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# Innovative Revenue Management Practices with Probabilistic Elements

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INNOVATIVE REVENUE MANAGEMENT PRACTICES  
WITH PROBABILISTIC ELEMENTS

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## ABSTRACT

Sale of products with a probabilistic nature, where customers do not know which product they will receive at the time of service, has become popular over the recent years. In the revenue management literature, there has been a growing interest in understanding these modern approaches using analytical techniques. On the other hand, customer-centric revenue management has been replacing the long-standing inventory-centric approach because of the availability of rich data sets by focusing on understanding and predicting customer behavior and then optimizing price and/or quantity related decisions. In this dissertation, we take a customer-centric approach and do not only provide analytical results, but also empirically investigate how customers make their decisions, which is crucial in order to implement appropriate strategies.

We first focus on an innovative hotel revenue management practice called standby upgrades, i.e., a practice where the guest is only charged for the discounted upgrade if it is available at the time of arrival. In particular, Chapter 2 discusses how to optimally price standby upgrades and evaluates their benefits through an analytical model. Chapter 3 uses a major hotel chain's booking and standby upgrades data to investigate the extent of strategic guest behavior through empirical analysis. Then, we focus on another innovative revenue management practice, but in the mega event industry, called team-specific ticket options. Chapter 4 studies fans' decision-making process for the 2015 College Football season using a unique data set.

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# CHAPTER 1

## OVERVIEW

### 1.1 WHAT IS REVENUE MANAGEMENT?

Every seller of a product or service faces a number of fundamental decisions such as when to sell and how much to ask. There may be a significant amount of uncertainty in the demand side, therefore the decision-making is not simple, and can become even more complex because of the multi-dimensional nature of the demand. The business must consider the set of products it sells, the types of customers it serves and their purchasing behaviors, the prices and time to sell.

Revenue management is concerned with such demand-management decisions and addresses the structural, price, timing and quantity decisions a firm makes to exploit the potential of this demand landscape (Talluri and Van Ryzin, 2006). Therefore, revenue management can be defined as the wide range of techniques, decisions, methods, processes, and technologies that predict customer behavior, optimize availability and price with an objective of increasing revenues. The most practical definition is quoted by Robert G. Cross, “selling the right product to the right customer at the right time for the right price” (Cross, 1997).

### 1.2 BRIEF HISTORY OF REVENUE MANAGEMENT

In the early 1970s, airlines started to experiment with several discounted fare options to fill the seats that would otherwise fly empty (McGill and Van Ryzin, 1999). Because of the demand-shift threat (i.e., high fare passengers who were going to fly re-

ardless of the price would choose the discounted options), several restrictions for the discounted fares were created, such as advance-purchase requirement and minimum-stay conditions (Cross et al., 2009).

Following this initial effort, American Airlines soon realized that demand patterns were fluctuating by route and time (time-of-day, day-of-week, and season). In 1976, the company started to use large databases and computer systems to better forecast and monitor the demand, and to better allocate discount seats. This practice was called “Yield Management” by Bob Crandall, then Senior Vice President of Marketing for American (Cross et al., 2011).

With the Airline Deregulation Act of 1978, U.S. Civil Aviation Board loosened control of airline prices. This led to a new era with several low-cost low-fare airlines like PeoplExpress which could even charge less than established carriers’ discounted fares. Bob Crandall, then American’s President, accelerated the development of DYNAMO (Dynamic Inventory Optimization and Maintenance Optimization) tool to respond to the threat of low-cost low-fare airlines, and American started a new non-refundable advanced-purchase discounted fare (with multiple restrictions), which was even lower than the fares offered by PeoplExpress. This system increased American’s revenues significantly while PeoplExpress got out of business soon. Following American, airlines like Delta, United and Southwest also started to use Yield Management (Talluri and Van Ryzin, 2006; Cross et al., 2011).

Since hotels had a similar problem to airlines, i.e., managing a fixed capacity generally sold in advance, initial hotel systems were patterned after the airline systems. Marriott International was the first hotel chain to use Yield Management. Since *yield* is an airline term, Marriott called the practice “Revenue Management”. The other hotel chains and casinos followed Marriott (Cross et al., 2009, 2011).

Today, revenue management is used in rental car, cruise ship, passenger rail, event, tourism, shipping, media and broadcasting, retailing, manufacturing, and energy in-

dustries (Talluri and Van Ryzin, 2006)

### 1.3 HOTEL REVENUE MANAGEMENT

The science of airline yield management was based on forecasting demand at the fare class level and then opening and closing the fares to fill the airplane to maximize revenue (Talluri and Van Ryzin, 2004). On the other hand, the hotel industry developed more granular forecasts of demand for individual rate categories and implemented optimization systems to predict the demand and optimize the rate classes offered (Cross et al., 2009). Although airlines mainly use advance-purchase restriction and non-refundable ticket discounts, hotels often use weekend rate for price differentiation (Friday and Saturday night stays).

In addition, some of the factors that hotels face are not an issue for airlines<sup>1</sup>. Guests determine their length of stay, and hotel rooms are often blocked by group commitments. Plus, ancillary revenues from food and beverage are a significant portion of the hotel revenues.

Existence of several room types (e.g., suites, deluxe rooms, standard rooms) and room differentiation within the same room type (e.g., rooms with a view or high-floor rooms) make the capacity-control and pricing problem more complex. In Chapter 2, we focus on how to use premium room capacity in a flexible manner through standby upgrades and how to price premium rooms and these upgrades simultaneously. In Chapter 3, we investigate the different type of customer behaviors facing this program.

