2013

Hare And Tortoise: How Do Price Change Patterns Affect Propensity To Book

Zhuoyang Li
Purdue University, lizhuoyang0607@gmail.com

Graduate School ETD Form 9
(Revised 12/07)

PURDUE UNIVERSITY
GRADUATE SCHOOL
Thesis/Dissertation Acceptance

This is to certify that the thesis/dissertation prepared

By Zhuoyang Li

Entitled
HARE AND TORTOISE: HOW DO PRICE CHANGE PATTERNS AFFECT PROPENSITY TO BOOK

For the degree of Master of Science

Is approved by the final examining committee:

CHUN-HUNG TANG
Chair

HOWARD ADLER

ANNMARIE J. NICELY

To the best of my knowledge and as understood by the student in the *Research Integrity and Copyright Disclaimer (Graduate School Form 20)*, this thesis/dissertation adheres to the provisions of Purdue University's "Policy on Integrity in Research" and the use of copyrighted material.

Approved by Major Professor(s): CHUN-HUNG TANG

Approved by: BARBARA ALMANZA 12/02/2013
Head of the Graduate Program Date

HARE AND TORTOISE: HOW DO PRICE CHANGE PATTERNS AFFECT PROPENSITY TO BOOK

A Thesis

Submitted to the Faculty

of

Purdue University

by

Zhuoyang Li

In Partial Fulfillment of the

Requirements for the Degree

of

Master of Science

December 2013

Purdue University

West Lafayette, Indiana

谢谢你永远在我身边

ACKNOWLEDGEMENTS

I would like to extend my sincere gratitude to my advisor, Dr. Chun-Hung Tang, for his invaluable support, guidance, and encouragement throughout this project as well as my graduate education. Without his kind instructions and help, this thesis could not have been possible. Besides, it is my honor to have Dr. Howard Adler and Dr. Annmarie J. Nicely as my committee members. I am very thankful for their helpful comments and advices throughout the completion of my research.

Thanks to my husband and my parents, for their endless love and support. I would also like to thank my friends, Jiaqi Zhu, Mengwei Yue and Ruoyang Zhang, for their help and encouragement.

TABLE OF CONTENTS

Page

LIST OF TABLES viii

ABSTRACT xi

CHAPTER 1. INTRODUCTION 1

1.1 Background 1

1.2 Definition of Key Words 3

1.3 Research Questions 3

1.4 Significance of the Study 4

CHAPTER 2. LITERATURE REVIEW 5

2.1 Revenue Management and Dynamic Pricing 5

2.2 Applications of Dynamic Pricing in Non-hospitality Industry 8

2.3 Internet's Effects on Dynamic Pricing 9

2.4 Consumer Booking Behavior 11

2.4.1 Consumer Purchase Decision Process 17

2.4.2 The Prospect Theory and Price Changes 18

2.4.3 Sell-out Risk, Expectation of Future Price, and Propensity to Book 19

2.5 Hypotheses 21

2.5.1 Correlation between Perceived Risks and Propensity to Book 21

2.5.2 Leaping Effects 22

Page

2.5.3 Effects of Price Trends 23

CHAPTER 3. METHODOLOGY 25

3.1 Treatments 26

3.2 Experiment Control 28

3.3 Research Procedures and Data Collection 30

3.4 Statistical Inference about Multiple Population Typical Scores by Ranks 31

3.4.1 Checking Model Assumptions 31

3.4.2 Kruskal-Wallis One-Way Analysis of Variance by Ranks 32

3.4.3 Kruskal-Wallis's Multiple Comparisons between Treatments 33

3.5 Questionnaire Design and Hypotheses 34

3.5.1 Test for Propensity to Book as the Dependent Response Variable 34

3.5.2 Surrogate Log Linear Regression Model for Perceptions as Dependent Variables 35

3.5.3 Multinomial Logistic Regression Model for Perceptions as Dependent Variables 37

3.5.4 Proportional Odds Regression Model for Perceptions as Dependent Variables 38

3.5.5 Generalized Liner Regression Used in the Specific Cases 39

CHAPTER 4. RESULTS 42

4.1 Descriptive Statistics 43

4.1.1 Demographic Information of Respondents 43

Page

4.1.2 Travel and Internet Experience......46
4.1.3 Descriptive Statistics of Response Variables......48
4.2 Test of Hypotheses by Statistical Inference and Modeling......53
4.2.1 Results of Hypothesis 1 Testing 53
4.2.2 Results of Hypothesis 2 Testing 58
4.2.3 Results of Hypothesis 3 Testing 60
4.2.4 The Effect of Price Changes on Expectations of Getting a Lower Price......61
4.2.5 The Effect of Price Changes on Expectations of Future Price Changing Direction 66
4.2.6 The Effect of Price Changes on Perceived Sell-Out Risk 69
4.3 Testing of Compounding Effects 71
CHAPTER 5. CONCLUSION 73
5.1 Summary and Discussion of Findings 73
5.2 Theoretical Implications 75
5.3 Practical Implications......76
5.3.1 Choose the Correct Change Pattern for Different Price Change Trends......77
5.3.2 Affect Consumers' Propensity to Book through Information Control......77
5.3.3 Other Ways to Increase Propensity to Book......78
5.3.4 Travelers......78
5.4 Limitations and Future Research 79
REFERENCES 82

Page

APPENDICES

Appendix A Cover Letter of Questionnaire..87

Appendix B Example of Questionnaires 89

LIST OF TABLES

Table Page

Table 3.1 Room Rates of the Past 3 Days and Today 27

Table 4.1 Demographic Characteristics 45

Table 4.2 Travel and Internet Experience Variables 47

Table 4.3 Descriptive Statistics for Expectations of Future Price Change Direction, Perceived Sell-Out Risk, Perceived Fairness, Expectations of Getting a Lower Price, and Propensity to Book as Response Variables 49

Table 4.4 Normality Test for Expectation of Future Price Change Direction (Q1) as the Response with Respect to Gradual Increase Price (Group 1) 51

Table 4.5 Kruskal-Wallis Rank Sum Test for Questions 1-5 among Different Groups ... 52

Table 4.6 Summary of Logistic Model for Propensity to Book (Question 5) vs. Expectations of Future Price Change Pattern (Question 1) 55

Table 4.7 Probabilities from Logistic Model for Propensity to Book vs. Expectations of Future Price Change Pattern 55

Table 4.8 Summary of Logistic Model for Propensity to Book vs. Expectations of Getting a Lower Price (Question 4) 55

Table 4.9 Probabilities from Logistic Model for Propensity to Book vs. Expectations of Getting a Lower Price 56

Table Page

Table 4.10 Summary of Logistic Model for Propensity to Book vs. Perceived Sell-Out Risk (Question 2) ... 57

Table 4.11 Probabilities from Logistic Model for Propensity to Book (Question 5) vs. Perceived Sell-Out Risk (Question 2) ... 57

Table 4.12 Summary of Logistic Model for Propensity to Book (Question 5) vs. Perceived Fairness (Question 3) ... 58

Table 4.13 Probabilities from Logistic Model for Propensity to Book (Question 5) vs. Perceived Fairness (Question 3) ... 58

Table 4.14 Multiple Comparisons with Propensity to Book as the Response ... 60

Table 4.15 Multiple Comparisons with Expectations of Getting a Lower Price as the Response ... 63

Table 4.16 Summary of Surrogate log linear Regression for Expectations of Getting a Lower Price (Q4) ... 65

Table 4.17 Probabilities from Multinomial Regression for Expectations of Getting a Lower Price ... 66

Table 4.18 Probabilities from of Proportional Odds Model for Expectations of Getting a Lower Price ... 66

Table 4.19 Summary of Surrogate log linear Regression for Expectations of Future Price Changing Direction (Q1) ... 68

Table 4.20 Probabilities from Multinomial Regression for Expectations of Future Price Changing Direction ... 69

Table 4.21 Multiple Comparisons with perceived sell-out risk as the Response ... 70

Table Page

Table 4.22 Summary of Surrogate log linear Regression for Perceived sell-out Risk 71

ABSTRACT

Li, Zhuoyang. M.S., Purdue University, December 2013. Hare and Tortoise: How Do Price Change Patterns Affect Propensity to Book. Major Professors: Chun-Hung Tang.

With an increasing using of online booking, hotel room rate changing information becomes nearly transparent to consumers. And this trend encourages deal-seeking consumer behaviors, which are based on price change information. So hotels can influence consumers' propensity to book through managing price changes. The present study aims at examining consumers' propensity to book in a more realistic context by introducing two conditions: different price changing patterns and interaction between price-moving trends and price patterns. It is important for hotel managers to understand the impact of different price change trends and patterns because price changes can directly affect consumer perception and booking behavior. Results indicated that, hotels should choose different price change patterns for specific price change trend for the following reasons that: first, leaping price change patterns generally have greater effects on consumers' propensity to book; second, price change trends moderate the effect of leaping patterns on consumers' propensity to book. Additionally, finding also showed that hotels could affect consumers' propensity to book by influencing consumers' perceived sell-out risk and expectation of future price.

CHAPTER 1. INTRODUCTION

1.1 Background

It has been indicated by many studies that revenue management principles incorporating the concept of demand-based variable pricing, and dynamic pricing have been used by the hospitality industry as a primary approach to achieve the maximum profits (Gallego & Ryzin, 1994; Chiang, Chen & Xu, 2007). However, recent scholars suggested that the increasing usage of online searching and booking has greatly challenged the effectiveness of traditional revenue management (O'Connor & Frew, 2002; Carroll & Siguaw, 2003), because online reservation reduces the information asymmetry between hotels and consumers.

The Internet has greatly changed the nature, intensity, and frequency of booking behaviors of travelers at the time of need recognition and service consumption (Jang, 2004; Weber & Roehl, 1999). Customers who have an aptitude for making full use of the Internet are well acquainted with basic hotel revenue management principles. As a result, they become proficient at finding the best price for their upcoming hotel consumptions. Due to revenue management practices, these consumers are likely to observe room rates that are changing considerably over time, they try to understand and summarize the principles of room rate changes through observation in a certain period of time (Schwartz, 2000; 2006a; Chen & Schwartz, 2008a). Therefore, understanding the behaviors of these deal-seeking travelers has become an important topic of revenue management studies.

For companies like hotels who offer the same products with different prices with the change of capacity and time, adoption of a dynamic pricing strategy can effectively influence consumers' judgment about capacity and future price changes. A study from Chen and Schwartz (2008a) based on deal-seeking consumers' online hotel booking decisions indicated that through the internal reference price, consumers' perceived risks toward capacity and future price as well as propensity to book could be affected by price change trends of increasing, decreasing, no-change or fluctuating of price.

In a realistic commercial environment system, price can change in various patterns (including frequencies and intensities) even with the same trend. Consumers react to price changing patterns in addition to price changing trends. Generally, infrequent and intense changing patterns exert stronger impacts on people's cognition. For instance, a study about the frequency and depth of discount by Alba et al.'s (1999) study indicated that, deep and infrequent discounts make people have lower perceived prices compared to shallow and infrequent discounts.

Consumers' reaction to price changing patterns can be moderated by different price changing trends. As Thaler (1985) argued, psychologically, people perceive multiple gains as more rewarding than a single gain of the same amount, but multiple losses can be regarded as more punishing than a single loss. However, current literatures do not determine the interaction between price changing trends and price changing patterns, especially in the hotel room online booking context. Clarifying the interaction and its impact on consumers' perception and judgment during the buying process is crucial for both practical application and future theoretical research.

1.2 Definition of Key Words

Key words used in this study are given as follows:

1. "Price change trends" is used to represent the changing direction of room rates. The study focused on only two major trends, price increasing and price decreasing.
2. "Price change patterns" represents different intensities for price changes. There were two price patterns mentioned in this study, gradual pattern and leaping pattern.
3. The term "gradual pattern" means that the price changes continuously for a period of time (in this study, four days). From day to day, the amount of change is around 5% of the average price during this period.
4. "Leaping pattern" means that the price has a sudden change at the last day of the four-day period with a great amount that is 15% of the average price during this period.

1.3 Research Questions

The purpose of this study is to explore people's propensity to book towards different price change patterns. To achieve this, the following research questions are addressed in this study:

1. Do leaping patterns have greater effects on consumers' propensity to book than gradual patterns?
2. Do different price change trends moderate the leaping effects towards consumers' propensity to book?
3. Is there any correlation between consumers' expectation of future price, future capacity and consumers' propensity to book?

1.4 Significance of the Study

Hotel managers must understand the different impacts of price changing forms on consumers' perceptions and judgments to control the magnitude of price volatility based on targeting consumers' attitude toward price changes. Previous studies showed that hotels manipulate the two elements in various ways to induce a higher consumers' propensity to book at any given room rate. If the adjustment of price changing patterns and price magnitudes proves to be effective in managing consumers' perceptions, hotel managers can use this feasible approach to maximize bookings and profits. Importantly, hotel managers need to respond to demand estimates and adjust room rates following their revenue management strategies.

CHAPTER 2. LITERATURE REVIEW

The first section of Chapter 2 begins with a definition of revenue management and how dynamic pricing strategies have been used in the hospitality industry to achieve the goal of revenue management. The second section of the chapter presents the changes and challenges brought by the Internet, especially the changes of hotels' dynamic pricing strategies and customers' attitudes. The third section reviews consumers' buying behaviors, and how buying behaviors might be affected by observed dynamic pricing changes. The final section focuses on presenting the hypotheses of the study.

2.1 Revenue Management and Dynamic Pricing

Revenue management refers to the strategies and tactics used by a number of industries to manage the allocation of their capacity to different fare classes over time in order to maximize revenue (Phillips, 2005). It has become an important approach widely used by many industries, such as airline companies, hotels, and rental car companies to maximize expected contributions from their constrained perishable inventory resources by selling them to the most profitable mixture of customers. According to Phillips (2005), revenue management is practiced under the following conditions: (i) sellers are selling a fixed stock of perishable capacity, (ii) customers are booking prior to usage, and (iii) sellers have the availability to change the price over time.

Revenue management applies disciplined tactics that predict consumer behaviors at the micro-market level, and optimize price and product availability to accomplish the objective of maximized profit (Cross, 1997). Due to the fact that customers of these industries are abundant and they naturally have different attitudes and behaviors, it has become important to understand consumer's value judgment and behavior to make hotels' marketing strategies more targeted. By a thorough understanding of targeted customers, a firm can design service packages for different market segments using appropriate combinations of attributes such as price, amenities, purchase restrictions, and distribution channels (Chiang, Chen & Xu, 2007).

