
28						
29						
30			.817 (2.06)	.817 (2.06)		

.... – positive coefficient
 – negative coefficient

"hill" – "road is at hill" indicator variable
 "driver" – "primary cause of accident is driver-related" indicator variable
 "env" – "primary cause of accident is environment-related" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	hl5 [X ₂₂]		help [X ₂₂]		hl10 [X ₂₂]	
	fatality	injury	fatality	injury	fatality	injury
1					1.00 (8.01)	
2						
3						
4a						
4b						.805 (2.12)
4c				-.0809 (-3.77)		
5						
6						
7						.658 (3.75)
8						
9						
10						
11					.905 (3.76)	.905 (3.76)
12						
13						
14						
15						
16	.676 (10.5)	.676 (10.5)				
17						
18	.752 (6.14)	.752 (6.14)				
19					.567 (4.93)	.567 (4.93)
20						
21						
22a					.692 (13.2)	.692 (13.2)
22b	.671 (12.3)	.671 (12.3)				
22c					.770 (.687)	.770 (.687)
23		.784 (4.69)				
24					.867 (10.5)	.867 (10.5)
25						1.01 (5.04)
26		.756 (2.84)				
27						
28	.647 (5.72)	.647 (5.72)				
29			-.0871 (-2.93)	-.0871 (-2.93)		
30		.677 (2.42)				

.... – positive coefficient
 – negative coefficient

"hl5" – "help arrived in 5 minutes or less after the crash" indicator variable
 "help" – "time when help arrived after the crash" indicator variable
 "hl10" – "help arrived in 10 minutes or less after the crash" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	hl20 [X ₂₂]		car [X ₂₅]		moto [X ₂₅]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3	.910 (18.7)				3.36 (9.64)	3.13 (19.4)
4a	-1.19 (-6.06)	-1.19 (-6.06)				
4b						
4c						
5						
6	1.06 (4.31)	1.06 (4.31)			2.46 (5.05)	2.46 (5.05)
7						
8	1.57 (4.29)	1.57 (4.29)				
9	1.71 (2.19)	.651 (5.74)			4.58 (5.63)	2.89 (5.44)
10	.578 (3.80)	.578 (3.80)				
11				.560 (2.35)		
12	.929 (5.83)	.929 (5.83)			4.41 (6.05)	2.65 (5.76)
13	1.10 (4.48)	1.10 (4.48)				
14						
15	.952 (12.3)	.952 (12.3)			3.25 (16.4)	3.25 (16.4)
16						
17						
18						2.37 (6.54)
19						
20						
21					4.63 (4.32)	4.63 (4.32)
22a						
22b						
22c						
23				.519 (3.06)		
24					2.35 (9.76)	2.35 (9.76)
25						
26						
27	.950 (7.15)	.950 (7.15)				3.47 (8.12)
28						
29						
30					3.38 (3.05)	3.38 (3.05)

.... – positive coefficient
.... – negative coefficient

"hl20" – "help arrived in 20 minutes or less after the crash" indicator variable
 "car" – "the vehicle at fault is a car" indicator variable
 "moto" – "the vehicle at fault is a motorcycle" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	pickup [X ₂₅]		vage [X ₂₆]		voldg [X ₂₆]	
	fatality	injury	fatality	injury	fatality	injury
1						
2	2.76 (2.11)	1.02 (2.20)				
3			.0376 (9.76)	.0376 (9.76)		
4a						
4b						
4c						
5						
6			.0543 (3.24)	.0543 (3.24)		
7						
8						
9			.0372 (3.67)	.0372 (3.67)		
10						
11						
12					.318 (2.55)	.318 (2.55)
13						
14						
15			.0373 (6.55)	.0373 (6.55)		
16						
17						
18						
19						
20						
21						
22a						.137 (3.19)
22b						.142 (2.63)
22c					.237 (2.46)	.237 (2.46)
23			.0333 (2.31)	.0333 (2.31)		
24			.0145 (2.35)	.0145 (2.35)		
25						
26						
27			.0375 (4.20)	.0375 (4.20)		
28						
29						
30			.0566 (2.14)	.0566 (2.14)		