### 1.4 EVENT REVENUE MANAGEMENT

By event industry, we refer to stage events (e.g., theaters, orchestras) and sports events. These events have many characteristics that suit well to revenue management

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<sup>1</sup>Note that airlines also focus on complex problems on its network of flights (e.g., connecting flights, round-trips)

methods. Variable pricing where the price for a seat changes based on the expected demand (for different times) has been common in this industry for a long time. Also, the prices for each event depend on factors such as the seat location relative to stage (or field), group affiliation of customers, and advance-purchase restrictions (Talluri and Van Ryzin, 2006). Over the last few years, we also see dynamic pricing practices gaining popularity for sports events with most teams enjoying significant revenue improvements.

One of the interesting issues in this industry different than airline and hotel industries is the existence of “scalpers” who can charge extreme prices for popular events. This creates a big potential in the event industry for the use of revenue management methods. There are several organizers and teams who have created their own marketplace for resale of tickets to deal with this problem. An alternative is to use ticket options, where customers initially buy an option to buy a ticket and then exercise it at a later date. In Chapter 4, we focus on a specific type of ticket options where fans can make a team-specific reservation for the right and obligation to purchase a face value ticket if their team qualifies for the final game.

## 1.5 REVENUE MANAGEMENT WITH PROBABILISTIC ELEMENTS

Some revenue management tools introduce an uncertainty in to the assignment of products to customers by using “probabilistic elements”. At the time of the purchase, customers only know the set of the distinct products they may get, such as a retailer’s red or green probabilistic sweater, where customer does not know which color they will get (Fay and Xie, 2008).

In the hospitality and airline industries, we see probabilistic selling practices such as opaque selling, flexible products, upgradable tickets and standby upgrades. In opaque selling (e.g. Hotwire’s Hot Rate Hotels and Priceline’s Express Deals), the identity of the hotel/airline is hidden until a nonrefundable booking is made. This



provides airlines and hotels with an additional way to price discriminate between guests who are brand loyal and those who are willing to face uncertainty concerning brands for reduced prices (Shapiro and Shi, 2008). In flexible products (e.g., Blind Booking at Germanwings), a hotel/airline sells a menu of two or more alternatives, where customers do not know where they will fly to or stay in exchange for a lower price. This allows for supply side substitution even after sales (Gallego and Phillips, 2004; Post and Spann, 2012). In upgradable tickets (e.g., Alaska's Upgradable fare), airlines sell coach-class fares at a higher price and give customers a chance of enjoying first class only if first-class seats remain unsold (Biyalogorsky et al., 2005). In standby upgrades (e.g., Nor1's e-standby upgrades), hotels offer discounted, availability-based upgrades to guests who book a standard room, however the customer only pays if the upgrade is awarded (Cui, 2015; Yilmaz et al., 2017).

In the events industry domain, we see probabilistic selling practices such as regular options, team-specific tickets, conditional packages, and team-specific ticket options. In regular options (e.g., OptionIt), the customer initially buys an option to reserve a ticket from face value to exercise at a later date. In team-specific tickets (e.g., Optional team-specific tickets of FIFA World Cup), the customer reserves a ticket and has to pay for the ticket only if his/her team advances to the specified game. In conditional packages (e.g., On Location Experiences packages at the NFL Super Bowl), the customer reserves packages (i.e., flight, hotel, and game tickets) for a final game at a neutral site and has to buy the package only if his/her team advances to final. Finally, in team-specific ticket options, fans make a team-specific reservation for the right and obligation to purchase a face value ticket, if their team qualifies for the final game.

## 1.6 POSITIONING OF THIS DISSERTATION

Revenue management addresses three basic categories of demand-management decisions: Structural (e.g., which selling format or differentiation method to choose), price (e.g., how to set posted prices, individual offers, markdowns), and quantity (e.g., how to allocate capacity to different segments, whether to accept or reject an offer). Traditional revenue management uses capacity control as a tactic by selling different “products”, which are all supplied using the same, homogeneous capacity (Talluri and Van Ryzin, 2004).

On the other hand, given that firms now have rich data sets, customer-centric revenue management has been replacing the long-standing inventory-centric approach in modern era by focusing on understanding and predicting customer behavior and then optimizing price and/or quantity related decisions (Cross and Dixit, 2005).

In this dissertation, we focus on two innovative revenue management practices, hotel standby upgrades and team-specific ticket options, which create a flexibility in capacity through probabilistic elements. We provide analytical insights on how to price and how (and when) to use these products. In addition, using unique data sets, we empirically investigate the customer behavior for these practices, which is crucial in order to implement appropriate pricing strategies.

In particular, Chapter 2 discusses how to optimally price hotel standby upgrades and evaluates their benefits through an analytical model. The paper from this chapter has been published in *Manufacturing & Service Operations Management*.<sup>2</sup> Chapter 3 uses a major hotel chain’s booking and standby upgrades data to investigate the extent of strategic guest behavior through empirical analysis. Chapter 4 studies fans’ decision-making process for College Football Playoff team-specific ticket options using a unique data set.

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<sup>2</sup>Throughout this dissertation, we cite this paper as Yilmaz et al. (2017).

