OVERBOOKING PRACTICES IN THE HOTEL INDUSTRY AND THEIR IMPACT ON HOTELS' FINANCIAL PERFORMANCE

by

Arash Riasi

A dissertation submitted to the Faculty of the University of Delaware in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Financial Services Analytics

Summer 2018

OVERBOOKING PRACTICES IN THE HOTEL INDUSTRY AND THEIR IMPACT ON HOTELS' FINANCIAL PERFORMANCE

by

Arash Riasi

Approved: ______________________________

Bintong Chen, Ph.D.

Director of the Institute for Financial Services Analytics

Approved: ______________________________

Bruce W. Weber, Ph.D.

Dean of the Lerner College of Business and Economics

Approved: ______________________________

Douglas J. Doren, Ph.D.

Interim Vice Provost for the Office of Graduate and Professional Education

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ____

Zvi Schwartz, Ph.D.

Professor in charge of dissertation

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ____

Srikanth Beldona, Ph.D.

Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ____

Michael Collins, Ph.D.

Member of dissertation committee

I certify that I have read this dissertation and that in my opinion it meets the academic and professional standard required by the University as a dissertation for the degree of Doctor of Philosophy.

Signed: ____

Sandeep Patel, Ph.D.

Member of dissertation committee

ACKNOWLEDGMENTS

I would like to dedicate this dissertation to my wife, Shirin, who has been a constant source of support and encouragement during my PhD studies. I am truly thankful of having you in my life.

This work is also dedicated to my parents and my brother, who have always supported me and taught me to work hard for the things that I aspire to achieve.

I would like to sincerely thank my dissertation advisor, Dr. Schwartz, for his guidance, patience, support, and immense knowledge.

TABLE OF CONTENTS

LIST OF TABLES ……………………………………………………………..……... ix
LIST OF FIGURES ………………………………………………………..….....….. xi
ABSTRACT ……………………………………………………………..…..……. xii

Chapter

1 INTRODUCTION ……………………………………………...………….. 1

1.1 Overbooking in Service-Related Industries ……………………..……………. 1
1.2 Purpose of the Study ……………………………………………….………..... 7
1.3 Significance of the Study ……………………………………….……….....…… 10
1.4 Organization of the Dissertation ……………………………......………. 11

2 REVIEW OF THE LITERATURE ……………………………...……..…….. 12

2.1 Different Approaches to Overbooking ……………………………..…………... 12
2.2 Overbooking in Hotel Industry ……………………………………………..…..… 16

2.2.1 Overbooking and Room Allocation ………………………………. 19
2.2.2 Overbooking Level Optimization ………………...………………. 21
2.2.3 Static and Dynamic Overbooking Limits ……………….………… 25
2.2.4 Overbooking and Denied Service …………………………………. 27
2.2.5 Overbooking and Online Distribution Channels ………………….. 32
2.2.6 Ethical and Legal Considerations Surrounding Overbooking …….. 34
2.2.7 Overbooking Costs …………………………………………...…… 36
2.2.8 Cost Savings of Overbooking ……………………………………...… 41

2.3 Cancellations and Overbooking ……………………………..………… 42

2.4 Literature Gaps ……………………………………………………………...…. 45

2.4.1 Overbooking and Room Allocation ……………………...………. 46
2.4.2 Overbooking Level Optimization ………………………..…….. 47
2.4.3 Static and Dynamic Overbooking Limits …………………………. 48
2.4.4 Overbooking and Denied Service …………………………………. 49
2.4.5 Overbooking and Online Distribution Channels ………..………… 51
2.4.6 Ethical and Legal Considerations Surrounding Overbooking …..… 51
2.4.7 Overbooking Costs …………………………………………….... 52
2.4.8 Cost Savings of Overbooking ……………………………...…… 53
2.4.9 Hotel Cancellation Policies and Overbooking Practices ……..…… 54

2.5 Literature Gaps Addressed in this Study ……………………….……… 54

3 CONCEPTUAL MODEL ………………………………………………….… 56

3.1 Introduction …………………………………………………………… 56
3.2 Data Availability and Overbooking …………………………………… 57
3.3 Data Availability and Financial Performance ………………………… 59
3.4 Overbooking and Financial Performance …………………………….... 62
3.5 Cancellation Policies and Overbooking ……………………………….. 64
3.6 Denied Service and Satisfaction ……………………………………….. 66
3.7 Cancellation Policies and Financial Performance …………………….... 68
3.8 Summary of Research Hypotheses and Conceptual Model …………………. 72

4 METHODOLOGY ………………………………………………………... 74

4.1 Data Collection Procedure …………………………………….………. 74

4.1.1 Cancellation Policies Data Set ………………………….……… 74
4.1.2 Overbooking Policies Data Set ………………………….……… 80

4.2 Performance Measures ……………………………………………… 86

4.2.1 Occupancy Rate ………………………………………………………... 86
4.2.2 Occupancy Index ……………………………………………………. 86
4.2.3 Average Daily Rate (ADR) ……………………………………….. 87
4.2.4 ADR Index …………………………………………………………... 88
4.2.5 Revenue Per Available Room (RevPAR) ……………….……… 89
4.2.6 RevPAR Index ………………………………………………………… 90

4.3 Data Cleaning …………………………………………………..……… 92

4.3.1 Cleaning the Cancellation Policies Data Set ……………………… 92
4.3.2 Cleaning the Overbooking Policies Data Set ………………..…….. 93

4.4 Data Analysis Techniques ……………………………………………... 93

4.4.1. Analysis of Variance (ANOVA) …………………………………. 94
4.4.2 Kruskal-Wallis Test ………………………………………………. 95
4.4.3 Independent Samples T Test …………………………………… 96
4.4.4 Mann-Whitney Test ………………………………………………. 97
4.4.5 Stepwise Multiple Regression Analysis ...………………………… 97
4.4.6 Multivariate Multiple Regression Analysis ………………….……. 98
4.4.7 Spearman Correlation Test ……………………………….…….. 99

5 RESULTS AND DISCUSSION ………………………………...………….. 100

5.1 Sample Characteristics …………………………………………..…… 100

5.1.1 Sample Characteristics for Cancellation Policies Data Set ………. 100
5.1.2 Sample Characteristics for Overbooking Policies Data Set …...…. 101

5.2 State of Cancellation Policies ……………………………...……………. 103
5.3 State of Overbooking Policies ………………………...………………… 106
5.4 Results of Hypothesis Testing ……………………………………...… 109

5.4.1 Hypothesis H1b 109
5.4.2 Hypothesis H3b 111
5.4.3 Hypothesis H2 116
5.4.4 Hypothesis H1c 129
5.4.5 Hypothesis H3c 132
5.4.6 Hypothesis H1a 134
5.4.7 Hypothesis H3a 137

6 CONCLUSIONS 141

6.1 Summary of Findings and Implications 141
6.2 Research Limitations 145
6.3 Directions for Future Research 147

REFERENCES 149

Appendix

A DATA COLLECTION INSTRUCTIONS FOR CANCELLATION DATA 171
B IRB REVIEW RESULT 178
C SURVEY RECRUITMENT EMAIL 179
D OVERBOOKING POLICIES SURVEY 181

LIST OF TABLES

Table 4.1: Variables in the cancellation policies data set ……………………………….. 77

Table 4.2: Variables in the overbooking policies data set ……………………………… 82

Table 5.1: Hotel characteristics – cancellation policies data set …………………...…... 101

Table 5.2: Hotel characteristics – overbooking policies data set ……………...……….. 103

Table 5.3: State of cancellation policies in the US hotel industry as of April 2017 …… 106

Table 5.4: State of overbooking policies in the US hotel industry as of February 2018 . 108

Table 5.5: Stepwise multiple regression results for H1b ………………….…………… 110

Table 5.6: Stepwise multiple regression results for H3b ………………….…………… 115

Table 5.7: Stepwise multiple regression results for H2 ………………………….…….. 127

Table 5.8: Stepwise multiple regression results for H1c ……………………….……… 131

Table 5.9: Stepwise multiple regression results for H3c ……………………….……… 133

Table 5.10: Multivariate multiple regression results for H1a ……………………….…. 136

Table 5.11: Multivariate multiple regression results for H3a ………………………….. 139

Table A.1: Free cancellation window choices …………………………………………. 172

Table A.2: Cancellation penalty choices ………………………………………………. 174

Table A.3: Prepayment refund choices ……………………………..………………. 175

LIST OF FIGURES

Figure 3.1: Conceptual model ……………………………………………….…………….. 73

Figure 5.1: Average RevPAR index values across different cancellation windows ….... 112

Figure 5.2: Average RevPAR index values across different cancellation penalties …… 113

Figure 5.3: Average RevPAR index for hotels that overbook versus those that never overbook …………......……………………………..………... 117

Figure 5.4: Average RevPAR index across different overbooking frequencies ……….. 118

Figure 5.5: Average RevPAR index across different overbooking approaches ……..….. 120

Figure 5.6: Average RevPAR index by most common overbooking day ……………… 121

Figure 5.7: Average RevPAR index across different levels of maximum overbooking limit …………………...…………………………………… 123

Figure 5.8: Average RevPAR index for hotels with static vs. dynamic overbooking …. 124

ABSTRACT

Hotel overbooking occurs when the number of rooms available for reservation exceeds the capacity. Hotels overbook with the goal of maximizing their revenue and improving their profitability. Despite its prevalence, many aspects of the hotel overbooking have never been researched. This study provides a clear picture of the current state of overbooking in the US hotel industry and explores the relationship between overbooking practices, cancellation policies, data availability and financial performance.

Two data sets were used to answer the research questions. For the first data set, a group of data collectors recorded the cancellation policies of nearly 600 US hotels by manually checking their websites and going through the reservation process. For the second data set, a survey was distributed among a random sample of 10,000 US hotels asking them about different aspects of their overbooking policies. A survey response rate of 3.77% was achieved. Following data cleaning, the overbooking data set contained 365 hotels while the cancellation policies data set contained 492 hotels. After anonymizing the hotels, their performance indicators were added to the data sets. Analysis of Variance (ANOVA), independent samples T Test, Kruskal-Wallis test, Mann-Whitney test, Spearman correlation, stepwise multiple linear regression and multivariate multiple regression were the statistical methods used in this study.

Results indicated that overbooking (vs. not overbooking) results in better hotel performance. Among the four major overbooking approaches (i.e., deterministic, risk-based, service-level and hybrid), findings indicated that risk-based overbooking results in the highest RevPAR index values. It was also found that keeping overbooking limit at minimum (i.e., less than 5% of capacity) and overbooking frequency at moderate levels (i.e., 6-10 days in a month) results in the best performance, while excessive overbooking (i.e., more than 10% of capacity and/or more than 20 days in a month) could result in lower RevPAR index values. Data analysis revealed that neither data availability nor cancellation policy can moderate the relationship between the four major overbooking approaches (i.e., deterministic, risk-based, service-level and hybrid) and the RevPAR index. Finally, analysis of the cancellation policies data indicated that moderate cancellation policies are associated with better performance.

Chapter 1

INTRODUCTION

1.1 Overbooking in Service-Related Industries

Overbooking is the process in which a “seller with a constrained capacity sells more units than he has available or believes he will have available” (Phillips, 2005). Despite its benefits in terms of revenue maximization and profit augmentation, overbooking have always been a controversial revenue management tool in service-related industries (Krawczyk et al., 2016). Although overbooking was originally considered as a revenue management tool for improving the capacity utilization in the airline industry, it is now being practiced in many industries and has been researched in various settings including the hotels (e.g., Baker & Collier, 1999; Capiez & Kaya, 2004; Corney, 1984; Dong & Ling, 2015; Enghagen, 1996; Guo et al., 2014, 2016; Hadjinicola & Panayi, 1997; Hwang & Wen, 2009; Ivanov, 2006, 2007, 2015; Koide & Ishii, 2005; Lambert et al., 1989; Lefever, 1988; Liberman & Yechiali, 1978; McCollough, 2000; Noone & Lee, 2011; Phumchusri & Maneesophon, 2014; Rothstein, 1974; Sparks & Fredline, 2007; Talluri & van Ryzin, 2004; Toh & Dekay, 2002; Williams, 1977; Wilson et al., 1994, 1995; Wirtz et al., 2003), airlines (e.g., Gosavii et al., 2002; Karaesmen & van Ryzin, 2004; Klophaus & Pölt, 2007; Rothstein, 1985; Shlifer & Vardi, 1975;

Suzuki, 2002, 2006; Williamson, 1992), car rentals (e.g., Carroll & Grimes, 1995; Geraghty & Johnson, 1997), restaurants (e.g., Kimes, 2005; Tse & Poon, 2016), cruise lines (e.g., Li, 2014; Toh et al., 2005), golf courses (Kimes, 2000), health care providers (e.g., Kim & Giachetti, 2006; LaGanga & Lawrence, 2007, 2012; Lee et al., 2013), computer networks (e.g., Milbrandt et al., 2006; Zhao & Chen, 2007), grid computing (e.g., Sulistio et al., 2008; Urgaonkar et al., 2002), etc.

An airline selling seats in excess of its aircraft's capacity, a restaurant accepting reservations in excess of its table capacity, a car rental company renting more cars than it has available, a hotel or a cruise line accepting reservations in excess of their room capacity, a golf course accepting more reservations than its capacity, a medical clinic accepting more patients than its resource availability, and even a computer network accepting more users than its actual computing capacity are all examples of overbooking practices. Service providers claim that they overbook because there is a possibility for cancellations and no-shows (Phillips, 2005; Toh et al., 2005; Wilson et al., 1994). In other words, the sellers claim that by overbooking they are trying to guarantee themselves against revenue losses that might occur due to cancellations and no-shows (Klophaus & Pölt, 2007). However, this might not be always the case based on the real-world overbooking practices. In fact, many service providers still overbook even though they have the strictest cancellation and no-show policies that ensure them full protection against revenue losses. Therefore, it is more accurate to say that service providers overbook in order to increase their revenues and profits rather than merely protecting themselves against revenue losses.

The overbooking problem should be examined in conjunction with revenue management practices (Hadjinicola & Panayi, 1997; Kimes, 1989). Revenue management is considered as a set of tools for maximizing the revenue or profit (Belobaba, 1989; Karaesmen & van Ryzin, 2004) by enabling the firm to sell the right inventory unit to the right type of customer, at the right time and for the right price (Choi & Kimes, 2002; Hadjinicola & Panayi, 1997; Ivanov, 2015; Kimes, 1989). In fact, a good revenue management system can help a business to effectively manage its pricing and capacity allocation (Belobaba, 1989; Karaesmen & van Ryzin, 2004). Good revenue management also helps decision makers to determine how much from each type of inventory (whether it be seats on an airplane, rooms in a hotel or a cruise, cars in a car rental facility, tables in a restaurant, operation rooms in a hospital or network capacity on a server) should be allocated to different types of demand (Kimes, 1989). When revenue managers allocate units to different types of demand or when they try to determine unit prices, they need to consider the probabilities of no-shows and cancellations and they must think about overbooking possibilities. In other words, revenue managers should consider overbooking opportunities at every step of unit pricing and allocation. Additionally, revenue management controls should be utilized in order to determine which segments should be overbooked and to what extent. Despite the interconnectedness of revenue management and overbooking, there is a subtle distinction between overbooking and the core pricing and capacity control problems that revenue managers deal with on a daily basis. Overbooking is mostly focused on calculating the maximum number of reservations or bookings in excess of the actual capacity in order to increase the revenue and profitability rather than optimizing the mix of demand which is the goal of most revenue management systems (Klophaus & Pölt, 2007; Talluri & van Ryzin, 2004).

Overbooking in service-related industries occurs due to both perishability of services (i.e., inability to store service capacity for future sales) and simultaneous production and consumption (i.e., coproduction) (McCollough, 2000). It is known that a necessary condition for revenue management systems to work is the perishability of the product or service (Schwartz, 1998). Hospitality industry is highly impacted by the perishable nature of its services. For instance, any hotel room not sold for a given night cannot be inventoried and resold later (Baker & Collier, 1999). Similarly, in the airline industry, where the perishable assets are the flight seats, no revenue can be gained from the empty seats once an airplane departs (Baker & Collier, 1999). Therefore, a room in a hotel or a seat on a flight that is not filled represents lost revenue for the firm. This perishability feature incentivizes service providers to engage in revenue management practices such as overbooking to avoid the loss of revenue, maximize their capacity utilization, and increase their profitability. Another service feature that necessitates the use of overbooking is simultaneous production and consumption (aka coproduction). For instance, a restaurant or a hotel is partially dependent on the customers' effort to deliver a high-quality service. In other words, the overall service quality will be negatively impacted if the customers fail in their coproduction efforts (McCollough, 2000). In the restaurant example, the coproduction failure occurs when a customer who reserved a table fails to show up to complete his/her purchase. Similarly, if a customer who reserved a hotel room does not show-up or cancel the reservation at the last minute, the coproduction fails. In the restaurant case, there is typically no penalty for not showing up and the loss of revenue cannot be avoided unless the restaurant overbooks or receives enough walk-ins. In the hotel case, although there might be some sort of penalty for cancellations or no-shows in order to cover the loss of revenue, the capacity will not be maximally utilized unless the hotel overbooks and fills the empty rooms with guests. Interestingly, if the restaurant is oversold (i.e., number of customers who show up exceed the restaurant's capacity), customers who failed in the coproduction by not showing up will not bear the penalty for their actions while customers who completed their purchase and showed up will be discomforted by experiencing long wait times until tables become available for them (Kimes, 2005). Similarly, if the hotel is oversold, guests who successfully participated in the coproduction process by showing up at the hotel to complete their reservations will be discomforted by being denied service (McCollough, 2000).

Without overbooking, a large portion of revenue for businesses that carry the risk of cancellations and no-shows will be diminished and their profitability will be negatively impacted. However, overbooking may result in overselling, meaning that the number of overbooked units might exceed the actual number of cancellations or no-shows (Rothstein, 1985). In this case, the seller will be unable to service some of its customers and will need to either deny them or provide them with an alternative service. For instance, if due to overbooking, the number of flight passengers who show-up at the gate with a valid ticket exceeds the capacity of the airplane, the airline should either deny boarding the extra passengers or it should offer them a voucher to fly at a later time with the same airline or a with a different carrier (Phillips, 2005). The same situation could happen in the car rental industry. A customer might arrive at the car rental facility and notice that because of overbooking, the specific model which he/she booked is not available to rent. In this case, the car rental company should send the customer to a competitor rental facility, or move that specific model from a nearby location to its own location, or offer a free/discounted upgrade to a better model. In either case, the airline or the car rental company will suffer both monetary and non-monetary losses due to overselling. The monetary loss in the first example is the extra compensation that the airline should provide to the customers in order to encourage them to fly with a different plane at a later time. In the second example, the monetary loss incurred by the rental company is the discount that it should provide to the customer in order to upgrade his/her booking, the expenses associated with moving cars from another location, or the cost of renting a car from a competitor. The non-monetary loss for the airline or the rental company is the loss of customers' goodwill due to being denied service. Therefore, even though overbooking helps businesses to optimize the utilization of their finite capacity, it can be negatively perceived by customers when they experience denied service as a result of overselling (Guo et al., 2016). Previous studies have found that in some cases, due to the negative impacts of overselling on firm reputation and customers' satisfaction with their service providers, a revenue increase resulting from overbooking could be merely short-term in nature (Kimes, 2002). This will be further discussed in the literature review section.

1.2 Purpose of the Study

Following the successful implementation of overbooking strategies in the airline industry, several other service providers including hotel managers started to think about taking advantage from these strategies. Historically, revenue maximization and profitability augmentation have been the ultimate goal of overbooking in the hotel industry. However, the practice of overbooking in the hotel industry have always been controversial due to the concerns regarding its legality (Enghagen, 1996; Wilson et al., 1994), impact on customer satisfaction and loyalty (Capiez & Kaya, 2004; Guo et al., 2016; Hwang & Wen, 2009; McCollough, 2000; Noone & Lee, 2011; Sparks & Fredline, 2007; Wirtz et al., 2003), long-term effects on demand and profitability (Corney, 1984; Lefever, 1988; Wilson et al., 1995), compensation of walked guests (Badinelli, 2000; Hwang & Wen, 2009; Lefever, 1988; Noone & Lee, 2011; Salomon 2000), etc. These concerns and other unique features of the hotel industry motivated the researchers to investigate the problem of hotel overbooking from different aspects.

On one hand, a large group of researchers consider overbooking as an appropriate strategy toward revenue maximization and have developed models for improving the overbooking policies through inventory management, room allocation, and booking level optimization (e.g., Baker & Collier, 1999; Bitran & Gilbert, 1996; Corney, 1984; Ivanov, 2006, 2007, 2015; Karaesmen & van Ryzin, 2004; Koide & Ishii, 2005; Lambert et al., 1989; Lan, 2009; Liberman & Yechiali, 1978; Netessine & Shumsky, 2002; Phumchusri & Maneesophon, 2014; Talluri & van Ryzin, 2004; Toh, 1985; Toh & Dekay, 2002; Williams, 1977). On the other hand, a relatively smaller group of scholars who oppose hotel overbooking policies, have focused their research on investigation of customers' responses to overbooking practices (e.g., Capiez & Kaya, 2004; Guo et al., 2016; Hwang & Wen, 2009; McCollough, 2000; Noone & Lee, 2011; Sparks & Fredline, 2007; Wirtz et al., 2003), and have even challenged its legality and ethicality (Enghagen, 1996; Wilson et al., 1994).

Despite all these efforts, there are still several aspects of hotel overbooking which have never been examined. For instance, a clear picture of the current state of overbooking policies in the hotel industry is needed in order to identify the degree to which different overbooking strategies are being practiced by the hotels. Additionally, it is necessary to determine whether there is any relationship between cancellation policies, overbooking policies and hotels' financial performance. Furthermore, due to the importance of data availability in managerial decision making, it is important to identify the extent to which data availability can impact overbooking decisions. Lastly, since room cancellations can impact the show rate for varying room types, it is important to examine the potential relationship between cancellation policies and overbooking practices. The main purpose of this study is to investigate these relationships by finding plausible answers to the following research questions:

1. Which overbooking policies are most commonly practiced in the hotel industry?
2. What is the nature of the relationship between overbooking policies and financial performance?

3. How does data availability impact the overbooking decision making process and hotel performance?

4. What is the nature of the relationship between cancellation policies and overbooking practices?

5. What is the nature of the relationship between hotel cancellation policies and financial performance?

There are several aspects of hotel overbooking that will not be studied in this research. For instance, overbooking may result in overselling (which is generally perceived as an unpleasant incident in the hotel-guest relationship); identifying the major strategies that hotels utilize in order to deal with oversold inventory and the potential impact of adopting those strategies on hotels' financial performance indicators is beyond the scope of this dissertation. Additionally, the impact of overbooking, overselling and cancellations on customer satisfaction and customer goodwill are not investigated in this research. Accordingly, answering the following questions is beyond the scope of this study:

1. What strategies are most commonly used by hotels when they are oversold? How do these strategies impact their financial performance?

2. How do hotels handle the loss of customer goodwill and satisfaction resulting from overbooking? How do these strategies impact their financial performance?

3. How to quantify the loss of customer goodwill resulting from overselling?

4. How do hotel cancellation policies impact the customers' goodwill?

1.3 Significance of the Study

The significance of this study is due to its unique approach toward hotel overbooking problem. In addition to providing a summary of the current state of hotels overbooking policies, this study looks at the overbooking problem in a broader domain by investigating its relationship with issues such as cancellation policies, data availability and financial performance. To be more specific, the significance of this study is due to the following theoretical contributions:

First, this study evaluates the current state of overbooking in the hotel industry, identifies the most commonly practiced overbooking policies and examines the relationship between these policies and key performance indicators (KPIs). Since this is the first study that attempts to identify the most popular overbooking strategies in the hotel industry and since the relationship between different overbooking policies and hotel KPIs have not been investigated before, this study will broaden the scope of the hotel overbooking literature. Second, this study looks at the issue of data availability and its impacts on hotels' overbooking decisions. Particularly, the possible linkages between data availability and overbooking planning are investigated and the potential relationship between data availability and hotel performance is examined. Third, since room cancellations are one of the primary factors that justify the use of overbooking policies, this study explores the potential relationship between hotels' cancellation policies and overbooking strategies.

1.4 Organization of the Dissertation

This study is organized across six chapters. The first chapter defines the concept of overbooking and provides an overview of overbooking practices in service-related industries. This discussion is followed by an overview of research objectives, study goals, and expected theoretical contributions. Chapter two starts by introducing different approaches to overbooking. This is followed by a comprehensive review of hotel overbooking literature and a categorization of previous studies in this domain. The chapter ends with a rigorous analysis of literature gaps in hotel overbooking research and outlines the literature gaps that are addressed in this study. Chapter three introduces the conceptual model for this study and develops the research hypotheses. Chapter four describes the data collection procedure and the data analysis techniques used for testing the research hypotheses. In chapter five, the results of the analysis are reported and a detailed discussion of the findings is provided. Chapter six provides a conclusion based on the research findings and discusses the research limitations along with suggestions for future research.

Chapter 2

REVIEW OF THE LITERATURE

2.1 Different Approaches to Overbooking

The potential benefits associated with overbooking practices are subject to proper utilization, implementation, and understanding of the underlying overbooking models (Krawczyk et al., 2016). Due to the technological advancements, most overbooking models are now added to revenue management systems, therefore, unlike the time when overbooking was an emerging phenomenon and managers required decision science background in order to understand the models and implement them in their businesses, they can now simply input the data into the revenue management systems and expect to get optimal results. In other words, instead of being involved in the overbooking modelling phase, revenue managers now play an input assessment role. However, despite all these technological upgrades, managerial judgement and comprehension are still vital in order to choose the optimal overbooking policy regardless of how sophisticated the underlying model is (Krawczyk et al., 2016; Phillips, 2005). In other words, in order to practice overbooking, the firm's revenue manager has to decide what objective function(s) he is going to maximize. There are four commonly practiced overbooking policies that revenue managers generally choose from (Phillips, 2005):

1. Deterministic heuristic: Revenue manager calculates a booking limit (i.e., maximum number of rooms that can be sold) according to the total capacity and expected no-show rates. More specifically, the booking limit is calculated by dividing the capacity by the historical show rate. Therefore, this approach gives the revenue manager a very simple tool for determining the overbooking limit which is based on the past experience and historical data.

2. Risk-based policy: Revenue manager determines the booking limits such that the total revenue after deducting the overbooking expenses (i.e., estimated cost of denied service) is maximized. This approach is considered to be the best overbooking policy in terms of revenue optimization because it takes overbooking costs into account. In addition to the cost of alternative accommodation at a nearby property in case of overselling, the risk-based approach can take loss of customer goodwill into account. However, in order to take intangible costs such as the loss of loyalty and satisfaction into account, the firm should use convoluted mathematical models to quantify each of these cost categories.

3. Service-level policy: Revenue manager determines the highest booking limit such that denied-service incidents will not exceed the managerial expectations. This policy is very useful when the service provider intends to minimize the impact of denied service on customer goodwill and firm's reputation.

4. Hybrid policy: Revenue manager calculates both risk-based and service-level booking limits and then selects the minimum of the two as the optimal booking

limit. In other words, under this approach, the revenue manager calculates the optimal overbooking limit such that the total revenue after deducting costs is maximized while the optimal overbooking limit is constrained at a specified service-level.

As discussed above, the most basic approach toward overbooking is the deterministic heuristic which only relies on the accurate recording of historical show rates. Conversely, the other three approaches are more convoluted in nature and require deeper data analysis. For instance, unlike the deterministic strategy, the service-level policy is very sensitive to the long-term impacts of denied service. Many firms that adopt the service-level approach argue that although overbooking is necessary for revenue maximization and optimized capacity utilization, the negative impact of unrestricted denied service on customer goodwill can outweigh the benefits of overbooking (Krawczyk et al., 2016). Therefore, the subscribers of this policy set a curb for maximum denied service instances in a given period and overbook such that the denied service limit is not breached. Many companies in the airline industry (Phillips, 2005), hotel industry (Toh & Dekay, 2002) and car rental industry (Geraghty & Johnson, 1997; Phillips, 2005) have adopted service-level policies in order to maintain a good brand image while taking advantage from overbooking benefits.

In the service-level approach, the company sets the booking limit b such that:

$$E[\big((s|b) - C\big)^{+}] = qE[\min\big((s|b), C\big)] \tag{2.1}$$

Where $(s|b)$ refers to number of shows given booking limit b, q represents the target denied service fraction, and $E[\min\big((s|b), C\big)]$ is the expected sales given a booking limit of b (Phillips, 2005).

The biggest advantage of risk-based policy over simple methods such as the deterministic approach, is its ability to take the costs of overbooking including the cost of denied service into account. In order to calculate a risk-based overbooking limit the revenue manager should use cancellation and no-show data along with the estimated costs of denied service (Krawczyk et al., 2016). Given, these values the expected net revenue can be calculated as:

$$E[R|b] = pE[\min(b, d) - x] - DE[(\min(b, d) - x - C)^{+}] \qquad (2.2)$$

Where $E[R|b]$ is the expected net revenue from bookings, p is price for a room night, $\min(b, d)$ is the minimum of booking limit and demand for bookings, x is the expected no-show rate, D is the cost of service denial and C is the capacity (Krawczyk et al., 2016; Phillips, 2005). Using this equation, a revenue manager can determine the optimal booking level by finding the booking level which results in the highest possible net revenue.

Despite the advantages of the risk-based approach and the service-level policy, these two strategies have several limitations. For instance, quantifying the loss of customer goodwill might be very difficult and the managerial estimates for this cost category may not always reflect the true loss. Additionally, the mathematical complexities of the risk-based approach reduce the interpretability of this approach from a managerial point of view (Phillips, 2005). On the other hand, since adopting the service-level policy may result in conservative booking limits, the firm might incur opportunity loss due to having a capped overbooking limit.

Beside the four major policies described in this section, there are several other approaches for setting the optimal overbooking limit. Two of the most well-known approaches that were not discussed here are the Markovian decision process and the simulation approach (see Lambert et al., 1989; Lee et al., 2013; Liberman & Yechiali, 1978; Rothstein, 1974, 1985; Shlifer & Vardi, 1975; Suzuki, 2006). Despite the relative popularity of these two approaches among a group of researchers there is no indication of their implementation by practitioners.

It can be concluded that in order to have an efficient overbooking policy it is necessary to have accurate information about historical no-shows and cancellations (Kimes & Chase, 1998). This is mainly because the ability to accurately forecast future cancellation and no-show rates enables the firms to overbook while minimizing the risk of overselling. It is important to note that choosing the best overbooking policy depends on several factors including data availability, forecasting ability, degree of competition, demand structure, firm characteristics, company policies, etc.

2.2 Overbooking in Hotel Industry

Many hotels require their customers to guarantee room reservations with a credit card, in order to address the problems caused by no-shows and late cancellations. By requiring a credit card guarantee or a prepayment, hotels can easily penalize guests who do not show up or cancel their reservations after a pre-specified free cancellation deadline. Some hotels have also attempted to address the other end of the no-show/cancellation problem, by imposing penalties on guests who depart earlier than their original check-out date (Toh & Dekay, 2002). Even though a portion of the losses associated with no-shows, cancellations and early departures can be avoided by imposing monetary penalties, hotels may still suffer revenue losses from these events. For instance, a credit card guarantee may compensate the hotel for one night of stay in case of a no-show or cancellation, but the hotel might still lose potential revenue if the guest had a multiple-night reservation (Toh & Dekay, 2002). Furthermore, even if the cancellation and prepayment policies of the hotel allow charging a penalty which is large enough to cover the total revenue loss for multiple nights of stay, the hotel's capacity is not maximally utilized if a room remains empty for several nights. Revenue managers have attempted to solve both problems (i.e., revenue losses and imperfect capacity utilization) by introducing overbooking policies.