.... – positive coefficient
.... – negative coefficient

"pickup" – "the vehicle at fault is a pickup" indicator variable
 "vage" – "age (in years) of the vehicle at fault" quantitative variable
 "voldg" – "the vehicle at fault is more than 7 years old" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	X ₂₇		Ind [X ₂₈]		othUS [X ₂₈]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3	.200 (8.23)	.200 (8.23)				
4a						
4b						
4c						
5	2.15 (2.74)	2.15 (2.74)				
6						
7						
8						
9	.385 (4.20)	2.89 (5.44)				
10						
11						
12						
13						
14						
15						
16						
17						
18			.433 (2.05)	.433 (2.05)		
19						
20						
21						
22a	-.127 (-3.76)	-.127 (-3.76)				
22b						
22c					.617 (2.08)	.617 (2.08)
23						
24	.105 (2.66)	.105 (2.66)	.585 (4.28)	.585 (4.28)		
25						
26						
27	.415 (3.83)				.621 (2.54)	.621 (2.54)
28						
29						
30						

.... – positive coefficient
 – negative coefficient

"X₂₇" – "number of occupants in the vehicle at fault" quantitative variable
 "Ind" – "license state of the vehicle at fault is Indiana" indicator variable
 "othUS" – "license state of the vehicle at fault is a U.S. state except Indiana and its neighboring states (IL, KY, OH, MI)" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	neighs [X ₂₈]		lnm [X ₃₀]		priv [X ₃₀]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4a						
4b						
4c						
5						
6						
7						
8						
9						
10						
11						
12						
13	-.858 (-2.44)	-.858 (-2.44)				
14						
15						
16						
17						
18						
19						
20						
21						
22a	-.266 (-2.64)	-.266 (-2.64)			-1.41 (-5.03)	-1.41 (-5.03)
22b					-.973 (-3.14)	-.973 (-3.14)
22c					-1.49 (-2.02)	-1.49 (-2.02)
23						
24						-.616 (-4.35)
25						
26						
27						
28						
29						
30			.587 (2.01)			

.... – positive coefficient
 – negative coefficient

"neighs" – "license state of the vehicle at fault is Indiana's neighboring states (IL, KY, OH, MI)" indicator variable
 "lnm" – "road traveled by the vehicle at fault is multi-lane" indicator variable
 "priv" – "road traveled by the vehicle at fault is a private drive" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	rmu2 [X ₃₀]		stopsig [X ₃₁]		nosig [X ₃₁]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4a						
4b						
4c						
5						
6	.588 (1.97)	.588 (1.97)				
7						
8						
9						
10						
11						
12						
13			.557 (2.44)	.557 (2.44)		
14			2.29 (2.93)			
15						
16						
17						
18						
19						
20						
21						
22a						
22b						-.141 (-2.00)
22c					-.488 (-3.97)	-.488 (-3.97)
23						
24						
25						
26						
27						
28						
29						
30					-.845 (-2.91)	-.845 (-2.91)

.... – positive coefficient
.... – negative coefficient

"rmu2" – "road traveled by the vehicle at fault is multi-lane AND undivided two-way" indicator variable

"stopsig" – "traffic control device for the vehicle at fault is a «stop sign»" indicator variable

"nosig" – "no any traffic control device for the vehicle at fault" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	sig [X ₃₁]		other [X ₃₁]		sign [X ₃₁]	
	fatality	injury	fatality	injury	fatality	injury
1					2.14 (2.04)	
2						
3						
4a						
4b						.848 (2.28)
4c						
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						
16						
17						
18						
19						
20		1.98 (2.66)				
21	1.03 (2.12)	1.03 (2.12)				
22a						
22b						
22c						
23						
24		.487 (4.25)				
25						
26						
27						
28			7.18 (4.14)			
29						
30						