## CHAPTER 2

# WOULD YOU LIKE TO UPGRADE TO A PREMIUM ROOM? EVALUATING THE BENEFITS OF OFFERING STANDBY UPGRADES

### 2.1 INTRODUCTION

In the hotel and airline industries, the sale of products with a probabilistic nature has become a popular way to price discriminate between customer segments and deal with the uncertainty in demand. In the revenue management literature, there has been a growing interest in investigating the benefit of these modern approaches compared to more traditional practices such as dynamic pricing and the reserving of capacity for higher value segments. Opaque selling is one example of probabilistic selling, where the identity of the hotel/airline is hidden until a non-refundable booking is made. Opaque selling provides airlines and hotels with an additional way to price discriminate between guests who are brand loyal and those who are willing to face uncertainty concerning brands for reduced prices (Shapiro and Shi, 2008). This selling mechanism has been shown to dominate last-minute discounting, the other common practice to dispose unsold capacity, except in the case where consumer valuations are high and the probability of high demand is low (Jerath et al., 2010). Flexible products, where a hotel/airline sells a menu of two or more alternatives (e.g., *Blind Booking* at Germanwings), is a similar mechanism to opaque selling that allows for supply-side substitution even after sales (Gallego and Phillips, 2004; Post and Spann,

2012). Partially refundable fares is another example, where a fixed portion of the fare is refundable if the traveler decides not to travel for any reason. This mechanism has been shown to bring higher revenues than using non-refundable and fully refundable fares (Gallego and Şahin, 2010).

While opaque selling, flexible products, and partially refundable fares mainly help service providers manage their regular product capacity, such as a standard room at a hotel or a coach seat on a plane, there are other forms of probabilistic selling that are used for the management of premium product capacity. Upgradable airline tickets (i.e., coach-class fares that customers pay extra for and enjoy first class only if first-class seats remain unsold) are used in the airline industry (Biyalogorsky et al., 2005). A similar program, called standby upgrades, has recently been adopted by many hotel chains ([www.nor1.com/solutions/estandby-upgrade/](http://www.nor1.com/solutions/estandby-upgrade/)) and a few airlines ([www.optiontown.com/](http://www.optiontown.com/)). In the hotel industry, standby upgrades are discounted, availability-based upgrades offered to guests who book standard rooms. They serve as an alternative for front-desk upselling, which is argued to provide inconsistent performance and is not widely adopted due to lack of execution by hotel front desk personnel. While both standby upgrades and upgradable tickets are typically offered at the time of initial purchase, they differ in that guests only pay for a standby upgrade if the upgrade is awarded.

For this research, we partnered with a major hotel chain to assess the existing functionality of standby upgrades in the hotel industry and determine what improvements can be made to the current practices. This hotel chain uses industry provider Nor1's standby upgrade solution called *eStandby*<sup>®</sup> upgrades. The system works as follows: After a guest (she) completes a hotel reservation through the hotel chain's website, she sees a link (in the website or via email) indicating that customized upgrade offers are available. If she clicks the link, a list of discounted upgrade offers is displayed (see Figure 2.1). These offers include room upgrades (e.g., standard gue-

stroom to a suite), room features (e.g., city view), amenities (e.g., internet), early check-in/late check-out, parking, spa services, etc. The guest selects the upgrade(s) she is willing to purchase on standby. At the time of check-in, the guest learns whether the upgrade(s) is awarded. If awarded, the guest is automatically charged the agreed upon price for the upgrade; otherwise, she keeps the originally booked room and pays nothing extra. This program is marketed as being beneficial for the hotel by monetizing premium room inventory that may otherwise go unused, creating awareness for add-on services (e.g., internet, spa), advertising room features (e.g., city view) and improving guest satisfaction and loyalty. While our partner hotel chain sees value in the service for selling auxiliary services such as internet and spa, they fear that potential cannibalization of premium room sales may negate any benefit achieved from the selling of standby upgrades for room upgrades. Thus, the primary focus of this research is to investigate this concern and find out how these upgrades can be used as a price discrimination tool for better capacity management.

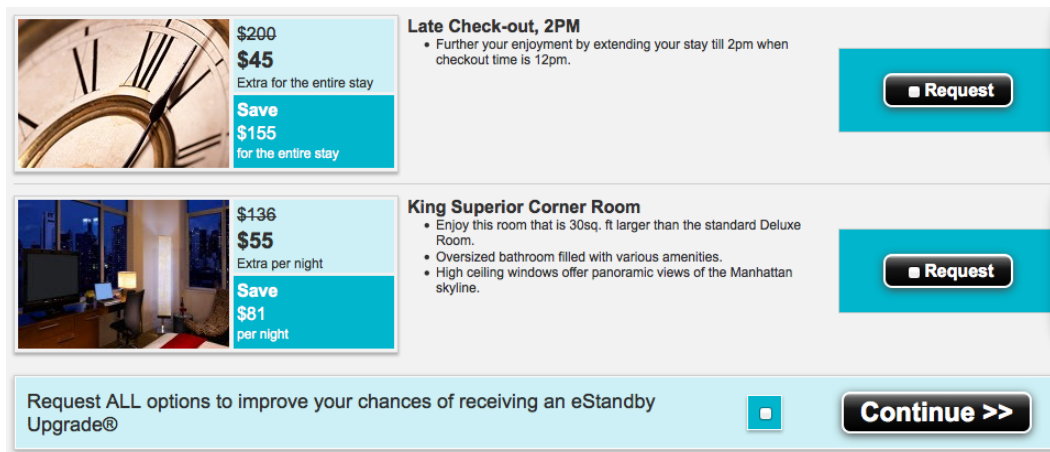


Figure 2.1 Screenshot of e-Standby Upgrade Offers

Our partner’s properties set the price of their standard rooms using state-of-the-art price optimization software. In contrast, these same properties set the premium room price by simply adding a differential to the standard room price: 80 out of 91 hotel properties in our partner’s pricing data use the same differential every day and

the remaining 11 change the differential only for certain days of stay. Moreover, since the hotel properties are not directly owned by the hotel chain (they are franchised), each individual property is responsible for making a decision on whether to implement a standby upgrade program.