For companies like hotels, they own a fixed capacity of resources consumed in the process of producing and offering multiple products, and the product must be consumed over a limitative time horizon. The firm will be faced up with a problem that is to maximize its total expected revenue by selecting appropriate dynamic controls. According to Maglaras and Messner (2006), there are generally two choices: either choosing a dynamic pricing strategy for each product or, if the prices are fixed, selecting a dynamic rule that controls the allocation of capacity to requests for different products. Previous literatures have demonstrated that, in terms of practicing revenue management, dynamic pricing is often the most serviceable approach used for revenue management (Talluri & Van Ryzin, 2005). Due to the fact that hotels have the availability to change their room rates over time, consequently, dynamic pricing strategies have become the preferred choices.

Price is regarded as a distinct signal of product-related information (Bagll & Riordan, 1991), such as product quality and inventory. In the lodging industry, price has also proved to have another signal role: which is to directly affect customers' expectation about future price and capacity changes (Schwartz & Chen, 2010a).

When there are similar products provided with different prices in the market, customers' attitudes and buying decisions can be affected by not only the products themselves but also prices, especially when information asymmetry between retailers and customers occurs in the market cause uncertain situations tend to bring out various reacts of different people (Chen & Schwartz, 2006). Consequently, affecting the cognition of customers by setting or even changing the price has been an applicable method of merchants.

The core of revenue management principles lies in the concept of demand-based pricing (Choi & Matila, 2004). There are four primary levels of revenue management: pricing, inventory, marketing, and channels. Since the adoption of revenue management practices in the early 1980s, dynamic pricing strategies have been adopted in the entire hospitality industry, and have been witnessed with conspicuous successes for the following decades to today (Choi & Mattilia, 2004).

According to Bitran and Mondschein (1995), Choi and Mattilia (2004), and Talluri and Van Ryzin, (2005), hotels first identify differences in price sensitivity among customers, and then segment customers according to the price customers are willing to pay in order to maximum revenue. In addition, hotels must observe and forecast room demands at the segment level, and then set room rates accordingly. Furthermore, rooms become available only to consumers who are willing to pay the highest price. On the contrary, during the low demand periods, rooms become available to everybody at relatively lower discounted rates. Such pricing policy results in differences, between customers and across customer stays, as well as in the room rates quoted for the same type of room at the same hotel.

2.2 Applications of Dynamic Pricing in Non-hospitality Industry

Dynamic pricing is a set of pricing strategies that aimed at increasing profits. According to McAfee and Te Velde (2006), dynamic pricing as a strategy for revenue management is most useful when two product characteristics exist simultaneously. First, the product expires at a time point. These products include hotel rooms, airline flights, generated electricity, and other time-dated products. Second, capacity is fixed well in advance and can be augmented only at a relatively high marginal cost. These characteristics create the potential for very large swings in the opportunity cost of sale, because the opportunity cost of sale is a potential foregone subsequent sale. The value of a unit in a shortage situation is the highest value of an unserved customer. Forecasting this value given current sales and available capacity represents dynamic pricing.

However, for other industries that are not offering products with those two specific characteristics, dynamic pricing is still very useful to help them achieve maximized profits. Many former researchers made tremendous contributions to the exploration of how to maximize the effects of dynamic pricing in different fields. For instance, in the retail industry, Mela, Jedidi, and Gupta (1999) found that deep discounts, rather than frequent discounts, affect brand choice and purchase quantity; furthermore, Alba et al. (1999) showed that people have different perceived prices towards different discounts forms. Another example is about agricultural commodities, dynamic pricing can play an important role in agricultural economy based on seasonal situations and different market conditions (Heien, 1980). Biller, Chan, Simchi-Levi, and Swann (2005) also showed that, for the automotive industry, dynamic pricing as an important tool to improve supply chain efficiency in manufacturing is motivated by a collaborative effort with a manufacturer of automobiles.

However, because of the Internet, how dynamic pricing strategies function in all industries is gradually changing, and there is no exception for the hospitality industry.

2.3 Internet's Effects on Dynamic Pricing

The growth of the Internet as a marketing tool and communication tool has been adjusted upwards daily since its inception. Like other industries, hotels have enjoyed the superb advantages brought by the Internet as a sales and marketing tool (Murphy et al., 1996; Walle, 1996). The Internet provides various distribution channels for hotels to reach current and potential customers expediently. It also shortens the time of information transmission, a crucial influence on time sensitive industries like lodging.

The Internet is not only a new distribution channel, but it is a revolutionary approach for hotels to connect, understand and even impact their customers (Gilbert, Poll-Perry &

Widijoso, 1999). Hotels can use either their own websites or the third party distribution sites to solicit customers regardless of national borders. Even the burgeoning social media has been widely used as an interactive platform to build compact relationships with customers (Wei, S., et al, 2001).

The Internet also offers greater opportunities for dynamic pricing due to the reasons that customer information can be more easily collected and list prices can be more easily changed (Dolan & Moon, 2000). Furthermore, it is easier to check competitors' prices and availability of products. With such information, the dynamics of supplies and demands can be better understood and prices better adjusted accordingly.

One important outcome of this trend is that price-conscious hotel customers who look for the best deal on hotel room booking websites often find that they are quoted different room rates over time. The change in room price over time as the date of stay comes nearer is a result of the lodging industry's dynamic pricing practices (Chen & Schwartz, 2008).

Apart from customers' arising perceptions of unfairness toward the state that the same hotel room are always charged so differently (Kimes, 1994; Wirt et al., 2002), another direct consequence of this awareness of dynamic pricing is that, sophisticated online booking travelers are adept at finding the corresponding countermeasures to maximize their own interests. As the use of the Internet for pre-travel arrangements intensifies, and the exposure to the b's low, travel-related prices mentality increases, travelers become more sophisticated. In order to minimize their costs to maximize their expected utility, customers adopted various strategies as an advanced booking strategy to obtain good products with better prices. (Weatherford & Kimes, 2003; Schwartz, 2006a; 2008)

For consumers, the Internet has become the optimal way for both searching relevant hotel information and making a veritable staying plan to customers, because of its convenient and economic characteristics. The Internet has provided unprecedented price visibility to consumers. The Instead of relying on travel agents or other traditional distribution channel, price-conscious customers can surf the net for bargains for basically 24 hours a day. This increases the pressure for hotels companies to continue to manage their prices and availabilities in the conventional way (Phillips, 2005).

2.4 Consumer Booking Behavior

Admittedly, there have been many research studies done in the area of menu labeling. Of these studies, two (conducted in New York City and King County, Washington) are important in that they had implemented mandatory calorie information disclosure on menu boards for food service establishments prior to the national mandate for calorie information disclosure. They may be viewed as pilot programs in testing the efficacy of menu labeling.

King County, Washington, fully implemented the nutritional labeling regulation on August 1st, 2009 (King County Board of Health, 2008). Chain restaurants with 15 or more national locations that were permitted by the Public Health Department in Seattle and King County were required to provide calorie information on menu boards (including drive-through menu boards) with all other information available at the point of ordering in a flyer, pamphlet, or other approved method. The nutrition labeling regulation was implemented in three phases. Phase 1 (August 1st to December 31st, 2008): chain restaurants were required to complete nutrition labeling for standard menu items or to show their Public Health inspectors that they were taking steps toward meeting the regulations; Phase 2 (January 1st, 2009 to August 1st, 2009): nutrition labeling regulation went into full effect, but drive-through areas of chain restaurants were exempt at this phase; and Phase 3 (August 1st, 2009 and after): drive-through areas of chain restaurants were required to have nutrition information posted (King County Board of Health, 2008).

Several studies were done before, during and after the implementation of this particular regulation (Krieger, Chan, Saelens, Ta, Solet & Fleming, 2013; Finkelstein, Strombotne, Chan & Krieger, 2011; Tandon, Zhou, Chan, Lozano, Couch et al., 2011). The results of the intervention were found to be mixed.

One experiment studied the influence that menu-labeling regulations had on calories purchased at chain restaurants. This study was conducted from the fall of 2008 to the spring of 2010 with one baseline stage (pre-intervention) and two post-intervention stages (post-intervention stage one: four to six months after nutrition information was made available and post-intervention stage two: 16-18 months after) in King County, Washington. The results indicated that mean calories per purchase decreased 18 months after implementation of menu labeling in some restaurant chains, especially taco and coffee establishments. The gender difference was obvious, with a significant decrease in calories for women, but not for men. No difference was found in the impact of labeling on calories purchased in low-income or ethnically diverse areas compared to other areas of the county (Krieger et al., 2013).

Another study conducted by the same group of researchers focused on a Mexican fast-food chain restaurant with locations within and adjacent to King County. The experiment had two post intervention phases, one immediately following the implementation of the law (January 2009) until the posting of drive-through menu boards (July 2009) and the other following the drive-through postings (August 2009 to January 2010). Each sales transaction and the calories per transaction were compared with the baseline data that were collected from January 2008 through December 2008. The results showed no significant impact of mandatory menu labeling on monthly sales transactions and calories sold per transaction in King County, Washington. Neither the total monthly sales transactions nor the calories per transaction were affected immediately by the legislation or affected later when calorie information was added to the drive-through menu boards (Finkelstein et al., 2011).

Another study focused on a different target population produced similar results. Children and parents' purchasing behaviors were assessed in King County, Washington immediately after the implementation of the regulation. Only English-speaking parents who indicated that their child ate at a fast-food chain restaurant that was required to have menu labeling were eligible. Researchers found an increase in consumer awareness.

Unfortunately, the awareness did not translate into purchasing fewer calories (Tandon et al., 2011).

New York City, on the other hand, implemented mandatory menu labeling even earlier. The Department of Health and Mental Hygiene of New York City proposed to repeal and reenact ∮81.50 of the New York City Health code, which requires chain food service establishments within the City of New York with 15 or more locations nationwide to have the total number of calories derived from any source for every menu item they list on all menus, menu boards, and item tags. The amended regulation took effect on March 31, 2008, and full enforcement began on July 18, 2008 (Department of Health and Mental Hygiene, New York City, 2007).

Some researchers conducted a study one year after New York City became the first jurisdiction in the United States to require restaurant chains to post calorie information on menus and menu boards. The results showed that methods of providing caloric values elsewhere in the store instead of on the menu board at the point of purchase were far less effective at communicating this information to consumers. Also, calorie labeling on menus and menu boards had a substantial impact on customer awareness and use of calorie information, even in restaurants where calories had already been posted elsewhere in the store (Dumanovsky, Huang, Bassett, & Silver, 2010).

Another research study focused on racial and ethnic minorities residing in relatively low-income areas in New York City produced similar results. The findings did show that there was a sharp increase in the percentage of consumers who reported noticing calorie information. However, out of the 50% of consumers who noticed the calorie information, only a quarter of them claimed that the information influenced their food choices. Even those who indicated that the calorie information influenced their food choices did not actually purchase fewer calories (Elbel, Kersh, Brescoll, & Dixon, 2009).

A study on fast-food choices of adolescents, and children and their parents in low-income communities under the influence of calorie labeling regulation in New York City were compared to Newark, NJ. Survey and receipt data were collected before and after implementation of the menu-labeling regulation and included four of the largest chains located in these two areas. No evidence was found to prove that labeling influenced adolescent food choices or parent's food selections for their children (Elbel, Gyamfi, &Kersh, 2011).

It seems that for these two pilot areas for mandatory menu labeling, the results of posting calorie information on menu boards for fast food establishments were mixed. Generally speaking, the implementation of calorie information on menu boards increased the number of people who noticed and saw the information and their awareness of counting calories in what they ordered. However, under certain conditions, people did not always make healthy choices due to other reasons. Other factors that influence consumers' choices may need to be considered.

Existing research on places other than King County, Washington and New York City has produced mixed findings as well. Admittedly, several studies found promising effects of calorie labeling on calories purchased. Research conducted by Burton, et al. (2006) indicated that since most consumers were unaware of the high levels of calories, fat, saturated fat and sodium found in many regular menu items, implementation of nutrition information on restaurant menus could potentially have a positive impact on reducing the consumption of less-healthful foods. Another experiment conducted in a university food service operation compared the energy content of entrees purchased by patrons when nutrition labels were made available at the point of selection with when the nutrition information was removed. The results showed an immediate drop in average energy content of entrees following the provision of nutrition information, and it gradually increased when nutrition information was removed. These changes occurred without a negative impact on overall sales and revenue for the establishment (Chu, Frongillo, Jones, & Kaye, 2009).

However, other research studies have suggested that there is little or no impact from calorie labels. A sandwich study conducted by Downs, Loewenstein and Wisdom (2009) found that the provision of calorie information had a limited effect on food choice, and there was some evidence of a perverse, calorie-increasing effect of providing this information to dieters. Another study focused on both the effect of calorie labeling and value size pricing among adolescents and adults. Their results suggested that providing calorie information for food items in fast food restaurant menus had little effect on food choices, especially for those who regularly ate at these establishments and for those who lacked knowledge about how to use nutrition information (Harnack, French, Oakes, Story, Jeffery, & Rydell, 2008).

Why do studies have such different or even contradictory results? More research is necessary to understand which factors account for the different findings. Also, more research is needed in how to effectively present calorie information to increase the new regulation's impact (Liu, Roberto, Liu, &Brownell, 2012).

2.4.1 Consumer Purchase Decision Process

Pervious researches about consumer behavior describe the purchase cycle of consumers as being composed of five consecutive major steps (Solomon, 1996; Mathieson & Wall 1982; Morrison 2002; Zaltman & Wallendorf, 1979). According to this theory, consumers' buying process starts with need arousal: the need reaches a level such that the consumer seeks gratification. The second stage is called information search. In this stage, the consumer either becomes alerted to information relevant to the aroused need or actively seeks information. The third step is evaluation of alternatives. During the evaluation phase, the consumer first establishes his or her beliefs about the attributes of the various products under consideration. Then, based on their utility function, consumers develop brand preferences through some evaluation procedure. The purchase decision is based on preferences formatted in the previous phase, but sometimes it is also influenced by unanticipated situational factors. The final step of the buying cycle is post-purchase evaluation, when feelings are derived by expectations and the products' perceived performance.

The purchase cycle theory stipulates that in the evaluation phase, consumers form attitudes or preferences toward alternatives. In the purchase decision phase, consumers choose, purchase and (with services) consume a single choice that maximizes their expected utility. As noted by Schwartz (2000), the traditional purchase cycle does not adequately describe consumers' choice of perishable items, such as hotel rooms. Travelers' advanced-booking decision is believed to be more complex than the binary purchase decision that typifies the traditional five-stage purchase cycle of other products and services.

2.4.2 The Prospect Theory and Price Changes

Kahneman and Tversky's (1979) famous dictum that losses loom larger than gains implies that people impute greater value to a given item when they give it up than when they acquire it. According to prospect theory, people's tendency is to strongly prefer avoiding losses to acquiring gains. Besides, losses are psychologically much more powerful than gains. Following the prospect theory, Kahneman and Tversky (1984) indicated that most people are easily satisfied and tend to avoid risks when facing gains, however, many people tend to prefer risks when facing losses. When not comparing with other people's gain or loss and only considering the price issue, people generally regard price decreasing for the same product as a gain because they can save money; a price increase could be considered as a loss because more money needed to be spent on the product.