.... – positive coefficient
.... – negative coefficient

"sig" – "traffic control device for the vehicle at fault is a signal" indicator variable
 "other" – "traffic control device for the vehicle at fault is an «other regulatory sign or marking»" indicator variable
 "sign" – "traffic control device for the vehicle at fault is an any sign" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	signal [X ₃₁]		X ₃₃		X ₃₄	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3			2.29 (6.96)		.0127 (2.30)	
4a						
4b						
4c						
5						
6						
7						
8						
9						
10						
11						
12						
13			2.48 (2.00)		.0103 (2.50)	.0103 (2.50)
14						
15			1.91 (2.87)	.793 (2.11)	.0153 (2.24)	
16					.0626 (3.10)	
17						
18						
19						
20						
21			2.87 (2.56)	2.87 (2.56)	-.0153 (-2.26)	-.0153 (-2.26)
22a			1.60 (4.89)	1.60 (4.89)		
22b			2.13 (5.16)	2.13 (5.16)		
22c			1.75 (2.41)	1.75 (2.41)		
23						
24			1.29 (2.97)	1.29 (2.97)		
25		-.605 (-2.36)				
26						
27			1.76 (2.24)			
28						
29			5.91 (3.29)		.089 (2.80)	
30			3.03 (2.43)			

.... – positive coefficient
 – negative coefficient

"signal" – "traffic control device for the vehicle at fault is an any signal" indicator variable
 "X₃₃" – "at least one of the vehicles involved was on fire" indicator variable
 "X₃₄" – "age (in years) of the driver at fault" quantitative variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	age1 [X ₃₄]		age2 [X ₃₄]		age5 [X ₃₄]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4a			-1.46 (-3.43)	-1.46 (-3.43)		
4b						
4c	-.789 (-2.09)					
5						
6						
7						
8						
9						
10						
11						
12						
13						
14						
15						
16						
17						
18						
19						
20						
21						
22a						
22b						
22c						
23						
24					.291 (3.46)	.291 (3.46)
25						
26						
27						
28						
29						
30

– positive coefficient
– negative coefficient

"age1" – "age of the driver at fault is ≥ 18 and < 24" indicator variable
 "age2" – "age of the driver at fault is ≥ 24 and < 30" indicator variable
 "age5" – "age of the driver at fault is ≥ 50 years" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	X ₃₅		v3o [X ₂₆]		voldo [X ₂₆]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3		.226 (4.92)				
4a						
4b						
4c						
5						
6	.439 (2.22)	.439 (2.22)				
7	.356 (2.02)	.356 (2.02)				
8						.735 (2.96)
9						
10		.450 (3.55)				
11						
12		.444 (3.59)				
13						
14						
15		.330 (5.16)				
16				-.332 (-3.14)		
17	.892 (3.16)	.892 (3.16)				
18		.483 (3.86)				
19						
20						
21						
22a						
22b						
22c						
23						
24		.278 (3.93)				
25	.439 (2.32)	.439 (2.32)				
26					.625 (2.65)	.625 (2.65)
27	.293 (2.91)	.293 (2.91)				
28	-.537 (-3.57)	-.537 (-3.57)				
29						
30						

.... – positive coefficient
 – negative coefficient

"X₃₅" – "gender of the driver at fault: 1 – female, 0 – male" indicator variable
 "v3o" – "age of the oldest vehicle involved is > 1 and ≤ 3 years" indicator variable
 "voldo" – "age of the oldest vehicle involved is > 7 years" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	maxpass [X ₂₇]		age2y [X ₃₄]		olddrv [X ₃₄]	
	fatality	injury	fatality	injury	fatality	injury
1	.457 (2.58)	.182 (3.14)				
2						
3						
4a	-.661 (-6.51)					
4b						
4c						
5						
6						
7						
8						
9						
10	.140 (2.68)	.140 (2.68)				
11						
12						
13						
14						
15						
16		.138 (4.77)				
17						
18						
19		.290 (5.67)				
20						
21						
22a		.275 (9.91)				
22b	.143 (5.93)	.143 (5.93)				
22c	.128 (3.22)	.128 (3.22)				
23			.512 (2.76)	.512 (2.76)		
24						
25					.133 (2.40)	.133 (2.40)
26						
27						
28	.133 (2.61)					
29						
30						