In this paper, we investigate the dynamics of standby upgrade programs and answer the following research questions: When can standby upgrade programs provide additional value over traditional revenue management practices? Which hotel environments and market characteristics reap the most benefit from standby upgrade programs? What are the possible issues that hotels should be aware of while using the standby upgrade programs?

To the best of our knowledge, Cui (2015) is the only other academic paper investigating hotel standby upgrades. In their analytical framework, strategic guests arrive stochastically and have heterogeneous valuations for standard and premium rooms, which are both assumed to have exogenous static prices. They focus on optimizing the standby upgrade price, and use a fluid model approximation due to the complexity of the stochastic model. In our paper, we also ignore the problem of standard room pricing because of the existence of sophisticated price optimization software for this. However, we focus on the problem of simultaneously optimizing the prices of the premium rooms and the standby upgrades based on the hotel's premium room capacity and market characteristics for a specific day of stay, considering both myopic and strategic customer scenarios. Accordingly, our problem is similar to the pre-announced single-discount problem in the markdown pricing literature (see Shen and Su, 2007; Netessine and Tang, 2009, for a review). In the pre-announced pricing problem, the seller uses a higher price during the initial stage of the selling horizon and a pre-announced discounted price at the end. Customers decide between buying the item at the time of their arrival or waiting until the end of the horizon in the hope of achieving a lower price. If the customers wait to purchase, however, the item may

become unavailable. Similarly, in the case of standby upgrades, the hotel sells premium rooms at a higher price and offers the standby upgrade at a discounted price. Here, guests make a decision between a premium room (i.e., booking a premium room initially or requesting a guaranteed upgrade after reserving a standard room) and the standby upgrade, but they receive the premium room through the standby upgrade only if there is remaining premium room capacity at the time of check-in.

Despite these similarities, there are also differences between our hotel environment and retail environments where pre-announced price discounts are typically practiced. First, in the standby upgrade problem, guests consider whether to buy or standby for an upgrade from a standard room to a premium room (rather than a physical product). Therefore, the standard room capacity of the hotel property has an effect on the market size for this product. Our analysis shows that this market size also presents a higher level of uncertainty (compared to the retail industry) because of the market dynamics. These key differences require us to solve an optimization problem where extreme scenarios (e.g., very low premium room demand) are possible and the market size changes based on the hotel's relative room capacities. In addition, hotels may utilize standby upgrades to accommodate overbooked standard room demand, which does not apply for the retail industry. Accordingly, we make the necessary adjustments to the pre-announced discount models and develop a model where a hotel simultaneously sets the prices for the premium room differential and the standby upgrade.

#### *Contributions and Key Insights*

Several tactics for price differentiation are discussed in the literature, including group pricing, channel pricing, and product versioning (see Phillips, 2005, for a review). In this paper, we present an alternative for premium room pricing using standby upgrades that is also flexible in accommodating different standard room pricing tech-

niques.

We first discuss our modeling contributions. We provide a practical framework with simultaneous arrivals and an uncertain market size, which is a better fit for our hotel setting compared with the modeling frameworks previously used in the pre-announced pricing literature: those that assume simultaneous arrivals assume a fixed market size, and those that assume stochastic arrivals lead to complicated models that do not allow for closed-form solutions. When guests are strategic, this framework allows us to demonstrate the existence of a rational expectations equilibrium, i.e., an equilibrium between the guests' belief about the fill rate (the probability of getting a premium room through standby upgrades) and the expected realization of the outcome. We show that the equilibrium fill rate can be less than 1 for days/hotels where the market size for premium rooms is large, and thus standby upgrades can act as a price discrimination tool. We also investigate how standby upgrades can be used to facilitate the overbooking of standard rooms, where the hotel has to use some of the premium room capacity to satisfy excess standard room demand.

Our paper provides several key insights for hoteliers. First, we show that the benefit of offering standby upgrades is highest when the market size for premium rooms is small and guests are myopic. If guests are strategic, however, we find that standby upgrades can be beneficial only when the market size for premium rooms is large. We also analyze the consequences of making incorrect assumptions on the type of guest behavior and show that misidentifying strategic guests as myopic, or myopic guests as strategic can result in a significant revenue loss. Additionally, we show conditions where standby upgrades can provide revenue improvement over front-desk upsells and that standby upgrades may offer additional benefits when the hotel satisfies overbooked standard room demand using premium room capacity. Finally, using our partner's data, we identify the hotel types and environments that are most suitable for standby upgrades.



## 2.2 MODEL OVERVIEW

In this section, we go through our model assumptions. Since we investigate how standby upgrades can be used for price discrimination, we omit the type of standby upgrades whose main benefit is to create awareness for ancillary products with nearly unlimited capacity (e.g., spa, internet) and luxury upgrades (e.g., executive suites) with extremely low likelihood of an upgrade. We instead focus on incremental room upgrades (e.g., higher floor, ocean view, a standard suite) where we believe that the market for the premium rooms is closely connected to the standard room demand, which will be explained further.