In the hotel industry, overbooking is defined as the process of reserving rooms in excess of the hotel's actual capacity (Rothstein, 1974; Wilson et al., 1994). Revenue managers claim that they engage in overbooking practices to protect themselves against no-shows, cancellations, and early departures that could leave some rooms unoccupied (Hwang & Wen, 2009; Ivanov, 2015; Kimes and Chase, 1998). However, the primary objective of overbooking is to maximize the revenue and improve profitability. In other words, overbooking not only increases the likelihood of filling potentially unsold rooms

(Toh & Dekay, 2002) but also augments the hotel revenues (Hwang & Wen, 2009). For instance, assume that a hotel has 100 rooms and the revenue manager has forecasted that based on the historical trends, the hotel has a combined no-show and cancellation rate of 20%. In this case the hotel can make 120 rooms available for reservation (instead of 100 rooms) through different distribution channels to increase the likelihood of operating at full capacity. In this case, the revenue manager uses overbooking to maximize the capacity utilization of the hotel and to generate more revenue. Overbooking plays a big role in a hotel's revenue management strategy. With few best practices for overselling and walking guests, revenue managers can help hotels to generate more money and increase their profitability (Hoisington, 2017). To sum up, the primary overbooking question from a hotel revenue management perspective is:

> Given a distribution of no-shows and cancellations, how many rooms does a hotel need to overbook in order to maximize the expected profits or minimize the expected loss? (Hadjinicola & Panayi, 1997)

Overbooking has been discussed in the hospitality management literature, mainly in the context of room allocation and inventory management (e.g., Baker & Collier, 1999; Koide & Ishii, 2005; Liberman & Yechiali, 1978; Toh & Dekay, 2002), booking level optimization (e.g., Bitran & Gilbert, 1996; Corney, 1984; Ivanov, 2006, 2015; Lambert et al., 1989; Netessine & Shumsky, 2002; Phumchusri & Maneesophon, 2014; Toh, 1985; Williams, 1977), costumers' reactions to overbooking practices and denied service (e.g., Capiez & Kaya, 2004; Guo et al., 2016; Hwang & Wen, 2009; McCollough, 2000; Noone & Lee, 2011; Sparks & Fredline, 2007; Wirtz et al., 2003), static and dynamic overbooking limits (e.g., Bitran and Gilbert, 1996; Ivanov, 2006, 2007; Karaesmen & van Ryzin, 2004; Lan, 2009; Netessine & Shumsky, 2002; Talluri & van Ryzin, 2004), online distribution channel management (e.g., Dong & Ling, 2015; Guo et al., 2014), ethical and legal considerations surrounding overbooking (e.g., Enghagen, 1996; Wilson et al., 1994), overbooking costs (e.g., Corney, 1984; Lefever, 1988; Wilson et al., 1995), and overbooking cost savings (e.g., Hadjinicola & Panayi, 1997; Phumchusri & Maneesophon, 2014; Toh, 1985). Each of these overbooking research directions and some of the most prominent studies under each category are reviewed in the following sections:

2.2.1 Overbooking and Room Allocation

Revenue management is an intelligent approach toward dynamic reservation control and perishable asset pricing across different customer types (Baker & Collier, 1999). Reservation control is defined as the process in which a perishable asset becomes available or unavailable to customers. In other words, reservation control deals with systematic acceptance or rejection of reservation requests so that the hotel's revenue is maximized (Baker & Collier, 1989; Liberman & Yechiali, 1978). For instance, for a hotel with a fixed number of rooms that can be rented to different types of customers at different rates and for varying length of stay, the reservation control deals with deciding which customers should be admitted, how available rooms must be allocated across different customer groups and what rates should be quoted to each customer in order to maximize the hotel's revenue (Liberman & Yechiali, 1978).

Reservation control has two unique aspects: room allocation and overbooking. Room allocation involves the use of dynamic reservation limits which are placed on different categories of hotel guests. Where the dynamic nature of reservation limits is due to having stochastic customer demand (Baker & Collier, 1999). On the other hand, the overbooking aspect involves placing limits on the total amount of rooms being overbooked (i.e., rooms reserved in excess of the hotel's capacity) (Toh & Dekay, 2002). At any point of time, revenue managers have three different options with respect to reservation control: They can keep the inventory at the existing level by declining all new booking requests; they can increase the overbooking limit and accept some of the new requests, or they can cancel some of the previously confirmed reservations to decrease the level of inventory (Liberman & Yechiali, 1978). The optimal decision is one which maximizes hotel's expected revenues and profits.

Many studies have attempted to address the room allocation problem by taking overbooking into account (e.g., Baker & Collier, 1999; Koide & Ishii, 2005; Liberman & Yechiali, 1978; Toh & Dekay, 2002). Baker & Collier (1999) developed two hotel-specific algorithms which both integrated room allocation decisions with overbooking decisions. More specifically, they added overbooking to the original nested network method (Williamson, 1992) and the bid price method (Williamson, 1992). Koide & Ishii (2005) constructed a simple model for room allocations by considering early discount services, cancellations and overbookings. They defined an expected total sale function and proved that this function is unimodal with respect to the number of rooms allocated for early discount in a certain condition as well as to the number of overbookings. They showed that optimal room allocations and the overbooking limits can be easily derived by using functional analysis. Liberman & Yechiali (1978) developed an N-period control model of the overbooking and room allocation problem where the objective was to find an optimal strategy that would maximize the net profit. Their study considered both maximization of the expected total net profit and the maximization of the expected discounted net profit. They formulated the decision problem as an N-stage dynamic programming problem and solved for the optimal strategy. Similarly, Toh & Dekay (2002) developed a model for establishing the optimal level of overbooking with respect to the room allocation and inventory management problem. Their model assumed that revenue manager determines the optimal rates to charge, and that the objective is to sell as many rooms to fill the capacity according to the predetermined optimal customer-service-level. Therefore, their optimal overbooking model can be categorized within the broader framework of an optimal revenue management strategy.

2.2.2 Overbooking Level Optimization

Overbooking strategies are designed to minimize costs in situations where reserved service may not always be honored (Corney, 1984). Overbooking practices can be effective ways for minimizing both the total service cost and the overall negative impact on the consumer and have wide applicability throughout the hospitality industry.

However, determining an optimal overbooking strategy is a relatively difficult task and requires solving an optimization problem by taking several factors into account (Corney, 1984). The main goal of overbooking optimization is to find the optimal booking level for each room type such that the total cost for the hotel is minimized. Where the total cost consists of two primary parts: The opportunity cost of being unable to sell rooms that are left unoccupied due to cancellations or no-shows (Phumchusri & Maneesophon, 2014; Toh, 1985) and the overselling cost associated with having insufficient rooms (i.e., being oversold) due to having greater number of arrivals than the hotel's capacity (Lambert et al., 1989; Phumchusri & Maneesophon, 2014; Toh, 1985).

Several approaches toward overbooking level optimization have been proposed in the literature. Bitran and Gilbert (1996) proposed a dynamic optimization policy to simultaneously manage the walking of customers and the acceptance of walk-in guests on the booking date by including the room allocation decisions which are made on the targeted booking date. Corney (1984) developed a basic overbooking optimization technique which was based on calculating the expected cost relationships for different overbooking alternatives. More specifically, the optimization model took into account the long and short costs (i.e., costs associated with vacant rooms and costs related to not honoring a confirmed reservation) as well as the no-show probabilities, in order to calculate the expected costs of alternative overbooking strategies. The model provided a simple platform which was capable of making rapid recalculations under changing circumstances. Ivanov (2006) proposed an optimization technique to find the optimal overbooking level for hotels with two different room types. The study also extended the basic mathematical model by considering the positive marginal revenues from unoccupied rooms, the simultaneous solution of the optimal overbooking levels for two different room types, and the optimal level of overbooking for two or more hotels which coordinate their reservation policies. In a follow-up study, Ivanov (2015) extended the original mathematical model in order to accommodate the calculation of optimal overbooking level for a hotel with three types of rooms (i.e., high-, mid-, and low-price) and with upgrade and downgrade constraints. The optimization model adopted the marginal revenue technique to determine the optimal overbooking limit for each room type. The primary advantage of the enhanced model was its ability to simultaneously find the optimal solution for each room type. Besides, the incorporation of upgrades and downgrades in the optimization model resulted in a more realistic mathematical model which was very close to real-world industry practices. Netessine and Shumsky (2002) developed an optimization method to find the optimal overbooking level for a hotel with one type of room. The focus of their study was to find a single cap or overbooking limit for the number of rooms to sell in advance to leisure travelers; however, they did not consider various types of overbooking distribution and multiple room types. Phumchusri & Maneesophon (2014) contributed to the overbooking optimization literature by considering the marginal cost for every room that is left unsold due to the no-shows and by taking into account the marginal cost for each walking guest. Therefore, the objective cost function presented by Phumchusri & Maneesophon (2014) considered the incurred costs from both leftover rooms and insufficient rooms. They developed an overbooking optimization model for the hotels having either one or two different room types. Toh

(1985) examined the institutional parameters and operating constraints of the hotel industry in order to find the optimal overbooking level. The proposed inventory depletion overbooking model balanced the opportunity cost of having unsold rooms with the negative consequences of being oversold and systematically established optimal overbooking levels. By using historical data to estimate the probability distribution of reservations, Williams (1977) formulated an optimization model which could calculate an optimal reservation level that minimized the expected cost of overbooking and underbooking for a given number of scheduled check-outs and stayovers.

To sum up, an optimal overbooking level is the result of a set of optimization and forecasting models capable of accurately predicting room availability and total costs. These models should be able to determine the maximum number of reservations to accept for any given arrival date, room type and length of stay. Some of the models that have been proposed so far require sophisticated software and costly computer processing, while others are too simple to be effective in practice (Lambert et al., 1989). An effective overbooking optimization model should be capable of considering important variables such as opportunity cost of having unsold rooms, volume and timing of potential walk-in guests, upgrade and downgrade prospects, impact of overbooking on customer goodwill, impact of overselling on employee morale and hotel profitability, proximity of other hotels and cost of providing alternative accommodations, etc. (Toh, 1985).

2.2.3 Static and Dynamic Overbooking Limits

The implementation and day to day handling of overbooking strategies is a convoluted process which requires a variety of considerations. Among other things, revenue managers have to define optimal number of overbookings by utilizing the demand forecasts and by analyzing the market conditions (Lambert et al., 1989). Empirically, it is extremely difficult to find out how many rooms will be reserved for a specific date, and how cancellations or no-shows will impact the number of rooms that can be eventually sold (Ivanov, 2006). Many theoretical models have been developed in order to identify the optimal overbooking limits. The hospitality literature suggests that overbooking limits set by revenue managers are either static or dynamic. The static approach suggests that once an optimal overbooking level is set, that limit will no longer change. On the other hand, the dynamic approach allows overbooking limits to change overtime. More specifically, as a hotel revenue manager tracks the pattern of customer reservations and cancellations overtime, the demand forecasts might be updated and therefore, the previously determined overbooking limits may no longer be optimal. In other words, the dynamic approach reruns the models to accommodate the changing circumstances and presumes that a hotel should overbook whenever its expected marginal revenues from the overbooking exceeds its expected marginal costs of overbooking (Ivaonv, 2007).

In the dynamic approach, the revenue manager considers the changes in forecasts/demand patterns and updates the optimal overbooking limit (Netessine & Shumsky, 2002). For instance, the hotel may increase the booking limit for a specific room type if the demand patterns indicate a decline in reservations compared to what was originally forecasted. Therefore, for one week, a customer may be told that the selected room type is sold out, while a week later the customer might recheck the hotel's website and notice that the same room type is available for reservation for the same check-in and check-out dates (Netessine & Shumsky, 2002).

Although, in reality, the reservations, cancellations, and no-shows occur sequentially over time and a dynamic overbooking approach toward setting the optimal overbooking limit might be a more plausible technique (Karaesmen & van Ryzin, 2004), many studies have solved a simpler, static overbooking problem. Static overbooking models simply ignore the dynamics of customer cancellations, no-shows and new arrivals; and determine a maximum number for total reservations (i.e., overbooking limit) for the current time given estimates of the cancellation and no-show rates from the current time until the expected date of service (Talluri & van Ryzin, 2004). Karaesmen & van Ryzin (2004) considered a static overbooking problem with multiple reservation and inventory classes, in which the multiple inventory classes were allowed to be used as substitutes in order to satisfy the demand of a given reservation class. By using a two-stage model and by taking the substitution option into account, they determined static overbooking levels for different reservation classes. Lan (2009) calculated static overbooking limits under two different scenarios: The first scenario involved limited information regarding no-shows which is the case when historical data is not sufficiently available. The second scenario assumed that no-shows can be fully characterized by using a probabilistic model. Netessine and Shumsky (2002) calculated static optimal overbooking limits that could balance the lost revenue from unsold rooms, the financial loss associated with having walked customers, and the loss of customer goodwill due to overselling.

Since the static models did not explicitly consider the dynamics of reservations, arrivals, cancellations and no-shows over time (Talluri & van Ryzin, 2004), some scholars attempted to find a dynamic solution for the optimal overbooking limit. In one of the earliest attempts, Bitran and Gilbert (1996) used Monte Carlo simulation to determine a statistical estimate for the upper bound of the optimal overbooking limit under dynamic conditions. They estimated the expected optimal overbooking limit by repeatedly generating realizations of the random coefficients and by solving the resulting linear programs. In other words, they formulated the problem as a stochastic dynamic program and derived the optimal overbooking limits. Ivanov (2007), addressed the problem of dynamic overbooking by showing how the optimal overbooking limits should be adjusted when there is a change in the guaranteed/non-guaranteed reservations ratio. The major weakness of the proposed model was that it assumed all hotel rooms to be identical and complete substitutes.

2.2.4 Overbooking and Denied Service

Service providers use various strategies to control and predict the customers' use of a given service. These strategies may include the use of penalties, service guarantees, forecasting, and process redesign (Kimes & Chase, 1998; Noone & Lee, 2011). In the hotel industry, overbooking plays a focal role in managing guests' arrival uncertainty. Hotels use overbooking practices to make more rooms available for reservation than their actual capacity, to protect themselves against the lost revenue associated with reservation cancellations and no-shows (Noone & Lee, 2011; Wangenheim & Bayón, 2007). Hotels overbook with the expectation that the number of overbooked rooms will equal the number of cancellations and no-shows (Phumchusri & Maneesophon, 2014). In order to ensure that this balance is achieved, revenue managers must carefully forecast the demand and calculate the optimal number of rooms to overbook (Hadjinicola & Panayi, 1997; Ivanov, 2006; Koide & Ishii, 2005; Netessine & Shumsky, 2002; Phumchusri & Maneesophon, 2014; Pullman & Rodgers, 2010). Although the revenue managers' objective is to overbook such that all reservations can be honored and no customers are denied service, in reality, service denials due to overselling can occur unpredictably (Hoisington, 2017).

Denials typically occur when cancellation rates and/or no-shows are lower than expected (Guo et al. 2016; Hwang & Wen, 2009; Noone & Lee, 2011). When arrivals for a specific room type exceed the hotel's capacity, the hotel will typically upgrade the customers to a better room category (e.g. from a double room to a suite) (Hwang & Wen, 2009). However, if the overbooked customers had a reservation for the best and most expensive room category or if all room upgrades are exhausted, the overflow customers are usually given accommodations at nearby hotels (i.e., they are "walked" to another hotel) (Badinelli, 2000; Salomon 2000). Therefore, it is necessary for all hotels to establish partnerships with other hotels before the need to walk a guest arises

(Hoisington, 2017). There are several considerations that hotels should take into account before starting the walking process. For instance, the hotels should try their best not to walk business travelers and guests that are members of the hotel's loyalty club even if they are oversold. Many hotels start tracking the cancellation and no-show patterns early in the morning and once they realize that there might be a need to walk guests to another hotel, they start to determine which guests might be more amenable to a walk (Hoisington, 2017). Therefore, most hotels have a hierarchy of desirability regarding which guests may be walked and which guests may not (Hwang & Wen, 2009). Generally, members of the loyalty club program, regular corporate guests, association officers, meeting planners and conventioneers, families on multiple-night stays, unaccompanied minors, and single women are not walked (Hoisington, 2017; Hwang & Wen, 2009; McConnell & Rutherford, 1990; Dekay et al., 2004). On the other hand, customers with a single-night reservation, families on leisure travel, and late-arrivals are usually candidates for being walked (Dekay et al., 2004; Hwang & Wen, 2009).

From the customer perspective, denied service as a result of overbooking can be regarded as a service failure (Noone & Lee, 2011; Wangenheim & Bayón, 2007) and an undesirable service experience (Guo et al., 2016; Hannigan, 1980; Lindenmeier & Tscheulin, 2008). Service providers may also incur disrepute and economic losses when they have no choice but to walk the overbooked customers to a nearby hotel (Guo et al., 2016). Compensation might be considered as a service recovery option for hotels when overbooking results in service failure (Noone & Lee, 2011; Smith et al., 1999). The standard best practice employed by hotel managers in case of overselling is to provide the walked guest with free accommodation in a comparable hotel until rooms become available at the original hotel, plus transportation, and a free long-distance call (Badinelli, 2000; Hwang & Wen, 2009; Noone & Lee, 2011; Salomon 2000). However, some hotels go beyond this norm and offer extra compensation in the form of a free night on a future stay, bonus reward program points, restaurant vouchers, or cash compensation (Dekay et al., 2004; Noone & Lee, 2011; Salomon, 2000). However, some walked guests may still consider the additional compensation negligible compared with the discomfort that they have experienced (Guo et al., 2016). For example, a business traveler who booked a hotel mainly due to its proximity to the business district may not be willing to move to another hotel.

Several studies have examined the impacts of denied service (caused by overselling) on customers' satisfaction and loyalty. For instance, after surveying a large sample of hotel guests, Capiez & Kaya (2004) found that in the hotel industry, customer satisfaction is relative not only to the traditional measures of service quality but also to practices of revenue management including overbooking. They also found that guest satisfaction variables are positively associated with the performance of the hotel. Guo et al. (2016) examined overbooking from the customers' perspective by calculating the probabilities of denied service under different levels of monetary compensation that is paid to denied customers. They suggested that hotels should pay high monetary compensations to denied guests and must publicize their compensation amounts in order to ensure the customers that their reservations will be most likely honored. Hwang and Wen (2009) studied the impact of hotel overbooking on customers' perceptions of fairness and loyalty and investigated the effects of customer gender, reservation time, membership status, length of stay, payer source, and reservation channel on their perceptions. By looking at invisible costs of overbooking, they found that guests who perceive a hotel's overbooking practices as being unfair are less likely to stay at the hotel in the future. McCollough (2000), studied the effect of attributions in the case of service failure and service recovery on the relationship between guest satisfaction and service quality by examining the service failures caused due to overbooking. The study showed that the ability to perform service recovery can mitigate the harm caused by service failure. Particularly, it was shown that in the hospitality industry, the relationship between post-recovery satisfaction and service quality is mediated by failure and recovery attributions. Noone and Lee (2011) investigated the role of overcompensation in shaping customers' reactions to denied service due to overselling. Their findings indicated that cash-based overcompensation results in significantly higher satisfaction ratings compared to voucher-based overcompensation or normal compensation alone. Additionally, they found that compared to normal compensation, overcompensation does not significantly influence customers' repatronage intentions. Sparks and Fredline (2007), examined the role of explanations in mitigating the effect of service failure on hotel guests' satisfaction and loyalty. They surveyed experienced hotel customers using different scenarios which represented different levels of service failure severity, varying types of explanation (referential or justification) and disparate degrees of explanation thoroughness. They found that when service failure was more severe, the referential explanations were associated with higher levels of satisfaction and loyalty compared to justifications. Wirtz et al. (2003) investigated the conflicts that arise between service providers and customers as a result of overbooking and other revenue management practices and suggested that overbooking is not necessarily incompatible with providing high quality service. Additionally, they noted that if the cost of walking hotel guests can be reduced, hotels can become more aggressive with their overbooking policies while maintaining or even increasing the level of customer satisfaction.

2.2.5 Overbooking and Online Distribution Channels

With the expansion of e-commerce, many traditional providers began to establish an online channel for selling their products and/or services. Providers sell products or services online in order to reduce their expenses, increase their revenues by accessing a wider customer base, and to provide a more convenient shopping experience to their customers (Guo et al., 2013). The increased popularity of online shopping also altered the way that hotels used to accept reservations for their rooms (Guillet & Law, 2010; O'Connor, 2002). In other words, since shoppers from all around the world use the internet to search for best prices, hotels had no choice but to use the online distribution channels to rent their rooms (Buhalis & Laws, 2001; Guillet & Law, 2010). However, unlike many other industries, most hotels do not have a strong direct online distribution channel (Bastakis e al., 2004). Therefore, they need to cooperate with well-known third-party websites such as Expedia, Priceline, Hotels.com, etc. and use their technological and marketing infrastructure to rent the rooms to a larger group of travelers at a shorter time (Guo et al., 2013; Ling et al., 2014).

There are four main reasons for the growth in the use of the online channels in hotel bookings (Toh et al., 2011). First, as discussed above, the internet is perfectly suited for purchasing intangible goods or services such as hotel rooms. Second, the online channels allow the customers to quickly compare prices and reduce their searching costs (Sahay, 2007). Third, the traditional methods of receiving reservations by mail, phone, or through travel agencies are not only inefficient and inconvenient but are also expensive for customers (O'Connor, 2001). Finally, customers expect services purchased online to be less expensive than those purchased through other channels, mainly due to the expectation that online distribution has lower expenses for the provider (Guo et al., 2013; Toh et al., 2011).

A relatively new topic in overbooking literature, is the study of hotels' overbooking strategies in the context of cooperation with multiple third-party websites. Evaluating how these strategies influence the cooperation process between customers, hotels and third-party websites is the primary area of investigation in this subdomain of the overbooking literature. In a recent study, Dong and Ling (2015) used mathematical models to evaluate hotels' overbooking strategies in conjunction with third-party online distribution channels. They found that although higher compensations (i.e., compensation for the inconvenience of denied customers) might have a minor impact on optimal room rates, they cause a sharp decline in the overbooking levels. Additionally, their results indicated that along with the increase in compensation coefficient, the third-party websites exert less effort in room reservations and attract fewer customers. In another study, Guo et al. (2014) reported that booking from a hotel's direct online distribution channel (i.e., hotel's branded website) gives more guarantee for room availability in case of overselling to customers compared to booking through an online travel agent (OTA). Therefore, they concluded that travelers might be better off if they use OTAs for price comparison, and then switch to the hotels' branded websites to finalize their reservations. However, they mentioned that the fact that some OTAs provide cash back or points to the travelers who make reservations through their websites might impact the optimal booking strategy for customers.

2.2.6 Ethical and Legal Considerations Surrounding Overbooking

Unlike the airline industry where the law explicitly sets the amount of compensation to be given to bumped customers in the event of overselling (Noone & Lee, 2011), there are currently no federal laws governing compensation rates for hotel guests that are walked (Dekay et al., 2004; Hwang & Wen, 2009; Noone & Lee, 2011). Therefore, it is the hotels' responsibility to determine the amount and the type of compensation that should be given to walked guests (Noone & Lee, 2011). Aside, from the compensation type and amount, walked guests may also question the legality of the hotels overbooking practices. Several legal theories for recovery might be applicable to a situation where a guest had a reservation but the hotel did not have the capacity to honor that reservation. Some of these legal theories are breach of contract, misrepresentation (or fraud), and violation of consumer protection statutes that forbid unfair and deceptive business practices (Wilson et al., 1994). Per the breach of contract theory, once the hotel and the customer enter into an agreement where the hotel is required to reserve a room for a specific duration and price, if either party (i.e., the hotel or the customer) breach this agreement, that party should become liable to the other party for damages (Jeffries, 1987; Wilson et al., 1994). An interesting legal case in which breach of contract was claimed is the case of Scher vs. Liberty Travel Service, Inc. (1971). In this case, the plaintiffs who were walked by the hotel due to overbooking, sued the hotel management and the court ruled in their favor and awarded them damages on the basis of breach of contract. Another legal theory that walked guests may use to sue a hotel is misrepresentation or fraud. In these cases, the plaintiffs typically believe that the amount of recoverable damages are significantly greater than those associated with the breach of contract. However, proving a misrepresentation case is relatively more difficult because the plaintiff must prove to the court that the hotel management knowingly or willfully misrepresented a material fact and/or intended not to sell them a room (Wilson et al., 1994). Lastly, the unfair and deceptive acts and practices statutes of most states allow walked guests to initiate a class action suit against the hotels. However, due to the small amount of recoverable damages, guests are generally not willing to file such legal suits.

Few studies have examined the legal and ethical aspects of hotel overbookings. Two of the most well-known studies in this domain are briefly reviewed here: Enghagen (1996), studied the legal and ethical aspects of hotel overbooking and suggested that a case should be made against these practices. They believed that researchers should have a deeper look into the hotel overbooking problem by considering customer and employee satisfaction, profitability, ethical issues, marketing issues and legal considerations in order to determine whether hotel overbooking practices are in fact justifiable and reasonable. In another study, Wilson et al. (1994) challenged the legality of hotel overbooking and examined the applicability of consumer protection statutes. They provided a comprehensive discussion of the legal issues related to the overbooking and reviewed the validity and enforcement of reservation contracts. Their study contributed to the literature by providing a thorough analysis of state statutes that prohibit unfair and deceptive business practices and the potential legal problems that these statutes can pose for hotel management companies.

2.2.7 Overbooking Costs

Hotel revenue managers are constantly trying to boost profits by minimizing costs and maximizing the revenues (Wilson et al., 1994). Overbooking is considered to be one of the most effective revenue management tools in order to maximize the hotel revenues; however, overbooking does not come without its costs.

Theoretically, it is possible to overbook a hotel without having to walk guests if revenue managers correctly determine the percentages of no-shows and cancellations and set overbooking limits that are totally optimized (Lefever, 1988). However, in reality, it is impossible to have perfect overbooking limits at all times due to the dynamic nature of cancellations, no-shows, and reservations. Every now and then, hotels have to walk guests that cannot be accommodated due to being oversold.

The direct cost of walking a guest consists of three major components including the average cost of a room at a nearby property, the cost of a long-distance call (in order to inform family or friends of the change in accommodation arrangements), and the cost of transporting the walked guest to the new hotel (Hwang & Wen, 2009; Lefever, 1988). Since, hotels are aware of the negative impacts of denied service on customer goodwill, they may also provide additional compensation to the walked customers (McConnell & Rutherford, 1990), for instance they might offer a voucher for future stay or they might provide a room upgrade at the new hotel. Therefore, the actual cost of walking guests may not be the same for different hotels and for different customers.

There are several ways for categorizing the overbooking expenses. A basic way to categorize these costs is to divide them by oversale and undersale costs (Baker & Collier, 1999). Under this categorization, oversale costs include the expected discounted future lost business due to walking customers who had reservations plus the cost of booking a room for the walked customers at a nearby hotel. The undersale costs are usually realized when the hotel sets a very low overbooking limit and despite overbooking, some rooms are left unsold (Lefever, 1988). Therefore, the undersale cost represents the opportunity cost for the unsold rooms (Baker & Collier, 1999).

Another way to categorize overbooking costs is to split them into long costs (i.e., having rooms available for which there are no guests or having more supply than demand) and short costs (i.e., having too many guests for the available rooms or having higher demand than supply) (Corney, 1984). In the hospitality industry, long costs represent the opportunity loss due to the absence of demand for the perishable inventory of rooms. These costs can be easily estimated by subtracting the variable costs of service from the revenue losses associated with having unsold rooms. On the other hand, approximating the short costs is more challenging due to having several components which could be subjective in nature. For instance, when the number of arrivals exceeds the number of available rooms and the hotel needs to find alternative accommodation for the walked guests, several costs might be incurred in order to maintain consumer goodwill (Corney, 1984; Hwang & Wen, 2009; Lefever, 1988; Noone & Lee, 2011; Smith et al., 1999). Short costs associated with overselling include the following:

- Labor and training costs: Extra labor expenses might be required to handle the overselling situations because hotels need to train their employees and teach them how to handle overselling. Employees should learn how to find and schedule alternative accommodations for walked guests and how to explain the situation to the walked customers (Corney, 1984; Toh, 1985).
- Transportation costs: It is a common business practice for hotels to pay for the transportation of walked guests to the new hotel (Badinelli, 2000; Corney, 1984; Hwang & Wen, 2009; Lefever, 1988; Noone & Lee, 2011; Salomon 2000).
- Costs of the complimentary long-distance call: Hotels usually offer a free long-distance call to their walked guests (Badinelli, 2000; Hwang & Wen, 2009; Lefever, 1988; Noone & Lee, 2011; Salomon 2000). The cost of the long-distance

call could be negligible if the walked guest is a domestic traveler, however, if the walked customer is an international traveler, the long-distance call might be costly for the hotel.

- Accommodation costs: When a customer is walked, the hotel usually finds a room at a nearby hotel and pays for the guest's stay. The accommodation cost of overselling may also include the cost of a complimentary room upgrade at the new hotel (Badinelli, 2000; Corney, 1984; Phumchusri & Maneesophon, 2014; Salomon 2000; Toh, 1985).
- Loss of future business from affected customers: The walked customers may never reserve a room at that specific hotel once they have a walking experience (Corney, 1984; Lefever, 1988; Phumchusri & Maneesophon, 2014; Wilson et al., 1995). They may even react to their walking experience by posting negative comments on social media or sharing their experience with friends and family.
- Loss of future business from potential customers: Those who learn about a hotel's failure to honor a reservation either through social media or word of mouth may be less likely to book a room from that hotel in the future (Corney, 1984; Lefever, 1988; Wilson et al., 1995). If the hotel is part of a larger branded chain, the negative impacts of the customers' reactions to their walking experiences might affect the brand image of the hotel chain as well.

Many studies have evaluated the costs of hotels' overbooking practices. For instance, Corney (1984), categorized the overbooking expenses and created expected cost relationships for different overbooking alternatives. These cost relationships were used as inputs for computer spreadsheets that could identify the optimal overbooking strategies. Karaesmen and van Ryzin (2004) considered real costs and loss of goodwill in the context of an overbooking problem with multiple inventory classes that could be substituted for one another (e.g., hotel customers could be upgraded from simple rooms to premium rooms if needed). In their problem, when overselling happened, multiple inventory classes could be used as substitutes to satisfy the demand of a given reservation class at a cost. They found that taking substitution opportunities into account while setting overbooking levels had a small yet significant impact on revenues and costs. In another study, Lefever (1988) proposed simple formulas for calculating the overbooking costs and concluded that the average cost of 365 walks in a year is more than the average cost of having 365 empty rooms. He believed that this cost disparity is the reason why hotel revenue managers adopt conservative booking policies that slightly favor underbookings. Wilson et al. (1995) analyzed the actual direct and indirect costs of overbooking by focusing on the impact of the loss of future room nights and marginal profits due to overselling. They believed that the impact of lost future revenue and marginal operating profits have been underestimated in the literature and argued that the true cost of overbooking combined with the amount of lost marginal profits is significantly high.

2.2.8 Cost Savings of Overbooking

As discussed earlier, overbooking practices can be very costly for the hotels if overselling occurs. However, if overselling does not occur and the hotel is able to maximize its revenue and capacity utilization through overbooking, then two major cost savings are expected, namely, cost savings from preventing the opportunity loss and costs savings from not offering last minute discounts. If a hotel does not overbook then there is high probability that some rooms might be left unsold and the hotel's capacity may not be optimally utilized. The cost incurred by these leftover hotel rooms as a result of no-shows or late cancellations, is a form of opportunity cost (Hadjinicola & Panayi, 1997; Phumchusri & Maneesophon, 2014; Toh, 1985) which can be minimized by having an effective overbooking policy. Additionally, when a hotel does not overbook or sets a conservatively low overbooking limit, the cancellations and no-shows may force the hotel to offer last minute discounts through travel agents in order to fill its unsold rooms (Buhalis, 2000; Dacko, 2004). Selling rooms at the last minute with low margins could be simply avoided by setting optimal overbooking limits. In other words, overbooking enables hotels to maximize their profits from room reservations by reducing the need for offering deep discounts at the last minute.