External changes always lead to internal cognition and conceptual changes, and People not only tend to compare things to get a general perception of value (Ariely, 2008), but they also tend to compare things that are easily comparable (Tversky & Kahneman, 1981), such as prices before and after an instant significant price change.

Any observed price in consumers' pricing environment can be defined as an external reference price. An external reference price could appear in the form of price change with different trends and patterns, comparing a price with the manufacturer's suggested retail price or comparing a price with competitors' prices (Bitta et al., 1981).

2.4.3 Sell-out Risk, Expectation of Future Price, and Propensity to Book

The degree of complexity involved in consumers' booking decision is influenced by several factors. These factors include the perishable nature of the travel product (Yeoman & Ingold, 1997), uncertainties and information asymmetry (Schwartz, 2007), and the proliferation of revenue management systems (Oliva, 2003, Middleton & Clarke, 2001). Of great significance is the dynamic and uncertain nature of travel products purchased in advance.

A traveler reserving a room considers various elements: price, quality, availability, and alternatives. When making traditional reservation booking decisions, travelers are often faced with considerable uncertainties about three aspects of the trip: quality and value of their planned tourism endeavor, as well as a risk about future capacity. In other industries, consumers seldom face such uncertainties simultaneously, and rarely with such intensity (Schwartz, 2006b). The Internet has made an indelible contribution in filling the information gap between hotels and travelers during recent decades, especially from the perspective of consumers as information about hotel room quality and value can be captured easily. However, the information gap does not completely disappear because of the Internet.

A recent analytical model of advanced hotel-booking decisions based on deal seeking travelers determined two novel elements of consumer perception forward. (Schwartz, 2000, 2006b, 2008) They are: (i) sell-out risk (consumers' assessment of the selling-out possibility of hotel rooms ahead of the date of stay), and (ii) better-deal risk (consumers' assessment of the possibility that the hotel quotes a lower rate for the same room at the same date).

As one important characteristic of hotel industry, capacity of hotel room is limited and commonly decreasing over time, and consumers comprehend it very ll. Previous studies have showed that comparing an updated price with the former price of the product has been widely referred to as an expectation of future price (Mazumdar, Raj & Sinha, 2005; Shirai & Bettman, 2005). Price and capacity shape the traveler's perception about the product as well as the traveler's willingness to pay (Schwartz, 2004). However, elements like these are precarious and likely to change during the pre-consumption period. These changes may occur not only prior to the day when the reservation is made but also during the period following the booking, up until the day of actual consumption. Hence, expectations regarding changes in the value of these variables—changes that are likely to occur after a decision is made—are also taken into account by the rational, advance-booking traveler.

In the absence of direct information, the room rate quoted by the hotel serves as a signal that affects consumers' propensity to book. Chen and Schwartz (2008a) indicated that propensity to book could indeed be influenced by the price trends they observed. People who experienced a price increasing or decreasing trend have higher booking proportions compared to those who experienced price fluctuation and no change in price.

2.5 Hypotheses

2.5.1 Correlation between Perceived Risks and Propensity to Book

In accordance with the principles of neoclassical economic theory, many previous studies (Jacobson & Obermiller, 1990; Mazumdar et al., 2005) have demonstrated that an expected future price as a reference price emerging from a price historical pattern constitutes part of the context of consumers' purchase decisions depending on time, or in another word, consumers' buying decision through the evaluation of perceived utility. It follows that if deal-seeking consumers believe that if future prices will be higher, they will accelerate their purchase. Also, if consumers perceive the sell-out risk to be high, they are more likely to book earlier; a low sell-out risk is expected to delay the purchase because consumers are more likely to wait for a better room rate. In addition, when consumers sense that the observed price is fair, they typically have a higher intensity to book.

Results of Chen and Schwartz's study (2008a) indicated that, consumers' perceptions or expectations towards future room price and the risk of a sellout affect their propensity to book regardless of the price change trend they have observed. Thus:

H1a: People with a higher expectation towards future price have a higher propensity to book.

H1b: People with a higher perceived sell-out risk have a higher propensity to book.

2.5.2 Leaping Effects

In the real market, customers face various price change trends and patterns every day, Ariely (2008) suggested that people tend to compare things to get a general perception of value, moreover, people tend to compare things that are easily comparable (Tversky & Kahneman, 1981). For instance, prices before and after an instant significant price change are easily compared, thus leaping patterns generally have a stronger cognitional and psychological impact to people than gradual changes.

The result of Mazumdar and Jun’s study (1993) demonstrated that a significant statement that direction of price changes is a strong determinant of the difference in subjects' evaluations. As demonstrated by Alba et al. (1999) in their study about discounts, deep and infrequent discounts lead to lower perceived prices compared to shallow and infrequent discounts. Thus, when price decrease, compare to those who observed gradual pattern, consumers who observed a leaping pattern have a higher propensity to book because they psychologically considered the price after single and intense discount is much lower. Considering the same intensity psychological impact of deep and infrequent price increase, the researcher can reasonably derive that, consumers who observed a leaping pattern have a higher propensity to book because they could psychologically considered the price after single and intense price increase is higher than price after frequent increasing. As a result, hypothesis 2 is proposed,

H2a: In the price increase trend, consumers who observed a leaping pattern have a lower propensity to book compared to consumers observed gradual pattern.
H2b: In the price decrease trend, consumers who observed a leaping pattern have a higher propensity to book compared to consumers observed gradual pattern.

2.5.3 Effects of Price Trends

According to prospect theory (Kahneman & Tversky's, 1979), people's tendency is to strongly prefer avoiding losses to acquiring gains. Furthermore, the theory indicated that most people are easily satisfied and tend to avoid risks when facing gains, however, many people tend to prefer risks when facing losses.

To use in this case, these findings of the prospect theory can be translated into that, generally, (i) when price decrease, more people tend to make booking decision because they are satisfied by saved money and tend to avoid potential risks about capacity and future price; (ii) when price increase, fewer people tend to make booking decision because they tend to take potential risks liker lower price in the future and higher capacity. Which turned out to be that multiple price decreases are evaluated more favorably than a single price decrease and a single price increase is less upsetting than multiple price increases.

Combined with finding of Chen and Schwartz (2008a) that, observed gradually increasing or decreasing price trend to have no significantly different impact on consumers' propensity to book. Therefore:

H3a: Gradual pattern has no different effect on propensity to book between price increasing trend and price decreasing trend.

H3b: Leaping pattern has a stronger effect on propensity to book in price decreasing trend than in price increasing trend.

CHAPTER 3. METHODOLOGY

Chapter 3 describes methodology employed to address the hypotheses developed in the previous chapter. It begins with instruction about the experimental design, and then introduces the research procedure and data collection. It ends with a detailed explanation of the questionnaire.

Quantitative study was achieved by a questionnaire survey. Utilizing this approach enables gathering a relatively large amount of data quickly and efficiently. Based on a thorough review of previous studies, the survey was designed to assess various aspects of customers' perceived future room rates and sell-out risk by introducing two treatment conditions: (i) different price changing patterns, and (ii) interactions between price changing trends and price changing patterns.

Together with the questionnaire sheet, a cover letter with an introduction and contact information of the researcher was attached (see Appendix A). The questionnaire (see Appendix B) was divided into two sections. The first section was the introduction, which explained a scenario for the survey participants. In the second section, questions were asked to test participants' perceptions towards different price change patterns, and their propensity to book. The second section also included demographic and travel related online searching and booking questions.

3.1 Treatments

The introduction explained a scenario for the survey participants:

"You have been planning a trip that will start after a week from today. You finally decided to book a room of Spring Creek Hotel from its website.

Spring Creek Hotel is a full-service midscale hotel with amenities, service convenience, and ambiance you can find at a typical 3-star hotel.

You kept checking the room rate on their website for the past three days. Your check-in date will be one week from today. Today, you go to the website again, and the flowing is the room rate for past 3 days and today:"

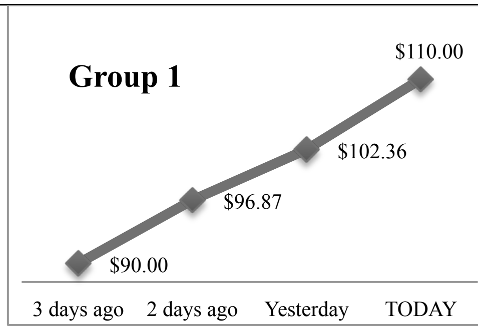
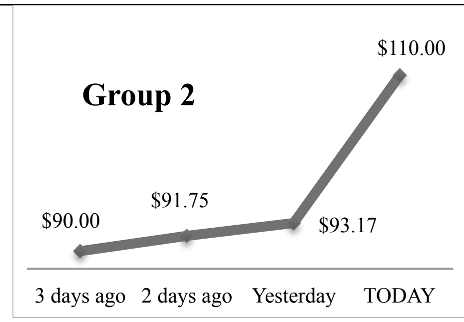
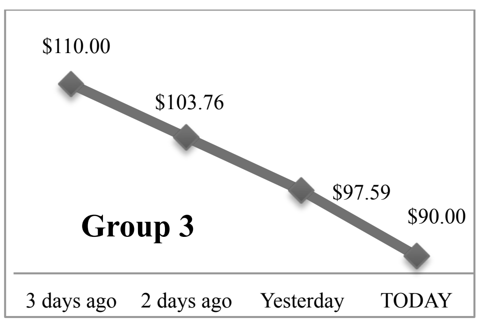
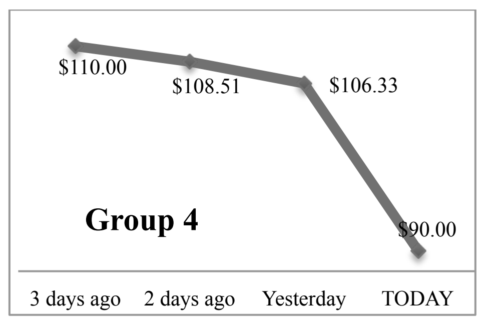
Next, each participant was given one chart about 4-day price changes (treatment condition) from Table 3.1 in accordance with the group to whom he/she was assigned.

The treatment effects are examined using a 2 (price change trend: increase versus decrease) × 2 (price change pattern: leap versus gradual change) design. Survey participants are randomly assigned to the four groups generated from the 2x2 design (see Table 3.1). For Group 1, the treatment condition was price increasing gradually and for Group 2, price barely changed at the beginning but performed a sudden growth afterwards. For Group 3, the treatment condition was price decreasing gradually, and for

Group 4, price barely changed at the beginning but showed a dramatic sudden decrease afterwards.

Table 3.1

Room Rates of the Past 3 Days and Today

	Price Leap Change	Price Gradual Change
Price Increase		
Price Decrease		

After the above scenario introduction, participants answered survey questions designed to test how different price change trends and patterns affect people's perceptions of future room rates and sell-out risk, as well as propensity to book.

Following the approaches from relevant literature review, the researcher required participants to answer questions based on their observations of the price patterns. Specifically, based on questions used in Chen and Schwartz's study (2008a), the researcher designed two questions to test participants' expectations of future price, one question to test participants' sell-out risk. Finally, participants are asked whether they would like to make the booking decision immediately or keep waiting. Next, to capture participants' behavior differences, questions about the frequency of travel and the usage of the Internet to book hotel rooms were also asked. Additionally, participants were asked to answer some demographic questions.

3.2 Experiment Control

The scenarios used in the experiments were designed to simulate as realistically as possible an upcoming trip and possible price patterns presented to the survey participants. Importantly, the fictitious trip was set to be a leisure trip because leisure travelers are generally more sensitive to room price than business travelers. Additionally, business travelers tend to spend less time online searching for related hotel information. Previous studies demonstrated that customers of upscale or luxury hotels are less price sensitive and they spend less time booking hotel rooms compared to customers of other hotels. Hence, a mid-scale hotel was chosen for the scenario.

No specific time of the year was presented for the sake of avoiding seasonal impact. The time in the fictitious scenario might be seen as the exact time when participants were involved in the experiment. Since customers' attitudes and perceptions can be dramatically influenced by complicated and interlaced reasons as the time approaches the real check-in date, the time of the scenario was set to be one week before the check-in date to avoid the influence of unknowable reasons (Chen & Schwartz, 2008b; Schwartz 2008). As a result, participants were asked to respond to questions a week before the real check-in date to avoid the impact of these unrelated factors.

In Chen and Schwartz's study (2008a), to test customers' perception based on their observed price change trend, participants involved in the experiments were shown a weekly price change pattern that included consecutive 14-week prices. However in reality, few customers would spend such a long time checking hotel room rates from either the Internet or other approaches. In this study, to capture customers' rate and risk perceptions as well as propensity to book with respect to different price change patterns and trends during a reasonable period of time, a chart characterizing a four-day room price change was shown to the participants in the experiment.

Based on a two-week observation of room price changes of 5 mid-scale hotels via the Expedia website, the researcher set price change ranges of the same type of hotels to be from $90 to $110 (for both leap and gradual change patterns each with an increase and a decrease trend). Consequently, the researcher created a $100 average price.

For gradual changing patterns, the price change in consecutive days was set to be approximately 5 dollars (about 5% of the average price). For leaping changing patterns, a major price jump or drop of approximately 15 dollars (about 15% of the average price) was set to appear at the fourth day ("Today" as shown in the experiment). In addition, the former three days shared a total of 5 dollars (about 5% of the average price) price change. To more accurately simulate the real situation, all price changes excluding the jump or drop changes in the leaping groups were randomly chosen from within a range of ±\$2 using Microsoft Excel. To facilitate unified comparisons, the starting and ending price for all four different price change groups were set either at \$90 or \$110, depending on the price change trend and pattern combination to which it belonged.

3.3 Research Procedures and Data Collection

After the design and review by the researcher, the questionnaire was first submitted to the Institutional Review Board (IRB) and then sent to the participants after approval. Convenience sampling was used in the study. The majority of participants included students, faculty, and staff at the West Lafayette campus of Purdue University in Indiana. Two recruitment methods were utilized to approach potential respondents. 175 Students, faculty, and staff from the Purdue campus were surveyed through direct distribution and emails. From April to May of 2013, the majority of subjects were randomly reached in the libraries (e.g. Hicks Undergraduate Library, Mathematical Sciences Library) and offices in school buildings (e.g. Marriot Hall, Agricultural & Biological Building). They are first asked for their identity (e.g. over 18 or not; graduate student or faculty) before requested to answer the survey. The completed questionnaires were directly collected from them face-to-face. To increase the diversity of the sample, questionnaires were also sent to 86 employees of an investment bank in Chicago through emails during May of 2013. These participants sent back the completed questionnaires through emails.