**Assumption 2.1.** *Premium Room Capacity: The hotel has two types of rooms: standard and premium. Without loss of generality, the premium room capacity,  $C$ , is normalized to one.*

In our partner's data set, each hotel has one standard room type and one or more premium room types. For simplicity, we model a hotel with only one type of premium room (with capacity  $C = 1$ ) and one type of standby upgrade offer, i.e., an upgrade from a standard room to a premium room. Most hotels at our partner's properties employ pricing techniques for their standard rooms that adjust prices dynamically to achieve a target occupancy rate, e.g., increasing the price when the expected demand rate is higher than the target rate. While standby upgrades can also be used to relieve oversold situations for hoteliers, our base model assumes that standard room demand is never constrained and the benefit of standby upgrades is expected to come from monetizing premium room inventory that may otherwise go undervalued or unsold. Therefore, the results of our base model only apply to the cases where standard rooms do not sell out. We later relax the unconstrained standard room demand assumption in §2.3.4, and consider a setting where the standard rooms are overbooked, i.e., standard room demand exceeds standard room capacity. In this

setting, we demonstrate how standby upgrade programs can be used to relieve the pressure on standard room capacity.

**Assumption 2.2.** *Pricing Decisions: At the beginning of the selling horizon for a specific day-of-stay, based on the market size expectation, the hotel determines a fixed premium room differential,  $p$ , and standby upgrade price,  $p_S$ , that is pegged to the standard room price ( $s$ ) throughout the selling horizon.*

We only focus on the pricing of the premium rooms because hotels generally use sophisticated techniques for setting the standard room prices based on different demand patterns (Koushik et al., 2012; Pekgün et al., 2013), and our hotel partner was not interested in changing the way they set their standard room prices. The data set from our partner and other examples from the industry show that it is common practice to set the premium room price as a function of the standard room price through fixed differentials. Accordingly, we set the premium room price as a function of the standard room price in our model. We include two decision variables: the premium room differential and the standby upgrade price. Note that we also allow the hotel to make changes to the differentials based on the market size expectation for a specific day. By focusing on the differential between standard and premium room prices, our approach can be used in conjunction with any standard room pricing approach, static or dynamic.

**Assumption 2.3.** *Allocation of Premium Rooms: After observing the demand for premium rooms,  $D_P$ , and the demand for standby upgrades,  $D_S$ , the hotel uses a random allocation policy for the premium room capacity if the number of remaining premium rooms is less than the number of the standby upgrades requested.*

For a given day of stay, the hotel first determines  $p$  and  $p_S$ . Nature then draws a market size for premium rooms,  $x$  (see Assumption 5 for details about the market size). Guests arrive and each guest makes a booking decision—and a standby upgrade decision if a standard room is booked. If the premium room demand,  $D_P$ , turns out

to be greater than the premium room capacity, this would be equivalent to a real-life scenario of a premium room sell-out before the end of the selling horizon. On the other hand, if the premium room demand,  $D_P$ , turns out to be less than the premium room capacity, the leftover premium capacity can be used to satisfy the standby upgrade demand using an allocation mechanism. In our partner’s data set, we were not able to identify any particular allocation patterns, therefore we assume a random allocation policy if the number of remaining premium rooms is less than the number of the standby upgrades requested,  $D_S$ . Note that  $p_S$  will be charged only when the standby upgrade request is granted (see Figure 2.2 for the order of the events).

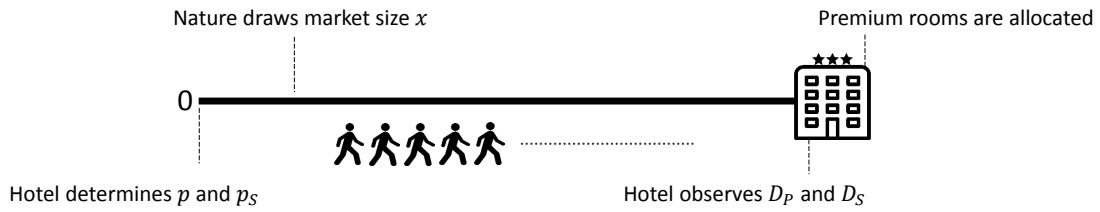


Figure 2.2 The Order of the Events

**Assumption 2.4.** *Valuation Distribution for the Premium Room Differential:* A guest’s valuation for the premium room differential,  $v$ , is uniformly distributed in the interval  $[0, 1]$  and is constant over time.

Without loss of generality, we focus on the valuation for the premium room differential and assume a uniform distribution, which is commonly used for guest valuations (aka a linear price-demand model) in the markdown literature (Zhang and Cooper, 2008; Liu and van Ryzin, 2011). Moreover, Cohen et al. (2016) study the price-demand curve estimation problem for new products and show that the assumption of a linear demand results in very minor profit penalties even if the true demand curve is far from linear.<sup>1</sup>

<sup>1</sup>To help validate our linear price-demand model assumption, we utilize our partner’s data on the booking and standby upgrade decisions. The details of this study and further discussion on our approach can be found in the Appendix A.

**Assumption 2.5.** *Market Size for Premium Rooms:* The size of the market for premium rooms observed for a specific day,  $x$ , is uniformly distributed in the interval  $[0, X_U]$ .

A major difference in our model compared to the studies in the markdown pricing literature (Gallego et al., 2008; Liu and van Ryzin, 2008) is that the demand for premium rooms is not based on a fixed market size. Our partner's booking data shows that premium room demand is positively correlated with standard room demand, however there are many days where the standard room demand is high while the premium room demand is relatively low.<sup>2</sup> Therefore, it is important to factor in uncertainty for the estimation of premium room demand.