Cost savings of overbooking have not been thoroughly researched in the past and there are only few notable studies in this domain. Hadjinicola and Panayi (1997), compared the cost savings of overbooking at the hotel level and at the tour operator level and found that when overbooking policies are applied at the hotel level they give better cost savings compared to when they are applied at the tour operator level. In another study, Phumchusri and Maneesophon (2014) proposed a model which not only considered the overbooking costs in case of overselling but also took cost savings from preventing the opportunity loss of having unsold rooms into account. They noted that the cost savings from preventing this opportunity loss can be significant.

2.3 Cancellations and Overbooking

As discussed earlier, the possibility of cancellations and no-shows along with the hotels' desire to maximize their revenue and profits are the primary rationales for overbooking. To set optimal overbooking limits, hotels need to forecast the demand (Ivanov, 2006; Koide & Ishii, 2005; Netessine & Shumsky, 2002; Phumchusri & Maneesophon, 2014; Pullman & Rodgers, 2010), as well as early check-outs, overstays, no-shows and cancellations (Hadjinicola & Panayi, 1997; Lefever, 1988; Vinod, 2004). Although some of these factors cannot be controlled by the hotels, cancellation rates might be affected by hotels' cancellation policies. For instance, when a hotel sets a very strict cancellation policy, the cancellation rate is likely to reduce. Conversely, when a lenient cancellation policy is in place, cancellation rates may increase because customers will continue to search for better deals up until their expected check-in dates and will not hesitate to cancel their reservations if they find better offers (Chen et al., 2011). Therefore, cancellation policies may play an important role in determining the optimal number of rooms to overbook (Hoisington, 2017; Vinod, 2004). To further illustrate this, consider a hotel that allows free cancellations up to 14 days before the check-in date. For this hotel, the cancellation rate is expected to significantly drop after the free cancellation deadline, giving the revenue manager plenty of time to evaluate the reservation status and adjust the overbooking policy accordingly. Now assume that there is a similar hotel with a similar demand pattern but a more lenient cancellation policy that allows free cancellations until 6 PM of the check-in date. In this case, the revenue manager is facing a lot more uncertainty with respect to cancellations, because the leniency in the cancellation policy makes it very difficult to predict the cancellation patterns. Hence, the revenue manager's ability to adjust the hotel's overbooking policy will be limited because the overbooking decisions should be merely made based on cancellation forecasts.

These considerations are evident in the recent changes announced by major hotel chains such as Hilton and Marriott (Boarding Area, 2014a, 2014b; Wiener-Bronner, 2017). The changes have made the cancellation policies stricter by tightening the free cancellation windows and not allowing the guests to cancel their reservations without a penalty up until the day of their visit (Boarding Area, 2014a, 2014b; Wiener-Bronner, 2017). The bottom line is that hotels can resell their rooms easier if they know who is not going to show up, few nights before the check-in date, as opposed to only the afternoon in which the guests are expected to check-in (Boarding Area, 2014b). Although hotels can overbook to account for the cancellations and no-shows, but that's also a liability for them, since predicting the no-shows and cancellations is difficult, especially for airport hotels (Boarding Area, 2014b).

Cancellation forecasts are very useful for making appropriate overbooking decisions, however, they should be coupled with market analysis in order to deliver the optimal results (Hoisington, 2017). Assume that a city is hosting the soccer world cup. The hotels in that city are expected to be at extremely high demand for the game night and they might be sold out several months before the big game. However, since the two finalist nations are not determined until 2-3 days before the final match, and since many teams might be eliminated throughout the knockout stage, a large volume of cancellations is expected during the tournament (assuming that once a team is eliminated, its supporters will cancel their reservations). In this case, a hotel revenue manager cannot simply rely on the historical cancellation trends to make overbooking decisions; instead he/she should carefully analyze the market, follow the tournament results, ask experts to predict the potential finalists, and update the optimal overbooking level by taking these extra factors into account.

Hotel location and its typical customer base is another important factor that should be considered when using cancellation forecasts to make overbooking decisions. For example, for an airport hotel, the flight delays or airport shut down due to inclement weather can have huge impacts on the room cancellation patterns. Therefore, a revenue manager who works for an airport hotel should set overbooking limits by considering both historical cancellation trends and the probabilities of flight delays and airport shut down (Hoisington, 2017).

Although, it seems that there might be several linkages between cancellation policies and overbooking practices, these potential connections have never been investigated. This dissertation looks at some aspects of hotel cancellation policies and investigates some of the linkages between cancellation policies and overbooking practices.

2.4 Literature Gaps

Previous studies on hotel overbooking have presented practical insights for revenue managers to overbook more thoughtfully. Prior research suggests that overbooking should be based on algorithmic decision making, meaning that instead of relying on personal feelings, revenue managers should consider historical reservation patterns, cancellations and no-shows forecasts, as well as demand structure to determine the optimal overbooking strategies for their hotels (Wagener, 2017). In addition to research on optimization of overbooking limits there have been many studies on the operational aspects of overbooking. For instance, it is suggested that hotels should be prepared for handling operational aspects of overbooking by printing arrival lists and flagging potential walking candidates before the need for walking arises. It is recommended to label the guests with single night reservations, those who booked through third-party websites, guests with non-guaranteed bookings, and guests with low-rate reservations as the potential walking candidates. Additionally, studies have suggested hotel managers to establish overbooking partnership agreements with nearby hotels in order to ease the walking process. Also, to dwindle the negative impacts of walking, it is recommended to offer compensation in terms of discount for future stays or free meals (Wagener, 2017).

Despite the theoretical and practical contributions of previous studies on hotel overbooking, there are still several literature gaps and unanswered questions that should be addressed by future research. This section provides an analysis of literature gaps:

2.4.1 Overbooking and Room Allocation

Although many studies have investigated the room allocation problem in conjunction with overbooking (e.g., Baker & Collier, 1999; Koide & Ishii, 2005; Liberman & Yechiali, 1978; Toh & Dekay, 2002), there are still several aspects of this problem that have not been analyzed. For instance, a dynamic room allocation model in which overbooking policies could change overtime based on the reservations and cancellations status have not been developed so far. Clearly, such a model should be capable of handling a multi-period room allocation problem. Although recent room allocation studies have moved from deterministic demand optimization formulations to probabilistic ones, which are more consistent with the real-world conditions, there are still major limitations in these probabilistic models. For example, a major limitation of existing probabilistic room allocation models is that they assume continuous probability distribution functions and continuous probability density functions for the demand (e.g., Koide & Ishii, 2005) which is an unrealistic assumption. Therefore, future studies in this domain should modify the probability functions for demand and use discrete functions instead of continuous ones in order to better replicate the real-world demand characteristics. Additionally, the existing room allocation models that take overbooking into account can be enhanced by using demand functions that are dependent on price discounts.

2.4.2 Overbooking Level Optimization

Previous studies have attempted to find the optimal overbooking level under varying conditions (e.g., Bitran & Gilbert, 1996; Corney, 1984; Ivanov, 2006, 2015; Lambert et al., 1989; Netessine & Shumsky, 2002; Phumchusri & Maneesophon, 2014; Toh, 1985; Williams, 1977). Even though these optimization models have become more sophisticated over time, there are still several issues that have not been addressed. A major limitation of the existing models is that they do not consider the length of stay. Since length of stay can impact the average nightly room rates charged by the hotel (Riasi et al., 2017), customers with different stay durations may not have the same level of profitability for the hotel. Therefore, by ignoring the length of stay in the optimization models, the accuracy of the findings could be questionable. Another limitation of the existing overbooking optimization models is that they ignore the fact that hotel revenues do not only come from the rooms division (Ivanov, 2015). In real world, not all bookings are equally profitable for the hotel due to the differences in customers' purchases of non-room services (e.g., food and beverages, minibar, spa, casino, etc.). Therefore, to have a comprehensive optimization model, it is necessary to take guests' purchases of non-room services into account. Furthermore, most of the existing optimization models can find the optimal overbooking level for hotels with either one (e.g., Netessine and Shumsky, 2002), two (e.g., Ivanov, 2006; Phumchusri & Maneesophon), or three (e.g., Ivanov, 2015) room types. However, in practice, most hotels have more than three different room types; therefore, it is necessary to develop a more generalized optimization model capable of finding the optimal overbooking level for a hotel with N different room types.

2.4.3 Static and Dynamic Overbooking Limits

Several studies have focused on determining static and dynamic overbooking limits (e.g., Bitran and Gilbert, 1996; Ivanov, 2006, 2007; Karaesmen & van Ryzin, 2004; Lan, 2009; Netessine & Shumsky, 2002; Talluri & van Ryzin, 2004). A major weakness which is common among almost all of these studies is that they assume all rooms within a hotel to be identical and complete substitutes (Ivanov, 2007; Karaesmen & van Ryzin, 2004). This assumption limits the applicability of these models in the hotel industry; because in reality, hotels have different room types that cannot be substituted due to their varying features and prices. Therefore, future research should incorporate different room types in the static or dynamic overbooking models. In other words, the models must be able to distinguish among different inventory classes and should be able to calculate different static or dynamic overbooking limits for disparate room types at a given hotel.

Another limitation of the existing dynamic models is that they try to solve an approximation of the true dynamic problem (Karaesmen & van Ryzin, 2004). Therefore, in order to make these models more practical it is necessary to explicitly account for the dynamic nature of arrivals and cancellations and try to solve a more realistic dynamic problem. In addition, assignments of customers to different inventory classes may need to be performed prior to the realization of all cancellations, unlike the assignment under perfect information assumption which is used by the existing models. Furthermore, previous studies that use static models are somewhat limited because they assume that the hotel can make a joint allocation decision with perfect knowledge regarding the number of guests that eventually show-up. Since this is only an approximation of the reality, future research should develop models in which information about the show-rate is imperfect.

2.4.4 Overbooking and Denied Service

Research on consumers' reactions to overbooking practices and denied service is an emerging topic which has gained a lot of attention from hospitality scholars over the last two decades (e.g., Capiez & Kaya, 2004; Guo et al., 2016; Hwang & Wen, 2009; McCollough, 2000; Noone & Lee, 2011; Sparks & Fredline, 2007; Wirtz et al., 2003). Since this is a relatively new research domain there are several literature gaps that should be addressed by future studies. For example, previous studies in this domain only focused on the reputation loss of service provider when denied service occurred and ignored the fact that every single case of service denial might have a long-term influence on market demand. Therefore, it is necessary to consider the quantified impact of denied service on market demand when evaluating the customers' reactions to denied service.

Moreover, prior research only examined the probability of denied service under static overbooking strategies. Since overbooking policies have a dynamic nature, future research should consider the probabilities of denied service under dynamic overbooking conditions. Another limitation of previous studies is that they did not examine the impact of several variables that can potentially affect customers' reaction to denied service. For instance, factors such as prior customer experience with the hotel, time of day at which the service denial occurred, purpose of the hotel stay, quality of the alternative accommodation, satisfaction with the alternative accommodation, etc. have never been examined in previous studies that investigated customers' reactions to denied service.

Although previous research in consumer behavior has shown that attributions for service failure influence customers' behavioral responses (Folkes et al., 1987), the hotel overbooking literature have never examined the role of attribution theory (i.e., a theory that says individuals attempt to understand the behavior of others by attributing feelings, beliefs, and intentions to them) when guests react to denied service. Therefore, future research in this domain may investigate the role of attributions when a guest is walked.

2.4.5 Overbooking and Online Distribution Channels

Studying hotels' overbooking strategies in the context of cooperation with third-party websites is an evolving area of research. Since there have been only few published studies on this topic (e.g., Dong & Ling, 2015; Guo et al., 2014) there are still numerous unanswered questions that should be examined in order to get a better understanding of how online distribution channels could affect hotel overbooking practices. For instance, since existing literature only attempts to evaluate a hypothetical market with one hotel and few OTAs, it is worthwhile to study the impacts of online distribution on overbooking in a network setting consisting of multiple hotels and multiple OTAs. Additionally, since previous studies only evaluated static online demand for rooms, it is necessary to examine the impacts of online distribution on overbooking policies under dynamic conditions where demand for hotel rooms could change over time. Lastly, since prior research considered situations where only a single room type was offered by the hotel, future research may evaluate the impacts of online distribution on overbooking policies assuming that multiple room types are available and by considering the upgrade and downgrade constraints.

2.4.6 Ethical and Legal Considerations Surrounding Overbooking

Few studies have focused on the legal and ethical aspects of hotel overbooking practices (e.g., Enghagen, 1996; Wilson et al., 1994), therefore, there are still several literature gaps in this domain. For example, although previous studies claim that overbooking might have severe legal and ethical consequences for the hotels (e.g., Enghagen, 1996; Wilson et al., 1994) they never tried to quantify these legal and ethical risks. Therefore, in order to get a better understanding of the significance of these legal and ethical risks and in order to enable the hotel managers to compare the risks of overbooking with its potential benefits, future research should focus on quantification of these risks. Furthermore, although previous studies provided examples in which guests submitted legal claims after being walked by the hotels, the frequency of these legal claims and their success rates are still unknown. Future studies may examine the historical trends in legal challenges against hotel overbooking practices to see whether hotels should in fact consider the legal risk of overbooking as a threat.

2.4.7 Overbooking Costs

Although previous studies attempted to categorize overbooking expenses and offered simple formulas for calculating the total cost of overbooking (e.g., Corney, 1984; Lefever, 1988; Wilson et al., 1995), there are still some notable issues that have not been addressed in the literature. Most importantly, there is still no reliable model for quantifying the intangible costs of overbooking such as the loss of customer goodwill and the costs associated with customer dissatisfaction. Therefore, future research is needed in order to develop a model that could quantify these intangible costs.

Additionally, although the literature recognizes the fact that a hotel’s failure to honor a reservation can affect the hotel’s reputation through negative word of mouth

(Corney, 1984; Lefever, 1988; Wilson et al., 1995), the extent of this phenomenon is still unknown. The expansion of social media and online forums and the customers' increasing willingness to share their experiences with others through these channels, provides a unique opportunity for researchers to explore the extent to which negative word of mouth regarding a walking experience could impact a hotel's reputation. Therefore, social network analysis is needed to identify the true cost of negative word of mouth for hotels that practice overbooking.

2.4.8 Cost Savings of Overbooking

There are only few studies that investigated the cost savings associated with overbooking (e.g., Hadjinicola & Panayi, 1997; Phumchusri & Maneesophon, 2014; Toh, 1985). Therefore, there are still numerous research questions regarding the cost savings of overbooking that need to be addressed. For instance, it is still unknown whether having a single overbooking policy for the entire hotel provides more cost savings or having multiple overbooking policies for different room types. Additionally, it is still unknown how overbooked capacity should be allocated across different distribution channels in order to achieve higher cost savings. Lastly, since prior studies have merely focused on cost savings from opportunity loss prevention, it is necessary for future researchers to examine other potential costs saving that can be achieved through overbooking. For instance, future studies can quantify the cost savings of overbooking that are associated with the decreasing need for last minute discounts.

2.4.9 Hotel Cancellation Policies and Overbooking Practices

Research on hotel cancellation policies is relatively scant. Previously published studies on this topic mainly focused on the impact of cancellation policies on customer satisfaction (McCarthy & Fram, 2000), perceived fairness (Smith, 2012, Smith et al., 2015), and deal-seeking behavior (Chen et al., 2011). Previous studies have briefly mentioned some possible connections between cancellation policies and overbooking practices (e.g., Hoisington, 2017; Vinod, 2004), but they have never investigated the existence of a relationship between these two popular revenue management tools. This study will investigate some aspects of this potential relationship and will examine their underlying connections in the broader context of hotels' financial performance.

2.5 Literature Gaps Addressed in this Study

A complete analysis of gaps in hotel overbooking literature was provided in previous section. Additionally, possible directions for future research in different domains of overbooking literature were discussed. Although the gaps discussed in previous section covered a wide range of topics within the overbooking literature, the current study will only address some of these literature gaps:

First, a remarkable gap in overbooking literature is the lack of having a clear picture from the current state of overbooking practices in the hospitality industry.

Therefore, the primary objective of this research is to provide a comprehensive analysis of the current state of overbooking in the hotel industry by identifying the most commonly practiced overbooking strategies.

Second, prior research never examined the impact of data availability on overbooking decision making. Since overbooking decisions are made after careful examination of historical no-shows and cancellations while considering demand forecasts, it is necessary to investigate the potential impact of data availability on overbooking policies. The present study will address this literature gap by examining the relationship between data availability, overbooking practices and hotels' financial performance.

Third, although there are several indications that suggest a connection between cancellation policies and overbooking strategies, the relationship between hotels' cancellation leniency and overbooking limits have never been investigated. In order to address this literature gap, the current study examines the potential relationship between these two revenue management tools.

Lastly, even though the ultimate goal of cancellation polices and overbooking strategies is to maximize the hotels' revenue and profitability, prior research did not examine the impacts of these revenue management practices on hotels' financial performance indicators. To address this issue, the present study will investigate the relationship between KPIs and different cancellation policies and overbooking practices.

Chapter 3

CONCEPTUAL MODEL

3.1 Introduction

The theoretical contribution of this study is three-fold. First, this study evaluates the current state of overbooking in the hotel industry, identifies the most commonly practiced overbooking policies and examines the relationship between these policies and key performance indicators (KPIs). Second, the issue of data availability and its impact on overbooking decisions is studied and the possible linkages between data availability and overbooking planning are investigated. Third, since room cancellations are one of the primary factors that justify the use of overbooking policies, this study evaluates the potential relationship between cancellation policies, overbooking practices and financial performance. The above mentioned theoretical contributions are achieved by answering the following research questions:

1. Which overbooking policies are most commonly practiced in the hotel industry?
2. What is the nature of the relationship between overbooking policies and financial performance?
3. How does data availability impact the overbooking decision-making process and hotel performance?

4. What is the nature of the relationship between cancellation policies and overbooking practices?
5. What is the nature of the relationship between hotel cancellation policies and financial performance?

In the following sections, the research hypotheses are developed and the conceptual model of the study is presented.

3.2 Data Availability and Overbooking

Data availability is among the most important issues that revenue managers face when making overbooking decisions. It is important for hotels to have access to various data sources because their revenue managers need to have historical data in order to forecast the future market conditions. Although historical trends may not always be reflected in future reservation patterns, they are among the most useful resources utilized by demand forecasters. In other words, accurate forecasts of demand are at the heart of successful revenue management systems, and forecasting power relies on data availability (Weatherford & Pölt, 2002).

Like many other revenue management decisions, setting overbooking policies requires rigorous data analysis. As a starting point, revenue managers use historical cancellations, no-shows and reservations data to forecast future booking patterns (Kimes & Chase, 1998; Lan, 2009; Phillips, 2005; Phumchusri & Maneesophon, 2014). The next step for them is to make overbooking decisions by considering different factors including the forecasts (Krawczyk et al., 2016). Therefore, there is no doubt that overbooking decisions are extremely complicated and revenue managers need to have access to historical data in order observe cancellations, no-shows, and early departure patterns before making reliable overbooking decisions (Phumchusri & Maneesophon, 2014). It is expected that having access to more data could facilitate the overbooking decision making process for hotel revenue managers, enabling them to set overbooking limits such that the probability of denied service will be minimized and capacity utilization and revenues will be maximized.

Although it is rather clear that without having access to historical data it is almost impossible to set diligent overbooking strategies, the impact that different degrees of data availability can have on overbooking decisions is still unclear. More specifically, it is unclear whether different degrees of data availability can lead to certain overbooking policies (i.e., either deterministic, risk-based, service-level, hybrid policy). For instance, a hotel that only has access to historical show rates might be more willing to choose a deterministic overbooking approach, whereas another hotel with a broad access to historical cancellations, no-shows, and reservations data along with overbooking expenses data might be willing to engage in more complicated overbooking policies such as the risk-based approach. In other words, it is expected that data availability could impact the choice of the overbooking policy. Therefore, this study posits that a higher degree of data availability leads to more complex overbooking policies. In this study a complex overbooking policy is defined as a policy which requires a relatively large number of inputs and requires sophisticated mathematical modelling and analysis.

Hypothesis H1a: Data availability is positively associated with the complexity of overbooking approach.

3.3 Data Availability and Financial Performance

With the recent technological advancements and the improved data collection and data storage capabilities, companies exploit data to get competitive advantage over their rivals (Provost & Fawcett, 2013). However, since the volume and variety of data have far exceeded the capacity of conventional databases, many companies are not able to store all the data by themselves and therefore rely on third-party data providers. The hotel industry is no exception and many hotels have contracts with commercial data providers in order to satisfy their data needs. However, it is important to note that some hotels may not be able to afford the expenses associated with these contracts or may choose to rely on their in-house data collection efforts. Hence, different hotels have different degrees of data accessibility.

Prior research has found strong evidence that business performance can be substantially improved with data-driven decision making (Brynjolfsson et al., 2011). Therefore, it is believed that firms with access to a broader range of useful data and the power to process and analyze the data can expect a higher degree of business success (Provost & Fawcett, 2013). In an empirical study, Brynjolfsson et al. (2011) showed that firms that adopt data-driven decision making have 5- 6% higher output and productivity compared to what is expected given their other investments and information technology usage. Furthermore, they found that the impact of data-driven decision making on productivity is not due to reverse causality. They also found evidence that this positive relationship between data-driven decision making and performance appears in many other performance measures including asset utilization, return on equity and market value. There is also strong evidence in the general management literature that suggests information sharing and data availability can positively impact the decision-making process and can drive performance improvements (Cachon & Fisher, 2000; Chen, 1999; Croson & Donohue, 2003; Lee et al., 2000; McAfee & Brynjolfsson, 2012; Raghunathan, 2001).

Another supporting evidence is the recent explosion of digital data and the big data revolution that have enabled the managers to better understand their businesses and know more about their competitors. This increased data accessibility caused by big data revolution is expected to improve managers' decision-making power and business performance (McAfee & Brynjolfsson, 2012). It is therefore expected that the big data revolution might increase the potential of data to assist in making better overbooking decisions.

A subdomain of information systems literature focuses on data accessibility and suggests that the advancements in information technology, including information sharing capabilities and improved data availability can boost the firms' performance (Cantor & Macdonald, 2009; Dedrick et al., 2003; Malone et al., 1987; McAfee & Brynjolfsson, 2012). Studies have shown that in addition to financial performance amelioration, sharing information across the boundaries of the firm and having access to a broader range of data can also facilitate and improve many intangible performance indicators including communication, coordination and collaboration (Malone et al., 1987). These findings motivated this study to examine the impact of data availability and information sharing on hotels' performance. As discussed earlier, in addition to data availability, it is necessary for hotels to acquire the knowledge and the ability to analyze their data. However, while evaluating the impact of hotels' data analysis power on their financial performance is an interesting topic for research, this study will only investigate the relationship between data availability and financial performance.

Given the general management and information systems literature, it is expected that hotels with a broader access to databases would perform better compared to the ones that have access to limited data sources.

Hypothesis H1b: Data availability positively impacts hotels' financial performance.

Another important issue is the potential moderating role of data availability in the relationship between overbooking policies and hotel performance. As a hotel increases the complexity (sophistication) of its overbooking policy, the marginal contribution from that added complexity (i.e., the ability of that additional complexity to improve performance) might depend on data availability. This means that once an overbooking policy is in place, data availability might impact the effectiveness or the ability of that overbooking policy to generate more money.

Therefore, when a hotel adopts a complex overbooking policy, it will need broader data sources and more accurate data. Without having access to the required data, not only the overbooking policy will not work, but also it is likely for it to generate misleading outputs/recommendations and consequently it might exacerbate the performance instead of ameliorating it. Accordingly, it is hypothesized that data availability can moderate the relationship between overbooking policies and financial performance.

Hypothesis H1c: Data availability moderates the impact of overbooking policies on financial performance.

3.4 Overbooking and Financial Performance

Despite the potential negative impact of overbooking on customers' goodwill and satisfaction, hotel revenue managers justify the use of overbooking policies by emphasizing on its ability to boost revenues and profitability through optimization of capacity utilization (Ivanov, 2007; Phillips, 2005).

Although, there have not been any formal attempts to examine the impact of capacity overbooking on hotels' financial performance, studies in other service settings including medical clinics (e.g., LaGanga & Lawrence, 2007, 2012), computer networks (e.g., Milbrandt et al., 2006; Zhao & Chen, 2007) and grid computing (e.g., Sulistio et al., 2008; Urgaonkar et al., 2002) have proved the positive impact of overbooking on performance. For instance, in the healthcare industry, patient no-shows diminish the performance of the clinical service operations by reducing revenues, causing resources to stand idle, preventing other patients from obtaining timely service, and decreasing clinic productivity. Studies have shown that appointment overbooking strategies can improve performance of these clinics (LaGanga & Lawrence, 2012). Studies have also shown that overbooking provides greater utility when medical clinics serve larger numbers of patients, no-show rates are relatively high, and service variability is low (LaGanga & Lawrence, 2007). The computer network literature also suggests that overbooking the capacity is an optimal solution for improving the throughput (Milbrandt et al., 2006; Zhao & Chen, 2007). Similarly, in grid computing, studies have found that overbooking is a reliable approach for increasing resource utilization in shared hosting platforms (Sulistio et al., 2008; Urgaonkar et al., 2002). Furthermore, grid computing literature suggests that by overbooking, a resource provider can accept more reservations than its capacity and as a result, the total net revenue of the resource can be increased by up to 9% (Sulistio et al., 2008).

To sum up, although the hospitality literature suggests that overbooking policies are utilized by hotels with the goal of maximizing the revenue and improving the financial performance (Hwang & Wen, 2009; Ivanov, 2007; Toh & Dekay, 2002), there have not been any attempts to empirically test the impact of hotel overbooking on financial performance. On the other hand, overbooking literature in other service settings suggests that there is a positive relationship between overbooking and company performance (LaGanga & Lawrence, 2007, 2012; Milbrandt et al., 2006; Sulistio et al., 2008; Urgaonkar et al., 2002; Zhao & Chen, 2007). Motivated by these studies, it is hypothesized that overbooking practices have a positive impact on hotels' performance.

Hypothesis H2: Overbooking positively impacts hotels' financial performance.

3.5 Cancellation Policies and Overbooking

Along with revenue and profit maximization, the possibility of room cancellations is another factor that motivates hotels to overbook (Noone & Lee, 2011; Park & Jang, 2014; Phillips, 2005). Some travelers cancel their reservations before their expected arrival or do not utilize their reservations by not showing up at the expected check-in time (Bertsimas & Popescu, 2003; Phillips, 2005). In these cases, customers get full, partial or no refund depending on the cancellation policies that are being set by revenue managers. No matter what proportion of the reservation fee is refunded to travelers after cancellation, hotels must decide how to handle the extra capacity that becomes available as a result of cancellations (Bertsimas & Popescu, 2003). The industry wide approach toward dealing with these conditions is overbooking and the room cancellation data are among the most salient information that revenue managers can utilize in order to make accurate overbooking decisions. As discussed earlier, hotel revenue managers analyze historical cancellation patterns to make robust overbooking decisions (Kimes & Chase, 1998; Lan, 2009; Phillips, 2005; Phumchusri & Maneesophon, 2014) and to predict future market trends. Obviously, if a hotel expects too many cancellations for a specific date, the overbooking policy should be adjusted such that more rooms will be available for reservation. On the other hand, if the revenue managers forecast a relatively low cancellation rate for a particular day, the overbooking policy should be updated and fewer rooms should be overbooked (Phillips, 2005).

It is expected that the degree of leniency in a hotel's cancellation policy might also have an impact on the degree to which a hotel is willing to overbook. Because, on one hand, overbooking is implemented to diminish losses from cancellations and to minimize the number of rooms that are left empty due to cancellations (Ivanov, 2015; Phillips, 2005), and on the other hand, the degree of cancellation leniency can have an impact on the customers' propensity to cancel their reservations (Chen et al., 2011). Hotel cancellation literature suggests that when lenient cancellation policies are in place, customers are more willing to continue searching for better deals after their initial reservations (Chen et al., 2011) and as a result of this, the probability of room cancellations is higher. It is expected that under lenient cancellation policies, revenue managers will have a tendency to set higher overbooking limits in order to minimize the potential loss from room cancellations. Conversely, studies have indicated that a customer's intention to cancel a hotel reservation decreases as the temporal and monetary sunk costs associated with the cancellation increase (Park & Jang, 2014). Therefore, when strict cancellation policies are adopted, the probability of room cancellations is lower and lower overbooking limits are expected to be in place. This is somewhat consistent with the idea that the optimal level of overbookings is inversely related to the amount of the cancellation charges (Ivanov, 2006). In other words, the closer the cancellation penalty to the room rate, the lower the lost revenue from the unoccupied room, and the less the revenue manager's motivation to overbook (Ivanov, 2006). Therefore, this study hypothesizes that:

Hypothesis H3a: Stricter cancellation policies are associated with lower overbooking limits.

3.6 Denied Service and Satisfaction

Like strict cancellation policies, overbooking practices carry the risk of alienating customers (Hwang & Wen, 2009) because once the customers feel that they are being harmed by these practices, they might perceive them as unfair, and their satisfaction, goodwill, and probability of future purchase could be negatively impacted (Hwang & Wen, 2009; Kahneman et al., 1986; Kimes, 1994; Wirtz et al., 2002). Therefore, even though overbooking helps hotels to optimize the utilization of their finite capacity of rooms, it can be negatively perceived by customers when the hotel is oversold and walks them away (Guo et al., 2016). Thus, a revenue increase resulting from overbooking practices could be merely short term in nature (Kimes, 2002) and might eventually impact the financial performance of the hotel in a negative way. There is strong evidence in hospitality literature suggesting that guests' satisfaction is relative not only to the traditional measures of service quality but also to revenue management practices including overbooking and cancellation policies (Capiez & Kaya, 2004). Furthermore, studies have shown that guest satisfaction is positively associated with the hotel's financial performance (Capiez & Kaya, 2004).

Hotels are always facing a dilemma, whether they should overbook in order to maximize their inventory utilization or they should avoid overbooking in order to maintain the customers' goodwill and satisfaction. Although denied service resulting from overbooking can negatively impact customers' satisfaction (Hwang & Wen, 2009; Kahneman et al., 1986; Kimes, 1994; Wirtz et al., 2002), the dissatisfaction can be reduced by offering compensation packages to the denied customers (Badinelli, 2000; Noone & Lee, 2011; Smith et al., 1999). Studies across a variety of service-related contexts including the hotel industry have shown that offering compensation to denied customers is positively associated with repurchase intentions (e.g., Goodwin & Ross, 1989; Hoffman et al., 1995; Mack et al., 2000; Mount & Mattila, 2000; Sparks & McColl-Kennedy, 2001), customer satisfaction (e.g., Goodwin & Ross, 1989; Hocutt et al., 1997; Noone & Lee, 2011; Ruyter & Wetzels, 2000; Sundaram et al., 1997), and word of mouth activity (e.g., Gilly & Hansen, 1985; Mount & Mattila, 2000; Richins, 1983). Although literature supports the fact that compensating denied customers (i.e., partial, full, or over compensation) is better than not compensating them (e.g., Conlon & Murray, 1996; Goodwin & Ross, 1989; Mount & Mattila, 2000; Noone & Lee, 2011), there is still no consensus regarding the optimal compensation strategies for different service settings. To be more specific, although there are some commonly practiced strategies in the hotel industry in order to compensate the walked guests, there is still no indication of the optimal strategies in terms of timing, amount, and type of compensation.

Studying the direct and indirect impacts of overbooking and cancellation policies on guest satisfaction is beyond the scope of this study. Additionally, this dissertation will not study the hotels' strategies for handling denied service instances. However, these expected relationships are presented in the conceptual model of this study in order to emphasize the importance of guest satisfaction in the context of overbooking policies and financial performance. Further examination of these relationships and an in-depth analysis of optimal strategies for handling denied service instances are interesting topics for future research.

3.7 Cancellation Policies and Financial Performance

Since cancellation rates are among the most important factors considered by hotel revenue managers when making overbooking decisions (Kimes & Chase, 1998; Lan, 2009; Phillips, 2005; Phumchusri & Maneesophon, 2014), and since cancellation policies are expected to impact cancellation rates and overbooking strategies (see hypothesis H3a), this study examines the role of cancellation policies in the overbooking-performance framework by looking at the potential relationships between cancellation policies and performance indicators.