3.4 Statistical Inference about Multiple Population Typical Scores by Ranks

3.4.1 Checking Model Assumptions

Analysis of Variance (ANOVA) is the statistical method for analyses of the variability in data to infer about equality or inequality among population means. When one has two population means, one may use the student t test to determine the need to reject the null hypothesis if there is no significant difference between the two population means. When one has multiple (more than two) population means, repeated use of the t test each time to compare two independent population means tends to cause a high Type I error. To overcome such a high Type I error rate, the researcher used ANOVA, which considers all means in a single null hypothesis. The statistic used in ANOVA is an F statistic, named after R. A. Fisher, who introduced ANOVA half a century ago.

ANOVA has several model assumptions that need to be satisfied: (i) independent observations, (ii) residuals normally distributed, and (iii) constant variance. Independency can be achieved by carefully designed experimental trials. For diagnostics about the normality assumption, one may use a normal probability plot and statistical tests like the Shapiro-Wilk test. To make diagnostics about the constant variance assumption, one may use the residual plot or statistical tests like the Bartlett's or Levene's test. ANOVA is a parametric statistical approach since it assumes normally distributed errors, and the normal distribution itself is parametric. ANOVA is readily applicable for making statistical inferences about multiple population means provided that these model assumptions are satisfied.

Unfortunately, in the present research, the normality model assumption was violated, preventing the researcher from using the commonly used parametric ANOVA method. Four treatments were utilized in the survey data, which are the four price changing patterns (gradual increase, leaping increase, gradual decrease, and leaping decrease) shown to the survey participants. A total of thirteen questions that needed to be answered by participants, the first five out of which are response variables to be compared among the four different treatments. The rest eight questions provide control variables that characterize the age, income, occupation, and travel experience of those who responded to the survey. These will not be used for comparison among multiple populations yet checked in regression analysis for their effects on people's decision on the first four questions as response variables. The five response variables are all categorical/ordinal variables with two to five categories, and they do not follow normal distribution (test for normality results will be shown in Chapter 4); in that case, the researcher will yield nonparametric approach to test possible difference in response variable values from the four treatments. The researcher used the Kruskal-Wallis one-way analysis of variance-by-ranks test in the present study.

3.4.2 Kruskal-Wallis One-Way Analysis of Variance by Ranks

The Kruskal–Wallis one-way analysis of variance by ranks differs from the regular one-way analysis of variance (ANOVA) in that it is a nonparametric approach to test whether or not multiple samples originates from the same distribution. It does not assume normally distributed residuals, while it does assume for each treatment group an identically shaped and scaled distribution, except for any difference in medians. Similar to most nonparametric tests, it is performed on ranked data. The observations measured are converted to their ranks in the overall data set for use in the test.

When the Kruskal-Wallis test gives significant results, one may conclude that at least one of the samples is different from the other samples. However, the test does not identify more detailed information like where the differences happen and how many differences actually happen. Importantly, the use of ranks instead of actual observations may lead to loss of information that impedes the Kruskal–Wallis Test's accuracy. As a result, researcher should utilize ANOVA if the observed data is normally distributed.

In addition to its use in comparing more than two samples, the Kruskal-Wallis Test can also be used in comparing two samples. Then it generates the same *p* value as that of the regularly used Mann-Whitney U-test (or named as Wilcoxon Rank Sum Test) for comparing two samples while using a different statistic.

3.4.3 Kruskal-Wallis's Multiple Comparisons between Treatments

When the Kruskal-Wallis Test shows a significant result, it indicates that at least one of the treatment groups is different from at least one of the others. The Kruskal-Wallis's Multiple Comparisons will help determine which treatment groups are different with appropriately adjusted pairwise comparisons. If a pair of treatment groups has an observed difference that is higher than a calculated critical value, the two treatments are concluded to be different with statistical significance at a specific given α level. Importantly, this nonparametric multiple comparison method is similar to the Tukey, Bonferroni and Scheffe multiple comparisons used in parametric ANOVA, all of which are used to minimize the inflation of Type I error rate caused by simple pairwise comparisons.

In the present research, a total of four price change patterns are the treatment groups, with a total of five questions at the beginning of the survey used as response variables. The five response variables will be analyzed each at a time regarding the four different treatments. If the Kruskal-Wallis test statistic is significant, researcher will then work on the multiple comparisons to figure where and how the differences occur.

3.5 Questionnaire Design and Hypotheses

3.5.1 Test for Propensity to Book as the Dependent Response Variable

The researcher aims to test hypotheses regarding the effect of price on consumers' propensity to book. Question 5 in the survey is a yes/no Bernoulli case recording people's propensity to book. Apparently, it follows a binomial distribution and the researcher may use the logistic linear model to do regression analysis to investigate the effect of price. For $Y_i \sim \text{Binomial}(m_i, p_i)$, one has the following likelihood:

$$l_i(\theta_i; y_i) = y_i\theta_i - m_i \log(1 + e^{\theta_i}) + \log C_{y_i}^{m_i} \text{ , where } \theta_i = \log \frac{p_i}{1 - p_i}.$$

The researcher may use the logit link, which is $\eta = \log(p/(1-p))$, or the probit link, which is $\eta = \Phi^{-1}(p)$. The logit link is the canonical link, by means of which the researcher fit a logistic linear model for consumers' propensity to book, with an artificially defined categorical variable describing the four price changing curves as the independent variable to study the effects of price patterns on people's propensity to book. The researcher may also study the effect of consumers' expectations of future price, perceived sell-out risk, and perceived fairness on propensity to book using the same modeling scheme. The researcher can estimate a probability for people's real booking behavior ("yes" for Question 5) with respect to different categories of the independent variables.

Note: the "glm" function in the R programming language is used to fit a logistic regression model.

3.5.2 Surrogate Log Linear Regression Model for Perceptions as Dependent Variables

The first four questions characterize consumers' expectations of future price, perceived sell-out risk, and perceived fairness. They are categorical variables that have four to five ansrs as categories, different from the two categories for the fifth question measuring people's propensity to book. These four questions as response variables can be fitted using the multinomial distribution.

Considering the Poisson and multinomial distributions, suppose $Y_i \sim \text{Poisson}(\lambda_i)$, where i=1, 2, … , c, and Y_i's are independent, then $\boldsymbol{Y}|(\Sigma_i(Y_i = z)) \sim \text{Multinomial}(z; p_1, p_2, \ldots, p_c)$. $\boldsymbol{Y}$ is a vector of Y_i's, $p_i = \lambda_i/\Sigma_i\lambda_i$, and $Z = \Sigma_i Y_i \sim \text{Poisson}(\lambda)$, where $\lambda = \Sigma_i\lambda_i$. Conversely, if one has $\boldsymbol{Y}|Z \sim \text{Multinomial}(Z; p_1, p_2, \ldots, p_c)$ and $Z = \Sigma_i Y_i \sim \text{Poisson}(\lambda)$, then you will have $Y_i \sim \text{Poisson}(\lambda_i)$, where $\lambda_i = \lambda p_i$, and Y_i 's are independent. In order to estimate $\lambda_i = \lambda p_i$, the researcher has the likelihood,

$$\prod_{i=1}^{c} \frac{\lambda_i^{y_i} e^{-\lambda_i}}{y_i!} = \left(\frac{\lambda^z e^{-\lambda}}{z!}\right)\left(\frac{z!}{\prod_{i=1}^{c} y_i!} \prod_{i=1}^{c} p_i^{y_i}\right).$$

The above likelihood actually factors into two separated terms. The first term yields $\hat{\lambda}$ = $z = \Sigma_i y_i$ as the Poisson maximum likelihood estimate, and the second term yield the multinomial likelihood estimate of p_i.

Now one can check the surrogate log linear model, considering a two-way table with counts y_{ij} coupled with and covariates x_i. Assume $Y_{ij} \sim$ Poisson(λ_{ij}), where $\lambda_{ij} = \exp(\alpha_i + \boldsymbol{X}_i^T \beta_j)$. Then the researcher will have the likelihood of the observation (y_{ij}, $\boldsymbol{X}_i$) as follows:

$$\prod_{j=1}^{c} \frac{\lambda_i^{y_{ij}} e^{-\lambda_{ij}}}{y_{ij}!} = \left(\frac{\lambda^{z_i} e^{-\lambda_i}}{z_i!}\right)\left(\frac{z_i!}{\prod_{j=1}^{c} y_{ij}!} \prod_{j=1}^{c} p_{ij}^{y_{ij}}\right),$$

where $z_i = \Sigma_j Y_{ij}$, $\lambda_i = \Sigma_j \lambda_{ij} = \exp(\alpha_i)\Sigma_j \exp(\boldsymbol{X}_i^T \beta_j)$, and $p_{ij} = \lambda_{ij}/\lambda_i = \exp(\boldsymbol{X}_i^T \beta_j)/\Sigma_j \exp(\boldsymbol{X}_i^T \beta_j)$. Using the surrogate log linear models, the researcher can fit the first four questions one by one as multinomial response variables with each cell considered as a Poisson count, along with the a categorical variable characterizing the four price changing curves as the covariate. This can help directly predict the probability ($p_{ij} = \lambda_{ij}/\lambda_i$) of respondents choosing each answer category of a question with respect to different price changing curves. In this way the researcher are using a parametric regression approach to validate the results of the nonparametric Kruskal-Wallis Rank Sum Test and to determine more information about possible leaping effects. An additional advantage of the surrogate log linear model in this research is that the researcher can incorporate the eight control variables characterizing respondents' information as additional covariates into the model to investigate whether a specific piece of information matters in consumers' expectations of future price, perceived sell-out risk, and perceived fairness.

Note: The "glm" function in the R programming language is used to fit a surrogate log linear regression model.

3.5.3 Multinomial Logistic Regression Model for Perceptions as Dependent Variables

Multinomial logistic regression is an alternative approach of surrogate log linear models. It provides a direct way to estimate the probability of respondents choosing each answer category of a question with respect to different price changing curves. The researcher used it in combination with surrogate log linear models.

For $(Y_{i1}, Y_{i2}, \ldots , Y_{ik}) \sim$ Multinomial$(m_i, p_{i1}, p_{i2}, \ldots , p_{ik})$, the researcher has the following probability function,

$$f(\vec{y}_i \mid \vec{p}_i) = \frac{m_i!}{y_{ij}!\ldots y_{ik}!} p_{i1}^{yi1} \ldots p_{ik}^{yik}$$

The difference is that this is not a one parametric exponential family if one has k>2. Here the researcher has E[$\mathbf{Y_i}$] = $m_i p_i$, var[$\mathbf{Y_i}$] = $m_i(\text{diag}(\boldsymbol{p_i}) - \boldsymbol{p_i p_i^T})$. As a result, the likelihood function as,

$$l_i(\vec{p}_i; \vec{y}_i) = \sum\nolimits_{j=1}^{k} y_{ij} \log p_{ij} + C_{ij}(\vec{y}_i) .$$

With $p_{ij} = \exp(\eta_{ij})/\Sigma_j \exp(\eta_{ij})$, the researcher may specify a model $\eta_{ij} = \boldsymbol{X_i^T \beta_j}$. The difference from the surrogate log linear model is that $p_{ij}/p_{ij} = \exp(\boldsymbol{X_i^T(\beta_j - \beta_{j'})})$, so the researcher only have the contrasts among $\boldsymbol{\beta_1}$'s that are estimable, and it is convenient to set $\boldsymbol{\beta_1} = 0$ as the baseline.

Note: The "multinom" function in the {nnet} library of the R programming language is used to fit a multinomial logistic regression model.

3.5.4 Proportional Odds Regression Model for Perceptions as Dependent Variables

Further consideration for Questions 2, 3 and 4 as ordinal variables may need to be explored. Apparently, answer categories for each of the three questions have a semi-quantitative order. If one considers these three response variables as ordinal variables, one may work on cumulative probabilities to obtain more parsimonious and interpretable models, such as the proportional odds model.

When dealing with ordinal categories, a proportional odds model may be defined as the following,

$$\log \frac{P_{ij}}{1-P_{ij}} = \zeta_j + \vec{X}_i^T \vec{\beta}\ , \text{ where } j = 1, 2, \ldots, \text{k-1}.$$

Here $P_{ij} = \Sigma_{l=1}^{j} p_{il}$, and $\zeta_1 \leq \ldots \leq \zeta_{k-1}$. Then the odds ratio expressed as follows:

$$\frac{P_{ij}(1-P_{ij})}{P_{i'j}(1-P_{i'j})} = \exp((\vec{X}_i - \vec{X}_{i'})^T \vec{\beta})\ .$$

The odds ratio is independent of j. The researcher consider using a latent variable Z that follows a logistic distribution, i.e. $P(Z + \boldsymbol{X^T\beta} \leq x) = \exp(x) / (1 + \exp(x))$. Furthermore, let us suppose that one can only observe $Y = j$ when $\zeta_{j-1} \leq Z \leq \zeta_{j-1}$. As a result of the above, the researcher can calculate the cumulative probability as,

$$P(Y \leq j) = (Z \leq \zeta_j) = \exp(\zeta_j + \boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{\beta}) / (1 + \exp(\zeta_j + \boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{\beta})).$$

The proportional odds model on ordinal categories of Questions 2, 3, and 4 again provides a direct way to estimate the probability of respondents choosing each answer category of each of the three questions with respect to different price changing curves.

Note: The "polr" function in the {MASS} library of the R programming language is used to fit a logistic or probit proportional odds model.

3.5.5 Generalized Liner Regression Used in the Specific Cases

The researcher will use the regression analysis to study the effect of the four treatments (price changing curves) on respondents' perceived fairness, perceived sell-out risk, and expectation of future price. The researcher will analyze the five response variables each at a time, with a categorical variable characterizing the four treatments as the predictor variable or covariate in the regression. Surrogate log linear models are fitted using the following scheme:

$$Freq \sim Group + Question + Group{:}Question.$$

Freq is the occurring frequency for each answer category from each question facing each price-changing curve. *Group* is the categorical variable characterizing the four treatment groups. *Question* is the categorical variable characterizing the answer categories for a specific question as the response variable. *Group* is set as the covariate associated with the categories of *Question*. The researcher are interested in whether the interaction term

Group: Question is significant or not. Multinomial logistic and proportional odds models with a logit link are fitted using the following scheme,

Question ~ Group, with Freq as the weight

The difference between multinomial and proportional odds models is that the latter is working on cumulative probabilities. These two models are used to estimate the probability of respondents choosing each answer category of a question with respect to different price changing curves. The logistic regression model for Question NO. 5 is as follows:

$$\log(\, p/(1-p)\,) = \beta_0 + \beta_1 Group.$$

p is the estimated probabilities of Question 5, taking the answer “yes” for each of the four price changing curves.