We assume a stochastic market size that lies between a lower bound of 0 and an upper bound of  $X_U$ . With a heterogeneous market captured through a uniform willingness-to-pay distribution and a stochastic market size, the premium room demand and standby upgrade demand are  $(D_P, D_S) = [x(1 - p), x(p - p_S)]$  where  $x \sim U(0, X_U)$ . Given the characteristics of the hotel industry, we list two main factors that affect the upper bound of the market size,  $X_U$ : (i) The demand for standby upgrades (and premium room bookings) mainly comes from customers who have a positive utility for the standard rooms and thus consider booking a standard room. For a typical day, the potential demand for premium rooms is inversely proportional to the premium-to-standard room capacity ratio, i.e., the relative premium room capacity. Therefore, the upper bound  $X_U$  is a decreasing function of the relative premium room capacity. (ii) A hotel may have different target occupancy rates based on the characteristics of the day of stay (e.g., weekend vs. weekday, special event in town). Our analysis shows that  $X_U$  increases with the target occupancy rate (or expected occupancy). This is an indirect effect of the target occupancy rate - due to

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<sup>2</sup>A detailed discussion on the market size and an empirical study supporting this assumption can be found in the Appendix A.

the positive correlation between standard and premium bookings mentioned above.

**Assumption 2.6.** *Visibility of the Standby Upgrade Offer: A guest can see a standby upgrade offer only after completing a standard room booking.*

This assumption comes directly from the industry provider Nor1's website, which states that guests can see a standby upgrade offer only after booking a standard room.

**Assumption 2.7.** *Myopic Guest Behavior: A guest makes a choice between booking a standard room and a premium room at the time of booking. If she books a standard room, she receives the standby upgrade offer and makes a decision on the offer based on her valuation.*

In the standby upgrades problem, there are several reasons to expect that most hotel guests are myopic with respect to standby upgrades. First, many guests are not aware of the existence of standby upgrade offers prior to booking a room. These guests see and make a decision on the standby upgrade offer after making a decision between a standard room and a premium room. Second, even guests who are aware of standby upgrade offers will have difficulty estimating the chance of getting a premium room through standby upgrades because they have limited information about the past award rates of upgrade requests. Third, our hotel partner believes that the vast majority of their guests would act myopically when making the standby upgrade decision.

In contrast to a myopic guest, a strategic guest always books a standard room first to see the standby upgrade price and then makes a decision between the standard room, premium room or standby upgrade based on her valuation and the perceived chance of obtaining a premium room through standby upgrades. After discussing our base model, we analyze the scenario with strategic guests, who take rational actions based on expected award rates, in §2.4.

## 2.3 BASE MODEL WITH MYOPIC GUESTS

In this section, we develop a base model with myopic guests and investigate the benefits of standby upgrades compared to the three common practices in the industry through analytical and numerical analysis. We also present a model extension where the hotel utilizes premium room capacity to accommodate overbooked standard room demand through standby upgrades.

### 2.3.1 MYOPIC GUEST BEHAVIOR

Figure 2.3 presents the decision making process of a myopic guest in our model (dashed arrows represent uncertainty in the outcome): For a price set  $(p_S, p)$ , a myopic guest books the premium room initially if her valuation is  $v \in [p, 1]$ . If  $v < p$ , she books a standard room and sees the standby upgrade offer. If  $v \in [p_S, p)$ , she accepts the offer, otherwise she rejects.

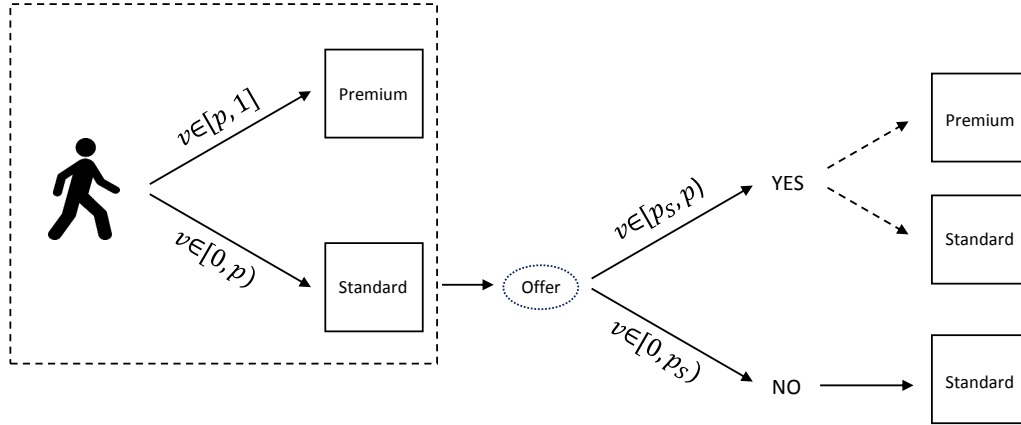


Figure 2.3 Myopic Guest's Decision Making Process

For a specific day with a realized market size  $x$ , premium room demand ( $D_P$ ) is equal to  $x(1 - p)$  and standby upgrade demand ( $D_S$ ) is equal to  $x(p - p_S)$ . However, these demands may not be fully satisfied because of the capacity constraint. Given a price set  $(p_S, p)$  and a realized market size  $x$ , we use the notation  $(C_P, C_S)$  for the premium room capacity allocated to premium room bookings and standby upgrades,

respectively, for a specific day. Since regular bookings of premium rooms occur immediately, the allocation of remaining premium rooms to the standby upgrade request may result in three different cases of  $(C_P, C_S)$ , each of which is referred to as an *outcome* ( $O_i$ ):