... – positive coefficient
 ... – negative coefficient

"maxpass" – "the largest number of occupants in all vehicles involved" quantitative variable
 "age2y" – "age of the youngest driver is ≥ 24 and < 30 years" indicator variable
 "olddrv" – "the driver at fault is older than the other driver involved" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	age0o [X ₃₄]		age2o [X ₃₄]		age4o [X ₃₄]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4a						
4b						
4c						
5						
6						
7			1.75 (1.99)			
8						
9						
10						
11						
12						
13						
14						
15						
16						.214 (2.93)
17						
18						
19						
20						
21						
22a	-1.25 (-4.40)	-1.25 (-4.40)				
22b	-2.20 (-3.03)	-2.20 (-3.03)				
22c						
23						
24						
25						
26						
27						
28						
29						
30						

.... – positive coefficient
 – negative coefficient

"age0o" – "age of the oldest driver is < 18 years" indicator variable
 "age2o" – "age of the oldest driver is ≥ 24 and < 30 years" indicator variable
 "age4o" – "age of the oldest driver is ≥ 40 and < 50 years" indicator variable

Table C.6 (Continued)

#	Coefficient (t-ratio)					
	ff [X ₃₅]		mm [X ₃₅]		mf [X ₃₅]	
	fatality	injury	fatality	injury	fatality	injury
1						
2						
3						
4a						
4b						
4c						.920 (2.84)
5						
6						
7						
8						
9						
10						
11					.534 (2.25)	.534 (2.25)
12						
13						
14						
15						
16				-.240 (-3.39)		
17						
18						
19						
20						
21						
22a			-.217 (-4.11)	-.217 (-4.11)		
22b			-.193 (-3.13)	-.193 (-3.13)		
22c			-.266 (-2.63)	-.266 (-2.63)		
23				-.451 (-2.64)		
24						
25						
26						
27						
28	.725 (4.24)	.725 (4.24)				
29						
30						

.... – positive coefficient
 – negative coefficient

"ff" – "two female drivers involved into a two-vehicle accident" indicator variable
 "mm" – "two male drivers involved into a two-vehicle accident" indicator variable
 "mf" – "male and female drivers involved into a two-vehicle accident" indicator variable

Table C.7 Tests of car-SUV separation in 2004 accident severity study²⁴

#	Model name			M	K	$LL(\beta_m)$	$\sum LL(\beta_m)$	df	p-value	conclusion*
1	County road	rural	(car/SUV)+(car/SUV)	3	17	-1636.3	-1616.3	34	0.22	Car = SUV
2			(car/SUV)+(truck)	2	9	-250.47	-248.11	9	0.86	Car = SUV
4		urban	(car/SUV)+(car/SUV)	3	10	-683.95	-678.39	20	0.94	Car = SUV
5			(car/SUV)+(truck)	2	5	-104.80	-100.71	5	0.15	Car = SUV
7	Interstate	rural	(car/SUV)+(car/SUV)	3	4	-456.77	-451.09	8	0.18	Car = SUV
8			(car/SUV)+(truck)	2	9	-318.00	-308.75	9	0.03	Car $\neq$ SUV
10		urban	(car/SUV)+(car/SUV)	3	13	-710.09	-699.64	26	0.75	Car = SUV
11			(car/SUV)+(truck)	2	6	-336.87	-334.52	6	0.58	Car = SUV
13	State route	rural	(car/SUV)+(car/SUV)	3	12	-1302.1	-1292.1	24	0.69	Car = SUV
14			(car/SUV)+(truck)	2	11	-362.86	-359.27	11	0.78	Car = SUV
16		urban	(car/SUV)+(car/SUV)	3	12	-1649.1	-1630.5	24	0.04	Car $\neq$ SUV
17			(car/SUV)+(truck)	2	5	-173.40	-172.27	5	0.81	Car = SUV
19	City street	rural	(car/SUV)+(car/SUV)	3	12	-1358.7	-1353.1	24	0.99	Car = SUV
20			(car/SUV)+(truck)	2	9	-68.07	-64.80	9	0.69	Car = SUV
22		urban	(car/SUV)+(car/SUV)	3	23	-14547	-14524	46	0.53	Car = SUV
23			(car/SUV)+(truck)	2	10	-885.98	-877.16	10	0.06	Car $\neq$ SUV
25	US route	rural	(car/SUV)+(car/SUV)	3	11	-978.44	-969.45	22	0.71	Car = SUV
26			(car/SUV)+(truck)	2	12	-270.09	-262.03	12	0.19	Car = SUV
28		urban	(car/SUV)+(car/SUV)	3	12	-2345.1	-2334.3	24	0.60	Car = SUV
29			(car/SUV)+(truck)	2	9	-311.62	-305.06	9	0.16	Car = SUV