Although the hospitality and tourism literature have never investigated the impact of cancellation policies on financial performance, there have been several attempts in the marketing literature in order to examine the relationship between return/cancellation policies and retailers' financial performance (e.g., Guo, 2009; Mukhopadhyay & Setoputro, 2004; Padmanabhan & Png, 1995, 1997; Wood, 2001; Xie & Gerstner, 2007). Since hotel reservation cancellations are a variant of product returns (Chen & Xie, 2013), the insights from the marketing literature can be a starting point to think about the real impact of hotels' cancellation policies on their performance indicators. The marketing literature suggests that although lenient return policies increase sales, they only increase the profitability if the return rates are not significantly high (Wood, 2001). Studies have also shown that when demand conditions are certain, a lenient return policy can increase the wholesalers' profitability by increasing the intensity of retail competition (Padmanabhan & Png, 1995, 1997).

The marketing literature also suggests that return policies should be evaluated by having a deeper look into the implications of different policies for customers and retailers (Mukhopadhyay & Setoputro, 2004; Wood, 2001). From the customers' point of view, if a retailer provides a clearly explained and lenient return policy, they will be motivated to purchase and therefore the overall market demand will be augmented. From the manufacturer's point of view, offering a lenient return policy can proliferate the revenues, but will also surge the costs due to the increased likelihood of returns (Mukhopadhyay & Setoputro, 2004). Since offering a lenient return policy can impact both sides of the profit equation by increasing revenues and costs at the same time, the need for finding an optimal return policy that would maximize the profits arises. By considering both sides of this equation, Mukhopadhyay and Setoputro (2004) found that when customer demand is sensitive to the leniency of the return policy, offering a highly generous return policy will augment the sales. Interestingly, they found that although lenient return policies augment the return rate, the retailers' profits are not negatively impacted. A possible explanation for their finding is that when customers are sensitive to the leniency of return policy, retailers can charge higher prices to offset the cost increase due to offering a more lenient return policy and therefore keep the profitability at a high level.

An opposite view in support of moderate return policies was offered by Xie and Gerstner (2007) and Guo (2009). They suggest that when advance purchase is possible as it is the case for the hotel reservations, by offering a partial refund (i.e., a moderate cancellation policy) to cover the cost of cancellations, the seller encourages the advance buyers to cancel their purchase as soon as they find a better deal. Cancellations under a partial refund policy (i.e., moderate policy) can be more profitable compared to cancellations under a full refund policy (i.e., lenient policy) because once the customer cancels a service and receives a partial refund, the firm can then sell the service to another customer (Xie & Gerstner, 2007). In other words, a partial refund policy enables the firm to sell the service or product twice (once to the advance buyer and the second time to the late-arriving buyer) while having a coverage for the cancellation expenses due to offering only a partial refund (Guo, 2009). Therefore, unlike full refund policies that can become profitable by charging higher prices in exchange for the refundability or by having a relatively low return rate (Mukhopadhyay and Setoputro, 2004), partial refund policies can be profitable without increasing the service price and without being worried about the cancellation rate (Xie & Gerstner, 2007).

Since hotel room reservations are more similar to advance purchase settings like the ones introduced by Xie and Gerstner (2007) and Guo (2009), it is expected that moderate room cancellation policies should be associated with better financial performance. This is mainly because moderate cancellation policies create opportunities for multiple selling (i.e., collecting cancellation fees from travelers who reserve in advance and cancel, and then reselling the freed rooms) without incurring very high cancellation costs (as it is the case for lenient policies) or discouraging customers from reservation (as it is the case for strict policies). However, it is important to note that if cancellation policies are very strict and no refunds are offered for cancelled reservations, the cancellation rate will significantly drop and there will be only few opportunities for multiple selling (Xie and Gerstner, 2007). Therefore, in order to take advantage from multiple selling opportunities, hotels should at least offer some sort of partial refund to cancelled reservations to motivate the guests to cancel their reservations as soon as they find a better deal. Additionally, it is worth mentioning that overbooking strategies can help hotels to gain the most advantage from these multiple selling opportunities. It is hypothesized that a moderate room cancellation policy (like partial refund) is expected to bring the best financial performance. In other words, it is expected that the relationship between cancellation policy leniency and financial performance is nonlinear and inverse U-shaped, where lenient and strict policies are associated with relatively undesirable performance and moderate cancellation policies provide the best financial performance.

Hypothesis H3b: Moderate cancellation policies are associated with better financial performance.

Besides hypothesizing that cancellation policies can directly impact the financial performance; this study also posits that cancellation policies can moderate the relationship between overbooking policies and financial performance. In other words, as a hotel increases the complexity of its overbooking policy, the marginal contribution from that added complexity (i.e., the ability of that additional complexity to improve performance) might depend on the cancellation policy which is in place. Meaning that once an overbooking policy is adopted, the cancellation policy could impact its effectiveness and its ability to generate more money. Accordingly, it is hypothesized that cancellation policies can moderate the relationship between overbooking policies and financial performance.

Hypothesis H3c: Cancellation policies moderate the impact of overbooking policies on financial performance.

3.8 Summary of Research Hypotheses and Conceptual Model

This chapter provided a conceptual development for the research hypotheses that are tested in this dissertation. To summarize, this study will test the following hypotheses:

H1a: Data availability is positively associated with the complexity of overbooking approach.

H1b: Data availability positively impacts hotels' financial performance.

H1c: Data availability moderates the impact of overbooking policies on financial performance.

H2: Overbooking positively impacts hotels' financial performance.

H3a: Stricter cancellation policies are associated with lower overbooking limits.

H3b: Moderate cancellation policies are associated with better financial performance.

H3c: Cancellation policies moderate the impact of overbooking policies on financial performance.

Based on the hypothesis development and the discussion regarding the role of guest satisfaction in the overbooking-performance framework, a conceptual model is created (see Figure 3.1). The dotted lines in the conceptual model are the relationships that are not examined in this study. These relationships are only displayed to show the role of guest satisfaction in the overall overbooking-performance framework. The solid lines in the conceptual model indicate the research hypotheses and the arrows show the expected direction of causality. Hypothesis numbers are displayed above corresponding arrows.

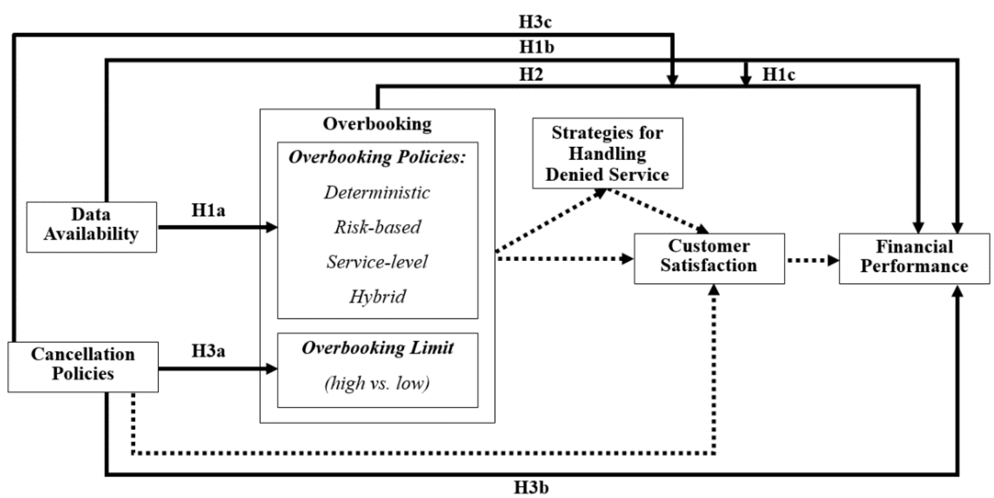

Figure 3.1: Conceptual model

Chapter 4

METHODOLOGY

4.1 Data Collection Procedure

Two data sets were used to answer the research questions, that is, to examine the relationship between cancellation policies, overbooking practices, data availability, and financial performance.

4.1.1 Cancellation Policies Data Set

A random sample of almost 600 US hotels was obtained from Smith Travel Research Inc. (STR) in September 2016. The sample provided by STR contained hotel names, locations (i.e., city and state), and zip codes. A team of 6 graduate students were employed to collect a variety of information about the cancellation policies of these hotels. More specifically, the data collectors were instructed to collect information regarding cancellation penalty (i.e., the fee charged upon cancellation), free cancellation window (i.e., the time frame in which the reservation can be cancelled free of charge), cancellation deadline time, prepayment refund options, whether the hotel has a different cancellation policy for its loyalty club members, and whether customers can pay a higher room rate to avoid a cancellation fee. The data collectors recorded these information for each of the 600 hotels across four different booking windows (i.e., same day reservation, 7 days ahead, 14 days ahead and 30 days ahead bookings), three different length of stay (LOS) (i.e., 1, 2 and 3 nights), and three different room rate categories (i.e., highest rate under best available rate category, lowest rate under best available rate category and highest rate under AAA category).

All the information regarding the cancellation policies were collected from the hotels' own branded websites. In case, the cancellation policy was not specifically discussed on a hotel's website, the data collectors were instructed to look for this information on *Hotels.com* website. *Hotels.com* was selected as the secondary data source for cancellation policies because unlike many other online travel agents (OTAs) it does not manipulate or pre-negotiate the cancellation policies with the hotels, therefore, each of the listed hotels is solely responsible for setting its own cancellation policies that are then displayed on *Hotels.com* (Roomer Travel, 2017). Finally, the data collectors were instructed to record the *TripAdvisor* rating for every hotel that they searched. The data collection process took almost 5 months from December 2016 until April 2017. Appendix A provides a complete description of the data collection instructions.

After consolidating the data files from different data collectors and removing the hotels for which no data was collected (either because the hotel went out of business or had no availability for the requested duration of stay), 6379 observations from 569 hotels were obtained.

This consolidated data file was returned to STR in order to obtain the performance indicators and basic property information for each hotel. STR anonymized the data by removing the hotel names and other identifiable information and added 6 annual performance indicators, namely, Occupancy, ADR, RevPAR, Occupancy Index, ADR Index, and RevPAR Index to the data set. STR also provided information about hotel operation type, class, size, location segment, etc. for each of these 569 hotels.

Table 4.1 displays the list of variables that were recorded in the cancellation policies data set. The cancellation policies data set was only used for testing hypothesis H3b. To facilitate the data analysis some of these variables were converted into categorical (i.e., 0-1) variables.

Table 4.1: Variables in the cancellation policies data set

Variable	**Possible Values**	**Description**
Operation	Chain Owned and/or Managed, Franchised, Independent	This is how STR defines a hotel operation.
Class	Luxury, Upper Upscale, Upscale, Upper Midscale, Midscale, Economy	Class is an industry categorization which includes chain-affiliated and independent hotels.
Size	Less Than 75 Rooms, 75-149 Rooms, 150-299 Rooms, 300-500 Rooms, Greater than 500 Rooms	Hotel size based on the number of rooms.
TripAdvisor Rating	0, 0.5, 1, …, 4.5, 5	Hotel's rating on *TripAdvisor.com*
Number of Days in Advance	0, 7, 14, 30	Number of days before check-in that the data collector used to search for room availability and record the cancellation policy.
Length of Stay	1, 2, 3	The length of stay used by data collector to search for room availability and record the cancellation policy.
Room Rate Category	Best Available (highest), Best Available (lowest), AAA (highest), Single Rate	Room rate category used by data collector to search for room availability and record the cancellation policy. "Single Rate" was selected when a hotel did not have multiple rate categories.
Free Cancellation Window	Same Day Cancellation	When the cancellation policy allows free cancellation until the check-in date.
	X Day(s) Before Check-In	When the cancellation policy allows free cancellation until a certain number of days before the check-in date (for example, 1 day before check-in)
	Non-Refundable	When the room is non-refundable and customers can never cancel their reservations for free.
	No Deadline	When the customers can cancel their reservations free of charge whenever they wish.
	Other	When the free cancellation deadline is different than all of the above options.
	Not Found	When the free cancellation deadline cannot be found on the hotel's website or on *Hotels.com*.
Cancellation Deadline Time	12 AM, 1 AM, …, 10 PM, 11 PM, Not Specified	The cancellation deadline time. If the cancellation deadline time is not reported in the hotel's cancellation policy, then "Not Specified" was selected
Pay More to Avoid Cancellation Penalty?	Yes, No	Specifies whether an option that would allow paying more money in order to avoid the cancellation penalty is discussed in the cancellation policy.

Table 4.1 Continued:

Different Cancellation Policy for Loyalty Club?	Yes, No	Based on the information provided in the cancellation policy, indicates whether a different cancellation policy exists for loyalty club members
Cancellation Penalty	1 Night Fee Plus Taxes	When customers can cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty equal to the fee for 1 night of stay plus taxes (i.e., the average nightly rate for the duration of stay).
	First Night Fee Plus Taxes	When customers can cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty equal to the fee for the first night of stay plus taxes (i.e., the fee for the first night of the reservation).
	Entire Stay Plus Taxes	When customers can cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty equal to the fee for their entire length of stay plus taxes (i.e., the fee for the entire reservation).
	Fixed dollar amount - Less than 1 Night Fee Plus Taxes	When customers can cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty which is less than the rate for 1 night of stay at the hotel.
	Fixed dollar amount - More than 1 Night Fee Plus Taxes	When customers can cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty which is more than the rate for 1 night of stay at the hotel.
	Non-Refundable	When the cancellation policy states that the room is non-refundable and customers can never cancel their reservations for free.
	No Cancellation Fee	When the cancellation policy states that the hotel does not charge any cancellation fee and customers can cancel their reservations free of charge whenever they wish.
	Other	When the cancellation penalty is different than all of the above options.
	Not Found	When the cancellation penalty cannot be found on the hotel's website or on *Hotels.com*.

Table 4.1 Continued:

Prepayment Refund	Yes – Full Refund to Customer's Credit Card	The cancellation policy states that in case of cancellation, full prepayment refund is made to customer's credit card
	Yes – Credit Toward Future Reservations	The cancellation policy states that in case of cancellation, prepayment refund is made in the form of credit toward future reservations from the same hotel or hotel chain.
	No	The cancellation policy states that in case of cancellation, no prepayment refund is made.
	Not Specified	The cancellation policy does not discuss the prepayment refund policy.
Location	Urban	A hotel in a densely populated area in a large metropolitan area. (e.g. Atlanta, Boston, San Francisco).
	Suburban	A hotel in the suburb of a metropolitan market. Examples are Sag Harbor and White Plains, New York, near New York City, USA. Distance from center city varies based on population and market orientation.
	Airport	A hotel in close proximity of an airport that primarily serves demand from airport traffic. Distance may vary.
	Interstate/Motorway	A hotel in close proximity of major highways, motorways or other major roads whose primary source of business is through passerby travel. Hotels located in suburban areas have the suburban classification.
	Resort	Any hotel located in a resort area or market where a significant source of business is derived from leisure/destination travel. Examples are: Orlando, Lake Tahoe, Daytona Beach, Hilton Head Island, Virginia Beach.
	Small Metro/Town	Areas with either smaller population or limited services, in remote locations. Size can vary dependent on market orientation. Suburban locations do not exist in proximity to these areas. In North America, metropolitan small town areas are populated with less than 150,000 people.
Occupancy	A numeric value between 0 and 1	Average hotel occupancy rate for a 12-month period ending March 2017.
ADR	A numeric value	Average hotel ADR for a 12-month period ending March 2017.
RevPAR	A numeric value	Average hotel RevPAR for a 12-month period ending March 2017.

Table 4.1 Continued:

Occupancy Index	A numeric value	Average hotel occupancy index for a 12-month period ending March 2017.
ADR Index	A numeric value	Average hotel ADR index for a 12-month period ending March 2017.
RevPAR Index	A numeric value	Average hotel RevPAR index for a 12-month period ending March 2017.

4.1.2 Overbooking Policies Data Set

A survey was designed to collect information regarding hotels overbooking practices. The survey was submitted to the University of Delaware’s Institutional Review Board (IRB) and was granted “exempt status” on September 26, 2017 (see Appendix B). In October 2017, the survey was distributed among a group of hospitality management professors and hotel professionals to collect feedback regarding the wording and structure of the survey questions. The survey contained various questions regarding different aspects of overbooking policies, overselling strategies and data availability. Survey recruitment email and survey questions are displayed in Appendix C and Appendix D respectively.

A random sample of 10,000 US hotels was obtained through STR in November 2017. The survey was then distributed among these hotels via email between December 2017 and February 2018. Hotels had an option to opt-out from the mailing list. Those which did not unsubscribe from the mailing list received up to 5 reminder emails at different time intervals. Out of 10,000 hotels which were invited to participate in the survey, 377 of them completed the survey; hence a participation rate of 3.77%.

Cancellation policy elements of window and penalty for these hotels were manually collected for a booking window of 30 days, LOS of 2 nights and the lowest rate under best available rate category from the hotels own branded websites. In case, the cancellation policy was not specifically discussed on the hotel's website, the cancellation data was collected from *Hotels.com*. The cancellation data was collected only for one booking window, one LOS, and one room rate category because initial analysis on cancellation policies data set revealed that hotels' cancellation policies do not depend on any of these 3 factors. These cancellation policy elements were then added to the overbooking data which were collected through the survey.

The final data set was returned to STR to obtain the performance indicators and basic property information for each hotel. STR anonymized the data by removing the hotel names and other identifiable information and added 6 monthly performance indicators, namely, Occupancy, ADR, RevPAR, Occupancy Index, ADR Index, and RevPAR Index to the data set. For each hotel, these performance indicators were provided for 6 different months; hence, the data set had approximately 6 observations per each hotel. STR also provided information about hotel operation type, class, size, location, etc.

Table 4.2 displays the list of variables that were recorded in the overbooking policies data set. The overbooking policies data set was used for testing hypotheses H1a, H1b, H1c, H2, H3a and H3c. To facilitate the data analysis some of these variables were converted into categorical (i.e., 0-1) variables.

Table 4.2: Variables in the overbooking policies data set

Variable	Possible Values	Description
Operation	Chain Owned and/or Managed, Franchised, Independent	This is how STR defines a hotel operation.
Class	Luxury, Upper Upscale, Upscale, Upper Midscale, Midscale, Economy	Class is an industry categorization which includes chain-affiliated and independent hotels.
Overbooking Frequency	Never Overbooks, 1-5 Days in a Month, 6-10 Days in a Month, 11-20 Days in a Month, More than 20 Days in a Month	Number of days in a month that the hotel is overbooked.
Most Common Overbooking Day	No Difference Between Weekdays and Weekends, Weekdays, Weekends	Day of the week on which the hotel tends to overbook more.
Maximum Overbooking Limit on a Single Day	Less than 5% of Capacity, 5-10% of Capacity, More than 10% of Capacity	Highest percentage of rooms that the hotel overbooks on a given day.
Overbooking Dynamicity	Static	Once an optimal overbooking level is set, that limit will no longer change for the decision period.
	Dynamic	The pattern of customer reservations and cancellations are tracked over time, and the optimal overbooking limit is updated according to the changes in these patterns.
Overbooking Approach	Deterministic	To determine the overbooking limit for the hotel, the hotel capacity is simply divided by the historical show rate.
	Risk-based	At the hotel, the overbooking limit is calculated by considering demand distributions, expected revenues and expected overbooking expenses (e.g., cost of walking guests, etc.).
	Service-level	At the hotel, the overbooking limit is determined such that the number of denied service incidents (total number of walked guests) will not exceed the managerial expectations, thereby reflecting the hotel's commitment to service.
	Hybrid	At the hotel, both risk-based overbooking limit (that is considering demand distributions, expected revenues and expenses) and service-level overbooking limit (that is number of walked guests not exceeding managerial expectations) are calculated; then the minimum of the two limits is selected.
	Other	None of the above.

Table 4.2 Continued:

Historical Data Usage	Never, Seldom, About Half the Time, Usually, Always	The extent to which the hotel uses "historical data" to make overbooking decisions. For example, historical no-shows, cancellation rates, etc.
Market Data Usage	Never, Seldom, About Half the Time, Usually, Always	The extent to which the hotel uses "current market data" to make overbooking decisions. For example, market demand, competition, etc.
Turn Away Data Usage	Never, Seldom, About Half the Time, Usually, Always	The extent to which the hotel uses "turn-away/unconstrained demand data" to make overbooking decisions. That is, an estimate of the number of rooms that could have been sold if the hotel had unlimited capacity.
Third Party Data Usage	Never, Seldom, About Half the Time, Usually, Always	The extent to which the hotel uses data provided by "third parties" such as STR and Travel Click to make overbooking decisions.
Shared Data Usage	Never, Seldom, About Half the Time, Usually, Always	The extent to which the hotel uses data obtained through "sharing agreements with other chains/properties" to make overbooking decisions
Respondent Job Title	General Manager, Reservations Manager, Rooms Director, Accommodations/Front Office Manager, Revenue Manager, Sales Manager, Group Manager, Other	The job title of the survey respondent.
Free Cancellation Window	Same Day Cancellation	When the cancellation policy allows free cancellation until the check-in date.
	X Day(s) Before Check-In	When the cancellation policy allows free cancellation until a certain number of days before the check-in date (for example, 1 day before check-in)
	Non-Refundable	When the room is non-refundable and customers can never cancel their reservations for free.
	No Deadline	When the customers can cancel their reservations free of charge whenever they wish.
	Other	When the free cancellation deadline is different than all of the above options.
	Not Found	When the free cancellation deadline cannot be found on the hotel's website or on *Hotels.com*.

Table 4.2 Continued:

Cancellation Penalty	1 Night Fee Plus Taxes	When customers can cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty equal to the fee for 1 night of stay plus taxes (i.e., the average nightly rate for the duration of stay).
	First Night Fee Plus Taxes	When customers can cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty equal to the fee for the first night of stay plus taxes (i.e., the fee for the first night of the reservation).
	Entire Stay Plus Taxes	When customers can cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty equal to the fee for their entire length of stay plus taxes (i.e., the fee for the entire reservation).
	Fixed dollar amount - Less than 1 Night Fee Plus Taxes	When customers can cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty which is less than the rate for 1 night of stay at the hotel.
	Fixed dollar amount - More than 1 Night Fee Plus Taxes	When customers can cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty which is more than the rate for 1 night of stay at the hotel.
	Non-Refundable	When the cancellation policy states that the room is non-refundable and customers can never cancel their reservations for free.
	No Cancellation Fee	When the cancellation policy states that the hotel does not charge any cancellation fee and customers can cancel their reservations free of charge whenever they wish.
	Other	When the cancellation penalty is different than all of the above options.
	Not Found	When the cancellation penalty cannot be found on the hotel's website or on *Hotels.com*.

Table 4.2 Continued:

Location	Urban	A hotel in a densely populated area in a large metropolitan area. (e.g. Atlanta, Boston, San Francisco).
	Suburban	A hotel in the suburb of a metropolitan market. Examples are Sag Harbor and White Plains, New York, near New York City, USA. Distance from center city varies based on population and market orientation.
	Airport	A hotel in close proximity of an airport that primarily serves demand from airport traffic. Distance may vary.
	Interstate/Motorway	A hotel in close proximity of major highways, motorways or other major roads whose primary source of business is through passerby travel. Hotels located in suburban areas have the suburban classification.
	Resort	Any hotel located in a resort area or market where a significant source of business is derived from leisure/destination travel. Examples are: Orlando, Lake Tahoe, Daytona Beach, Hilton Head Island, Virginia Beach.
	Small Metro/Town	Areas with either smaller population or limited services, in remote locations. Size can vary dependent on market orientation. Suburban locations do not exist in proximity to these areas. In North America, metropolitan small town areas are populated with less than 150,000 people.
Size	Less Than 75 Rooms, 75-149 Rooms, 150-299 Rooms, 300-500 Rooms, Greater than 500 Rooms	Hotel size based on the number of rooms.
Occupancy	A numeric value between 0 and 1	Average hotel occupancy rate for a 1-month period.
ADR	A numeric value	Average hotel ADR for a 1-month period.
RevPAR	A numeric value	Average hotel RevPAR for a 1-month period.
Occupancy Index	A numeric value	Average hotel occupancy index for a 1-month period.
ADR Index	A numeric value	Average hotel ADR index for a 1-month period.
RevPAR Index	A numeric value	Average hotel RevPAR index for a 1-month period.

4.2 Performance Measures

After anonymizing the data sets and removing all identifying information, STR added 6 different performance indicators to each hotel. These key performance indicators (KPIs) are briefly introduced in this section:

4.2.1 Occupancy Rate

A property's occupancy rate is the percentage of its available rooms that were sold during a specific period. Therefore, it is calculated by dividing the number of rooms sold during that period by the number of available rooms. For instance, if a hotel has 100 rooms available for a specific period and sells 70 of them, the occupancy rate for that hotel will be 70%.

$$Occupancy\ Rate = \frac{Number\ of\ Rooms\ Sold}{Number\ of\ Available\ Rooms} \tag{4.1}$$

4.2.2 Occupancy Index

The occupancy index also known as the market penetration index (MPI), measures a hotel's occupancy performance relative to its competitive set (i.e., a peer group of hotels that competes for business and is used to benchmark the subject hotel's performance) (STR Global, 2017). If everything is equal, then a hotel's occupancy index is equal to 100 compared to the aggregated group of hotels in its competitive set. An occupancy index of more than 100 indicates that the hotel's occupancy performance is better than its competitors. On the other hand, an occupancy index below 100 represents a weaker occupancy performance compared to the competitive set. The occupancy index is calculated as follows:

$$Occupancy\ Index = \frac{Occupancy\ Rate_i}{Occupancy\ Rate_{compset}}\ x\ 100 \tag{4.2}$$

Where i represents the subject hotel and $compset$ represents the competitive set (STR Global, 2017).

For example, if the subject hotel's occupancy rate is 70%, and the occupancy rate for its competitive set is also 70%, then the subject hotel's occupancy index is 100. If the subject hotel's occupancy is equal to 84%, then its occupancy index is 120, indicating that the hotel has captured more than its expected share. Finally, if the subject hotel's occupancy is 63%, its occupancy index is 90, indicating that the property captured less than its expected share.

4.2.3 Average Daily Rate (ADR)

ADR is the average room income per paid occupied room in a given period (Little Hotelier, 2017). It is calculated by dividing the room revenue by the number of rooms sold (Reid & Bojanic, 2009).

$$ADR\ = \frac{Total\ Room\ Revenue}{Number\ of\ Rooms\ Sold} \tag{4.3}$$

For instance, if the total room revenue over a 30-day period was $90,000 and 40 rooms were sold every night, then the property's ADR is equal to $75.

4.2.4 ADR Index

The ADR index measures a hotel's ADR performance compared to its competitive set. An ADR index of 100 equals fair share of ADR, compared to the aggregated group of hotels in the competitive set. An ADR index greater than 100 indicates that the hotel's ADR is higher than its competitive set. Finally, an ADR index below 100 indicates that the subject property's ADR is lower than its competitors (STR Global, 2017).

The ADR index is calculated as follows:

$$ADR\ Index = \frac{ADR_i}{ADR_{compset}}\ x\ 100 \qquad (4.4)$$

Where i represents the subject hotel and $compset$ represents the competitive set (STR Global, 2017).

For example, if the subject hotel's ADR is $75 and the ADR of its competitive set is also $75, then the ADR index for the subject property is equal to 100. If the subject hotel's ADR is $90, its ADR index would be 120, indicating the hotel has captured more than its fair share. Finally, if the subject property's ADR is equal to $57, the ADR index would be 76, indicating that the hotel has captured less than its fair share.

4.2.5 Revenue Per Available Room (RevPAR)

RevPAR is calculated by dividing the hotel's total room revenue by the number of available rooms and has been the de facto industry standard for many years (Mauri, 2013). The RevPAR measure was developed with investors in mind and is commonly used by hotel revenue managers to evaluate performance (Schwartz et al., 2016). RevPAR is one of the most important KPIs used in the hotel industry, because it "incorporates both room rates and occupancy, and provides a convenient snapshot of how well a company is filling its rooms, as well as how much it is able to charge" (Investing Answers, 2017).

$$RevPAR = \frac{Total\ Room\ Revenue}{Number\ of\ Available\ Rooms} \tag{4.5}$$

For instance, if the total room revenue over a 30-day period was \$90,000 and the hotel had 50 rooms, then the property's RevPAR is equal to \$60.

RevPAR can also be derived by multiplying the hotel's ADR by its occupancy rate (Reid & Bojanic, 2009):

$$RevPAR = ADR\ x\ Occupancy\ Rate \tag{4.6}$$

For example, if a hotel has an occupancy rate of 75% and an ADR of \$80, its RevPAR is equal to \$60.

4.2.6 RevPAR Index

The RevPAR index measures a hotel's RevPAR performance compared to its competitive set. If everything is equal, a hotel's RevPAR index will be 100, meaning the hotel performs as good as the aggregated group of hotels in the competitive set. A RevPAR index greater than 100 indicates that the hotel's RevPAR is higher than its competitive set; and a RevPAR index below 100 indicates that the subject property's RevPAR is lower than its competitors (STR Global, 2017). The RevPAR index is calculated as follows:

$$RevPAR\ Index = \frac{RevPAR_i}{RevPAR_{compset}}\ x\ 100 \qquad (4.7)$$

Where i represents the subject hotel and $compset$ represents the competitive set (Queenan et al., 2011; STR Global, 2017).

For example, if the subject property's RevPAR is $75 and the RevPAR of its competitive set is $75, then the RevPAR index for the subject hotel is equal to 100. If the subject hotel's RevPAR is $90, its RevPAR index would be 120, indicating the hotel has captured more than its fair share. Finally, if the subject hotel's RevPAR is equal to $57, its RevPAR index would be 76, indicating that the hotel has captured less than its fair share. The composition of the set of competitive hotels selected for calculating the RevPAR index is of great importance. In fact, in order for RevPAR index to be truly relevant, "it should truly reflect the competitive options that the potential guests face when choosing a hotel in the location and of the product type concerned" (Rivera, 2011).

Many argue that the RevPAR index provides the best indication of how competitive a hotel is compared to its competitive set (Altin, 2015; Rivera, 2011). This is primarily because the RevPAR index uses a competitive set, which serves as a proxy for hotels that are often located in the same region and have similar service levels (Altin, 2015; Queenan et al., 2011) Additionally, using the RevPAR index as a performance measure helps revenue managers to control outside economic factors (Queenan et al., 2011). The industry-wide dominance of the RevPAR index is also partially due to the data accessibility and availability that facilitate the calculation of this important KPI (Schwartz et al., 2016).

After considering various performance indices in the initial analysis, RevPAR index was selected as the best measure of a hotel's financial performance. There are three main reasons that justify this decision. First, RevPAR index incorporate both room rates (i.e., ADR) and occupancy, whereas ADR and occupancy rate each incorporate only one of these factors. Second, RevPAR index is normalized (i.e., calculated per available room). Lastly, RevPAR index indicates how competitive a hotel is compared to its competitive set (Altin, 2015; Rivera, 2011).

4.3 Data Cleaning

4.3.1 Cleaning the Cancellation Policies Data Set

Tukey method (Hoaglin et al., 1986; Tukey, 1977) was used in order to remove the outliers from the cancellation policies data set. The method uses the interquartile range (IQR) to filter out very small or very large observations. After calculating the interquartile range for each of the variables, the following formulas are used to establish a low fence and a high fence for the variable:

$$Low\ Fence = Q1 - 1.5(IQR) \tag{4.8}$$

$$High\ Fence = Q3 + 1.5(IQR) \tag{4.9}$$

Where $Q1$ is the first quartile (i.e., 25th percentile), $Q3$ is the third percentile (i.e., 75th percentile) and IQR is the interquartile range (i.e., $Q3 - Q1$). Any number that is lower than the low fence or higher than the high fence is considered as an outlier. In this study the low and high fences were established for RevPAR Index. After establishing the fences for this variable, the outliers were removed from the data set.

Initially, the cancellation policies data set had 6379 observations from 569 hotels. Following the removal of outliers (Hoaglin et al., 1986; Tukey, 1977) and records with missing information, the final data set contained 5564 observations (unique records) from 492 hotels.