In  $O_1$ , the hotel can fully satisfy premium room and standby upgrade demand ( $D_S + D_P \leq 1$ ). In  $O_2$ , the hotel can fully satisfy the premium room demand ( $D_P < 1$ ) but can only partially satisfy the standby upgrade demand ( $D_S + D_P > 1$ ). In  $O_3$ , the premium room demand exceeds the capacity ( $D_P \geq 1$ ), i.e., premium rooms are sold out during the sale horizon and none of the standby upgrades can be awarded. We can write  $(C_P, C_S)$  as follows:

$$(C_P, C_S) = \begin{cases} (D_P, D_S) & \text{if } D_S + D_P \leq 1 \\ (D_P, 1 - D_P) & \text{if } D_P < 1 \text{ and } D_S + D_P > 1 \\ (1, 0) & \text{if } D_P \geq 1 \end{cases}$$

Since the capacities allocated to premium room bookings and standby upgrades change in each case, the revenue functions are also different. For a given  $(p_S, p)$ , the realized market size  $x$  is the only factor that affects  $(C_P, C_S)$ , and we can write the conditions for each outcome and resulting revenues as follows:

$x$	Outcome	Revenue
$0 \leq x \leq \frac{1}{1-p_S}$	$O_1$	$R_1 = (x(1-p))p + (x(p-p_S))p_S$
$\frac{1}{1-p_S} < x < \frac{1}{1-p}$	$O_2$	$R_2 = (x(1-p))p + (1-x(1-p))p_S$
$\frac{1}{1-p} \leq x$	$O_3$	$R_3 = p$

Note that for a specific day with a given  $(p_S, p)$  and  $X_U$ ,  $O_1$  is always a possible outcome because  $x$  can take a value of 0 ( $x \sim U(0, X_U)$ ). However,  $O_2$  and  $O_3$  may not be observed in all cases. For example, consider a day when  $X_U = 3$ . For price set  $(0.4, 0.6)$ , the hotel observes  $O_1$  for  $0 \leq x \leq \frac{5}{3}$ ,  $O_2$  for  $\frac{5}{3} < x < \frac{5}{2}$  and  $O_3$  for  $\frac{5}{2} \leq x \leq 3$ , i.e., the prices are too low and a sell-out is possible (see Figure 2.4). If the hotel uses

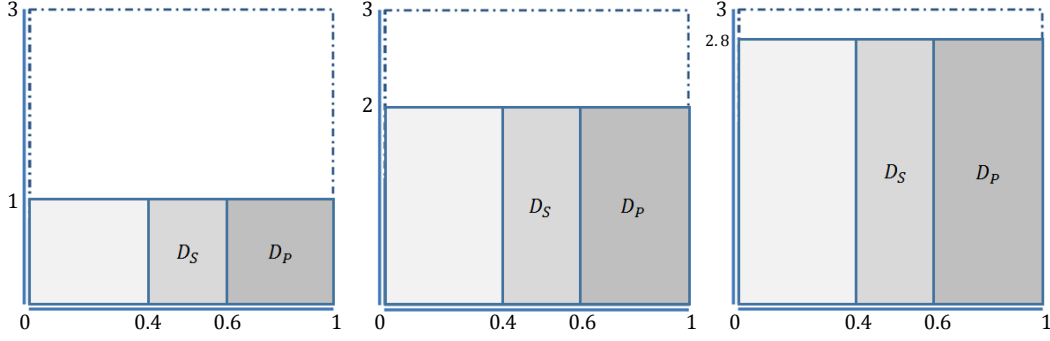


Figure 2.4 Possible Outcomes for Price Set  $(0.4, 0.6)$  when  $X_U = 3$

*Left ( $O_1$ ):* For  $x = 1$ ,  $D_S + D_P = 0.6 \leq 1$ . *Center ( $O_2$ ):* For  $x = 2$ ,  $D_P = 0.8 < 1$  but  $D_S + D_P = 1.2 > 1$ . *Right ( $O_3$ ):* For  $x = 2.8$ ,  $D_P = 1.12 \geq 1$ .

price set  $(0.5, 0.75)$ , it observes  $O_1$  for  $0 \leq x \leq 2$  and  $O_2$  for  $2 < x \leq 3$ , but not  $O_3$ . For price set  $(0.7, 0.8)$ , the hotel can only observe  $O_1$  ( $D_P + D_S = 0.6 + 0.3 < 1$  even for the extreme case  $x = 3$ ), i.e., the prices are too high and the hotel cannot fill its capacity.

### 2.3.2 OPTIMAL PRICING PROBLEM WITH MYOPIC GUESTS (MY)

The hotel's expected revenue for premium rooms can be written as:

$$\Pi(p, p_S, X_U) = \int_0^{X_U} [pC_P(p_S, p, x) + p_S C_S(p_S, p, x)] dx \quad (2.1)$$

Since our realized market size for premium rooms is stochastic, different price sets may lead to different sets of outcomes based on  $x$  for a given  $X_U$ . We use the term *strategy* to group different price sets leading to the same set of outcomes. As we discussed above,  $\{O_1\}$ ,  $\{O_1, O_2\}$ , and  $\{O_1, O_2, O_3\}$  are the feasible outcome sets that we can observe. Therefore, a hotel can use one of three possible strategies for a given day of stay. We use binary variables  $I_1$ ,  $I_2$ , and  $I_3$  to represent each strategy:

**Strategy 1** ( $I_1 = 1$ ): Choosing a price set  $(p_S, p)$  that satisfies  $X_U(1 - p_S) \leq 1$  leads to an outcome set  $\{O_1\}$  since  $x(1 - p_S) \leq 1$  for all  $x$ . The hotel's expected revenue is:



$$\Pi_{MY1} = \int_0^{X_U} \frac{R_1}{X_U} dx. \quad (2.2)$$

**Strategy 2** ( $I_2 = 1$ ): Choosing a price set  $(p_S, p)$  that satisfies  $X_U(1 - p_S) > 1$  and  $X_U(1 - p) < 1$  leads to an outcome set  $\{O_1, O_2\}$ . The hotel's expected revenue is:

$$\Pi_{MY2} = \int_0^{1/(1-p_S)} \frac{R_1}{X_U} dx + \int_{1/(1-p_S)}^{X_U} \frac{R_2}{X_U} dx. \quad (2.3)$$