* For models 8, 16 and 23 we find that “Car $\neq$ SUV”, which means that for these models cars and SUVs must be considered separately in our accident severity study. For all other models we find that “Car = SUV”, which means that cars and SUVs can be considered together.

²⁴ For explanation of these tests refer to footnote 21 on page 106.

Table C.8 Tests of car-SUV separation in 2006 accident severity study

#	Model name			M	K	$LL(\beta_m)$	$\sum LL(\beta_m)$	df	p-value	conclusion*
1	County road	rural	(car/SUV)+(car/SUV)	3	10	-832.13	-826.10	20	0.91	Car = SUV
2			(car/SUV)+(truck)	2	8	-113.99	-109.77	8	0.39	Car = SUV
4		urban	(car/SUV)+(car/SUV)	3	2	-782.85	-777.77	4	0.04	Car $\neq$ SUV
5			(car/SUV)+(truck)	2	4	-16.716	-13.652	4	0.19	Car = SUV
7	Interstate	rural	(car/SUV)+(car/SUV)	3	9	-459.31	-447.45	18	0.16	Car = SUV
8			(car/SUV)+(truck)	2	6	-271.78	-269.97	6	0.73	Car = SUV
10		urban	(car/SUV)+(car/SUV)	3	9	-853.29	-846.69	18	0.78	Car = SUV
11			(car/SUV)+(truck)	2	9	-252.55	-246.81	9	0.24	Car = SUV
13	State route	rural	(car/SUV)+(car/SUV)	3	11	-560.40	-550.05	22	0.54	Car = SUV
14			(car/SUV)+(truck)	2	5	-72.403	-71.805	5	0.95	Car = SUV
16		urban	(car/SUV)+(car/SUV)	3	12	-3225.9	-3212.7	24	0.34	Car = SUV
17			(car/SUV)+(truck)	2	5	-192.97	-192.09	5	0.88	Car = SUV
19	City street	rural	(car/SUV)+(car/SUV)	3	8	-1068.2	-1061.9	16	0.67	Car = SUV
20			(car/SUV)+(truck)	2	2	-146.45	-145.98	2	0.63	Car = SUV
22		urban	(car/SUV)+(car/SUV)	3	17	-9505.6	-9481.4	34	0.05	Car $\neq$ SUV
23			(car/SUV)+(truck)	2	12	-520.63	-517.29	12	0.88	Car = SUV
25	US route	rural	(car/SUV)+(car/SUV)	3	9	-380.51	-367.95	18	0.12	Car = SUV
26			(car/SUV)+(truck)	2	8	-237.97	-231.83	8	0.14	Car = SUV
28		urban	(car/SUV)+(car/SUV)	3	7	-967.22	-961.02	14	0.57	Car = SUV
29			(car/SUV)+(truck)	2	7	-185.87	-182.84	7	0.53	Car = SUV

* For models 4 and 22 we find that “Car $\neq$ SUV”, which means that for these models cars and SUVs must be considered separately in our accident severity study. For all other models we find that “Car = SUV”, which means that cars and SUVs can be considered together.