4.3.2 Cleaning the Overbooking Policies Data Set

Tukey method (Hoaglin et al., 1986; Tukey, 1977) was used to remove the outliers from the overbooking policies data set in the same manner as it was applied to the cancellation policies data set. After establishing the low and high fences for RevPAR index, the outliers were removed from the data set.

Initially, the overbooking policies data set had 2262 observations from 377 hotels. Following the removal of outliers (Hoaglin et al., 1986; Tukey, 1977) and records with missing information, the final data set contained 2147 observations from 365 hotels.

4.4 Data Analysis Techniques

In this section, the statistical methods used to analyze the data are discussed. Since the study had multiple parts, various techniques were employed to answer the research questions and to test the hypotheses. To analyze the current state of overbooking and cancellation policies in the hotel industry, descriptive statistics were employed. Means were compared using Analysis of Variance (ANOVA), independent samples T test, non-parametric Kruskal-Wallis test and non-parametric Mann-Whitney test. The relationships between the hotels' cancellation policies, overbooking policies, data availability elements and their performance were assessed using the Spearman correlation test and stepwise multiple linear regression. Finally, multivariate multiple regression was used to test how data availability impacts the choice of overbooking approach and to test how strictness of the cancellation policy affects the overbooking limit.

4.4.1. Analysis of Variance (ANOVA)

ANOVA is a statistical method used to compare the means of different groups of observations (Bartlett et al., 2000). The null hypothesis in ANOVA is that means for all groups of observations are equal. Accordingly, rejection of the null hypothesis indicates that the means for all the groups that are being analyzed are not equal and there is at least one group which has a statistically significant different mean compared to the others. ANOVA test provides an F-statistic, which is used to calculate a p-value. If the p-value for the ANOVA test is less than or equal to 0.05 the null hypothesis can be rejected meaning that the means of the study variable are not equal across all groups (Creech, 2017).

Although ANOVA indicates whether there is at least one group which has a statistically significant different mean compared to the others, it does not indicate were the differences exactly are. Post-hoc pairwise comparison tests are used to address this issue. In this study, ANOVA was complemented by two post-hoc pairwise comparison tests, namely, Tukey Honest Significant Difference (HSD) and Games-Howell test. Tukey HSD is a post-hoc test based on the studentized range distribution which compares all possible pairs of means and shows specifically which groups have statistically significant different means. Unlike the Tukey HSD test which assumes equal variances, the Games-Howell test compares the means across different combinations of groups without assuming equal variances or sample sizes. Games-Howell test is based on Welch's degrees of freedom correction and uses the studentized range statistic.

In this study, ANOVA and post-hoc pairwise comparisons were used for testing hypotheses H2 and H3b. Particularly, ANOVA was used to confirm that RevPAR index is not equal across different levels of overbooking (H2) or cancellation policy (H3b) elements.

4.4.2 Kruskal-Wallis Test

The ANOVA test assumes that the samples come from normally distributed populations that have the same standard deviations. If this assumption is not viable, then its non-parametric equivalent called Kruskal-Wallis test could be used. Like ANOVA, the Kruskal-Wallis test examines whether the mean value for a variable is equal across different groups (Kruskal & Wallis, 1952). Therefore, the null hypothesis for the Kruskal-Wallis test is that all groups have equal distributions. If the p-value is less than or equal to 0.05 the null hypothesis can be rejected indicating that not all groups have equal distributions.

In this study, Kruskal-Wallis test was used for testing hypotheses H2 and H3b. Specifically, Kruskal-Wallis test was used to confirm that RevPAR index is not equal across different levels of overbooking (H2) or cancellation policy (H3b) elements.

4.4.3 Independent Samples T Test

Independent samples T test is used to statistically compare the means of two independent groups. More specifically, the T test determines whether the means of two independent groups are significantly different from one another. Although both T test and ANOVA are used to compare the means across different groups, the T test can only be used to compare the means of two groups, while ANOVA is used when more than two groups are being compared.

Independent samples T test requires a continuous or ordinal dependent variable and a categorical independent variable. Another important requirement is that the observations should be independent meaning that the subjects in one group cannot be present in the other group. Additionally, the observations in either of the two groups cannot influence the observations in the other group. The null hypothesis of the T test states that the two population means are equal. If the p-value is less than or equal to 0.05 the null hypothesis can be rejected indicating that the two groups do not have equal means.

In this study, independent samples T test was used for testing hypothesis H2. Particularly, the test was used to find out whether RevPAR index is significantly different between hotels that have a dynamic overbooking approach and the ones that have a static overbooking approach.

4.4.4 Mann-Whitney Test

The Mann-Whitney test is the non-parametric equivalent of the independent samples T test; therefore, it is used when the sample data are not normally distributed and the dependent variables is either continuous or ordinal. Like the independent samples T test, the Mann-Whitney test is used to determine whether the means of two independent groups are significantly different from one another. The null hypothesis for this test states that the distributions of the two groups are equal. If the p-value is less than or equal to 0.05 the null hypothesis can be rejected indicating that the two groups do not have equal distributions. In this study, Mann-Whitney test was used for testing hypothesis H2.

4.4.5 Stepwise Multiple Regression Analysis

Stepwise regression is a method of regressing multiple variables while adding the strongest and removing the weakest correlated variables each time. In other words, the stepwise regression essentially runs multiple regression several times, and removes the least important variables and adds more important variables each time. This stepwise process continues until there is no justifiable reason to add or remove any variables.

Stepwise regression can be used for exploratory purposes or when testing for associations. The primary goal of this technique is to build the best model, given the predictor variables that are available, such that the resulting model accounts for the most variance in the outcome variable (R-squared) (Heidel, 2017). Stepwise regression is advantageous over simple regression because it can easily manage large amounts of potential predictor variables and can fine-tune the model such that the best predictors are selected. It is also considerably faster than other automatic model-selection techniques and allows the researcher to observe the order in which the variables are removed or added (Glen, 2015).

In this study, stepwise multiple regression was used for testing hypotheses H1b, H1c, H2, H3b and H3c, where in all cases the dependent variable was RevPAR index.

4.4.6 Multivariate Multiple Regression Analysis

Multivariate multiple regression is used when multiple dependent variables need to be predicted with a single set of predictor variables. The term multivariate refers to more than one dependent variable being involved in this method and the term multiple is used because this method requires more than one independent variable (Dattalo, 2013). In multivariate multiple regression, each dependent variable has a separate regression model:

$$Y_1 = \beta_{01} + \beta_{11} Z_1 + \cdots + \beta_{r1} Z_r$$

$$Y_2 = \beta_{02} + \beta_{12} Z_1 + \cdots + \beta_{r2} Z_r$$

$$Y_n = \beta_{0n} + \beta_{1n} Z_1 + \cdots + \beta_{rn} Z_r \tag{4.10}$$

In this study, the multivariate multiple regression was used to test hypotheses H1a and H3a. In hypothesis H1a, the dependent variables were the categorical variables that corresponded to different overbooking approaches. In hypothesis H3a, the dependent variables were the categorical variables representing different levels of maximum overbooking limit.

4.4.7 Spearman Correlation Test

Like other correlation tests, the Spearman correlation measures the strength and direction (negative or positive) of association between two variables. Spearman correlation test is a non-parametric test meaning that it does not have any assumptions regarding the distribution of the data and is therefore appropriate when the data is not normally distributed. The Spearman correlation coefficient also known as Spearman rho can take any value between -1 and +1. A rho value of +1 indicates that there is perfect positive association between the two variables, whereas, a rho value of -1 indicates a perfect negative association between the variables. If the rho value is equal to zero then it can be concluded that there is no association between the two variables. If the p-value associated with a correlation analysis is less than or equal to 0.05 it can be concluded that the correlation coefficient is statistically significant.

In this study, Spearman correlation was used for testing hypotheses H2 and H3b to find out how different elements of overbooking and cancellation policies correlate with the RevPAR index.

Chapter 5

RESULTS AND DISCUSSION

5.1 Sample Characteristics

5.1.1 Sample Characteristics for Cancellation Policies Data Set

Following the removal of outliers and records with missing information, the final data set contained 5564 observations from 492 hotels. An initial look at the characteristics of the sample indicated that the majority of hotels were franchised (86%) and belonged to the upper midscale class (32.5%). After removing missing data and outliers, the data set contained no luxury hotels. Upper upscale and upscale hotels accounted for 18.7% of the total observations while midscale and economy hotels accounted for 48.9% of the hotels. Furthermore, almost 88.3% of the hotels in the data set had less than 149 rooms, while only 2.5% of the hotels had 300 rooms or more. The majority of the hotels in the data set were located in the suburbs of metropolitan markets (44.8%). The second largest category of hotels based on location were the ones located in small metropolitan areas (i.e., towns with less than 150,000 people) (20.7%). Resort hotels were the smallest subcategory comprising only 4.9% of the records. Finally, more than half of the hotels had a TripAdvisor rating of 4.0 and higher (58.8%), whereas

41.2% of the properties had TripAdvisor ratings of 3.5 and lower. Table 5.1 summarizes the characteristics of hotels in the cancellation policies data set.

Table 5.1: Hotel characteristics – cancellation policies data set

Property Characteristics	**Values**	**Frequency[a]**	**Percent**
Operation	Chain Owned and/or Managed	636	11.4%
	Franchised	4786	86.0%
	Independent	142	2.6%
Location	Urban	357	6.4%
	Suburban	2494	44.8%
	Airport	425	7.6%
	Interstate/Motorway	866	15.6%
	Resort	273	4.9%
	Small Metro/Town	1149	20.7%
Size	Less than 75 Rooms	2011	36.1%
	75-149 Rooms	2902	52.2%
	150-299 Rooms	511	9.2%
	300-500 Rooms	95	1.7%
	Greater than 500 Rooms	45	0.8%
Class	Luxury	0	0.0%
	Upper Upscale	238	4.3%
	Upscale	801	14.4%
	Upper Midscale	1807	32.5%
	Midscale	1039	18.7%
	Economy	1679	30.2%
TripAdvisor Rating	1.0	4	0.1%
	1.5	51	0.9%
	2.0	140	2.5%
	2.5	316	5.7%
	3.0	649	11.7%
	3.5	1133	20.4%
	4.0	2068	37.2%
	4.5	1179	21.2%
	5.0	24	0.4%

[a] Frequencies correspond to the number of observations associated with each value

5.1.2 Sample Characteristics for Overbooking Policies Data Set

A total of 377 hotels participated in the overbooking policies survey. The majority of these hotels were franchised (90.2%) and belonged to the upper midscale class

(41.9%). The second and the third largest category of hotels were the upscale (20.2%) and midscale hotels (17.8%) respectively. Additionally, almost 83.8% of the hotels in the data set had less than 149 rooms, while only 2.4% of the hotels had 300 rooms or more. The majority of the hotels in the data set were located in the suburbs of metropolitan markets (41.4%). The second largest category of hotels based on location were the ones located in small metropolitan areas (i.e., towns with less than 150,000 people) (23.1%). Resort hotels were the smallest subcategory accounting for only 4% of the survey participants. Finally, more than two thirds of the survey respondents indicated that their job title is general manager (68.8%). Table 5.2 summarizes the characteristics of hotels in the overbooking policies data set as well as the job titles of the survey respondents.

Table 5.2: Hotel characteristics – overbooking policies data set

Property Characteristics	Values	All Hotels		Hotels that Overbook	
		Frequency[a]	Percent	Frequency[a]	Percent
Operation	Chain Owned and/or Managed	20	5.3%	14	5.8%
	Franchised	340	90.2%	219	90.5%
	Independent	17	4.5%	9	3.7%
Location	Urban	38	10.1%	34	14.0%
	Suburban	156	41.4%	105	43.4%
	Airport	19	5.0%	17	7.0%
	Interstate/Motorway	62	16.4%	28	11.6%
	Resort	15	4.0%	11	4.5%
	Small Metro/Town	87	23.1%	47	19.4%
Size	Less than 75 Rooms	107	28.4%	44	18.2%
	75-149 Rooms	209	55.4%	145	59.9%
	150-299 Rooms	52	13.8%	45	18.6%
	300-500 Rooms	8	2.1%	7	2.9%
	Greater than 500 Rooms	1	0.3%	1	0.4%
Class	Luxury	7	1.9%	4	1.7%
	Upper Upscale	26	6.9%	22	9.1%
	Upscale	76	20.2%	69	28.5%
	Upper Midscale	158	41.9%	101	41.7%
	Midscale	67	17.8%	29	12.0%
	Economy	43	11.4%	17	7.0%
Respondent Job Title	General Manager	141	68.8%	141	68.8%
	Reservations Manager, Rooms Director, Accommodations/Front Office Manager	12	5.9%	12	5.9%
	Revenue Manager	9	4.4%	9	4.4%
	Sales Manager, Group Manager	20	9.8%	20	9.8%
	Other	23	11.2%	23	11.2%

[a] Frequencies correspond to the number of hotels associated with each value

5.2 State of Cancellation Policies

The cancellation policies data indicated that as of April 2017, the most common free cancellation window (i.e., the last day after which a canceled reservation is deemed non-refundable, or is subject to a cancellation fee) across the sample of US hotels which was analyzed in this study was "same day cancellation" (41.2%) followed by "1 day before check-in" (39.3%). Roughly 11.9% of the hotels had a "non-refundable" cancellation window which means that any time after initial reservation, a canceled reservation is deemed non-refundable, or is subject to a penalty.

Almost half of the hotels in this data set enforced a cancellation penalty of “1 night fee plus taxes” (i.e., the average nightly rate for the duration of stay) (48.5%). The next popular cancellation penalty was the “fixed dollar amount – more than 1 night feel plus taxes policy” (14.7%). According to this policy, cancelled reservations are subject to a penalty which is more than the average nightly rate for the duration of stay. Almost 2.7% of properties allowed customers to cancel free of charge until a specific deadline but charged a penalty equal to the fee for their entire length of stay plus taxes (i.e., the fee for the entire reservation) once the deadline was over. On the other hand, 6.4% of the hotels had a cancellation policy stating that the room is non-refundable and customers can never cancel their reservations for free.

More than one third of the hotels did not specify their cancellation deadline time (34.6%). However, among those that specified a cancellation deadline time, the majority of them allowed free cancellations until 6 PM on the last day of the cancellation window (31.2%). The second common cancellation deadline time was 4 PM (27.1%).

Interestingly, only 2% of the hotels allowed the customers to pay more during the reservation to guarantee themselves against paying cancellation penalties. The rest of the hotels either did not specify such an option or did not allow it (98.0%). The data also indicated that the majority of the hotels (85%) did not specify the conditions for prepayment refund in their cancellation policy. Only 9.3% of the hotels clearly indicated in their cancellation policy that in case of cancellation, full prepayment refund is made to customer's credit card, whereas 5.7% of the hotels stated that prepayments will not be refunded in case of cancellation. Finally, the data showed that most hotels (95.7%) treat loyalty club members the same way as they treat non-loyalty club members when cancellation occurs. Only 4.3% of the hotels specified a different cancellation policy for their loyalty club members. Table 5.3 provides more details regarding the current state of cancellation policies in the US hotel industry.

Table 5.3: State of cancellation policies in the US hotel industry as of April 2017

Cancellation Policy Elements	Values	Frequency[a]	Percent
Free Cancellation Window (FCW)	Same Day Cancellation	2294	41.2%
	1 Day Before Check-In	2184	39.3%
	2 Days Before Check-In	181	3.3%
	3 Days Before Check-In	170	3.15
	4 Days Before Check-In	1	0.0%
	5 Days Before Check-In	5	0.1%
	6 Days Before Check-In	2	0.0%
	7 Days Before Check-In	12	0.2%
	13 Days Before Check-In	4	0.1%
	14 Days Before Check-In	1	0.0%
	29 Days Before Check-In	2	0.0%
	Non-Refundable	662	11.9%
	Not Found or Other	46	0.8%
Cancellation Penalty (CP)	1 Night Fee Plus Taxes	2697	48.5%
	First Night Fee Plus Taxes	354	6.4%
	Fixed Dollar Amount - Less Than 1 Night Fee	171	3.1%
	Fixed Dollar Amount - More Than 1 Night Fee	817	14.7%
	Non-Refundable	357	6.4%
	Entire Stay Plus Taxes	150	2.7%
	Not Found or Other	1018	18.3%
Cancellation Deadline Time	12 AM	96	1.7%
	12 PM	69	1.2%
	3 PM	198	3.6%
	4 PM	1506	27.1%
	5 PM	9	0.2%
	6 PM	1738	31.2%
	7 PM	24	0.4%
	8 PM	1	0.0%
	Not Specified	1923	34.6%
Pay More to Avoid Cancellation Penalty?	No or Not Specified	5452	98.0%
	Yes	112	2.0%
Prepayment Refund	No	315	5.7%
	Not Specified	4730	85.0%
	Yes - Full Refund to Customer's Credit Card	519	9.3%
Different Cancellation Policy for Loyalty Club?	No	5323	95.7%
	Yes	241	4.3%

[a] Frequencies correspond to the number of observations associated with each value

5.3 State of Overbooking Policies

The overbooking policies data indicated that nearly one third of the US hotels who responded to the survey never overbooked (35.8%). Among the 377 hotels which participated in the survey, 39% of them specified that on average they overbook 1-5 days in a month. Surprisingly, 5.3% of the hotels claimed that they overbook more than 20 days in a month.

Among hotels which specified that they overbook at least once in a month, one third of them replied that they tend to overbook more on weekdays (33.6%), whereas 35.3% indicated that they overbook more on weekends. The remaining claimed that day of the week does not impact their overbooking frequency (31.1%).

When asked about the maximum overbooking limit as a percentage of the hotel's capacity, more than two thirds of the hotels replied that their overbooking limit never exceeds 5% of their capacity (68.4%). On the other hand, 4.2% of the hotels specified that their overbooking limit could exceed 10% of their capacity.

Hotels which overbooked at least once a month were also asked whether they have a dynamic overbooking policy or a static one. The majority of these hotels responded that they have a dynamic overbooking policy (88.3%) meaning that they observe the pattern of customer reservations and cancellations over time, and update their optimal overbooking limit accordingly. The rest of the hotels said that once they set an overbooking level they no longer update it, i.e., static overbooking policy (11.7%).

The most important part of the survey was the question about the overbooking approach. Of the hotels which overbooked, 61% of them indicated that they have a deterministic overbooking approach, meaning that they determine their optimal overbooking limit by simply dividing the hotel capacity by the historical show rate. The second most popular overbooking approach was the risk-based policy (30.3%) where the overbooking limit is calculated by considering demand distributions, expected revenues and expected overbooking expenses (typically by using a computer software). Finally, small number of hotels specified that they follow the service-level (4.1%), hybrid (0.9%) or other (3.7%) overbooking approaches. Table 5.4 provides more details regarding the current state of overbooking policies in the US hotel industry.

Table 5.4: State of overbooking policies in the US hotel industry as of February 2018

Overbooking Policy Elements	**Values**	**Frequency[a]**	**Percent**
Overbooking Frequency (OB_Freq)	Never Overbooks	135	35.8%
	1-5 Days in a Month	147	39.0%
	6-10 Days in a Month	55	14.6%
	11-20 Days in a Month	20	5.3%
	More than 20 Days in a Month	20	5.3%
Most Common Overbooking Day (OB_Day)	No Difference Between Weekdays and Weekends	75	31.1%
	Weekdays	81	33.6%
	Weekends	85	35.3%
Maximum Overbooking Limit on a Single Day (OB_Max_Lim)	Less than 5% of Capacity	162	68.4%
	5-10% of Capacity	65	27.4%
	More than 10% of Capacity	10	4.2%
Overbooking Dynamicity (OB_Dynamicity)	Static	26	11.7%
	Dynamic	197	88.3%
Overbooking Approach (OB_Approach)	Deterministic	133	61.0%
	Risk Based	66	30.3%
	Service Level	9	4.1%
	Hybrid	2	0.9%
	Other	8	3.7%

[a] Frequencies correspond to the number of hotels associated with each value

5.4 Results of Hypothesis Testing

In this section, the results of testing each of the hypotheses are presented, the findings are thoroughly discussed and both theoretical and practical implications are outlined.

5.4.1 Hypothesis H1b

Hypothesis H1b posits that hotel managers' perception of data availability positively impacts hotels' financial performance. To test this hypothesis, data collected from the overbooking survey were used.

The first step was to create an index for self-reported data availability using the 5 data availability questions in the survey. Survey respondents were asked to identify the extent to which they use historical data, current market data, turn-away/unconstrained demand data, third party data, and data obtained through sharing agreements with other hotel chains and/or properties. For each question they were given 5 choices based on a 5-point Likert scale ranging from "1 = never" to "5 = always". Respondents were also given the option to select "I don't know" for each of these 5 questions. The "data availability" index was created for each hotel by averaging the hotel's answers to these 5 data availability questions. In order to make sure that all 5 questions were appropriate components of the data availability index, inter-item correlations were calculated. Since all 5 items were positively correlated with one another, it was concluded that the data availability index was valid.

Stepwise multiple regression analysis (Table 5.5, Adjusted $R^2 = 0.11$) was performed to find out how data availability impacts financial performance. Results indicated that data availability is positively associated with RevPAR index ($B = 2.5$, $p = 0.014$), therefore providing support for H1b. It was also found that better class category and smaller property size are associated with higher values of RevPAR index.

Table 5.5, displays all significant coefficients resulting from the stepwise multiple regression analysis. All VIF scores were below 1.6 indicating no multicollinearity issues.

Table 5.5: Stepwise multiple regression results for H1b

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	144.2	7.277		19.8	0.000
Class [a]	-9.6	1.089	-0.3	-8.8	0.000
Location [b] = Small Metro/Town	9.2	2.260	0.1	4.1	0.000
Location [b] = Urban	-8.7	2.657	-0.1	-3.3	0.001
Location [b] = Interstate	-8.3	3.226	-0.1	-2.6	0.010
Size	-3.8	1.509	-0.1	-2.5	0.013
Data Availability	2.5	1.032	0.1	2.4	0.014

[a] Higher values of the class variable correspond to lower class hotels

[b] Location is a categorical variable. Benchmark is “suburban”

The positive relationship between data availability and RevPAR index identified in this study is consistent with literature in information systems and big data analytics which suggests that advanced information technology, information sharing capabilities and improved data availability can boost business performance (Cantor & Macdonald, 2009; Dedrick et al., 2003; Malone et al., 1987; McAfee & Brynjolfsson, 2012). It is worse mentioning, that higher data availability can also indirectly contribute to performance improvement by facilitating communication, coordination and collaboration (Malone et al., 1987) across business units. Support for H1b is a significant theoretical and practical contribution of this study; because it indicates that data availability is not only theoretically associated with better performance, but also it is a significant driver of better financial performance in the hotel industry. Hotel revenue managers that have access to more data are expected to make better decisions under different circumstances. For instance, when a hotel is experiencing high demand, a revenue manager who has access to several periods of historical cancellation rates, market demand and supply data, historical performance in comparison to competitors, etc. is expected to make better policy choices that can maximize the revenue and/or profitability.

5.4.2 Hypothesis H3b

Hypothesis H3b posits that moderate cancellation policies are associated with better financial performance. In order to test H3b, cancellation policies data set was used.

Before analyzing the relationship between cancellation policies and financial performance, the “free cancellation window” variable was regrouped: Fully refundable cancellation policies at any time were grouped as lenient (N = 2294 observations), free cancellation windows of 1-30 days before check-in as moderate (N = 2562 observations) and policies without any free cancellation option as strict (N = 662 observations).

Figure 5.1 shows that the average RevPAR Index for hotels with a moderate cancellation window was the highest. The ANOVA, as well as Kruskal-Wallis tests ($p < 0.001$) suggested that the average RevPAR index was not equal across these three strictness categories. Tukey HSD and Games-Howell post-hoc pairwise comparison tests indicated that the average RevPAR index is significantly different when comapring moderate vs. lenient cancellation windows ($p < 0.05$) and moderate vs. strict cancellation windows ($p < 0.05$).

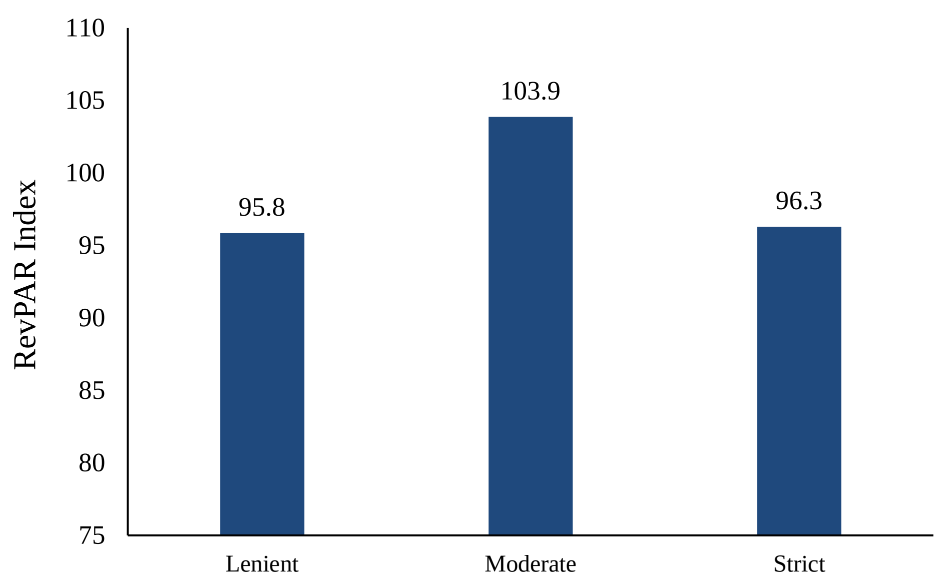

Figure 5.1: Average RevPAR index values across different cancellation windows

Hotels charging a cancellation penalty equal to “first night fee plus taxes” appeared to outperform hotels that charged other cancellation fees (Figure 5.2). ANOVA and the Kruskal-Wallis tests ($p < 0.001$) confirmed that not all six penalty categories had the same average RevPAR index. Tukey HSD and Games-Howell post-hoc pairwise comparison tests indicated that the average RevPAR index is significantly different when comparing the “first night fee plus taxes” penalty with each of the other cancellation penalties ($p < 0.05$) except “fixed dollar amount – more than 1 night fee plus taxes” ($p > 0.05$).

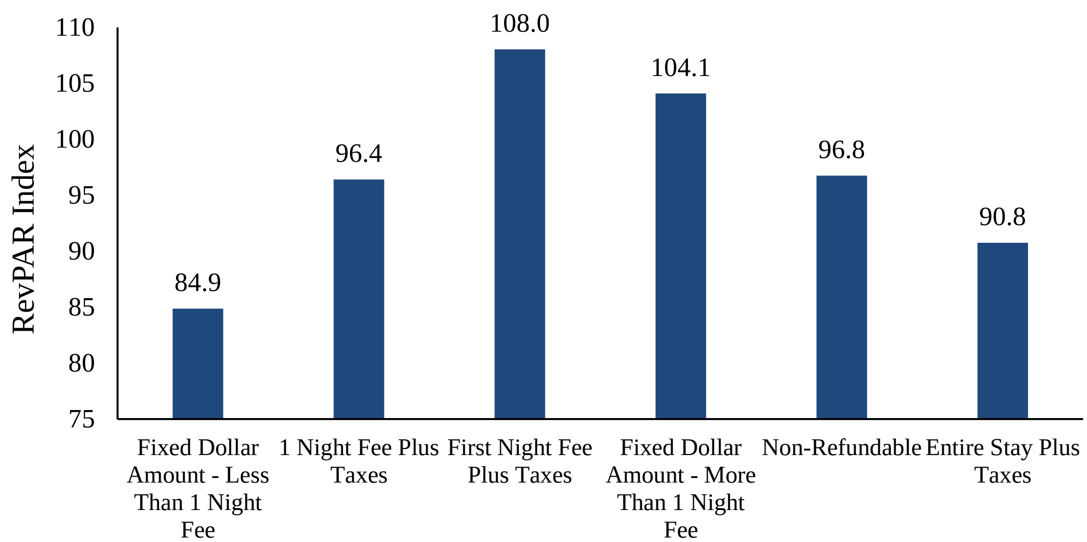

Figure 5.2: Average RevPAR index values across different cancellation penalties

To address a non-normality, the non-parametric Spearman correlation test was used, coding the windows and penalty levels as categorical variables with the “moderate” window (identified in Figure 5.1) and the “one night fee plus taxes” penalty (identified in Figure 5.2) as the benchmarks. The results indicated that both lenient (rho = -0.149, $p < 0.001$) and strict (rho = -0.064, $p < 0.001$) cancellation windows perform statistically significantly worse than the moderate one, providing support for H3b. Further support for H3b was found as the "first night fee plus taxes" (rho = 0.121, $p < 0.001$) and the "fixed dollar amount – more than one night fee plus taxes" (rho = 0.114, $p < 0.001$) were the only penalty levels that outperformed the benchmark. These two cancellation penalties are relatively moderate compared to other policies of entire stay, non-refundable and less than one night fee.

Consistent with the earlier analysis, the findings of the stepwise multiple regression (Table 5.6, Adjusted $R^2 = 0.27$) indicated that on average, hotels charging a cancellation penalty equal to the "first night fee plus taxes" had a RevPAR index which was 6.9 units higher than the ones with "one night fee plus taxes".

Interestingly, moderate cancellation windows appeared to be less productive to interstate hotels where the RevPAR index was 10.3 units higher (Lenient + Lenient*Interstate = -2.4 + 12.7) with a lenient policy, and 8 units higher (Strict + Strict*Interstate = 0 + 8) with a strict policy compared to a moderate one. For hotels in all other locations, the RevPAR index for the lenient cancellation window was 2.4 units lower than the moderate. Results indicated that strict cancellation penalties such as "entire stay plus taxes" and "non-refundable" had a negative impact on the RevPAR index compared to the benchmark, therefore, providing further support for H3b.

It was also found that better class category and higher TripAdvisor rating are associated with better financial performance. Finally, the stepwise multiple regression analysis indicated that property size is negatively associated with RevPAR index.

Table 5.6, displays all significant coefficients resulting from the stepwise multiple regression analysis. All VIF scores were below 3.7 indicating no multicollinearity issues.

Table 5.6: Stepwise multiple regression results for H3b

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	108.9	3.828		28.4	0.000
Class [a]	-6.8	0.386	-0.3	-17.5	0.000
TripAdvisor Rating	8.2	0.578	0.2	14.3	0.000
Size	-4.3	0.519	-0.1	-8.3	0.000
Operation [b] = Independent	-14.2	1.837	-0.1	-7.7	0.000
Cancellation Penalty = First Night Fee Plus Tax	6.9	1.161	0.1	5.9	0.000
Location [c] = Airport	-7.9	1.198	-0.1	-6.6	0.000
Location [c] = Interstate	-13.0	1.536	-0.2	-8.5	0.000
Lenient * Interstate	12.7	1.877	0.2	6.8	0.000
Cancellation Penalty = Entire Stay Plus Tax	-8.6	1.697	-0.1	-5.1	0.000
Operation [b] = Chain Owned/Managed	4.2	1.116	0.1	3.8	0.000
Cancellation Window = Lenient	-2.4	0.758	-0.1	-3.1	0.002
Strict * Interstate	8.0	2.633	0.0	3.1	0.002
Cancellation Penalty = Non-Refundable	-3.2	1.168	-0.0	-2.7	0.006

[a] Higher values of the class variable correspond to lower class hotels

[b] Operation is a categorical variable. Benchmark is “franchise”

[c] Location is a categorical variable. Benchmark is “suburban”

The support for H3b is a major theoretical and practical contribution; because it shows that on average, moderate cancellation policies appear to be mostly associated with better financial performance, when compared to more lenient, or to more strict cancellation policies. However, as discussed above this might not be universal in that some hotel characteristics could reverse the impact. Specifically, this study found that location matters: for interstate hotels, lenient and strict cancellation policies were found to be associated with higher RevPAR index values, whereas for all other hotel locations, moderate policies resulted in the best performance. This could be because interstate hotels' customers tend to make last minute reservations, are less concerned about cancelling their reservations and consequently care less about the leniency.