For Question 1 as the response variable, the researcher fit a surrogate log linear model and a multinomial logistic regression model because it has more than two answer categories. Thus, it cannot be simplified using a Binomial case. Furthermore, Question 1 does not behave like an ordinal categorical variable, and as a result the researcher will not fit a proportional odds model here.

For Questions 2, 3, and 4, they are behaving like ordinal categorical variables in a sense that their answer categories are ordered with semi-quantitative information included. As a result, the researcher will also fit a proportional odds model in addition to the surrogate log linear model and the multinomial logistic regression model.

For Question 5, the regular logistic regression model was used since it is a binomial variable with two answer categories. Importantly, for all the models fitted, the researcher will perform statistical model selection procedures to help identify a statistically significant model. Specifically, the researcher uses the stepwise model selection with deviance and AIC criteria for goodness of fit test.

CHAPTER 4. RESULTS

Chapter 4 has five sections, which are initial descriptive statistics, tests of the three hypotheses proposed, analyses of consumers' perceptions, and analyses of the control variables. Descriptive statistics helped depict the characteristic information of survey participants included in eight control variables (e.g. age, income), and create a broader overall distribution of respondents' answers to the first five survey questions as response variables measuring consumers' expectation of future price, perceived sell-out risk, perceived fairness, and propensity to book. Importantly, these statistics and graphics were summarized for each of the four price changing curves as groups or experimental treatments. Second, the researcher performed cross regression analysis with consumers' propensity to book as the response variable, and consumers' perceived fairness, perceived sell-out risk, expectation of future price as predictor variables to validate whether they affects the booking propensity. Third, the researcher performed and showed results of the nonparametric Kruskal-Wallis One-Way Analysis of Variance by Ranks Test and Kruskal-Wallis Multiple Comparisons used to check whether consumers' expectations of future price, perceived sell-out risk, perceived fairness, and propensity to book differed among the four price changing curves. Possible differences between gradual and leaping change patterns were investigated. Furthermore, the researcher utilized generalized linear models to achieve regression analysis of the response variables with price changing patterns as predictor variables to validate and expand the results from the Kruskal-Wallis Test. Finally, the researcher provided analytical results about possible effects on the response variables from the eight control variables, such as income and occupation. Results included simple descriptive statistics and more complex surrogate log linear models.

4.1 Descriptive Statistics

A total of 241 responses were received, but 12 of them were not completed which yielded a total of 229 effective responses. The response rate of face-to-face distribution was 96.57%, while the response rate via email was 82.8%. Email was used to collect responses to gain a larger sample size because some respondents could not be reached directly.

4.1.1 Demographic Information of Respondents

Demographic characteristics of the sample are presented in Table 4.1. Out of the 229 effective respondents, there were 134 (58.52%) males and 95(41.48%) females. The age of respondents ranged from 18 to 64 years; and the categorization of 5 age groups is shown in Table 4.1. A large group of participants were students (41.75%), 6.99% of participants had part-time employment, 46.29% held a full-time job, and 5.68% of participants homemakers. The majority of participants (a total around 75.11%) had an approximate yearly income under $75000, while the remainder had a yearly income greater than $75,000. Additionally, people with different demographic characteristics showed relatively similar answers to each of the five response questions about people's expectations of future price changing direction, perceived sell-out risk, perceived fairness, expectations of getting a lower price, and propensity to book, respectively. The researcher performed a regression analysis to test the significance of demographic characteristics on people's perceptions and booking propensity.

Table 4.1
Demographic Characteristics (N=229)

Demographic Characteristics	N	Mean Response Q1	Mean Response Q2	Mean Response Q3	Mean Response Q4	% of "yes" Response Q5
Gender						
Male	134	2.0316	3.3263	3.1158	2.6211	0.5789
Female	95	2.0746	2.8358	3.2687	3.1119	0.4552
Age						
18-25	76	1.9474	3.0526	3.3158	2.8421	0.6053
26-35	77	2.0260	3.0000	3.0130	2.8961	0.4156
36-45	43	2.2093	3.2326	3.2326	2.9302	0.5116
46-55	28	2.1429	2.9286	3.1786	3.0357	0.4286
56-64	5	2.4000	2.4000	4.4000	3.2000	0.8000
Employment						
Student	94	1.9894	3.0851	3.1064	2.9255	0.4149
Employed (part-time)	16	2.1875	3.2500	3.6250	2.1250	0.6875
Employed (full-time)	106	2.1038	3.0849	3.3208	3.0094	0.6226
Retired	0	NA	NA	NA	NA	NA
Homemaker	13	2.0000	2.0769	2.4615	2.9231	0.0000
Others	0	NA	NA	NA	NA	NA
Income						
Less than $15,000	45	1.9111	2.8000	3.3333	2.7333	0.4222
$15,000 to $24,999	50	1.7200	3.3200	3.0600	2.6800	0.5200
$25,000 to $49,999	43	1.9535	3.3953	3.3256	2.6977	0.4186
$50,000 to $74,999	34	2.2647	2.7353	2.5000	3.3529	0.4412
$75,000 to $99,999	22	2.3636	2.5000	3.3182	3.5000	0.6364
$100,000 to $149,999	17	1.8235	3.7059	3.0000	2.5882	0.7059
$150,000 or more	18	3.0555	2.6111	4.3888	3.2222	0.6667

4.1.2 Travel and Internet Experience

The information of the participants' travel and online searching & booking experience were acquired from 4 related questions: one was related to yearly travel frequency, while the others were related to usage of the Internet when planning for a hotel stay. The majority of the respondents (82.97%) traveled less than 6 times in a year, a total of 64.63% used the Internet to obtain hotel room related information less than 6 times in a year. Most of the respondents (74.67%) used the Internet to book their hotel rooms for all of their trips, but some respondents (6.15%) used the Internet to book their hotel rooms for less than half of their trips. Many respondents (41.05%) spent 1 hour searching hotel room information before their final booking decision, followed by those (23.14%) who wanted to spend 4-6 hours, those (20.52%) who wanted to spend 2-3 hours, and those (8.3%) who would spend more than 10 hours. The remainder of the respondents liked to spend 7-10 hours on online information searching. As with democratic characteristics, it was difficult to determine differences in respondents' answers to the five questions resulting from different travel and online experience variables. Analytically and statistically, regression analysis was performed to test the significance of these possible differences.

Table 4.2
Travel and Internet Experience Variables

Travel and Internet Experience	N	Mean Response Q1	Mean Response Q2	Mean Response Q3	Mean Response Q4	% of "yes" Response Q5
Time of travel yearly						
1~5 times	190	2.0684	2.9789	3.1263	2.9632	0.4947
6~10 times	21	2.2381	3.3333	3.4286	2.7143	0.5714
11~15 times	13	2.0000	2.6923	4.0000	2.3846	0.7692
> 15 times	5	1.0000	5.0000	3.2000	3.0000	0.0000
Time of getting hotel information via the Internet yearly						
1~5 times	148	2.1081	2.9662	3.2027	3.0946	0.4797
6~10 times	29	2.1379	3.3793	3.1034	2.6207	0.5862
11~15 times	26	2.0385	3.0385	3.3462	2.6923	0.6923
> 15 times	26	1.6923	3.0769	3.1923	2.3846	0.3846
Frequency of booking hotel room with the Internet						
Never	5	1.8000	1.4000	4.0000	2.8000	0.6000
Less than half of trips	9	1.8889	3.0000	3.2222	3.1111	0.3333
Half of trips	18	1.6667	3.3889	3.5556	2.8333	0.6667
More than half of trips	26	1.8077	3.3846	3.2308	2.9615	0.6154
All of trips	171	2.1520	3.0000	3.1404	2.9006	0.4795
Time willing to spend on the Internet for hotel information						
1 hour	94	2.1277	2.8723	3.4787	3.0851	0.5426
2-3 hours	47	2.1702	2.9362	3.1489	2.7021	0.5319
4-6 hours	53	2.1132	3.0943	3.0377	2.7736	0.4340
7-10 hours	16	1.7500	3.7500	2.8750	2.9375	0.3125
> 10 hours	19	1.5263	3.3684	2.7368	2.8947	0.6316

4.1.3 Descriptive Statistics of Response Variables

Data was grouped into four subgroups based on the four price changing curves as treatments. Descriptive statistics obtained were sample size and mean and standard deviation for each of the five response questions with respect to each of the four subgroup-treatments (For Question 5 about propensity to book, the mean was actually the percentage of people answering “yes”). Question 1 (future price change direction) and Question 4 (possibility to get a lower price) as response variables were measuring consumers’ expectations of future price. Question 2 and 3 measured people’s perceived sell-out risk and fairness, respectively. Question 5 measured people’s propensity to book facing different price changing curves.

Table 4.3
Descriptive Statistics for Expectations of Future Price Change Direction, Perceived Sell-Out Risk, Perceived Fairness, Expectations of Getting a Lower Price, and Propensity to Book as Response Variables

Question	Group #	N	Mean	Standard Deviation
Expectations of future price change direction	1	78	1.8462	1.2698
	2	46	2.5217	1.1103
	3	48	2.2083	1.0711
	4	57	1.8421	0.9781
Perceived sell-out risk	1	78	3.2692	1.2759
	2	46	3.0652	1.2365
	3	48	2.5000	1.2716
	4	57	3.1579	1.4116
Perceived Fairness	1	78	2.8333	1.2834
	2	46	2.3043	1.0723
	3	48	3.8333	1.3262
	4	57	3.9123	0.9871
Expectations of getting a lower price	1	78	2.7436	1.0374
	2	46	2.9565	1.0319
	3	48	3.3750	1.0644
	4	57	2.7018	0.9813
Propensity to book	1	78	0.5513	0.5006
	2	46	0.2391	0.4313
	3	48	0.3542	0.4833
	4	57	0.7895	0.4113

According to the above table, there was a difference in people's expectations of future price between gradual and leaping changing patterns regardless of the increasing or decreasing trends. Furthermore, it seemed that for different trends, the leaping effect behaved differently. To further test these differences statistically, the Kruskal-Wallis Test was necessary. Different from people's expectations of future price, one observed form

Table 4.3 that the leaping effect and the trend effect were not obvious with respect to consumers' perceived sell-out risk. However, the third treatment group (gradual price decrease) might have been different from the other three. For Question 3 about consumers' perceived fairness, there was a seemingly significant difference between increasing and decreasing trends (Group 1 & 2 vs. Group 3 & 4). However, the difference between gradual and leaping effects (Group 1 & 3 vs. Group 2 & 4) did not appear significant. Lastly about Question 5 that measured propensity to book, the researcher observed very different results for the four treatment groups. Both Kruskal-Wallis Test and Logistic Regression supported significant differences in people's propensity to book among the four treatments (to be shown later).

Unfortunately, considering the relatively large standard deviations and that the five questions as response variables were categorical/ordinal variables, the researcher could not easily draw a conclusion. Categorical variables should not be considered as normally distributed variables and as a result the researcher did not use the Student *t* Test and ANOVA for comparison of means. The normality tests proved that all the response variables and the eight control variables were far from a normal distribution; Table 4.4 summarizes the test results for Q1 (expectations of future price change direction) in the gradual price increase group as an example. The statistical tests for normality had very small p values (< 0.05), thus rejecting the normality hypothesis. The researcher considered the multinomial distribution for the response variables of expectations of future price change direction, perceived sell-out risk, perceived fairness, and expectations of getting a lower price (Questions 1-4), and the binomial distribution for propensity to book (Q5).

Table 4.4
Normality Test for Expectation of Future Price Change Direction (Q1) as the Response with Respect to Gradual Increase Price (Group 1)

Test	Statistic		*p*-value	
Shapiro-Wilk	W	0.628742	Pr < W	<0.0001
Kolmogorov-Smirnov	D	0.388438	Pr > D	<0.0100
Cramer-von Mises	W-Sq	2.362897	Pr > W-Sq	<0.0050
Anderson-Darling	A-Sq	13.64795	Pr > A-Sq	<0.0050

Due to the non-normality, the researchers performed the Kruskal-Wallis nonparametric analysis of variance. The "kruskal.test" function in the {stat} library of the R programming language, and the PROC NPAR1WAY procedure in the SAS software were used. Each of the response questions was analyzed about people's expectations toward future price, perceived sell-out risk, perceived fairness, and propensity to book. Results of the tests of multiple populations are shown in Table 4.5.

Table 4.5
Kruskal-Wallis Rank Sum Test for Questions 1-5 among Different Groups

Question	Kruskal-Wallis Chi-squared	Df	*p*-value
Expectations of Price Change Direction	18.8427	3	2.95E-04
Expectations of Getting a Lower Price	11.6005	3	0.008885
Perceived Sell-Out Risk	10.5604	3	0.01436
Perceived Fairness	52.8407	3	1.98E-11
Propensity to Book	36.3384	3	6.35E-08

The test results for expectations of price change direction, perceived fairness, expectations of getting a lower price, and propensity to book were significant at an α level of 0.01 (p values < 0.01) and the test result for perceived sell-out risk is significant at an α level of 0.05 (p value = 0.14). This suggested that for each of these five response variables with the four price changing curves as treatments, the researcher detected a significant difference in people's answers to the question among the four treatments, i.e. at least one of the four price changing curves had an effect on the response variable that was different from at least one of the other curves. To further compare treatment means with each of people's expectation of future price, perceived sell-out risk and propensity to book used as the response, the researcher performed Kruskal-Wallis nonparametric multiple comparisons using the "kruskalmc" function in the R {pgirmess} library, results of which were discussed in the following chapters.

4.2 Test of Hypotheses by Statistical Inference and Modeling

After the above initial descriptive analysis, the researcher had an overview about possible leaping and trend effects on consumers' perceived fairness, perceived sell-out risk, and expectations of future price. However, more solid statistical analyses were needed to test the hypotheses.

Generalized linear regression analysis (GLM) was performed to test Hypothesis 1 about the effects of people's expectations of future price and perceived sell-out risk (as independent variables) on people's propensity to book (as the dependent response variable). Nonparametric analysis of variance tools were used to validate the significance of leaping effects on people's propensity to book, expectations of future price and perceived sell-out risk. It confirmed the validity of Hypothesis 1, and tested different aspects of the cross effect of price trend and price pattern on people's propensity to book, as stated in Hypotheses 2 and 3. A different set of GLM was performed with a categorical variable describing the four price changing curves as the independent variable to further validate the results from the nonparametric analysis of variance.