Another surprising finding is that the "first night fee plus taxes" penalty is associated with the highest RevPAR Index. This could be because imposing this penalty, instead of the ADR of the stay duration (as in "one night fee plus taxes") is an indication that the hotel's revenue management is in general more sophisticated/advanced and thus the higher RevPAR Index.

5.4.3 Hypothesis H2

Hypothesis H2 states that overbooking positively impacts hotels' financial performance. To test this hypothesis, data from the overbooking policies data set were used.

To validate this hypothesis, average RevPAR index values for hotels that never overbooked was compared with the average RevPAR index for those who overbooked at least once in a month. Results indicated that on average hotels that overbooked had higher RevPAR indices compared to those that never overbooked (Figure 5.3). T test, as well as non-parametric Mann-Whitney test ($p < 0.001$) confirmed that the difference between average RevPAR index for hotels that overbook and those that do not overbook is statistically significant, thus providing support for H2.

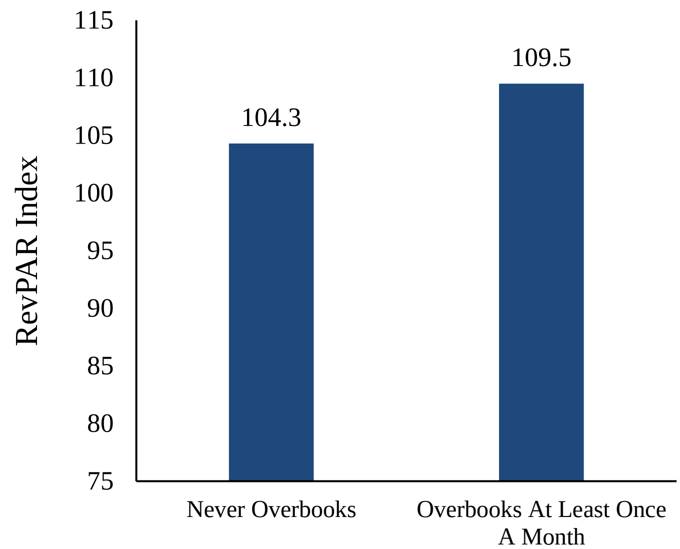

Figure 5.3: Average RevPAR index for hotels that overbook versus those that never overbook

To address a non-normality, the non-parametric Spearman correlation test was used, where overbooking versus not overbooking were coded as categorical variables with the “overbooking at least once a month” (identified in Figure 5.3) being the benchmark. The results indicated that hotels which never overbooked ($rho = -0.086$, $p < 0.001$) performed statistically significantly worse compared to those that overbooked, providing further support for H2.

Figure 5.4 shows how average RevPAR index varies across different levels of overbooking frequency. On average, hotels that overbooked 6-10 days in a month had the highest RevPAR index, whereas hotels which overbooked more than 20 days in a month and the ones that never overbooked had the lowest average RevPAR indices. ANOVA and Kruskal-Wallis tests ($p < 0.001$) confirmed that not all five levels of overbooking frequency had the same average RevPAR index. Tukey HSD and Games-Howell post-hoc pairwise comparison tests indicated that the average RevPAR index is significantly different when comparing "6-10 days in a month" overbooking frequency with each of the other overbooking frequency levels ($p < 0.05$) except "11-20 days in a month" ($p > 0.05$).

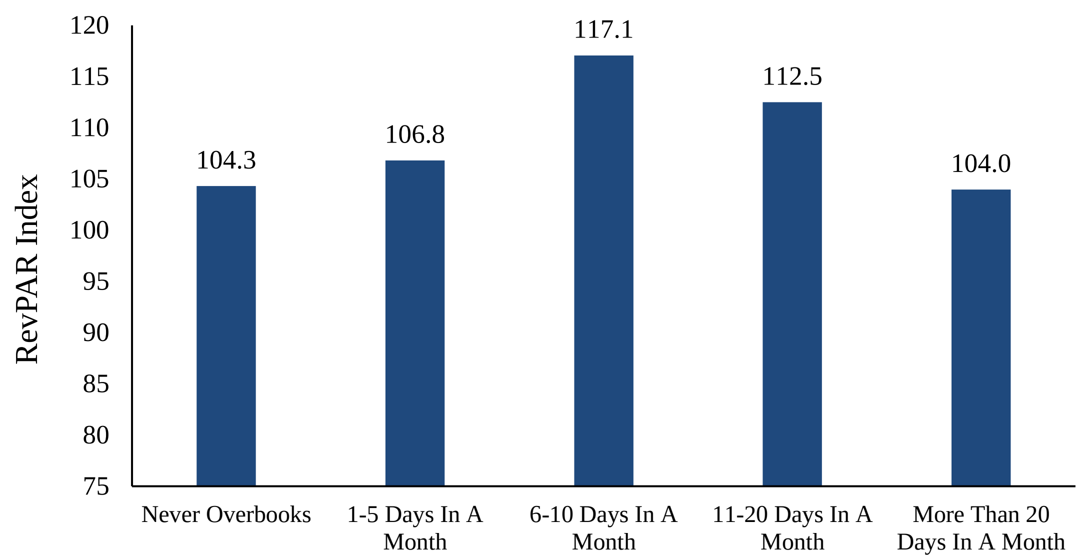

Figure 5.4: Average RevPAR index across different overbooking frequencies

Spearman correlation test was used, coding the overbooking frequency levels as categorical variables with the "1-5 days in a month" overbooking frequency (identified in Figure 5.4) as the benchmark. The results indicated that hotels that never overbooked (rho = -0.086, $p < 0.001$) performed statistically significantly worse than the benchmark, thus supporting H2. Correlation results also indicated that hotels which overbooked 6-10 days in a month (rho = 0.133, $p < 0.001$) or 11-20 days in a month (rho = 0.060, $p = 0.005$) outperformed the benchmark.

Next, average RevPAR index across different overbooking approaches was compared. As displayed in Figure 5.5, it was found that on average, hotels that had a risk-based overbooking approach outperformed the others. The second best overbooking approach in terms of average RevPAR index was the deterministic approach. Finally, hybrid, service-level and other overbooking approaches had relatively low RevPAR index values on average. ANOVA, as well as Kruskal-Wallis tests ($p < 0.001$) confirmed that not all overbooking approaches had the same average RevPAR indices. Furthermore, independent samples T test ($p < 0.001$) confirmed that the average RevPAR index was statistically significantly different between hotels that had a deterministic approach and those that had a risk-based overbooking approach. Tukey HSD and Games-Howell post-hoc tests indicated that the average RevPAR index is significantly different when performing pairwise comparisons of risk-based, deterministic and service-level approach ($p < 0.05$). It was also found that the average RevPAR index for the hybrid approach is not significantly different compared to the service-level approach ($p > 0.05$).

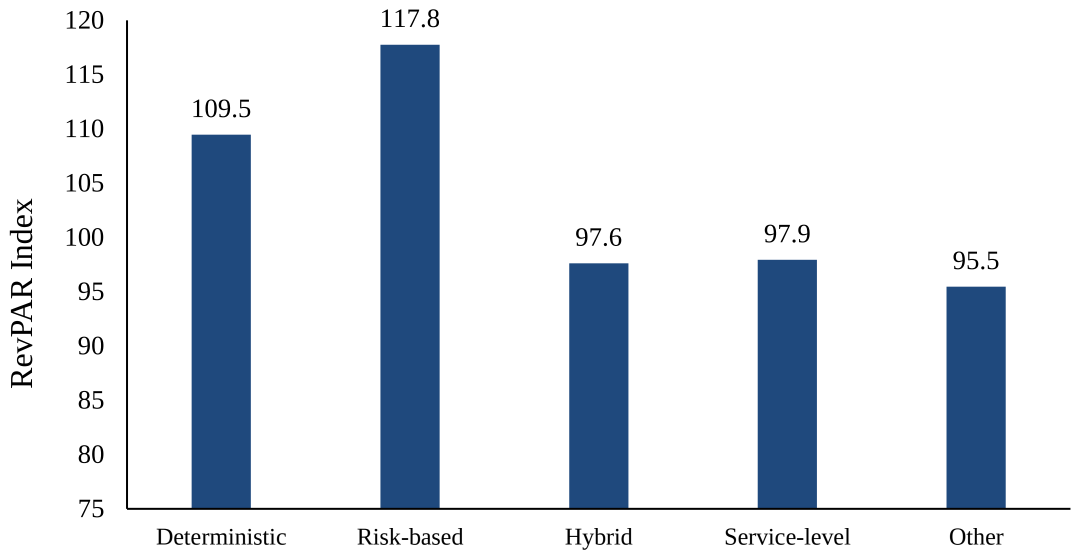

Figure 5.5: Average RevPAR index across different overbooking approaches

To perform Spearman correlation analysis, overbooking approaches were coded as categorical variables, with the "deterministic" approach (identified in Figure 5.5) being the benchmark. Based on correlation results, the only overbooking approach that outperformed the deterministic approach was the risk-based overbooking (rho = 0.157, $p < 0.001$). Service-level (rho = -0.109, $p < 0.001$), hybrid (rho = -0.056, $p = 0.048$) and other (rho = -0.100, $p < 0.001$) overbooking approaches all underperformed the benchmark.

Another aspect of the overbooking policy that was analyzed was the most common overbooking day. As depicted in Figure 5.6, on average, hotels that overbooked more on weekdays had higher RevPAR indices, whereas those which overbooked more on weekends had lower average RevPAR indices. ANOVA and Kruskal-Wallis tests ($p < 0.001$) confirmed that not all three categories of most common overbooking day had the same average RevPAR index. Furthermore, independent samples T test ($p < 0.001$) confirmed that the average RevPAR index was statistically significantly different between hotels that overbooked more on weekends and those that overbooked more on weekdays. Tukey HSD and Games-Howell post-hoc pairwise comparison tests showed that the average RevPAR index is significantly different when comparing hotels that overbook more often on weekends with those that overbook more often on weekdays ($p < 0.05$). However, it was found that the average RevPAR index for hotels that overbook more on weekdays is not significantly different compared to those that overbook irrespective of the day of the week ($p > 0.05$).

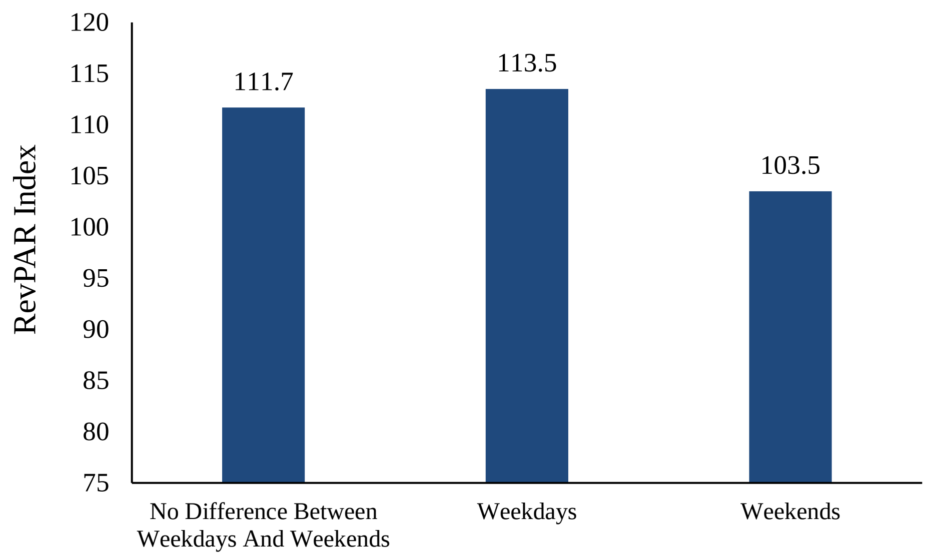

Figure 5.6: Average RevPAR index by most common overbooking day

Hotel managers' answers to the question of most common overbooking day were coded as categorical variables with the "no difference between weekdays and weekends" (identified in Figure 5.6) as the benchmark. Results of the Spearman correlation analysis revealed that hotels which overbooked more on weekends (rho = -0.151, $p < 0.001$) underperformed the benchmark, whereas hotels that overbooked more on weekdays outperformed the benchmark (rho = 0.088, $p = 0.001$).

The survey participants were also asked about their maximum overbooking limit as a percentage of their hotels' capacity. Figure 5.7 shows that on average, hotels that had a maximum overbooking limit of less than 5% had the highest RevPAR indices, while those which had a maximum overbooking limit of more than 10% had the worst performance. ANOVA and Kruskal-Wallis tests ($p < 0.001$) confirmed that not all three levels of maximum overbooking limit had the same average RevPAR index. Tukey HSD and Games-Howell post-hoc pairwise comparison tests indicated that the average RevPAR index is significantly different when comparing hotels that have a maximum overbooking limit of more than 10% with those that have a maximum overbooking limit of less than 5% ($p < 0.05$) or with the ones that have a maximum overbooking limit of 5-10% ($p < 0.05$).

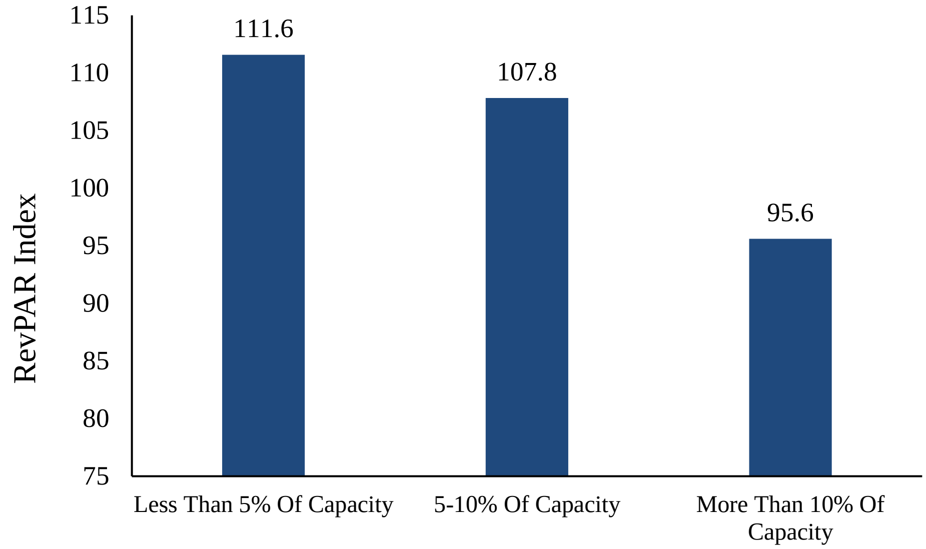

Figure 5.7: Average RevPAR index across different levels of maximum overbooking limit

Different levels of maximum overbooking limit were coded as categorical variables, where "less than 5% of capacity" (identified in Figure 5.7) was assigned as the benchmark. Spearman correlation results indicated that an overbooking limit of more than 10% (rho = -0.097, $p < 0.001$) results in a lower RevPAR index when compared to an overbooking limit of less than 5%.

The last overbooking policy element which was considered in this study was whether the hotel follows a dynamic overbooking approach or a static one. As shown in Figure 5.8, hotels with a dynamic overbooking policy had higher average RevPAR index values compared to those with a static approach. However, Independent samples T test showed that this difference was not statistically significant ($p = 0.145$).

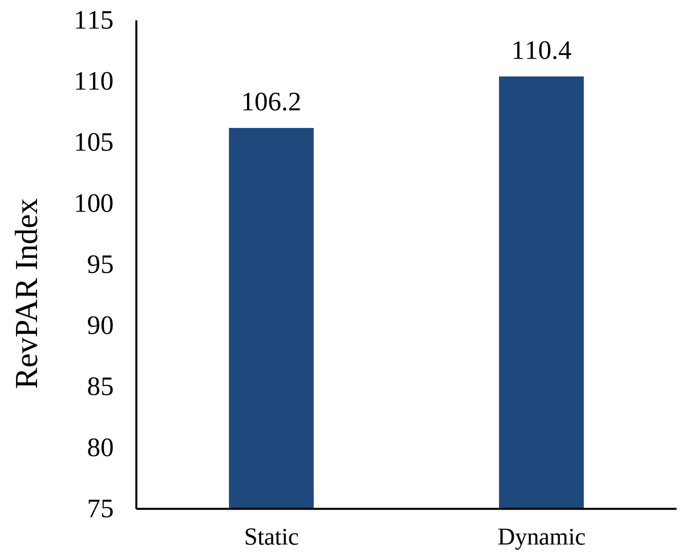

Figure 5.8: Average RevPAR index for hotels with static vs. dynamic overbooking

To better understand the real impact of different elements of the overbooking policy on hotel performance, stepwise multiple regression (Table 5.7, Adjusted R^2 = 0.16) was performed. RevPAR index was used as the dependent variable and overbooking policy elements (i.e., overbooking approach, maximum overbooking limit, most common overbooking day, overbooking frequency and overbooking dynamicity) as well as basic hotel characteristics (i.e., class, operation type, size and location) were used as independent variables. For each of the overbooking policy elements, every possible answer was converted to a categorical variable. The benchmark values were coded as follows: “deterministic” for the overbooking approach; “1-5 days in a month” for overbooking frequency; “no difference between weekdays and weekends” for the most common overbooking day; “less than 5% of capacity” for the maximum overbooking limit and “dynamic” approach for overbooking dynamicity.

Consistent with the earlier analysis, the findings of the stepwise multiple regression indicated that hotels with a risk-based overbooking approach had a RevPAR index which was 5.5 units higher than hotels with a deterministic overbooking approach. Furthermore, as shown earlier by the correlation analysis, service-level overbooking ($B = -11$, $p = 0.006$) and other overbooking approaches ($B = -12.9$, $p = 0.002$) resulted in lower RevPAR index values compared to the deterministic approach.

Stepwise multiple regression also showed that an overbooking frequency of 6-10 days in a month resulted in RevPAR index values which were 8.4 units higher than the benchmark (i.e., 1-5 days in a month). Conversely, it was found that RevPAR index of hotels which overbooked more than 20 days in a month was 8.4 units lower than the benchmark.

Consistent with earlier findings, regression results indicated that the RevPAR index for hotels which overbooked mostly on weekends was 7.7 units lower than the ones which overbooked irrespective of the day of the week.

In terms of maximum overbooking limit, it was found that a maximum overbooking limit of less than 5% of capacity (i.e., the benchmark) resulted in higher RevPAR index values when compared with maximum overbooking limits of 5-10% ($B = -5.7$, $p = 0.001$) or more than 10% ($B = -13.5$, $p < 0.001$).

Overbooking dynamicity (dynamic vs. static approach) was found to be an insignificant predictor of the RevPAR index. This is consistent with results of T test which indicated that the average RevPAR index is not significantly different between hotels with static overbooking and those with dynamic overbooking.

Finally, it was found that better class category and smaller property size are associated with higher values of RevPAR index. This is consistent with findings from H3b (where the cancellation policies data set was used) and H1b (for which the same data set as H2 was used).

Table 5.7, displays all significant coefficients resulting from the stepwise multiple regression analysis. All VIF scores were less than 1.8 indicating no multicollinearity issues.

Table 5.7: Stepwise multiple regression results for H2

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	150.0	5.898		25.4	0.000
Class [a]	-7.5	0.995	-0.3	-7.5	0.000
Size	-4.4	1.379	-0.1	-3.2	0.002
Location [b] = Small Metro/Town	10.1	2.065	0.1	4.9	0.000
Overbooking Day = Weekends	-7.7	1.657	-0.1	-4.6	0.000
Overbooking Approach = Risk-based	5.5	1.812	0.1	3.0	0.002
Overbooking Limit = More than 10%	-13.5	3.635	-0.1	-3.7	0.000
Overbooking Frequency = 6-10 Days/Month	8.4	1.933	0.1	4.3	0.000
Location [b] = Urban	-9.3	2.403	-0.1	-3.9	0.000
Overbooking Limit = 5-10%	-5.7	1.786	-0.1	-3.2	0.001
Overbooking Approach = Other	-12.9	4.150	-0.1	-3.1	0.002
Overbooking Approach = Service-level	-11.0	3.963	-0.1	-2.8	0.006
Overbooking Frequency = More than 20 Days/Month	-8.4	3.048	-0.1	-2.7	0.006

[a] Higher values of the class variable correspond to lower class hotels

[b] Location is a categorical variable. Benchmark is “suburban”

The above findings have major theoretical and practical implications for the hotel industry and the revenue management. First of all, the results showed that overbooking in general is associated with better financial performance for the hotels. To the best of the author’s knowledge, this is the first study that have empirically proved the positive impact of overbooking on hotels performance. This finding is consistent with previous studies that have shown a positive relationship between overbooking and performance across other industries (LaGanga & Lawrence, 2007, 2012; Milbrandt et al., 2006; Sulistio et al., 2008; Urgaonkar et al., 2002; Zhao & Chen, 2007). It was shown that although overbooking results in better performance, excessive overbooking (i.e., more than 20 days in a month) will result in deteriorated performance. The highest average RevPAR index values were shown to be associated with hotels that overbooked 6-10 days in a month.

Among the most commonly practiced overbooking approaches (i.e., deterministic, risk-based, service-level and hybrid), the results showed that the risk-based approach toward overbooking results in the best performance followed by the deterministic approach. The superior performance of the risk-based policy could be associated with its high level of sophistication and precision due to the involvement of computer algorithms that can take various factors as input and provide the most optimal overbooking recommendations to the hotel management. The finding that service-level approach does not result in a very good performance could most probably be due to the preeminent role of arbitrary human judgement in this approach which possibly leads to less effective overbooking decisions. Similarly, in the hybrid approach (i.e., the combination of the risk-based and the service-level approach) the role of arbitrary human judgement seems to be limiting and/or obstructing the superior advantages of the risk-based overbooking recommendations. In other words, the service-level aspect of the hybrid approach limits the advantages of its risk-based aspect. This explains why hybrid policies were found to be associated with lower RevPAR index values in this study.

The finding that a maximum overbooking limit of less than 5% of capacity is associated with better performance is another major contribution of this study. This finding is significant because it suggests that hotel managers should try to keep overbooking limit for any given day at minimum and should avoid excessive overbooking. This could be in part due to the fact that excessive overbooking on a single day could possibly increase the probability of being oversold and having to walk out customers. Since it is expensive for the hotels to walk customers in case of overselling, keeping daily overbooking limit at a minimum could be considered as an optimal overbooking policy.

It was shown that on average, hotels which overbook more on weekends have relatively lower RevPAR index values. One explanation for this finding is that hotels which overbook more on weekends are also the ones which receive more leisure travelers, whereas the hotels that overbook more on weekdays mostly receive business travelers. Since leisure travelers have more certain travel plans and tend to cancel their reservations less frequently compared to business travelers, hotels which overbook more on weekends could end up having more oversold rooms and lower RevPAR indices.

5.4.4 Hypothesis H1c

Hypothesis H1c posits that data availability moderates the impact of overbooking policies on financial performance. This hypothesis was tested by using data from the overbooking policies data set and by utilizing stepwise multiple regression (Table 5.8, Adjusted $R^2 = 0.20$). Results indicated that data availability does not moderate the relationship between the four major overbooking approaches (i.e., deterministic, risk-based, service-level and hybrid) and the RevPAR index. Although the interaction effect between data availability and “other” overbooking approaches was found to be significant, this coefficient cannot be explained due to the unknown nature of “other” overbooking approaches. Therefore, it is reasonable to claim that data availability does not appear to moderate the relationship between overbooking policies and RevPAR index. In other words, hypothesis H1c cannot be supported.

Consistent with prior analysis, it was found that better class category is associated with higher values of RevPAR index. This is consistent with findings from H3b, H1b and H2. Results of the stepwise regression also provided further evidence that an overbooking limit of 6-10 days in a month results in better performance compared to the benchmark (i.e., 1-5 days in a month). Furthermore, consistent with results from H2, it was shown that an overbooking maximum limit of less than 5% (i.e., benchmark) results in the best performance when compared with overbooking limits of 5-10% and more than 10% of capacity.

Table 5.8, displays all significant coefficients resulting from the stepwise multiple regression analysis. All VIF scores were less than 1.5 indicating no multicollinearity issues.

Table 5.8: Stepwise multiple regression results for H1c

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	144.0	3.991		36.1	0.000
Class [a]	-7.5	0.935	-0.3	-8.0	0.000
Location [b] = Small Metro/Town	12.3	2.247	0.2	5.5	0.000
Data Availability * Other Overbooking Approaches	-6.8	1.409	-0.1	-4.8	0.000
Overbooking Day = Weekends	-11.3	2.060	-0.2	-5.5	0.000
Location [b] = Resort	9.9	3.967	0.1	2.5	0.012
Overbooking Frequency = 6-10 Days/Month	8.3	2.036	0.1	4.1	0.000
Overbooking Approach = Service-level	-15.3	4.484	-0.1	-3.4	0.001
Overbooking Limit = More than 10%	-14.7	3.828	-0.1	-3.8	0.000
Location [b] = Urban	-9.6	2.584	-0.1	-3.7	0.000
Overbooking Frequency = More than 20 Days/Month	-10.4	3.435	-0.1	-3.0	0.003
Location [b] = Interstate	-9.6	3.126	-0.1	-3.1	0.002
Overbooking Limit = 5-10%	-4.4	1.930	-0.1	-2.3	0.021
Overbooking Day = Weekdays	-4.3	2.125	-0.1	-2.0	0.044

[a] Higher values of the class variable correspond to lower class hotels

[b] Location is a categorical variable. Benchmark is “suburban”

Rejection of H1c indicates that although data availability is positively associated with RevPAR index (see results for H1b), it does not moderate the relationship between any of the four major overbooking approaches and the RevPAR index. In other words, as hotels increase the complexity of their overbooking policy, the marginal contribution from that added complexity (i.e., the ability of that additional complexity to improve performance) does not depend on managers’ perception of data availability. Rejection of H1c also indicates that once an overbooking policy is selected, data availability does not impact its effectiveness.

5.4.5 Hypothesis H3c

Hypothesis H3c states that cancellation policies moderate the impact of overbooking policies on financial performance. Data from overbooking policies data set were used to test this hypothesis. Results of the stepwise multiple regression (Table 5.9, Adjusted $R^2 = 0.22$) indicated that cancellation policies do not moderate the relationship between the four major overbooking approaches (i.e., deterministic, risk-based, service-level and hybrid) and the RevPAR index. The only significant interaction effect was between "first night fee plus taxes" cancellation penalty and "other" overbooking approaches; however, this coefficient cannot be explained due to the unknown nature of "other" overbooking approaches. Therefore, it is reasonable to claim that cancellation policies do not moderate the relationship between overbooking policies and RevPAR index. In other words, hypothesis H3c cannot be supported.

Consistent with prior analysis, results of the stepwise regression revealed that neither lenient ($B = -16.6$, $p < 0.001$) nor strict ($B = -17.3$, $p < 0.001$) cancellation windows can outperform moderate (i.e., the benchmark) cancellation windows; therefore, providing further support for H3b. This is a significant finding because support for hypothesis H3b was established using two separate data sets: the cancellation policies data set used in section 5.4.2 and the overbooking policies data set used here. The finding that overbooking frequency of 6-10 days in a month results in better performance compared to the benchmark (i.e., 1-5 days in a month) further supports prior results (see results for H2 and H1c).

Table 5.9, displays all significant coefficients resulting from the stepwise multiple regression analysis. All VIF scores were less than 2 indicating no multicollinearity issues.

Table 5.9: Stepwise multiple regression results for H3c

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	164.3	6.015		27.3	0.000
Class [a]	-7.5	1.036	-0.3	-7.2	0.000
Size	-7.8	1.422	-0.2	-5.5	0.000
Cancellation Window = Lenient	-16.6	2.574	-0.2	-6.4	0.000
Cancellation Window = Strict	-17.3	3.515	-0.1	-4.9	0.000
Location [b] = Small Metro/Town	9.9	2.029	0.1	4.9	0.000
First Night Fee * Other Overbooking Approaches	-22.7	4.821	-0.1	-4.7	0.000
Overbooking Frequency = 6-10 Days/Month	7.9	1.938	0.1	4.1	0.000
Location [b] = Urban	-8.6	2.395	-0.1	-3.6	0.000
Cancellation Penalty = Less than One Night Fee	-11.2	3.632	-0.1	-3.1	0.002
Overbooking Frequency = More than 20 Days/Month	-8.9	2.967	-0.1	-3.0	0.003
Overbooking Limit = More than 10%	-13.9	3.490	-0.1	-4.0	0.000
Cancellation Penalty = More than One Night Fee	-9.3	2.724	-0.1	-3.4	0.001
Overbooking Approach = Hybrid	-19.5	7.530	-0.1	-2.6	0.010
Overbooking Day = Weekends	-6.4	1.937	-0.1	-3.3	0.001
Overbooking Approach = Service-level	-16.3	3.998	-0.1	-4.1	0.000
Operation [c] = Chain Owned/Managed	9.6	3.695	0.1	2.6	0.010
Overbooking Limit = 5-10%	-5.0	1.785	-0.1	-2.8	0.005
Overbooking Day = Weekdays	-4.4	1.883	-0.1	-2.3	0.021

[a] Higher values of the class variable correspond to lower class hotels

[b] Location is a categorical variable. Benchmark is “suburban”

[c] Operation is a categorical variable. Benchmark is “franchise”

It was shown earlier that not only overbooking policies can directly impact the RevPAR index (see results for H2), but also cancellation policies can affect this performance metric (see results for H3b). However, the above results indicated that cancellation policies do not play a moderating role in the relationship between overbooking approaches and RevPAR index. Rejection of hypothesis H3c also means that as hotels increase the complexity of their overbooking approaches, the marginal contribution from that added complexity (i.e., the ability of that additional complexity to improve performance) does not depend on the type of cancellation policy which is enforced. In other words, once an overbooking policy is chosen, the cancellation policy does not appear to impact its effectiveness or its ability to generate revenue.

5.4.6 Hypothesis H1a

Hypothesis H1a posits that data availability is positively associated with the complexity of the overbooking approach. Overbooking policies data set and multivariate multiple regression analysis were used to validate this hypothesis. Dependent variables were categorical variables corresponding to different overbooking approaches (i.e., deterministic, risk-based, service-level and hybrid) and independent variables were data availability and basic hotel characteristics (i.e., class, size, location and operation type). Note that "deterministic" overbooking approach was used as the benchmark for the categorical variables.

Results of the multivariate multiple regression suggested that the only significant models where those with risk-based overbooking approach (Table 5.10, Adjusted R^2 = 0.12) and service-level overbooking approach (Table 5.10, Adjusted R^2 = 0.03) as their dependent variable. Regression results indicated that the higher the data availability the lower the possibility of using risk-based overbooking as opposed to deterministic overbooking approach ($B = -0.06$, $p = 0.001$). Since risk-based approach is more complex than deterministic approach, this finding means that H1a cannot be supported. Furthermore, results showed that data availability is not a significant predictor of whether a hotel is more/less likely to choose service-level approach over deterministic approach ($B = -0.01$, $p = 0.065$). Table 5.10, displays the results of the multivariate multiple regression analysis.

Table 5.10: Multivariate multiple regression results for H1a

Dependent Variable	Parameter	B	Std. Error	t	Sig.
Overbooking Approach [a] = Risk-based	(Intercept)	0.96	0.113	8.50	0.000
	Size	0.01	0.025	0.54	0.588
	Location [b] = Airport	-0.24	0.053	-4.48	0.000
	Location [b] = Interstate	0.01	0.051	0.17	0.866
	Location [b] = Resort	0.13	0.064	2.03	0.042
	Location [b] = Small Metro/Town	-0.11	0.036	-3.04	0.002
	Location [b] = Urban	-0.02	0.044	-0.37	0.710
	Class [c]	-0.13	0.017	-7.46	0.000
	Operation [d] = Chain Owned/Managed	-0.02	0.063	-0.25	0.804
	Operation [d] = Independent	-0.23	0.077	-2.99	0.003
	Data Availability	-0.06	0.016	-3.39	0.001
Overbooking Approach [a] = Service-level	(Intercept)	0.16	0.048	3.36	0.001
	Size	-0.04	0.011	-3.49	0.001
	Location [b] = Airport	0.06	0.023	2.50	0.013
	Location [b] = Interstate	0.06	0.022	2.64	0.008
	Location [b] = Resort	-0.01	0.027	-0.21	0.838
	Location [b] = Small Metro/Town	0.05	0.016	2.89	0.004
	Location [b] = Urban	0.05	0.019	2.53	0.012
	Class [c]	-0.01	0.007	-1.34	0.179
	Operation [d] = Chain Owned/Managed	0.10	0.027	3.59	0.000
	Operation [d] = Independent	-0.03	0.033	-0.82	0.413
	Data Availability	-0.01	0.007	-1.85	0.065

[a] Overbooking approach is a categorical variable. Benchmark is “deterministic”

[b] Location is a categorical variable. Benchmark is “suburban”

[c] Higher values of the class variable correspond to lower class hotels

[d] Operation is a categorical variable. Benchmark is “franchise”

The finding that higher perception of data availability results in higher usage of the deterministic approach as opposed to the risk-based approach could be because risk-based overbooking relies upon sophisticated computer software with the ability to conduct complex calculations, whereas deterministic approach is not computationally intensive and can be easily done when data is available to hotel managers. Managers who do not have a computer program setting their overbooking limits are forced to calculate the overbooking limits themselves and therefore are forced to use data and acknowledge the importance of data availability. On the other hand, although the computer programs providing risk-based overbooking recommendations need more data to operate, they collect the data on their own while managers/users are not aware of the inputs. In other words, in the risk-based approach, the data is collected and processed by the revenue management system automatically and the managers have no reason to know about it.

One reason that data availability does not impact the choice of service-level versus deterministic approach could be the fact that both of these overbooking approaches require managers to actively analyze the data and make decisions based on their observations. Therefore, once more data is available both approaches are considered equally valuable to hotel managers.

5.4.7 Hypothesis H3a

Hypothesis H3a states that stricter cancellation policies are associated with lower overbooking limits. Overbooking policies data set and multivariate multiple regression analysis were used to validate this hypothesis. Dependent variables in the multivariate multiple regression were categorical variables corresponding to different levels of maximum overbooking limit with “less than 5% of capacity” being the benchmark.

Independent variables were cancellation policy elements of window and penalty as well as basic hotel characteristics (i.e., class, size, location and operation type). Note that both cancellation window (benchmark: moderate window) and cancellation penalty (benchmark: one night fee plus taxes penalty) were converted into categorical variables.

Results of multivariate multiple regression suggested that models with maximum overbooking limit of 5-10% (Table 5.11, Adjusted $R^2 = 0.02$) and more than 10% (Table 5.11, Adjusted $R^2 = 0.04$) as their dependent variable were both significant.

When overbooking limit of 5-10% was the dependent variable in the regression, the only significant cancellation policy predictor was the “lenient” cancellation window ($B = -0.10$, $p = 0.024$). The negative coefficient for this predictor variable means that if cancellation window is “lenient” as opposed to “moderate”, the possibility of observing a maximum overbooking limit of 5-10% is lower than the possibility of observing an overbooking limit of less than 5%. In other words, if the cancellation window is moderate (instead of lenient) it is more likely to see a higher overbooking limit.

When overbooking limit of more than 10% was the dependent variable in the regression, the only significant cancellation policy predictor was the “entire stay plus taxes” cancellation penalty ($B = -0.11$, $p = 0.024$). The negative coefficient for this predictor variable suggests that if cancellation penalty is “entire stay plus taxes” as opposed to “one night fee plus taxes”, the possibility of observing a maximum overbooking limit of more than 10% is lower than the possibility of observing a maximum overbooking limit of less than 5%. In other words, if the cancellation penalty is more moderate (instead of more strict) it is more likely to see a higher overbooking limit. Table 5.11, displays the results of the multivariate multiple regression analysis.

Table 5.11: Multivariate multiple regression results for H3a

Dependent Variable	Parameter	B	Std. Error	t	Sig.
Overbooking Limit [a] = 5-10%	(Intercept)	0.04	0.101	0.43	0.670
	Class [b]	0.03	0.018	1.76	0.079
	Size	0.09	0.025	3.49	0.001
	Operation [c] = Chain Owned/Managed	-0.13	0.063	-2.03	0.042
	Operation [c] = Independent	0.10	0.087	1.19	0.233
	Location [d] = Airport	-0.09	0.051	-1.68	0.093
	Location [d] = Interstate	-0.07	0.045	-1.62	0.105
	Location [d] = Resort	0.02	0.066	0.28	0.783
	Location [d] = Small Metro/Town	-0.10	0.037	-2.63	0.009
	Location [d] = Urban	-0.05	0.044	-1.20	0.230
	Cancellation Window [e] = Lenient	-0.10	0.044	-2.26	0.024
	Cancellation Window [e] = Strict	-0.09	0.061	-1.48	0.138
	Cancellation Penalty [f] = Entire Stay Plus Tax	-0.08	0.096	-0.79	0.428
	Cancellation Penalty [f] = More than One Night Fee	0.01	0.048	0.25	0.803
	Cancellation Penalty [f] = Less than One Night Fee	0.05	0.063	0.81	0.418
	Cancellation Penalty [f] = First Night Fee Plus Tax	-0.08	0.044	-1.71	0.088
Overbooking Limit [a] = More than 10%	(Intercept)	-0.08	0.050	-1.57	0.118
	Class [b]	0.02	0.009	2.26	0.024
	Size	0.02	0.012	2.01	0.044
	Operation [c] = Chain Owned/Managed	-0.06	0.031	-2.02	0.044
	Operation [c] = Independent	0.15	0.043	3.42	0.001
	Location [d] = Airport	0.02	0.025	0.85	0.395
	Location [d] = Interstate	-0.01	0.022	-0.26	0.794
	Location [d] = Resort	-0.06	0.033	-1.92	0.055
	Location [d] = Small Metro/Town	0.01	0.018	0.30	0.764
	Location [d] = Urban	0.06	0.022	2.67	0.008
	Cancellation Window [e] = Lenient	0.04	0.022	1.78	0.076
	Cancellation Window [e] = Strict	0.04	0.030	1.22	0.224
	Cancellation Penalty [f] = Entire Stay Plus Tax	-0.11	0.048	-2.26	0.024
	Cancellation Penalty [f] = More than One Night Fee	-0.05	0.024	-1.89	0.059
	Cancellation Penalty [f] = Less than One Night Fee	-0.05	0.031	-1.63	0.102
	Cancellation Penalty [f] = First Night Fee Plus Tax	-0.02	0.022	-0.86	0.390

[a] Overbooking limit is a categorical variable. Benchmark is “less than 5%”

[b] Higher values of the class variable correspond to lower class hotels

[c] Operation is a categorical variable. Benchmark is “franchise”

[d] Location is a categorical variable. Benchmark is “suburban”

[e] Cancellation window is a categorical variable. Benchmark is “moderate”

[f] Cancellation penalty is a categorical variable. Benchmark is “one night fee plus taxes”

To summarize, it is reasonable to claim that both strict and lenient cancellation policies are associated with lower overbooking limits, whereas, moderate cancellation policies are associated with higher overbooking limits. Therefore, H3a cannot be supported. Literature suggests that stricter cancellation policies are associated with fewer cancellations (Chen et al., 2011; Ivanov, 2006; Park & Jang, 2014) and fewer cancellations are expected to reduce the need for overbooking, therefore, resulting in lower overbooking limits. However, the finding that both strict and lenient cancellation policies (as opposed to moderate cancellation policies) are associated with lower overbooking limits suggests that the personality of some revenue managers might be overriding their overbooking logic; causing this unexpected and convoluted relationship between the strictness of cancellation policy and the maximum overbooking limit. In other words, aggressive revenue managers might be enforcing both strict cancellation policies and high overbooking limits at the same time, while those who have a more logical revenue management attitude would set lower overbooking limits when the cancellation policy is strict.

Chapter 6

CONCLUSIONS

6.1 Summary of Findings and Implications

Two data sets were used to answer the research questions. For the first data set, a group of data collectors recorded the cancellation policies of nearly 600 US hotels by manually checking their websites and going through the reservation process. For the second data set, a survey was distributed among a random sample of 10,000 US hotels asking them about different aspects of their overbooking policies. A survey response rate of 3.77% was achieved. After anonymizing the data, STR added the performance indicators to the hotels in both data sets. Following rigorous data cleaning, the cancellation policies data set contained 492 hotels and the overbooking policies data set had 365 hotels.

Cancellation policies data set revealed that the most popular cancellation penalty among the US hotels is “one night fee plus taxes”. Data also showed that the majority of hotels either allow free cancellations until the check-in day or have a free cancellation window of one day before check-in.

Overbooking policies data set indicated that more than one third of US hotels never overbook. Among those which overbook, the majority of them overbook on average 1-5 days in a month. The most popular overbooking approach is the deterministic overbooking followed by the risk-based approach. Additionally, the number of hotels that tend to overbook more on weekdays is almost the same as those which overbook mostly on weekends. When asked about the maximum overbooking limit on a single day, more than two thirds of hotels stated that they overbook less than 5% of their capacity on a given day. Finally, nearly 9 out of 10 hotels indicated that they follow a dynamic overbooking policy (as opposed to a static overbooking policy).

Results of hypothesis testing indicated that a positive relationship exists between data availability and RevPAR index. This finding is consistent with earlier studies across different disciplines such as information technology and big data analytics (Cantor & Macdonald, 2009; Dedrick et al., 2003; Malone et al., 1987; McAfee & Brynjolfsson, 2012) which showed more data results in better performance.

Data analysis showed that on average, moderate cancellation policies appear to be mostly associated with higher levels of RevPAR index, when compared to more lenient, or to more strict policies. This is a very important finding because it indicates that despite the fundamental differences that exist between hotel reservation cancellations and product returns, in both cases moderate policies result in better performance (see Xie and Gerstner (2007) and Guo (2009) for relevant product return literature).

It was found that overbooking (vs. not overbooking) results in better hotel performance. This finding is consistent with earlier studies that found a similar relationship across other industries (LaGanga & Lawrence, 2007, 2012; Milbrandt et al., 2006; Sulistio et al., 2008; Urgaonkar et al., 2002; Zhao & Chen, 2007). Among the four major overbooking approaches (i.e., deterministic, risk-based, service-level and hybrid), findings indicated that risk-based overbooking results in the highest RevPAR index values. This comes as no surprise, because risk-based overbooking recommendations are the final outputs of complex computer programs that take a range of revenue management factors into account. Moreover, it was found that service-level and hybrid approaches are less effective compared to the deterministic approach. This could be due to the dominant role of human judgement in both of these methods. Results also showed that keeping overbooking limit at minimum (i.e., less than 5% of capacity) and overbooking frequency at moderate levels (i.e., 6-10 days in a month) results in the best performance, while excessive overbooking (i.e., more than 10% of capacity and/or more than 20 days in a month) could result in lower RevPAR index values.

Analysis revealed that neither data availability nor cancellation policy can moderate the relationship between the four major overbooking approaches (i.e., deterministic, risk-based, service-level and hybrid) and the RevPAR index. This is an important finding which suggests that as hotels increase the complexity of their overbooking policy, the marginal contribution from that added complexity (i.e., the ability of that additional complexity to improve performance) does not depend on managers' perception of data availability or the type of cancellation policies that are in place.

Although it was hypothesized that data availability is positively associated with the complexity of the overbooking approach, results showed that the opposite is true.

Specifically, it was found that the higher the data availability the lower the possibility of using risk-based overbooking as opposed to deterministic approach. A possible explanation is that managers who do not have a computer program setting their overbooking limits are forced to calculate the overbooking limits themselves and therefore are forced to use data and acknowledge the importance of data availability. On the contrary, even though the computer programs providing risk-based overbooking recommendations need more data to operate, they collect the data on their own while managers/users are not aware of the inputs. This means that in the risk-based approach, data is collected and processed by the revenue management system automatically and the managers have no reason to know about it.

Finally, the results indicated that there is no linear relationship between the strictness of a hotel's cancellation policy and its overbooking limit. Instead, it was found that both strict and lenient cancellation policies are associated with lower overbooking limits, while moderate cancellation policies are associated with higher overbooking limits. This rather unexpected result could be partly due to the personality differences across hotel managers. For instance, aggressive revenue managers are expected to set both strict cancellation policies and high overbooking limits at the same time, whereas, revenue managers with a more logical attitude would ideally overbook less when a strict cancellation policy is in place.

The findings of this study provide a range of theoretical and practical implications. In terms of practical implications, hotel managers can use the findings of this research to get a better understanding of how different cancellation and overbooking elements impact hotel performance. By contemplating the optimal cancellation and overbooking policies identified in this study while considering the unique characteristics of individual hotels, revenue managers can make policy choices that will lead to better performance. In terms of theoretical implications, this study contributed to the revenue management literature by providing a clear picture of how cancellation and overbooking are practiced in the US hotel industry. The study also contributed to the existing literature by showing how data availability and cancellation policies can impact different elements of a hotel's overbooking policy. Most importantly, this study is the first to show how different elements of a hotel's cancellation and overbooking policies can impact the RevPAR index. This is a significant theoretical contribution because it underlines the importance of revenue management by showing how specific elements of revenue management can impact hotel performance.

6.2 Research Limitations

Although this study provided significant theoretical and practical implications, it should be realized that as with all studies, there have been a number of limitations.

A strong effort was made to collect a representative sample of US hotels for both the cancellation policies data set as well as the overbooking policies data set. However, the size of both data sets was limited due to data collection constraints as well as low survey response rate. When a larger data set is present, the research methods provide more reliable results and findings are more generalizable.

Furthermore, this study used RevPAR Index to measure hotels' financial performance. This indexed KPI is well received by both industry and academia, due to being normalized (per room) and context specific (compared to the hotel competitive set averages); but it has two drawbacks: RevPAR index does not account for profitability, and it might not fully reflect the connection with income from cancellation penalties. The latter is because some hotels record the income from cancellation penalties outside their P&L rooms' revenue section. For such hotels, this study only captures the indirect impact of the cancellation policies.

Before survey distribution, every effort was made to avoid jargon in the survey and various examples were added to the survey questions to simplify them and make them more understandable; however, it is possible that some survey responders may have still perceived the wording of the survey to be rather scientific. Therefore, due to the fairly technical wording of the survey, some responders may have not thoroughly read the questions before answering and simply responded with the most convenient or random answer. There is also a potential for the social desirability bias in the responses provided to the overbooking survey. In other words, some hotel managers might have provided socially desirable responses to the overbooking questions in the survey.

A further limitation is that the data availability measure in this study merely captured the managerial perception of data availability and did not account for important factors such as hotels' power to process and analyze the data. This is mostly because the study relied on survey data to collect information about data availability, therefore capturing hotels' data processing capabilities was beyond the scope of this research. Also, due to the use of a five-point Likert scale for data availability questions, the results might be skewed towards opposite ends of the scale (i.e., extreme responding).

6.3 Directions for Future Research

Future research could use a larger sample of US hotels to examine the hypothesized relationships. Moreover, by using a sample of non-US hotels, future studies can test whether the relationships identified in this study are only specific to the US market or can be observed elsewhere.

An important aspect of a hotel's revenue management strategy is handling overselling situations which typically occur due to excessive overbooking. Under these circumstances, hotel managers should decide how to compensate customers that cannot be accommodated. Denied service incidents could negatively impact customer satisfaction and could affect hotel's financial performance. Future studies, can explore the possible linkages between overselling strategies, overbooking policies and financial performance. For instance, researchers can explore how hotels handle the loss of customer goodwill and satisfaction resulting from overselling. They can also explore how loss of satisfaction resulting from overselling impacts hotel performance.

Future studies can examine the direct impact of cancellation and overbooking policies on customer goodwill. For instance, researchers can quantify the impact of a dollar increase in cancellation fees on customers satisfaction and goodwill. Researchers can also examine whether the increased satisfaction from booking lower priced non-refundable rooms outweighs the potential dissatisfaction caused by cancelling these same rooms and not being refunded at all. Another interesting aspect of cancellation policies which could be considered by future studies is how non-refundable cancellation policies impact the no-show rates. In other words, research can examine whether non-refundable cancellation policies result in higher than average no-shows (because customers have no monetary incentive to cancel their reservations and notify the hotel of their change of plans).

Finally, future research can consider using profitability metrics (as opposed to RevPAR index) to check whether cancellation and overbooking policies that were found to be associated with the highest RevPAR index values are also the most profitable ones.

REFERENCES

Altin, M. M. (2015). *An Examination of the Link between RM Implementation Strategies and Performance* (Doctoral dissertation). Retrieved online from https://vtechworks.lib.vt.edu/bitstream/handle/10919/72910/Altin_MM_D_2015.pdf?seqseque=1 on 6/30/2017.

Badinelli, R. (2000). An optimal, dynamic policy for hotel yield management. *European Journal of Operational Research*, *121*(3), 476-503. DOI: 10.1016/S0377-2217(99)00046-6

Baker, T. K., & Collier, D. A. (1999). A comparative revenue analysis of hotel yield management heuristics. *Decision Sciences*, *30*(1), 239-263. DOI: 10.1111/j.1540-5915.1999.tb01608.x

Bartlett, H. P., Simonite, V., Westcott, E., & Taylor, H. R. (2000). A comparison of the nursing competence of graduates and diplomates from UK nursing programmes. *Journal of Clinical Nursing*, *9*(3), 369-381. DOI: 10.1046/j.1365-2702.2000.00331.x

Bastakis, C., Buhalis, D., & Butler, R. (2004). The perception of small and medium sized tourism accommodation providers on the impacts of the tour operators' power in

Eastern Mediterranean. *Tourism Management*, *25*(2), 151-170. DOI: 10.1016/S0261-5177(03)00098-0

Belobaba, P. P. (1989). OR practice—application of a probabilistic decision model to airline seat inventory control. *Operations Research*, *37*(2), 183-197. DOI: 10.1287/opre.37.2.183

Bertsimas, D., & Popescu, I. (2003). Revenue management in a dynamic network environment. *Transportation science*, *37*(3), 257-277. DOI: 10.1287/trsc.37.3.257.16047

Bitran, G. R., & Gilbert, S. M. (1996). Managing hotel reservations with uncertain arrivals. *Operations Research*, *44*(1), 35-49. DOI: 10.1287/opre.44.1.35

Boarding Area (2014a). *Marriott Changing Global Cancellation Policy*, Retrieved online from http://onemileatatime.boardingarea.com/2014/10/12/marriott-changing-global-cancellation-policy/ on 7/28/2016.

Boarding Area (2014b). *Hilton Changing Global Cancellation Policy*, Retrieved online from http://onemileatatime.boardingarea.com/2014/11/10/hilton-changing-global-cancellation-policy/ on 7/28/2016.

Brynjolfsson, E., Hitt L. M., & Kim H. H. (2011). Strength in numbers: How does data-driven decision making affect firm performance? *Working Paper*. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1819486

Buhalis, D. (2000). Relationships in the distribution channel of tourism: Conflicts between hoteliers and tour operators in the Mediterranean region. *International Journal of Hospitality & Tourism Administration*, *1*(1), 113-139. DOI: 10.1300/J149v01n01_07

Buhalis, D., & Laws, E. (2001). *Tourism distribution channels: Practices, issues and transformations*, London, UK: Thomson.

Cachon, G. P., & Fisher, M. (2000). Supply chain inventory management and the value of shared information. *Management Science*, *46*(8), 1032-1048. DOI: 10.1287/mnsc.46.8.1032.12029

Cantor, D. E., & Macdonald, J. R. (2009). Decision-making in the supply chain: examining problem solving approaches and information availability. *Journal of Operations Management*, *27*(3), 220-232. DOI: 10.1016/j.jom.2008.09.002

Capiez, A., & Kaya, A. (2004). Yield management and performance in the hotel industry. *Journal of Travel & Tourism Marketing*, *16*(4), 21-31. DOI: 10.1300/J073v16n04_05

Carroll, W. J., & Grimes, R. C. (1995). Evolutionary change in product management: Experiences in the car rental industry. *Interfaces*, *25*(5), 84-104.

Chen, F. (1999). Decentralized supply chains subject to information delays. *Management Science*, *45*(8), 1076-1090. DOI: 10.1287/mnsc.45.8.1076

Chen, C. 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. DOI: 10.1016/j.ijhm.2010.03.010

Chen, C. C., & Xie, K. L. (2013). Differentiation of cancellation policies in the US hotel industry. *International Journal of Hospitality Management*, *34*(9), 66-72. DOI: 10.1016/j.ijhm.2013.02.007

Choi, S., & Kimes, S. E. (2002). Electronic distribution channels' effect on hotel revenue management. *The Cornell hotel and restaurant administration quarterly*, *43*(3), 23-31. DOI: 10.1016/S0010-8804(02)80015-5

Conlon, D. E., & Murray, N. M. (1996). Customer perceptions of corporate responses to product complaints: The role of explanations. *Academy of Management Journal*, *39*(4), 1040-1056. DOI: 10.2307/256723

Corney, W. J. (1984). The use of computer spreadsheets for overbooking optimization and analysis. *International Journal of Hospitality Management*, *3*(4), 153-157. DOI: 10.1016/0278-4319(84)90016-1

Creech, S. (2017). *ANOVA*, Retrieved online from https://www.statisticallysignificantconsulting.com/Anova.htm on 9/13/2017.

Croson, R., & Donohue, K. (2003). Impact of POS data sharing on supply chain management: An experimental study. *Production and Operations Management*, *12*(1), 1-11. DOI: 10.1111/j.1937-5956.2003.tb00194.x

Dacko, S. G. (2004). Marketing strategies for last-minute travel and tourism: Profitability and revenue management implications. *Journal of Travel & Tourism Marketing*, *16*(4), 7-20. DOI: 10.1300/J073v16n04_04

Dattalo, P. (2013). *Analysis of multiple dependent variables*, Oxford, UK: Oxford University Press.

Dedrick, J., Gurbaxani, V., & Kraemer, K. L. (2003). Information technology and economic performance: A critical review of the empirical evidence. *ACM Computing Surveys (CSUR)*, *35*(1), 1-28. DOI: 10.1145/641865.641866

Dekay, F., Yates, B., & Toh, R. S. (2004). Non-performance penalties in the hotel industry. *International Journal of Hospitality Management*, *23*(3), 273-286. DOI: 10.1016/j.ijhm.2003.11.003

Dong, Y., & Ling, L. (2015). Hotel overbooking and cooperation with third-party websites. *Sustainability*, *7*(9), 11696-11712. DOI: 10.3390/su70911696

Enghagen, L. K. (1996). The case against overbooking. *Journal of Hospitality & Leisure Marketing*, *4*(1), 51-62. DOI: 10.1300/J150v04n01_04

Folkes, V. S., Koletsky, S., & Graham, J. L. (1987). A field study of causal inferences and consumer reaction: the view from the airport. *Journal of consumer research*, *13*(4), 534-539. DOI: 10.1086/209086

Geraghty, M. K., & Johnson, E. (1997). Revenue management saves national car rental. *Interfaces*, *27*(1), 107-127. DOI: 10.1287/inte.27.1.107

Gilly, M. C., & Hansen, R. W. (1985). Consumer complaint handling as a strategic marketing tool. *Journal of Consumer Marketing*, *2*(4), 5-16. DOI: 10.1108/eb008139

Glen, S. (2015). *Stepwise Regression*, Retrieved online from http://www.statisticshowto.com/stepwise-regression/ on 9/13/2017.

Goodwin, C., & Ross, I. (1989). salient dimensions of perceived fairness jn resolution of service comiplaints. *Journal of Consumer Satisfaction, Dissatisfaction, and Complaining Behavior*, *2*, 87-92.

Gosavii, A., Bandla, N., & Das, T. K. (2002). A reinforcement learning approach to a single leg airline revenue management problem with multiple fare classes and overbooking. *IIE transactions*, *34*(9), 729-742. DOI: 10.1007/s00291-005-0018-z

Guillet, B. D., & Law, R. (2010). Analyzing hotel star ratings on third-party distribution websites. *International Journal of Contemporary Hospitality Management*, *22*(6), 797-813. DOI: 10.1108/09596111011063098

Guo, L. (2009). Service cancellation and competitive refund policy. *Marketing Science*, *28*(5), 901-917. DOI: 10.1287/mksc.1080.0457

Guo, X., Dong, Y., & Ling, L. (2016). Customer perspective on overbooking: The failure of customers to enjoy their reserved services, accidental or intended? *Journal of Air Transport Management*, *53*(6), 65-72. DOI: 10.1016/j.jairtraman.2016.01.001

Guo, X., Ling, L., Dong, Y., & Liang, L. (2013). Cooperation contract in tourism supply chains: The optimal pricing strategy of hotels for cooperative third party strategic websites. *Annals of Tourism Research*, *41*, 20-41. DOI: 10.1016/j.annals.2012.11.009

Guo, X., Zheng, X., Ling, L., & Yang, C. (2014). Online coopetition between hotels and online travel agencies: From the perspective of cash back after stay. *Tourism Management Perspectives*, *12*, 104-112. DOI: 10.1016/j.tmp.2014.09.005

Hadjinicola, G. C., & Panayi, C. (1997). The overbooking problem in hotels with multiple tour-operators. *International Journal of Operations & Production Management*, *17*(9), 874-885. DOI: 10.1108/01443579710171208

Hannigan, J. A. (1980). Reservations cancelled: consumer complaints in the tourist industry. *Annals of Tourism Research*, *7*(3), 366-384. DOI: 10.1016/0160-7383(80)90029-8

Heidel, E. (2017). *Stepwise regression*, Retrieved online from http://www.scalelive.com/stepwise-regression.html on 9/13/2017.

Hoaglin, D. C., Iglewicz, B., & Tukey, J. W. (1986). Performance of some resistant rules for outlier labeling. *Journal of the American Statistical Association*, *81*(396), 991-999. DOI: 10.2307/2289073

Hocutt, M. A., Chakraborty, G., & Mowen, J. C. (1997). The impact of perceived justice on customer satisfaction and intention to complain in a service recovery. *Advances in Consumer Research, 24*, 457-463.

Hoffman, K. D., Kelley, S. W., & Rotalsky, H. M. (1995). Tracking service failures and employee recovery efforts. *Journal of Services Marketing*, *9*(2), 49-61. DOI: 10.1108/08876049510086017

Hoisington, A. (2017). *What hoteliers should know about overbooking*, Retrieved online from http://www.hotelnewsnow.com/Articles/124365/What-hoteliers-should-know-about-overbooking on 3/22/2017.

Hwang, J., & Wen, L. (2009). The effect of perceived fairness toward hotel overbooking and compensation practices on customer loyalty. *International Journal of Contemporary Hospitality Management*, *21*(6), 659-675. DOI: 10.1108/09596110910975945

Investing Answers (2017). *Revenue per Available Room (RevPAR),* Retrieved online from http://www.investinganswers.com/financial-dictionary/ratio-analysis/revenue-available-room-revpar-807 on 6/22/2017.

Ivanov, S. (2006). Management of overbookings in the hotel industry – basic concepts and practical challenges. *Tourism Today, 6*(3), 19-32.

Ivanov, S. (2007). Dynamic overbooking limits for guaranteed and nonguaranteed hotel reservations. *Tourism Today, 7*(3), 100-108.

Ivanov, S. H. (2015). Optimal overbooking limits for a hotel with three room types and with upgrade and downgrade constraints. *Tourism Economics, 21*(1), 223-240. DOI: 10.5367/te.2014.0444

Jeffries, J. P. (1987). *Understanding hotel/motel law*, East Lansing, MI: Educational Institute of the American Hotel & Motel Association.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1986). Fairness and the assumptions of economics. *Journal of Business, 29*(4), 285-300.

Karaesmen, I., & van Ryzin, G. (2004). Overbooking with substitutable inventory classes. *Operations Research, 52*(1), 83-104. DOI: 10.1287/opre.1030.0079

Kim, S., & Giachetti, R. E. (2006). A stochastic mathematical appointment overbooking model for healthcare providers to improve profits. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans, 36*(6), 1211-1219. DOI: 10.1109/TSMCA.2006.878970

Kimes, S. E. (1989). Yield management: a tool for capacity-considered service firms. *Journal of Operations Management, 8*(4), 348-363. DOI: 10.1016/0272-6963(89)90035-1

Kimes, S. E. (1994). Perceived fairness of yield management. *The Cornell Hotel and Restaurant Administration Quarterly*, *35*(1), 22-29. DOI: 10.1016/0010-8804(94)90060-4

Kimes, S. E. (2000). Revenue management on the links: applying yield management to the golf-course industry. *The Cornell Hotel and Restaurant Administration Quarterly*, *41*(1), 120-127. DOI: 10.1016/S0010-8804(00)88891-6

Kimes, S. E. (2002). Perceived fairness of yield management: an update. *Cornell Hotel and Restaurant Administration Quarterly, 43*(1), 21-30.

Kimes, S. E. (2005). Restaurant revenue management: Could it work? *Journal of Revenue and Pricing Management*, *4*(1), 95-97. DOI: 10.1057/palgrave.rpm.5170132

Kimes, S. E., & Chase, R. B. (1998). The strategic levers of yield management. *Journal of Service Research*, *1*(2), 156-166. DOI: 10.1177/109467059800100205

Klophaus, R., & Pölt, S. (2007). Airline overbooking with dynamic spoilage costs. *Journal of Revenue and Pricing Management*, *6*(1), 9-18. DOI: 10.1057/palgrave.rpm.5160059

Koide, T., & Ishii, H. (2005). The hotel yield management with two types of room prices, overbooking and cancellations. *International Journal of Production Economics*, *93*(1), 417-428. DOI: 10.1016/j.ijpe.2004.06.038

Krawczyk, M., Webb, T., Schwartz, Z., & Uysal, M. (2016). Overbooking Research in the Lodging Industry: From Origins in Airlines to What Lies Ahead. In M. Uysal, Z. Schwartz & E. Sirakaya-Turk (Eds.), *Management Science in Hospitality and Tourism: Theory, Practice, and Applications* (pp. 251-268). Oakville, Canada: Apple Academic Press.

Kruskal, W. H., & Wallis, W. A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American statistical Association, 47*(260), 583-621.

LaGanga, L. R., & Lawrence, S. R. (2007). Clinic overbooking to improve patient access and increase provider productivity. *Decision Sciences, 38*(2), 251-276. DOI: 10.1111/j.1540-5915.2007.00158.x

LaGanga, L. R., & Lawrence, S. R. (2012). Appointment overbooking in health care clinics to improve patient service and clinic performance. *Production and Operations Management*, *21*(5), 874-888. DOI: 10.1111/j.1937-5956.2011.01308.x

Lambert, C. U., Lambert, J. M., & Cullen, T. P. (1989). The overbooking question: A simulation. *The Cornell Hotel and Restaurant Administration Quarterly, 30*(2), 14-20.

Lan, Y. (2009). *Robust revenue management with limited information: Theory and experiments* (Doctoral dissertation). Retrieved online from http://drum.lib.umd.edu/handle/1903/9606 on 4/6/2017.

Lee, H. L., So, K. C., & Tang, C. S. (2000). The value of information sharing in a two-level supply chain. *Management Science*, *46*(5), 626-643. DOI: 10.1287/mnsc.46.5.626.12047

Lee, S., Min, D., Ryu, J. H., & Yih, Y. (2013). A simulation study of appointment scheduling in outpatient clinics: Open access and overbooking. *Simulation*, *89*(12), 1459-1473. DOI: 10.1177/0037549713505332

Lefever, M. M. (1988). The gentle art of overbooking. *The Cornell Hotel and Restaurant Administration Quarterly, 29*(3), 7-8.