4.2.1 Results of Hypothesis 1 Testing

To test people's expectations about future price, the researcher asked two questions: (i) Q1 was about expectations of future price change direction with four possible answers (increase, decrease, not change, and not sure); (ii) Q4 was about people's thoughts about the possibility to get a lower price in the future, with five possible answers (very low, low, 50%-50%, high, and very high). And Q5 was asked to test people's propensity to book based on the observed price change, with possible answers "yes" and "no".

Generalized linear regression was used to validate Hypothesis 1a, which says that: "People with a higher expectation towards future price have a higher propensity to book". Table 4.6 and Table 4.7 summarize the regression significance and predicted probabilities with respect to Q1 (expectations of future price change direction). The model was significant from Table 4.6 because the p values of all answers were smaller that 0.05.

Importantly, the researcher summarized from Table 4.7 that there was a much higher probability for people to book when the price was expected to increase (62%) compared to the probability for booking when the price was expected to decrease (0.28%) or not to change (0.33%). In addition, from table 4.8 and 4.9 the researcher basically observed a decrease pattern of the propensity to book when people's perceived chance to get a lower price in the near future was increasing. Specifically, people who thought that the possibility to get a lower price was "very low" had the highest propensity to book (83%), followed by those who thought the possibility to get a lower price was "50%-50%" (75%), followed by those who thought the possibility to get a lower price was "low" (54%), followed by those who thought the possibility was "high" (22%), and people who thought the possibility to get a lower price in the future was "very high" almost had no intention to book.

Thus, Hypothesis 1a was supported, which stated that there was a positive relationship between people's expectations towards future price and their propensity to book.

Table 4.6
Summary of Logistic Model for Propensity to Book (Question 5) vs. Expectations of Future Price Change Pattern (Question 1)

	Estimate	Standard Error	*p* value
Intercept	0.5	0.2084	0.0164
Decrease	-1.4473	0.3413	2.22E-05
Not change	-1.1931	0.586	0.0418
Not sure	0.1008	0.3667	0.7834

Table 4.7
Probabilities from Logistic Model for Propensity to Book vs. Expectations of Future Price Change Pattern

Answer	Increase	Decrease	Not Change	Not Sure
Probability Answer "yes"	0.622449	0.2794118	0.3333333	0.6458333

Table 4.8
Summary of Logistic Model for Propensity to Book vs. Expectations of Getting a Lower Price (Question 4)

	Estimate	Standard Error	*p* value
Intercept	1.6094	0.6325	0.0109
Low	-1.4684	0.6757	0.0298
50%-50%	-0.5306	0.692	0.4432
High	-2.8946	0.7058	4.11E-05
Very high	-26.963	53867.9146	0.9996

Table 4.9
Probabilities from Logistic Model for Propensity to Book vs. Expectations of Getting a Lower Price

Answer	Very Low	Low	50%-50%	High	Very High
Probability Answer "yes"	0.8333333	0.5352113	0.7462687	0.2166667	9.75E-12

Question 2 was testing people's perceptions about the possibility that the rooms would be sold out from now to check-in date. It was asked to test people's perceived sell-out risk, and it had five possible answers (very low, low, 50%-50%, high, and very high). Generalized linear regression analysis was also used for this question to test H1b, which says that: "People with a higher perceived sell-out risk have a higher propensity to book."

Table 4.10 and Table 4.11 summarize the regression significance and predicted probabilities. This model although had larger *p* values for most of the regression terms, was retained after statistical stepwise model selection using the AIC and goodness-of-fit criteria. As a result, results of this model were still statistically useful for this study. From Table 4.11, the researcher observed a clear increase pattern of the probability to book synchronizing with an increasing perceived sell-out risk. Specifically, people who thought that the sell-out risk was "very high" had the highest possible to book (66%), followed by those who thought the sell-out risk was "50%-50%" (57%), followed by those who thought the sell-out risk was "high" (50%), and people who thought the sell-out risk was "low"/"very low" had the lowest propensity to book (37% /40%).

The above analyses supported H1b, which stated that people with a higher perceived sell-out risk had a higher propensity to book. In combination with the testing conclusions of H1a, Hypothesis 1 was completely validated.

Table 4.10
Summary of Logistic Model for Propensity to Book vs. Perceived Sell-Out Risk (Question 2)

	Estimate	Standard Error	*p* value
(Intercept)	-0.4274	0.3319	0.1978
Low	-0.1226	0.464	0.7916
50%-50%	0.7062	0.4158	0.0894
High	0.4274	0.4484	0.3404
Very High	1.0842	0.4676	0.0204

Table 4.11
Probabilities from Logistic Model for Propensity to Book (Question 5) vs. Perceived Sell-Out Risk (Question 2)

Answer	Very Low	Low	50%-50%	High	Very High
Probability Answer "yes"	0.3947368	0.3658537	0.5692308	0.5	0.6585366

Additionally, the researcher used the same method to test if there was correlation between people's perceived fairness towards prices after change (Q3) and their propensity to book. And from Table 4.12 and 4.13, the researcher found that there was a clear increase pattern of the probability to book when people's perceived fairness went from "very unfair" to "very fair".

Table 4.12
Summary of Logistic Model for Propensity to Book (Question 5) vs. Perceived Fairness (Question 3)

	Estimate	Standard Error	*p* value
Intercept	-1.3122	0.4258	0.00206
Somewhat unfair	0.7416	0.5493	0.17696
Neither Fair nor Unfair	1.089	0.4956	0.02799
Somewhat Fair	1.7177	0.5234	0.00103
Very Fair	2.6279	0.5446	1.40E-06

Table 4.13
Probabilities from Logistic Model for Propensity to Book (Question 5) vs. Perceived Fairness (Question 3)

Answer	Very Unfair	Somewhat Unfair	Neither Fair Nor Unfair	Somewhat Fair	Very Fair
Probability Answer "yes"	0.2121212	0.3611111	0.4444444	0.6	0.7884615

4.2.2 Results of Hypothesis 2 Testing

The researcher performed the nonparametric analysis of variance and multiple comparisons to validate Hypothesis 2, which states: a) In the price increase trend, consumers who observed a leaping pattern have a lower propensity to book compared to consumers who observed gradual pattern; and b) In the price decrease trend, consumers who observed a leaping pattern have a higher propensity to book compared to consumers who observed gradual pattern.

Table 4.14 summarizes the results of the nonparametric multiple comparisons for propensity to book that is a binary response. For either the increase or decrease trend, the observed difference was larger than the critical difference (35.7 > 32.5 for increase, and 49.9 > 34.2 for decrease). This suggested a significant difference between the effects of leaping and gradual price change patterns on consumers' propensity to book for either of the two trends. From the mean calculations in Table 4.3, the researcher noticed that the percentage of people making a final booking decision decreased from ~55% to ~24% when their observed price changing curve changed from a gradual increase one to a leaping increase one. In the price decrease trend, however, this percentage increased from ~35% to ~%79 when the observed price changing curve changed from a gradual decrease one to a leaping decrease one. In combination with the statistical significance obtained in multiple comparisons, the research drew a conclusion that consumers who observed a leaping increase pattern had a lower propensity to book compared to consumers who observed a gradual increase pattern, while in the price decrease trend, those who observed a leaping pattern had a higher propensity to book. This is exactly what was proposed in Hypothesis 2, thus its correctness has been validated here using the nonparametric assumption and statistical inference.

Table 4.14
Multiple Comparisons with Propensity to Book as the Response

Group Pair	Observed Difference	Critical Difference	Difference
Gradual Increase vs. Leaping Increase	35.74136	32.49322	TRUE
Gradual Increase vs. Gradual Decrease	22.56971	32.06458	FALSE
Leaping Increase vs. Leaping Decrease	63.0143	34.6426	TRUE
Gradual Decrease vs. Leaping Decrease	49.84265	34.24087	TRUE

4.2.3 Results of Hypothesis 3 Testing

Nonparametric analysis of variance and multiple comparisons (results shown in Table 4.14) were also use to validate Hypothesis 3 investigating the effects of price change trends. Specifically, Hypothesis 3 states: a) Gradual pattern has no different effect on propensity to book between price increasing trend and price decreasing trend; and b) Leaping pattern has a stronger effect on propensity to book in price decreasing trend than in price increasing trend.

The researcher observed from Table 4.14 that the difference in propensity to book was insignificant between the cases of gradual increase and gradual decrease (observed difference < critical difference), while the difference was significant between the leaping increase and the leaping decrease cases (observed difference > critical difference). Statistically, for gradual increase and gradual decrease, the observed difference was 22.6, which was smaller than the critical difference of 32.1. On the contrary, for leaping increase and leaping decrease, the observed difference was 63.0, which was much larger than the critical difference of 34.6 to conclude difference between the two comparison groups.

The researcher next observed that, in the price decrease trend, the observed difference in people's propensity to book between seeing the leaping and the gradual price change curves was much larger than the statistical critical difference (49.8 > 34.2), while the observed difference in the price increase trend was only slightly larger than the statistical critical difference (35.7 > 32.5). This supported that the difference between the effects of leaping pattern and gradual pattern on propensity to book was stronger in price decreasing trend than in price increasing trend.

The above nonparametric analysis results clearly helped the researcher draw a conclusion exactly the same as what was proposed in Hypothesis 3. As a result, the correctness of the statements in Hypothesis 3 was validated.

4.2.4 The Effect of Price Changes on Expectations of Getting a Lower Price

The researcher performed Kruskal-Wallis multiple comparisons with people's expectations of getting a lower price (Q4) as the response. Q4 was chosen because it was a semi-quantitative ordinal variable ranging from a low level to a high level, and this helped the researcher utilize the positive correlation conclusion from Hypothesis 1. Specifically, Hypothesis 1 suggested a positive correlation between expectations of future price and propensity to book. Taking the price increasing trend as an example, the researcher next need to prove that the leaping effect causes people to have a lower expectation of future price facing a leaping increase price than facing a gradual increase one. If this is true, the researcher can validate Hypothesis 2a by combining this leaping effect and the positive correlation between expectation of future price and propensity to book. The same criteria can be used to validate Hypothesis 2b.

Table 4.15 summarizes the comparison results for expectations of getting a lower price. The researcher did not observe a significant difference between the gradual and leaping changing patterns when the price was going up (observed difference < critical difference), but a significant one when the price was going down (observed difference > critical difference). According to Table 4.3, the mean of the answers to Q4 decreased from 3.38 in the gradual decrease case to 2.70 in the leaping decrease case. This was in favor of the idea that the expectations of getting a lower price changed in the high-to-low direction, i.e., the expectations of future price changed in the low-to-high direction. The leaping effect in the price decrease trend caused people to have higher expectations of future price, and as a result a higher propensity to book. This again validated Hypothesis 2b.

Table 4.15
Multiple Comparisons with Expectations of Getting a Lower Price as the Response

Group Pair	Observed Difference	Critical Difference	Difference
Gradual Increase vs. Leaping Increase	14.046265	32.49322	FALSE
Gradual Increase vs. Gradual Decrease	35.391827	32.06458	TRUE
Gradual Increase vs. Leaping Decrease	1.607625	30.45723	FALSE
Leaping Increase vs. Gradual Decrease	21.345562	36.06389	FALSE
Leaping Increase vs. Leaping Decrease	15.65389	34.6426	FALSE
Gradual Decrease vs. Leaping Decrease	36.999452	34.24087	TRUE

Nonparametric analysis of variance has a limitation of calculating asymptotic statistics instead of exact statistics. To further validate nonparametric test results and dig out more useful information and conclusions from survey data, the researcher performed parametric regression analyses based on generalized linear models with a categorical variable characterizing the four price changing curves as the independent variable. Parametric statistical analysis is based on the assumption of mathematically describable statistical distributions, thus the choice of distributions can influence the analytical results. It provides an alternative approach to help test the hypothesis. If the researcher can validate the researcher hypotheses using both approaches, they can generate a much more solid conclusion.

Table 4.16 summarizes the results of the finally fitted surrogate log linear regression for people's expectations of future price via the expectations of getting a lower price (Q4). In the table, "G" represents price change groups (gradual increase, leaping increase, gradual decrease and leaping increase) and "A" represents answer categories to the Q4 ("Very Low", "Low", "50%-50%", "High", and "Very High"). The same notation of "G" and "A" will be used from now on. In the surrogate log linear regression, if the combination terms (G#:A#) were significant, it meant that the effect of price changes (G) on expectations of getting a lower price (A) as the response was significant. Importantly, regression parameters for "G1" and "A1" were set to 0 to avoid over parameterization, so that there were no *p* values calculated for them. NA values were set for the terms "G2:A5" and "G4:A5", because no survey respondents chose the 5th answer ("Very High") when they were facing a leaping price increase or decrease. Although in Table 4.16 many of the *p* values for the parameter terms were not significant (> 0.05), there were still some significant *p* values (< 0.05). Besides, model selection via AIC and goodness-of-fit tests retained interaction terms for the model. This suggested that there were possible differences in people's expectation of getting a lower price with respect to different price change curves.

The researcher then checked the predicted probabilities of each answer category for Q4 with respect to each of the four price change groups (Table 4.17 and Table 4.18). The ordinal semi-quantitative effect (answers range from very low to very high) for the measured expectations of getting a lower price might be an essential factor to be considered in the proportional odds model. Combining the results form the two sets of model predictions, the researcher observed that most people expected a low probability of getting a lower future price facing a price leaping increase, while for the gradual price increase case, most people expected a high probability of getting a lower price. In another word, the researcher suggested that people had a higher expectation of getting a lower rate (i.e. lower expectation of future price) in the leaping increase case than in the gradual increase case. On the contrary, people had a lower expectation of getting a lower rate (i.e. higher expectation of future price) in the leaping decrease case than in the gradual decrease case. This again was in favor of both Hypothesis 2a and 2b about the leaping effects on people's propensity to book in each of the two price change trends.

Table 4.16
Summary of Surrogate log linear Regression for Expectations of Getting a Lower Price (Q4)

	Intercept	G2	G3	G4	A2	A3	A4
p value	4.06E-09	0.1474	0.04993	0.59425	0.00251	0.01009	0.07873
	A5	G2:A2	G3:A2	G4:A2	G2:A3	G3:A3	G4:A3
p value	0.1474	0.54012	0.44681	0.98389	0.79487	0.07136	0.90505
	G2:A4	G3:A4	G4:A4	G2:A5	G3:A5	G4:A5	
p value	0.12897	0.24655	0.80133	NA	0.00853	NA	

Note. "G" represents price change groups (gradual increase, leaping increase, gradual decrease and leaping increase), and "A" represents answer categories to the Q4 ("Very Low", "Low", "50%-50%", "High", and "Very High").