Li, B. (2014). A Cruise Line Dynamic Overbooking Model with Multiple Cabin Types from the View of Real Options. *Cornell Hospitality Quarterly, 55*(2), 197-209. DOI: 10.1177/1938965513507126

Liberman, V., & Yechiali, U. (1978). On the hotel overbooking problem - an inventory system with stochastic cancellations. *Management Science*, *24*(11), 1117-1126. DOI: 10.1287/mnsc.24.11.1117

Lindenmeier, J., & Tscheulin, D. K. (2008). The effects of inventory control and denied boarding on customer satisfaction: The case of capacity-based airline revenue management. *Tourism Management*, *29*(1), 32-43. DOI: 10.1016/j.tourman.2007.04.004

Ling, L., Guo, X., & Yang, C. (2014). Opening the online marketplace: An examination of hotel pricing and travel agency on-line distribution of rooms. *Tourism Management*, *45*, 234-243. DOI: 10.1016/j.tourman.2014.05.003

Little Hotelier (2017). *Calculate your Average Daily Rate*, Retrieved online from http://www.littlehotelier.com/calculate-average-daily-rate/ on 6/22/2017.

Mack, R., Mueller, R., Crotts, J., & Broderick, A. (2000). Perceptions, corrections and defections: implications for service recovery in the restaurant industry. *Managing Service Quality: An International Journal*, *10*(6), 339-346. DOI: 10.1108/09604520010352256

Malone, T. W., Yates, J., & Benjamin, R. I. (1987). Electronic markets and electronic hierarchies. *Communications of the ACM*, *30*(6), 484-497. DOI: 10.1145/214762.214766

Mauri, A. G. (2013). *Hotel Revenue Management: Principles and Practices*. Milano-Torino, Italy: Pearson.

McAfee, A., & Brynjolfsson, E. (2012). Big data: the management revolution. *Harvard Business Review*, *90*(10), 60-68.

McCarthy, M. S., & Fram, E. H. (2000). An exploratory investigation of customer penalties: assessment of efficacy, consequences, and fairness perceptions. *Journal of Services Marketing*, *14*(6), 479-501.

McCollough, M. A. (2000). The effect of perceived justice and attributions regarding service failure and recovery on post-recovery customer satisfaction and service quality attitudes. *Journal of Hospitality & Tourism Research*, *24*(4), 423-447. DOI: 10.1177/109634800002400402

McConnell, J. P., & Rutherford, D. G. (1990). Hotel reservations: The guest contract. *The Cornell Hotel and Restaurant Administration Quarterly*, *30*(4), 61-65.

Milbrandt, J., Menth, M., & Junker, J. (2006). *Experience-based admission control with type-specific overbooking*. Paper presented at the International Workshop on IP Operations and Management. DOI: 10.1007/11908852_7

Mount, D. J., & Mattila, A. (2000). The final opportunity: the effectiveness of a customer relations call center in recovering hotel guests. *Journal of Hospitality & Tourism Research*, *24*(4), 514-525. DOI: 10.1177/109634800002400406

Mukhopadhyay, S. K., & Setoputro, R. (2004). Reverse logistics in e-business: optimal price and return policy. *International Journal of Physical Distribution & Logistics Management*, *34*(1), 70-89. DOI: 10.1108/09600030410515691

Netessine, S., & Shumsky, R. (2002). Introduction to the theory and practice of yield management. *INFORMS Transactions on Education*, *3*(1), 34-44. DOI: 10.1287/ited.3.1.34

Noone, B. M., & Lee, C. H. (2011). Hotel overbooking: the effect of overcompensation on customers' reactions to denied service. *Journal of Hospitality & Tourism Research*, *35*(3), 334-357. DOI: 10.1177/1096348010382238

O'Connor, P. (2001). Room rates on the internet - is the web really cheaper? *Journal of Services Research*, *1*(1), 57-72.

O'Connor, P. (2002). An empirical analysis of hotel chain online pricing strategies. *Information Technology & Tourism*, *5*(2), 65-72. DOI: 10.3727/109830502108751055

Padmanabhan, V., & Png, I. P. (1995). Returns policies: Make money by making good. *Sloan Management Review*, *37*(1), 65-72.

Padmanabhan, V., & Png, I. P. (1997). Manufacturer's return policies and retail competition. *Marketing Science*, *16*(1), 81-94. DOI: 10.1287/mksc.16.1.81

Park, J. Y., & Jang, S. S. (2014). Sunk costs and travel cancellation: Focusing on temporal cost. *Tourism Management*, *40*, 425-435. DOI: 10.1016/j.tourman.2013.08.005

Phillips, R. L. (2005). *Pricing and Revenue Optimization*. Stanford, CA: Stanford University Press.

Phumchusri, N., & Maneesophon, P. (2014). Optimal overbooking decision for hotel rooms revenue management. *Journal of Hospitality and Tourism Technology*, *5*(3), 261-277. DOI: 10.1108/JHTT-03-2014-0006

Provost, F., & Fawcett, T. (2013). Data science and its relationship to big data and data-driven decision making. *Big Data*, *1*(1), 51-59. DOI: 10.1089/big.2013.1508

Pullman, M., & Rodgers, S. (2010). Capacity management for hospitality and tourism: A review of current approaches. *International Journal of Hospitality Management*, *29*(1), 177-187. DOI: 10.1016/j.ijhm.2009.03.014

Queenan, C. C., Ferguson, M. E., & Stratman, J. K. (2011). Revenue management performance drivers: An exploratory analysis within the hotel industry. *Journal of Revenue and Pricing Management*, *10*(2), 172-188. DOI: 10.1057/rpm.2009.31

Raghunathan, S. (2001). Information sharing in a supply chain: A note on its value when demand is nonstationary. *Management Science*, *47*(4), 605-610. DOI: 10.1287/mnsc.47.4.605.9833

Reid, R. D., & Bojanic, D. C. (2009). *Hospitality Marketing Management*. Hoboken, NJ: John Wiley & Sons.

Riasi, A., Schwartz, Z., Liu, X., & Li, S. (2017). Revenue Management and Length-of-Stay-Based Room Pricing. *Cornell Hospitality Quarterly*, *58*(4), 393-399. DOI: 10.1177/1938965517704372

Richins, M. L. (1983). Negative word-of-mouth by dissatisfied consumers: A pilot study. *The Journal of Marketing*, *47*, 68-78.

Rivera, M. (2011). *RevPAR-Adjusted Budgets: The Only Ones worth Looking at*. San Francisco, CA: HVS Asset Management & Advisory.

Roomer Travel (2017), *Hotel Cancellation Policies*, Retrieved online from https://www.roomertravel.com/cancellation/hotel_cancellation_policies on 2/8/2017.

Rothstein, M. (1974). Hotel overbooking as a Markovian sequential decision process. *Decision Sciences*, *5*(3), 389-404.

Rothstein, M. (1985). OR and the airline overbooking problem. *Operations Research*, *33*(2), 237-248. DOI: 10.1287/opre.33.2.237

Ruyter, K., & Wetzels, M. (2000). Customer equity considerations in service recovery: a cross-industry perspective. *International Journal of Service Industry Management*, *11*(1), 91-108. DOI: 10.1108/09564230010310303

Sahay, A. (2007). How to reap higher profits with dynamic pricing. *MIT Sloan management review*, *48*(4), 53-60.

Salomon, A. (2000). *Overbooking: Hotels talk the talk to avoid the walk*, Retrieved online from http://www.hotelinteractive.com/article.aspx?articleID=626 on 4/11/2017.

Scher vs. Liberty Travel Service, Inc. (1971). 328 N.Y.S.2d 386.

Schwartz, Z. (1998). The confusing side of yield management: Myths, errors, and misconceptions. *Journal of Hospitality & Tourism Research*, *22*(4), 413-430. DOI: 10.1177/109634809802200406

Schwartz, Z., Altin, M., & Singal, M. (2016). Performance measures for strategic revenue management: RevPAR versus GOPPAR. *Journal of Revenue and Pricing Management*, Advance online publication. DOI: 10.1057/rpm.2016.23

Shlifer, E., & Vardi, Y. (1975). An airline overbooking policy. *Transportation Science, 9*(2), 101-114. DOI: 10.1287/trsc.9.2.101

Smith, A. K., Bolton, R. N., & Wagner, J. (1999). A model of customer satisfaction with service encounters involving failure and recovery. *Journal of marketing research*, 356-372. DOI: 10.2307/3152082

Smith, S. J. (2012). *The relationship between perceived personal fairness, social fairness, hotel cancellation policies and consumer patronage* (Doctoral dissertation). Retrieved online from http://etd.fcla.edu/CF/CFE0004269/FINAL_COPY_Scott_Smith_All_chapters_Apr_12_2012.pdf on 7/27/2016.

Smith, S. J., Parsa, H., Bujisic, M., & van der Rest, J. (2015). Hotel Cancellation Policies, Distributive and Procedural Fairness, and Consumer Patronage: A Study of the Lodging Industry. *Journal of Travel & Tourism Marketing*, 32(7), 886-906. DOI:10.1080/10548408.2015.1063864

Sparks, B., & Fredline, L. (2007). Providing an explanation for service failure: Context, content, and customer responses. *Journal of Hospitality & Tourism Research*, *31*(2), 241-260. DOI: 10.1177/1096348006297292

Sparks, B., & McColl-Kennedy, J. R. (2001). Justice strategy options for increased customer satisfaction in a services recovery setting. *Journal of Business Research*, *54*(3), 209-218. DOI: 10.1016/S0148-2963(00)00120-X

STR Global (2017). *A Guide to Our Terminology*, Retrieved online from https://www.strglobal.com/resources/glossary on 6/22/2017.

Sulistio, A., Kim, K. H., & Buyya, R. (2008). *Managing cancellations and no-shows of reservations with overbooking to increase resource revenue*. Paper presented at the 8th IEEE International Symposium on Cluster Computing and the Grid. DOI: 10.1109/CCGRID.2008.65

Sundaram, D. S., Webster, C., & Jurowski, C. (1997). Service failure recovery efforts in restaurant dining: The role of criticality of service consumption. *Hospitality Research Journal*, *20*, 137-150.

Suzuki, Y. (2002). An empirical analysis of the optimal overbooking policies for US major airlines. *Transportation Research Part E: Logistics and Transportation Review*, *38*(2), 135-149. DOI: 10.1016/S1366-5545(01)00016-3

Suzuki, Y. (2006). The net benefit of airline overbooking. *Transportation Research Part E: Logistics and Transportation Review*, *42*(1), 1-19. DOI: 10.1016/j.tre.2004.09.001

Talluri, K. T., & van Ryzin, G. J. (2004). *The Theory and Practice of Revenue Management*, New York City, NY: Springer US. DOI: 10.1007/b139000

Toh, R. S. (1985). An inventory depletion overbooking model for the hotel industry. *Journal of Travel Research, 23*(4), 24-30. DOI: 10.1177/004728758502300404

Toh, R. S., & Dekay, F. (2002). Hotel room-inventory management: an overbooking model. *The Cornell Hotel and Restaurant Administration Quarterly, 43*(4), 79-90. DOI: 10.1016/S0010-8804(02)80044-1

Toh, R. S., Raven, P., & DeKay, F. (2011). Selling rooms: Hotels vs. third-party websites. *Cornell Hospitality Quarterly*, *52*(2), 181-189. DOI: 10.1177/1938965511400409

Toh, R. S., Rivers, M. J., & Ling, T. W. (2005). Room occupancies: cruise lines out-do the hotels. *International Journal of Hospitality Management*, *24*(1), 121-135. DOI: 10.1016/j.ijhm.2004.05.005

Tse, T. S. M., & Poon, Y. T. (2016). Modeling no-shows, cancellations, overbooking, and walk-ins in restaurant revenue management. *Journal of Foodservice Business Research*, 1-19. DOI: 10.1080/15378020

Tukey, J. W. (1977). *Exploratory Data Analysis*, Upper Saddle River, NJ: Pearson.

Urgaonkar, B., Shenoy, P., & Roscoe, T. (2002). Resource overbooking and application profiling in shared hosting platforms. *ACM SIGOPS Operating Systems Review*, *36*, 239-254. DOI: 10.1145/844128.844151

Vinod, B. (2004). Unlocking the value of revenue management in the hotel industry. *Journal of Revenue and Pricing Management*, *3*(2), 178-190. DOI: 10.1057/palgrave.rpm.5170105

Wagener, D. (2017). *Answering Questions About Hotel Overbooking and Walking Guests*, Retrieved online from http://duettoresearch.com/answering-questions-hotel-overbooking-walking-guests/ on 5/7/2017

Wangenheim, F. V., & Bayón, T. (2007). Behavioral consequences of overbooking service capacity. *Journal of Marketing*, *71*(4), 36-47. DOI: 10.1509/jmkg.71.4.36

Weatherford, L. R., & Pölt, S. (2002). Better unconstraining of airline demand data in revenue management systems for improved forecast accuracy and greater revenues. *Journal of Revenue and Pricing Management*, *1*(3), 234-254. DOI: 10.1057/palgrave.rpm.5170027

Wiener-Bronner, D. (2017). *Marriott cancels its 24-hour cancellation policy*, Retrieved online from http://money.cnn.com/2017/06/16/news/companies/marriott-cancellation-policy-change/index.html on 6/22/2017.

Williams, F. E. (1977). Decision theory and the innkeeper: An approach for setting hotel reservation policy. *Interfaces*, *7*(4), 18-30. DOI: 10.1287/inte.7.4.18

Williamson, E. L. (1992). *Airline network seat inventory control: Methodologies and revenue impacts* (Doctoral dissertation). Retrieved online from https://dspace.mit.edu/handle/1721.1/68123 on 3/23/2017.

Wilson, R. H., Enghagen, L., & Barishman, B. (1995). Overbooking: a new look at an old problem. *The Journal of Hospitality Financial Management*, *4*(1), 95-104. DOI: 10.1080/10913211.1995.10653674

Wilson, R. H., Enghagen, L. K., & Sharma, P. (1994). Overbooking: The Practice and the Law. *Journal of Hospitality & Tourism Research*, *17*(2), 93-105. DOI: 10.1177/109634809401700209

Wirtz, J., Kimes, S. E., Theng, J. H. P., & Patterson, P. (2003). Revenue management: resolving potential customer conflicts. *Journal of Revenue and Pricing Management*, *2*(3), 216-226. DOI: 10.1057/palgrave.rpm.5170068

Wood, S. L. (2001). Remote purchase environments: The influence of return policy leniency on two-stage decision processes. *Journal of Marketing Research*, *38*(2), 157-169. DOI: 10.1509/jmkr.38.2.157.18847

Xie, J., & Gerstner, E. (2007). Service escape: Profiting from customer cancellations. *Marketing Science*, *26*(1), 18-30. DOI: 10.1287/mksc.1060.0220

Zhao, Y. X., & Chen, C. J. (2007). A redundant overbooking reservation algorithm for OBS/OPS networks. *Computer Networks*, *51*(13), 3919-3934. DOI: 10.1016/j.comnet.2007.04.011

Appendix A

DATA COLLECTION INSTRUCTIONS FOR CANCELLATION DATA

Important: When the check-in date is the same as the searching date (i.e., booking a room zero day in advance of arrival) then collect the following data before 1 PM. In all other cases, you may collect the data at any time of the day.

1. Choose a hotel from the list of the hotels in your spreadsheet.

Go to *TripAdvisor.com*, search the hotel's name and record the traveler rating of the hotel under the column titled as *"TripAdvisor Rating"*.

The rating should be a number between 0 and 5.

If the hotel is not rated or is not available on *TripAdvisor.com* then record it as *"Not Rated"*.

2. Record the searching date in the spreadsheet under the column titled as *"Searching Date"*. This will be today's date. The date format should be mm/dd/yyyy.

After you enter the searching date, the check-in date and check-out dates will be automatically updated in your spreadsheet.

3. Go to the hotel's general website.

On the hotel's website, enter the check-in and check-out dates exactly as displayed in your spreadsheet.

4. On the hotel's website, select a room rate category according to your spreadsheet. Start with the general room category (also known as "*Best Available Rate*") and ignore all special discounts such as AAA, Senior, Government, etc.

5. Select the **highest** rate in the general category (i.e., highest rate within the *"Best Available Rate"* category).

6. Find the hotel's cancellation policy and collect the following information:

- **Free Cancellation Window:** Use the date for the cancellation deadline and the *"Check-In Date"*, to calculate and record the number of days before the check-in date that the room can be cancelled for free (for example, the deadline for cancellation is 1 day before check-in). If the cancellation window cannot be recorded in terms of *"Days Before Check-In"* then refer to table A.1 to make a selection.

Table A.1: Free cancellation window choices

Hotel's Policy	*Your Selection*
The cancellation policy states that the room is non-refundable and customers can never cancel their reservations for free.	Non-Refundable
The cancellation policy states that the customers can cancel their reservations free of charge whenever they wish.	No Deadline
Free cancellation deadline is different than all of the above options.	Other
Free cancellation deadline cannot be found in the hotel's website or in *Hotels.com.*	Not Found

Note: If cancellation deadline is not explicitly stated in the hotel's website, then try to find this info by searching the hotel's name in Hotels.com. Remember to choose the same check-in and check-out dates and the same room rate category, when using Hotels.com. If still no information is found, then select the "Not Found" option.

- **Describe if Cancellation Window is "Other":** Complete this box only if you selected *"Other"* for the *"Free Cancellation Window"*, otherwise leave it blank.
- **Cancellation Deadline Time:** Record the cancellation deadline time. If the cancellation deadline time is not reported in the hotel's cancellation policy, then select *"Not Specified".*
- **Cancellation Penalty:** Record the cancellation penalty. Refer to table A.2 to make a selection:

Table A.2: Cancellation penalty choices

Hotel's Policy	*Your Selection*
Customers may cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty equal to the fee for 1 night of stay plus taxes (i.e., the average nightly rate for the duration of stay). *Example 1:* The **average** nightly rate for the duration of stay is $100 plus taxes and the cancellation policy states that the cancellation fee is $100 plus taxes. *Example 2:* The cancellation policy states that the cancellation fee is equal to 1 night of stay plus taxes.	1 Night Fee Plus Taxes
Customers may cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty equal to the fee for the **first** night of stay plus taxes (i.e., the fee for the first night of the reservation). *Example 1:* The room rate for the **first** night of stay is $95 plus taxes and the cancellation policy states that the cancellation fee is $95 plus taxes. *Example 2:* The cancellation policy states that the cancellation fee is equal to **first** night of stay plus taxes.	First Night Fee Plus Taxes
Customers may cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty equal to the fee for their **entire** length of stay plus taxes (i.e., the fee for the entire reservation). *Example 1:* The reservation fee for the **entire** length of stay is $450 plus taxes and the cancellation policy states that the cancellation fee is $450 plus taxes. *Example 2:* The cancellation policy states that the cancellation fee is equal to **entire** stay plus taxes.	Entire Stay Plus Taxes
Customers may cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty which is less than the rate for 1 night of stay at the hotel. *Example:* The average nightly rate for the duration of stay is $100 plus taxes and the cancellation policy states that the cancellation fee is $55 plus taxes.	Fixed dollar amount - Less than 1 Night Fee Plus Taxes
Customers may cancel free of charge until a specific deadline but for cancellations after the deadline they will be charged a penalty which is more than the rate for 1 night of stay at the hotel. *Example:* The average nightly rate for the duration of stay is $100 plus taxes and the cancellation policy states that the cancellation fee is $135 plus taxes.	Fixed dollar amount - More than 1 Night Fee Plus Taxes
The cancellation policy states that the room is non-refundable and customers can never cancel their reservations for free.	Non-Refundable
The cancellation policy states that the hotel does not charge any cancellation fee and customers can cancel their reservations free of charge whenever they wish.	No Cancellation Fee
The cancellation penalty is different than all of the above options.	Other
The cancellation penalty cannot be found in the hotel's website or in *Hotels.com.*	Not Found

Note: If cancellation penalty is not explicitly stated in the hotel's website, then try to find this info by searching the hotel's name in Hotels.com. Remember to choose *the same check-in and check-out dates and the same room rate category, when using Hotels.com. If still no information is found, then select the "Not Found" option.*

- **Describe if Cancellation Penalty is "Other":** Complete this box only if you selected *"Other"* for the *"Cancellation Penalty"*, otherwise leave it blank.
- **Pay More to Avoid Cancellation Penalty:** Record if an option that would allow paying more money in order to avoid the cancellation penalty is discussed in the cancellation policy. Record *"Yes"* or *"No"*.
- **Prepayment Refund:** Refer to table A.3 to make a selection:

Table A.3: Prepayment refund choices

Hotel's Policy	*Your Selection*
The cancellation policy states that in case of cancellation, full prepayment refund is made to customer's credit card	Yes – Full Refund to Customer's Credit Card
The cancellation policy states that in case of cancellation, prepayment refund is made in the form of credit toward future reservations from the same hotel or hotel chain.	Yes – Credit Toward Future Reservations
The cancellation policy states that in case of cancellation, no prepayment refund is made.	No
The cancellation policy does not discuss the prepayment refund policy.	Not Specified

- **Different Cancellation Policy for Loyalty Club:** Based on the information provided in the cancellation policy, indicate whether a different cancellation policy exists for loyalty club members (e.g., Marriott Rewards, Hilton HHonors Rewards, Wyndham Rewards, etc.). If a different policy exists then record *"Yes"*, otherwise record *"No"*.
- **Data Collector ID:** Enter the data collector ID that is assigned to you.

7. Once you are done with this highest room rate in this room category go to the next row of your spreadsheet, and record the searching date in the spreadsheet.

In the hotel's website select the **lowest** room rate in this category for the same hotel (i.e., the lowest rate within *"Best Available Rate"* category).

Make sure that check-in and check-out dates entered in the hotel's website are exactly the same as those displayed in your spreadsheet.

8. Repeat step 6.

9. Once you are done with the lowest room rate in the general room category, go to the next row of your spreadsheet, and record the searching date in the spreadsheet.

In the hotel's website select *"AAA"* as the special discount and select the **highest** rate within the *"AAA"* category.

Make sure that check-in and check-out dates entered in the hotel's website are exactly the same as those displayed in your spreadsheet.

10. Repeat step 6.

11. With the same hotel select a check-in date a week from your first record (i.e., 7 days from today) and repeat steps 2 to 10. Make sure that check-in and check-out dates are exactly the same as those displayed in your spreadsheet.

12. With the same hotel select a check-in date two weeks from your first record (i.e., 14 days from today). Repeat steps 2 to 10. Make sure that check-in and check-out dates are exactly the same as those displayed in your spreadsheet.

13. With the same hotel select a new check-in date 30 days from your first record (i.e., 30 days from today) and repeat steps 2 to 10. Make sure that check-in and check-out dates are exactly the same as those displayed in your spreadsheet.

14. Go back to step 1 and repeat the same procedure for the next hotel.

Caveat 1: If a hotel does not have room availability for all or some check-in and/or check-out dates, then leave the respective row(s) in the spreadsheet blank and complete the rows for which the information is available.

Caveat 2: If a hotel does not have AAA rates for all or some check-in and/or check-out dates, then leave the respective row(s) in the spreadsheet blank and complete the rows for which the information is available.

Caveat 3: If a hotel only offers one rate type for all or some check-in and/or check-out dates, then leave the respective rows for Best Available (highest), Best Available (lowest), and AAA (highest) blank and record information in the row(s) marked as "Single Rate". In all other cases leave the rows marked as "Single Rate" blank.

Appendix B

IRB REVIEW RESULT

UNIVERSITY OF DELAWARE

RESEARCH OFFICE

210 Hullihen Hall
University of Delaware
Newark, Delaware 19716-1551
Ph: 302/831-2136
Fax: 302/831-2828

DATE:	September 26, 2017
TO:	Arash Riasi, PhD Student
FROM:	University of Delaware IRB
STUDY TITLE:	[1129642-1] Hotel Overbooking Practices Survey
SUBMISSION TYPE:	New Project
ACTION:	DETERMINATION OF EXEMPT STATUS
DECISION DATE:	September 26, 2017
REVIEW CATEGORY:	Exemption category # *(2)*

Thank you for your submission of New Project materials for this research study. The University of Delaware IRB has determined this project is EXEMPT FROM IRB REVIEW according to federal regulations.

We will put a copy of this correspondence on file in our office. Please remember to notify us if you make any substantial changes to the project.

If you have any questions, please contact Nicole Farnese-McFarlane at (302) 831-1119 or nicolefm@udel.edu. Please include your study title and reference number in all correspondence with this office.

Appendix C

SURVEY RECRUITMENT EMAIL

Study on Overbooking in the Hotel Industry - From the University of Delaware

Dear Hotel Manager,

We are researchers at the Alfred Lerner College of Business and Economics at the University of Delaware.

Overbooking is an integral part of any good revenue management system. This study aims to better understand common overbooking practices and evaluate their effectiveness. As an expert in the hotel industry, you are invited to participate in this study about overbooking practices in the US hotel industry. The study's findings will shed light on the topic and will be useful for determining strategies going forward.

We assure you that all information provided by survey respondents will remain completely confidential and will be fully anonymized before performing any kind of data analysis. The survey responses will only be reported in aggregate format and the survey administrators (Dr. Zvi Schwartz and Arash Riasi), will ensure that none of the responses will be linkable to the survey respondents and/or individual hotel properties participating in the survey.

The head of the research team is Dr. Zvi Schwartz, Professor of Hospitality Management at the University of Delaware. If you have any questions or concerns about the survey, please feel free to contact Dr. Zvi Schwartz (302-831-4803; zvi@udel.edu) or Arash Riasi (302-898-6249; riasi@udel.edu).

If you are knowledgeable about the overbooking practices at your hotel, please fill out the survey using the link below, otherwise, we would be grateful if you would mind forwarding this email to the appropriate person at your hotel.

Thanks for your cooperation.

Dr. Zvi Schwartz and Arash Riasi

University of Delaware

Appendix D

OVERBOOKING POLICIES SURVEY

Hotel Overbooking Practices Survey

Overbooking is an integral part of any good revenue management system. This study aims to better understand common overbooking practices and evaluate their effectiveness.

We assure you that all of the information you provide us will remain **completely confidential. All responses will be stripped of any identifiable information, and analysis and reports will be conducted on aggregate data only.**

To start the survey click on the **NEXT** button.

0% 100%

Typically speaking, how many times in a month does your property take more reservations than it can accommodate (overbooking)?

- Our hotel never overbooks
- 1-5 days in a month
- 6-10 days in a month
- 11-20 days in a month
- More than 20 days in a month
- I don't know

0% 100%

On which days of the week does your hotel tend to overbook more?

- Weekdays
- Weekends
- No difference between weekdays and weekends
- I don't know

0% 100%

What would you say is the highest percentage of rooms that your hotel will overbook on any given day?

- Less than 5% of capacity
- 5-10% of capacity
- 11-15% of capacity
- More than 15% of capacity
- I don't know

0% 100%

Which of the following approaches best describes the overbooking policy of your hotel:

- Once an optimal overbooking level is set, that limit will no longer change for the decision period.
- The pattern of customer reservations and cancellations are tracked over time, and the optimal overbooking limit is updated according to the changes in these patterns.
- I don't know

0% 100%

Which of the following overbooking approaches best describes the way in which your hotel determines an overbooking limit?

To determine the overbooking limit for the hotel, the hotel capacity is simply divided by the historical show rate.

Example: If the capacity is 100 rooms and the historical show rate is 97%, the booking limit is 103 rooms (100 ÷ 0.97 = 103).

- Yes
- No
- I don't know

0% 100%

At the hotel, the overbooking limit is calculated by considering demand distributions, expected revenues and expected overbooking expenses (e.g., cost of walking guests, etc.).

Example: The revenue management software considers probabilities and provides a suggested daily overbooking limit.

- Yes
- No
- I don't know

0% 100%

At the hotel, the overbooking limit is determined such that the number of denied-service incidents (total number of walked guests) will not exceed the managerial expectations, thereby reflecting the hotel's commitment to service.

Example: Management decides to set overbooking limit such that on average no more than two guests will be walked every month.

- Yes
- No
- I don't know

0% 100%

At the hotel, both risk-based overbooking limit (that is considering demand distributions, expected revenues and expenses) and service-level overbooking limit (that is number of walked guests not exceeding managerial expectations) are calculated; then the minimum of the two limits is selected.

- Yes
- No
- I don't know

0% 100%

If you have any other approach to determine the overbooking limit, please share it with us.

0% 100%

Overselling strategies: when the number of arriving guests exceeds the number of rooms available

How often does your property have more arrivals than the number of rooms available (overselling)?

- ◯ Never
- ◯ 1-5 days in a year
- ◯ 6-10 days in a year
- ◯ 11-20 days in a year
- ◯ More than 20 days in a year
- ◯ I don't know

0% 100%

In the event of overselling, which of the following customer categories are more likely to be walked?

- ◯ Leisure travelers
- ◯ Business travelers
- ◯ Travel purpose does not affect our walking priority

In the event of overselling, which of the following customer categories are more likely to be walked?

- ◯ Single night guests
- ◯ Multiple nights guests
- ◯ Length of stay does not affect our walking priority

0% 100%

In the event of overselling, which of the following customer categories are more likely to be walked?

- ○ Those who booked through direct channels (i.e., hotel website, voice reservations, walk-ins)
- ○ Those who booked through indirect channels (i.e., traditional OTA, GDS, travel agent, etc.)
- ○ Those who booked through opaque channels (i.e., Priceline.com and Hotwire.com)
- ○ Booking channel does not affect our walking priority

In the event of overselling, which of the following customer categories are more likely to be walked?

- ○ Loyalty/rewards club members
- ○ Non-loyalty club members
- ○ Membership in loyalty/rewards club does not affect our walking priority

In the event of overselling, customers from which of the following room types are more likely to be walked?

- ○ Normal rooms
- ○ Suites
- ○ Room type does not affect our walking priority

0% 100%

For each reservation characteristics (on the left) indicate its level of importance in making walking decisions when your hotel is oversold?

	Not at all important	Slightly important	Moderately important	Very important	Extremely important	I don't know
Trip purpose (leisure, business, etc.)	○	○	○	○	○	○
Length of stay	○	○	○	○	○	○
Booking channel (direct, indirect, etc.)	○	○	○	○	○	○
Loyalty status	○	○	○	○	○	○
Room type (normal room, suite, etc.)	○	○	○	○	○	○

0% 100%

Once a customer is walked due to overselling, how does your hotel usually compensate him/her (choose all that apply):

- ☐ Free stay at a nearby hotel
- ☐ Bonus reward/loyalty program points
- ☐ Voucher toward future stay
- ☐ Restaurant voucher
- ☐ Free transportation to alternative accommodation
- ☐ Cash compensation
- ☐ Free long-distance/international call
- ☐ Other, please specify: ____________

0% 100%

This last set of questions asks you about the type of data used in your hotel's overbooking decision making process:

To what extent does your hotel use "historical data" to make overbooking decisions? ***For example, historical no-shows, cancellation rates, etc.***

Never	Seldom	About half the time	Usually	Always	*I don't know*
○	○	○	○	○	○

0% 100%

To what extent does your hotel use "current market data" to make overbooking decisions? ***For example, market demand, competition, etc.***

Never	Seldom	About half the time	Usually	Always	*I don't know*
○	○	○	○	○	○

To what extent does your hotel use "turn-away/unconstrained demand data" to make overbooking decisions? ***That is, an estimate of the number of rooms that could have been sold if the hotel had unlimited capacity.***

Never	Seldom	About half the time	Usually	Always	*I don't know*
○	○	○	○	○	○

0% 100%

To what extent does your hotel use data provided by "third parties" such as STR and Travel Click to make overbooking decisions?

Never	Seldom	About half the time	Usually	Always	*I don't know*
○	○	○	○	○	○

To what extent does your hotel use data obtained through "sharing agreements with other chains/properties" to make overbooking decisions?

Never	Seldom	About half the time	Usually	Always	*I don't know*
○	○	○	○	○	○

0% 100%

What is you current job title?

- ○ Revenue Manager
- ○ General Manager
- ○ Reservations Manager, Rooms Director, Accommodations Manager, Front Office Manager
- ○ Sales Manager, Group Manager
- ○ Other, please specify:

0% 100%

Is there anything else that you would like to share with us regarding your hotel's overbooking policy?

If somebody else in your hotel is responsible for overbooking policies, please forward the email containing the survey link to him/her. Thank you.

0% 100%

Thank you very much for taking the time to complete our survey. We really appreciate your participation. If you would like to learn about the findings of this study, please feel free to contact us. We will be more than happy to share and discuss our findings with you.

0% 100%