Table 4.17
Probabilities from Multinomial Regression for Expectations of Getting a Lower Price

Group	Probability Very Low	Probability Low	Probability 50%-50%	Probability High	Probability Very High
Gradual Increase	0.10255908	0.3461556	0.2948836	0.2179385	0.0384633
Leaping Increase	0.06522395	0.3478329	0.1521707	0.4347724	9.75E-08
Gradual Decrease	0.02081707	0.1666748	0.437506	0.1666697	0.2083324
Leaping Decrease	0.10526853	0.3508836	0.2807062	0.2631416	5.79E-08

Table 4.18
Probabilities from of Proportional Odds Model for Expectations of Getting a Lower Price

Group	Probability Very Low	Probability Low	Probability 50%-50%	Probability High	Probability Very High
Gradual Increase	0.09641465	0.3579811	0.2887587	0.215818	0.04102752
Leaping Increase	0.06619115	0.2899992	0.3015896	0.2817145	0.06050556
Gradual Decrease	0.03722509	0.1945973	0.2800016	0.382576	0.10559998
Leaping Decrease	0.09998333	0.3644213	0.2863669	0.2097575	0.03947085

4.2.5 The Effect of Price Changes on Expectations of Future Price Changing Direction

Different from Q4 (expectations of getting a lower price), Q1 (expectations of future price change direction) as an alternative measurement of expectations of future price was a regular categorical variable without semi-quantitative information (i.e. level from low to high). Nonparametric analysis of variance was therefore not useful for Q1, but the researcher used regression analysis to study this question variable. Table 4.19

summarizes the results of the generalized linear regression analysis for people's expectations of future price change direction (Q1). Small p values (<0.05) obtained for most of the regression terms was in favor of the significance of the interaction between price change information and people's expectations of future price change direction. In another word, different price change curves might cause consumers to have different expectations of future price change.

Since the interaction term was significant, the researcher then fit a multinomial regression model for people's expectations of price change directions, which predicted a set of probabilities for people expecting future price to increase, decrease, perform no change, or be unclear, respectively, when they were faced up with different price change curves (Table 4.20). Clearly, it could be observed that for the first and fourth price change groups (gradual increase and leaping decrease), people most likely would expect a price increase in the future (Pr = 0.64 and Pr = 0.46). For the second and the third price change groups (leaping increase and gradual decrease), people most likely tended to expect a price decrease in the future (Pr = 0.30 and Pr = 0.52). The effect of leaping pattern compared to gradual pattern thus was significant taking people's expectation of future price change direction as the response. Furthermore, this leaping effect was significant for both the increase and decrease trends. More specifically, we concluded that people had a lower expectation of future price in the price leaping increase case than in the price gradual increase case. People had a higher expectation of future price in the price leaping decrease case than in the price gradual decrease case. Previously, Hypothesis 1 was validated stating a positive correlation between expectations of future price and propensity to book (people having a higher expectation of future price had a higher propensity to book), and this positive correlation helped us here to indirectly support Hypothesis 2 about the significance and functioning of the leaping effect on propensity to book in different price trends.

Table 4.19
Summary of Surrogate log linear Regression for Expectations of Future Price Changing Direction (Q1)

	Intercept	G2	G3	G4	A2	A3
p value	< 2E-16	3.38E-06	9.01E-06	0.00684	2.18E-06	0.000735
	A4	G2:A2	G3:A2	G4:A2	G2:A3	G3:A3
p value	0.00033	0.000192	1.21E-06	0.001938	0.012781	NA
	G4:A3	G2:A4	G3:A4	G4:A4		
p value	NA	0.023035	0.076351	0.343971		

Note. “G” represents price change groups (gradual increase, leaping increase, gradual decrease and leaping increase), and “A” represents answer categories to the Q1 (“Increase”, “Decrease”, “Not Change”, and “Not Sure”).

Table 4.20
Probabilities from Multinomial Regression for Expectations of Future Price Changing Direction

Group	Probability Increase	Probability Decrease	Probability Not Change	Probability Not Sure
Gradual Increase	0.6410229	0.1153853	1.42E-10	0.2435919
Leaping Increase	0.2173941	0.3043654	0.217	0.2608647
Gradual Decrease	0.2499823	0.5208441	2.37E-05	2.37E-05
Leaping Decrease	0.4561329	0.3508948	0.0877	0.1052591

4.2.6 The Effect of Price Changes on Perceived Sell-Out Risk

Perceived sell-out risk (Q2), like expectations of getting a lower rate (Q4) was also a semi-quantitative ordinal variable ranging from a low level to a high level. The researcher first performed nonparametric analysis of variance and multiple comparisons for perceived sell-out risk, results of which were listed in Table 4.21. Unfortunately, the researcher did not see a difference in perceived sell-out risk between the gradual increase and leaping increase (observed difference < critical difference), or between the gradual decrease and the leaping decrease (observed difference < critical difference), which suggested that the leaping effect had an insignificant effect on consumers' perceived sell-out risk.

Table 4.21
Multiple Comparisons with perceived sell-out risk as the Response

Group Pair	Observed Difference	Critical Difference	Difference
Gradual Increase vs. Leaping Increase	9.584448	32.49322	FALSE
Gradual Increase vs. Gradual Decrease	37.144231	32.06458	TRUE
Gradual Increase vs. Leaping Decrease	5.256073	30.45723	FALSE
Leaping Increase vs. Gradual Decrease	27.559783	36.06389	FALSE
Leaping Increase vs. Leaping Decrease	4.328375	34.6426	FALSE
Gradual Decrease vs. Leaping Decrease	31.888158	34.24087	FALSE

Next the researcher analyzed perceived sell-out risk using the surrogate log linear regression. Table 4.22 summarizes the results of the finally fitted surrogate log linear regression model for perceived sell-out risk. The researcher noticed that the interaction terms were deleted after model selection, suggesting that the leaping effect was not significant for people's perceived sell-out risk, which was in accordance with the results of nonparametric multiple comparisons.

Table 4.22

Summary of Surrogate log linear Regression for Perceived sell-out Risk

	Intercept	G2	G3	G4
p value	< 2E-16	0.0045	0.00813	0.07186
	A2	A3	A4	A5
p value	0.73578	0.00857	0.50797	0.73578

4.3 Testing of Compounding Effects

In the survey, the research also had eight control variables, gathering some information about those who attended this survey. These control variables included age, income, travel experience, occupation, and income. The researcher was wondering whether these control variables had an interaction effect with the treatment variable characterizing the four price change curves. The surrogate log linear model again was appropriate here for this analysis. For simplicity, the researcher did not consider the interaction effects among these control variables, and the researcher analyzed these control variables one by one in combination with the treatment variable to form the predictor set. Expectations of future price, perceived sell-out risk and propensity to book were response variables and were dealt with one by one. The surrogate log linear models were fitted using the following scheme,

Freq ~ (Group +Ctrl +Group:Ctrl) + (Question + Question:Group + Question:Ctrl)

The first term in the parentheses characterized the covariate matrix, while the second term was fitting the interactions between the response variable (*Question*) with the covariate matrix.

It was found that the majority of the control question variables proved to have no significant effect on people's expectations of future price, perceived risk and propensity to book. The effects of several control variables seemed to be significant with respect to people's propensity to book. These variables included people's age, gender, and current employment status. Furthermore, the researcher obtained a significant effect of employment status on people's expectations of future price. Interestingly, income did not have a significant impact on consumers' propensity to book.

CHAPTER 5. CONCLUSION

5.1 Summary and Discussion of Findings

In collusion, this study has led to several major findings that can be summarized as follows:

1. Respondents with a higher expectation towards future price, or in another word with a lower expectation of getting a lower price had a higher propensity to book. Similarly, people with a higher perceived sell-out risk had a higher propensity to book.

2. As expected, there was a leaping effect on customers' expectations of future price, i.e. the leaping pattern had a stronger effect than the gradual pattern on people's perceptions and propensity to book. More specifically, there was a difference in expectations of future price between those who observed a leaping price change and those who observed a gradual price change pattern, regardless of the price trend they faced (either increase or decrease).

3. Surprisingly, observed leaping effects in both the increase and decrease price trends had no significant impact on consumers' perceived sell-out risk. However, the leaping effects did significantly impact people's expectation of future price. An explanation to

this unexpected discrepancy could be that, when the price performs a leaping change, the strength of the price information provided to consumers becomes much higher, thus drawing more of people's attention from sell-out-risk to expected future price. This less attention on sell-out-risk mitigates the leaping effect on people's perceived risk.

4. In contrast to Chen and Schwartz's (2008a) findings, results of the present study demonstrated that customers facing a gradual price change had different attitudes toward perceived sell-out risk when they experienced different price trends. More specifically, people's perceived sell-out risk was lower in gradual increase compared to gradual decrease. This discrepancy may have stemmed from the buying game set in the experiment with a closer time distance to the real check-in date. Compared to the respondents studied by Chen and Schwartz (2008a), respondents may have had a different prediction about the room demand due to this timing issue.

5. Findings confirmed that people's propensity to book depended on both the observed price trend and pattern. More specifically, people who experienced a price decrease with a leaping discount had the highest propensity to book, followed by those who observed a gradual price increase, followed by those who observed a gradual price decrease, and last followed by those who observed prices with a leaping increase. Explanations for this finding may have been the following, (i) the leaping discount had the greatest impact on customers' cognition, which accelerated the booking decision, and (ii) a sharp leaping price increase brought the highest psychological price to customers, heavily strengthening customers' wait-and-see attitude.

6. The difference between the effects of leaping and gradual patterns on propensity to book was significantly stronger in a price decrease trend than in a price increase trend.

5.2 Theoretical Implications

The present study compensated for the extant literature about people's perceived risks and propensity to book toward hotel dynamic pricing strategies. Some important implications have been drawn from the findings. First, findings of this study agreed with Chen and Schwartz (2008a), which showed that consumers' perceived sell-out risk and expectations of future price could influence their propensity to book. This indicated for future researchers the importance to study consumers' perceptions together with their booking decisions.

Second, this study was theoretically important in that it was designed to investigate how different price trends and patterns together impact customers' perceived risks and booking decisions with respect to hotel online booking in a more realistic price change situation. Importantly, neither price change patterns nor price change trends could play a decisive role individually in the real commercial environment system.

Third, Alba et al.'s study (1999) only showed that the price pattern of leaping decrease would lead to a lower perceived price than that caused by the price pattern of gradual decrease. This study not only extended former studies by considering the price increase situation, but also explored how people's final buying decisions would be effected by different price change patterns.

Fourth, different from what was suggested by the prospect theory, findings of this study agreed with Chen and Schwartz (2008a), which showed that price change trends do not have a significant impact on consumers' propensity to book for gradual patterns. This finding may suggest that the prospect theory might be not applicable to study different price change trends' implication on consumers' propensity to book when price change gradually.

Finally, the present study expanded extant research about price change patterns by investigating price change patterns of service products with future consumptions considering an online consumption environment.

In summary, this study filled some gaps on extant researches about price change patterns. All the findings can be helpful for future researcher to further investigate the diversity affected by multifarious price change modalities.

5.3 Practical Implications

The main implication of the present study was linked with revenue management: the service providers' (hotels in this case) dynamic pricing strategies in an Internet-using environment. Findings suggest that the impact of price changing trends and patterns that hotels quote to their customers over time is an additional element hotels need to consider provided that they attempt to affect customers' expectations about future price, sell-out risk, and as a result the final purchase decisions. On the other hand, findings of this study are also useful to travelers.

5.3.1 Choose the Correct Change Pattern for Different Price Change Trends

Leaping patterns have stronger effects on consumers' propensity to book compared to gradual patterns. However, the effect works oppositely for price increase and decrease. Findings of this study can help hotels to choose the correct change pattern for different price change trends.

Specifically, (i) if a hotel wants to increase customers' perceived risks by rising room rates, so that customers tend to make more prompt booking decisions, it should increase the price gradually; (ii) on the contrary, if a hotel wants to stimulate consumption though price decrease, it should make the price decrease apparent and drastic so that consumers will make their booking decisions immediately because they consider the possibility of getting a lower price in the near future to be very low.

Furthermore, findings of this study showed that, for gradual patterns, there was no significant difference in consumers' propensity to book between price increasing and decreasing. As a result, if a hotel wants to maximize the profit without changing its room rates dramatically, it should choose to increase but not decrease its room rates.

5.3.2 Affect Consumers' Propensity to Book through Information Control

For gradual patterns, findings showed that there was no significant difference in propensity to book between price increasing and decreasing. However, if a hotel still wants to decrease the price gradually, it should emphasize the low capacity information and/or indicate that the possibility to get a lower price in the future is very low (e.g., give evidence that the market price is increasing).

For leaping patterns, findings suggested that, when the price information provided to costumers was strong enough (e.g. via a leaping change), consumers' attention could be drawn from capacity information to intense price information. Hence, when using leaping patterns, hotels should emphasize the low capacity information to increase consumers' perceived sell-out risk. Additionally, if hotels choose to increase their price using leaping patterns, they should also emphasize that the chance to get a lower price is low.

5.3.3 Other Ways to Increase Propensity to Book

Findings of this study showed that it sometimes could be very hard for hotels to effectively control consumers' expectations of future price and capacity during price changes. Hence, it is important for hotels to find other ways to influence consumers' perceptions and, consequently their propensity to book. For instance, hotel can influence consumers' perceived fairness towards given prices. Hotels can offer evidence showing that they are offering a lower price than competitors and market. Hotels can also emphasize other information like higher qualities and better services about the room to make consumers think the price is fair enough.

5.3.4 Travelers

Before making a final hotel room booking decision, customers should try to get more relevant information about the hotel itself, to spend some time on comparing prices of the alternatives in the market with the convenience introduced by the Internet, and to make decisions based on rational assessment and consideration rather than oversimplified observations of price changes. Hotel management uses all possible methods with all best efforts to achieve higher profit. For hotels, dynamic pricing strategy is definitely one of the most pervasive and effective approaches to achieve the profit goals. By changing price of the same room over time in many different ways, hotels want customers to feel the implicit shortage of supply and/or a future higher price; then customers can make the booking decision in the way they were expected to.

5.4 Limitations and Future Research

Since the study was conducted on a university campus and many respondents were students, the sample size was not extensive and a population bias may occur. Future study could try to raise a sample with a larger sample size and a more comprehensive participant base.

In the original experimental design of the study, to consecutively capture consumers' perceived risks in a circumstance more closely to reality, the researcher designed a simulative hotel room booking website based on the experiments from Chen and Schwartz's study (2008a). The researcher planned to perform a buying game experiment for seven consecutive days. However, the experiment did not follow the plan for various reasons. Future research could adopt this approach if possible.

There were some limitations for the instrument design. The hotel setting for the questionnaire of the experiment was mid-scale. Situations could be very different for other types of hotels: different hotels have various targeted customer groups with potentially differing psychological acceptance and awareness. Additionally, “mid-scale” and “3-star” were both mentioned in the scenario setting section, they could be confusing for some participants who might think that mid-scale hotels are more likely to be “4-star” ones. The length of stay could also be an important factor affecting people’s attitudes and cognition toward price changes; consequently, perceived risks may develop. It could be interesting for future researcher to take more possible factors into account and explore other possible outcomes.

Additionally, although the researcher brought different price change patterns in a more comprehensive manner to current studies regarding how price changes affect customers’ perceptions and propensity to book, the price changes in the real market environment remain more complex. Future research could gradually increase the multiplicity and complexity of actual price changes.

The study did not explore the causal relationships between people’s perceptions and booking intention. In the present study, booking intention was designed to be a binary variable. In future studies, booking intention could be measured as a continuous variable for the purpose of robust testing purpose.

Finally, the study focused on helping to understand customers' perceptions and propensity to book. However, facing a real booking choice, customers may exhibit different buying behavior due to the complexity and difficulty of situations in the real buying environment. This could be an interesting direction for future studies.

REFERENCES

REFERENCES

Almanza, B. A., Jaffe, W., & Lin, L. (1994). Use of the service attribute matrix to measure consumer satisfaction. *Journal of Hospitality & Tourism Research*, *17*(2), 63-75.

Alba, J. W., Mela, C. F., Shimp, T. A., & Urbany, J. E. (1999). The effect of discount frequency and depth on consumer price judgments. *Journal of Consumer Research*, *26*(2), 99-114.

Ariely D. (2008). *Predictably irrational - The hidden forces that shape our decisions.* New York, NY: Harpercollins

Bagll, K., & Riordan, M. H. (1991). High and declining prices signal product quality. *The American Economic Review, 81*(1), 224-239.

Bettman, J. R. (1973). Perceived risk and its components: a model and empirical test. *Journal of marketing research, 10*(2), 184-190.

Biller, S., Chan, L. M. A., Simchi-Levi, D., & Swann, J. (2005). Dynamic pricing and the direct-to-customer model in the automotive industry. *Electronic Commerce Research, 5*(2), 309-334.

Bitran, G. R., & Mondschein, S. V. (1995). An application of yield management to the hotel industry considering multiple day stays. *Operations Research, 43*(3), 427-443.

Bitta, A. J. D., Monroe, K. B., & McGinnis, J. M. (1981). Consumer Perceptions of Comparative Price Advertisements. *Journal of Marketing Research, 18*(4), 416-427.

Carroll B., & Siguaw, J. (2003). The evolution of electronic distribution: Effect on hotels and intermediaries. *Cornell Hotel and Restaurant Administration Quarterly, 44*(4), 38–50.

Chen, C., & Schwartz, Z. (2006). The Importance of Information Asymmetry in Customers' Booking Decisions A Cautionary Tale from the Internet. *Cornell Hotel and Restaurant Administration Quarterly, 47*(3), 272-285.

Chen, C., & Schwartz, Z. (2008a). Room rate patterns and customers' propensity to book a hotel room. *Journal of Hospitality & Tourism Research, 32*(3), 287-306.

Chen, C. C., & Schwartz, Z. (2008b). Timing matters: Travelers' advanced-booking expectations and decisions. *Journal of Travel Research, 47*(1), 35-42.

Chen, C., Schwartz, Z. & Vargas, P. (2011). The search for the best deal: How hotel cancellation policies affect the search and booking decisions of deal-seeking customers. *International Journal of Hospitality Management, 30*(1), 129-135.

Chen, D., & Freimer, M. (2004). Understanding the bid price approach to revenue management: A case of the Revenue Inn. In I. Yeoman & U. McMahon-Beattie (Eds.), *Revenue management and pricing: Case studies and applications* (pp. 174-183). London: Thomson.

Chiang, W. C., Chen, J. C. H., & Xu, X. (2007). An overview of research on revenue management: current issues and future research. *International Journal of Revenue Management, 1*(1), 97-128.

Choi, S., & Mattila, A. S. (2004). Hotel revenue management and its impact on customers' perceptions of fairness. *Journal of Revenue and Pricing Management, 2*(4), 303-314.

Dolan, R. J., & Moon, Y. (2000). Pricing and market making on the Internet. *Journal of Interactive Marketing, 14*(2), 56-73.

Dowling, G. R. (1986). Perceived risk: the concept and its measurement. *Psychology & Marketing, 3*(3). 193-210.

Dowling, G. R., & Staelin, R. (1994). A model of perceived risk and intended risk-handling activity. *Journal of consumer research, 21*(1), 119-134.

Fischhoff, B., Bostrom, A. & Quadrel, M. J. (1993) Risk perception and communication. *Annual review of public health, 14*(1). 183-203.

Gallego, G., & Van Ryzin, G. (1994). Optimal dynamic pricing of inventories with stochastic demand over finite horizons. *Management Science, 40*(8), 999-1020.

Heien, D. M. (1980). Markup pricing in a dynamic model of the food industry. *American Journal of Agricultural Economics, 62*(1), 10-18

Huang, J. H., Chang, C. T., & Chen, C. Y. H. (2005). Perceived fairness of pricing on the internet. *Journal of Economic Psychology, 26*(3), 343-361.

Horgen, K. B., & Brownell, K. D. (2002). Comparison of price change and health message interventions in promoting healthy food choices. *Health Psychology, 21*(5), 505.

Jang, S. (2004). The past, present, and future research of online information search. *Journal of Travel & Tourism Marketing, 17*(2-3), 41-47.

Jedidi, K., Mela, C. F., & Gupta, S. (1999). Managing advertising and promotion for long-run profitability. *Marketing science, 18*(1), 1-22.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1986). Fairness and the assumptions of economics. *Journal of business, 59*(4), 285-300.

Karpoff, J. M. (1987). The relation between price changes and trading volume: A survey. *Journal of Financial and Quantitative Analysis, 22*(1), 109-109.

Kimes, S. E. (1994). Perceived fairness of yield management. *The Cornell Hotel and Restaurant Administration Quarterly, 35*(1), 22-29.

Lynch Jr, J. G., & Zauberman, G. (2006). When do you want it? Time, decisions, and public policy. *Journal of Public Policy & Marketing, 25*(1), 67-78.

McAfee, R. P., & Te Velde, V. (2006). Dynamic pricing in the airline industry. Forthcoming in Handbook on Economics and Information Systems, Ed: TJ Hendershott, Elsevier.

Maglaras, C., & Meissner, J. (2006). Dynamic pricing strategies for multiproduct revenue management problems. *Manufacturing and Service Operations Management 8*(2), 136-148.

Manzumdar, T., & Jun, S. Y. (1993). Consumer Evaluations of Multiple Versus Single Price Change. *Journal of Consumer Research, 20*(3), 441-450.

Mazumdar, T., Raj, S. P., & Sinha, I. (2005). Reference price research: Review and propositions. *Journal of Marketing, 69*(4), 84-102.

Mela, C. F., Jedidi, K., & Bowman, D. (1998). The long-term impact of promotions on consumer stockpiling behavior. *Journal of Marketing Research, 35*(2), 250-262.

Murphy, J., Forrest, E. J., Wotring, C. E., & Brymer, R. A. (1996). Hotel Management and Marketing on the Internet An Analysis of Sites and Features. *Cornell Hotel and Restaurant Administration Quarterly, 37*(3), 70-82.

Oh, H. (2003). Price fairness and its asymmetric effects on overall price, quality, and value judgments: the case of an upscale hotel. *Tourism Management, 24*(4), 387-399.

O'Connor, P., and Frew, A. J. (2002). The future of hotel electronic distribution: expert and industry perspectives. *The Cornell Hotel and Restaurant Administration Quarterly, 43*(3), 33-45.

Phillips, R. Z. (2005). *Pricing and revenue optimization.* Redwood City, CA: Stanford University Press.

Schwartz, Z., & Chen, C. (2010). The peculiar impact of higher room rates on customers' propensity to book. *International Journal of Contemporary Hospitality Management, 22*(1), 41-55.

Schwartz, Z. and Chen, C. (2010b). Advanced Booking Decisions of Risk-Averse, Deal-Oriented Travelers. *Journal of Hospitality Marketing & Management, 19*(2), 188-197.

Schwartz, Z. (2000). Changes in hotel guests' willingness to pay as the date of stay draws closer. *Journal of Hospitality & Tourism Research, 24*(2), 180-198.

Schwartz, Z. (2006a). Advanced booking and revenue management: room rates and the consumers' strategic zones. *International Journal of Hospitality Management, 25* (3), 447-62.

Schwartz, Z. (2006b). Revenues and asymmetric information: How uncertainty about service quality and capacity management affect optimal advanced booking pricing. *Journal of Quality and Assurance in Hospitality & Tourism, 7*(4), 1-22.

Schwartz, Z. (2008). Time, Price, and Advanced Booking of Hotel Rooms. *International Journal of Hospitality & Tourism Administration, 9*(2), 128-146.

Shirai, M., & Bettman, J. R. (2005). Consumer expectations concerning timing and depth of the next deal. *Psychology & Marketing, 22*(6), 457-472.

Talluri, K. T., & Van Ryzin, G. J. (2005). *The theory and practice of revenue management*. New York, NY: Springer.

Thaler, R. (1985). Mental accounting and consumer choice. *Marketing science, 4*(3), 199-214.

Walle, A. H. (1996). Tourism and the Internet opportunities for direct marketing. *Journal of travel research, 35*(1), 72-77.

Weatherford, L. R., & Kimes, S. E. (2003). A comparison of forecasting methods for hotel revenue management. *International Journal of Forecasting, 19*(3), 401-415.

Weber, K., & Roehl, W. S. (1999). Profiling people searching for and purchasing travel products on the World Wide Web. *Journal of Travel Research, 37*(3), 291-298.

Wei, S., Ruys, H. F., van Hoof, H. B., & Combrink, T. E. (2001). Uses of the Internet in the global hotel industry. *Journal of Business Research, 54*(3), 235-241.

APPENDICES

Appendix A Cover Letter of Questionnaire

PURDUE UNIVERSITY

DEPARTMENT OF HOSPITALITY
AND TOURISM MANAGEMENT

Dear Participant:

Thank you for your participation in the study. This research is conducted by Zhuoyang Li, a Master student in the department of Hospitality and Tourism Management, Purdue University, for her thesis.

Your participation is very important in helping us to understand the consumer behavior in the hospitality industry. You participation and responses will be kept confidential until the completion of the study, at which time all data will be destroyed. Participants will not be able to search or deduct the information and participation of other participants in this survey.

The survey would take about 10 minutes. You may work on the questions at your own pace. You will not be asked to provide any personal identification information. You answers are anonymous; DO NOT put your name on the survey. Your responses will be seen only by the researcher. By completing the questions you are agreeing to participate in the research. Your participation is totally voluntary.

Questions or concerns about the questionnaire may be directed to Zhuoyang Li (li923@purdue.edu). You may also contact my thesis advisor, Hugo Tang (tang14@purdue.edu).

Additional questions or problems regarding your rights as a research participant should be addressed to Human Research Protection Program, Purdue University, Ernest C.

Young Hall 10^{th} Floor, Room 1032, 155 S. Grant Street, West Lafayette, Indiana 47907-2114; Phone: 765-494-5942; Email: irb@purdue.edu.

Thank you for your time and consideration.

Sincerely,

Zhuoyang Li

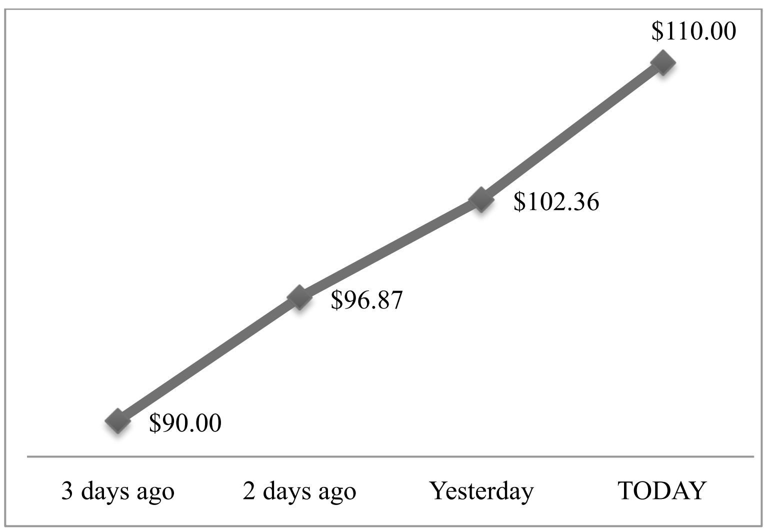
Student Researcher

Appendix B Example of Questionnaires

You had been planning a trip that will start after a week from today. You finally decided to book a room with Spring Creek Hotel on it's website.

Spring Creek Hotel is a full-service midscale hotel with amenities, service convenience and ambiance you can find in a typical 3-star hotel.

You have been checking the room rate in the past three days. The chart below shows the prices you have observed up to today. Based on the price trend you have observed, please answer the following questions.



1.I think the room price will _____ after today.

- increase
- decrease
- not change
- not sure

2. I think the chance that the rooms will be sold out from today to the check-in date is ___.

- Very Low
- Low
- 50%-50%
- High
- Very High

3. How fair do you think today's price is?

- Very Unfair
- Somewhat Unfair
- Neither Fair nor Unfair
- Somewhat Fair
- Very Fair

4. I think the chance to get a lower rate from today to the check-in date is ____.

- Very Low
- Low
- 50%-50%
- High
- Very High

5. You have to check in one week from today. Do you want to book the room today?

- Yes
- No, I'll keep waiting

6. How often do you travel in a year?

- 1~5 times
- 6~10 times
- 10~15 times
- More than 15 times

7. How often do you get information about hotel room via Internet in a year?

- 1~5 times
- 6~10 times
- 10~15 times
- More than 15 times

8. How often do you use the Internet to book a hotel room?

- Never
- Less than a half of my trips
- Half of my trips
- More than half of my trips
- All of my trips

9. How much time you'd like to spend on searching hotel room information before your final booking decision?

- 1 hour
- 2-3 hours
- 4-6 hours
- 7-10 hours
- Longer than 10 hours

10. What's your age?

- 18-25
- 26-35
- 36-45
- 46-55
- 56-64

11. What's your gender?

- Male
- Female

12. What's your current employment status? (Check all that apply)

- o Student
- o Employed (part-time)
- o Employed (full-time)
- o Retired
- o Taking care of the home
- o Others: please specify____________

13. What's your approximate yearly income?

- o less than $15,000
- o $15,000 to $24,999
- o $25,000 $49,999
- o $50,000 to $74,999
- o $75,000 to $99,999
- o $100,000 to $149,999
- o $150,000 or more