**Strategy 3** ( $I_3 = 1$ ): Choosing a price set  $(p_S, p)$  that satisfies  $X_U(1 - p) \geq 1$  leads to an outcome set  $\{O_1, O_2, O_3\}$ . The hotel's expected revenue is:

$$\Pi_{MY3} = \int_0^{1/(1-p_S)} \frac{R_1}{X_U} dx + \int_{1/(1-p_S)}^{1/(1-p)} \frac{R_2}{X_U} dx + \int_{1/(1-p)}^{X_U} \frac{R_3}{X_U} dx. \quad (2.4)$$

We solve the following revenue maximization problem to find the optimal price set  $(p_S^{MY}, p^{MY})$  for a given  $X_U$ :

$$\begin{aligned} & \max_{0 \leq p_S \leq p \leq 1} I_1 \Pi_{MY1} + I_2 \Pi_{MY2} + I_3 \Pi_{MY3} \\ \text{s.t. } & I_1[X_U(1 - p_S) - 1] \geq 0; \quad I_2[X_U(1 - p_S) - 1] \leq 0; \quad I_2[X_U(1 - p) - 1] \geq 0; \\ & I_3[X_U(1 - p) - 1] \leq 0; \quad I_1 + I_2 + I_3 = 1; \quad I_1, I_2, I_3 \in \{0, 1\} \end{aligned} \quad (2.5)$$

Lemma 2.1 presents the hotel's optimal pricing policy:<sup>3</sup>

**Lemma 2.1.** *When the hotel uses a standby upgrade program, the optimal price set  $(p_S^{MY}, p^{MY})$  for a given  $X_U$  under myopic guest behavior is as follows:*

$$(p_S^{MY}, p^{MY}) = \begin{cases} (\frac{1}{3}, \frac{2}{3}) & \text{if } X_U \leq \frac{3}{2} \\ (\frac{3X_U-4}{3X_U} - 2\Upsilon, \frac{3X_U-2}{3X_U} - \Upsilon) & \text{if } \frac{3}{2} < X_U < 4 \\ (1 - \frac{1}{\sqrt[3]{2X_U}}, 1 - \frac{1}{\sqrt[3]{(2X_U)^2}}) & \text{if } X_U \geq 4 \end{cases} \quad (2.6)$$

The resulting expected revenue  $\Pi_{MY}$  is:

$$\Pi_{MY} = \begin{cases} \frac{X_U}{6} & \text{if } X_U \leq \frac{3}{2} \\ \frac{9X_U(6\Upsilon(X_U(\Upsilon(X_U\Upsilon-2)+2)-3)+5)-44}{36X_U(3X_U\Upsilon+2)} & \text{if } \frac{3}{2} < X_U < 4 \\ 1 - \frac{3}{\sqrt[3]{(2X_U)^2}} + \frac{1}{X_U} & \text{if } X_U \geq 4 \end{cases} \quad (2.7)$$

<sup>3</sup>The details on the term  $\Upsilon$  and the proof of this lemma can be found in the Appendix B.

We can interpret the hotel's optimal policy as follows: When the upper bound of market size,  $X_U$ , for a specific day is low ( $X_U \leq \frac{3}{2}$ ), the hotel should choose Strategy 1 in which the premium room and standby upgrade demand are fully satisfied ( $D_S + D_P \leq 1$  for all  $x$ ). In this strategy, the hotel can only use the price discrimination power of standby upgrades because of the relatively low expected market size. On the other hand, when  $X_U$  for a specific day is high ( $X_U \geq 4$ ), the hotel should choose Strategy 3, where it charges relatively lower prices to generate more demand (with a risk of sell-out since  $D_P > 1$  for some  $x$ ) and benefit from higher occupancy rates. In this case, the hotel uses both the price discrimination and capacity management power of the standby upgrades. When  $X_U$  for a specific day is medium ( $\frac{3}{2} < X_U < 4$ ), the hotel should choose Strategy 2. In this strategy, the hotel does not reward all of the standby upgrades when the total premium room and standby upgrade demand is higher than the premium room capacity ( $D_S + D_P > 1$  for some  $x$ ); however, there is no risk of sell-out ( $D_P < 1$  for all  $x$ ).

### 2.3.3 COMPARISON WITH COMMON PRACTICES IN THE HOTEL INDUSTRY

To evaluate the benefits of standby upgrades, we make comparisons with the three common practices in the industry for premium room pricing as identified by our partner hotel chain. The common practices include no standby upgrade program, deploying a standby upgrade program without changing the premium room differential, and offering a discounted upgrade at the front-desk during the check-in process. We first introduce each practice, and then provide a numerical analysis on the comparison of benefits.

#### NO STANDBY UPGRADE PROGRAM (NS)

The common practice for setting the premium room prices for hotel properties is to add a fixed markup to the standard room prices, where the markup is typically not

optimized. In our first benchmark, we develop a model in which the hotel does not use a standby upgrade program, but does optimize the premium room differential,  $p$ , based on the market size distribution. The guest behavior is straightforward; guests with a valuation  $v \in [p, 1]$  book premium rooms and those with  $[0, p)$  book standard rooms (see the dashed box in Figure 2.3). In this setting, the optimal premium room differential,  $p^{NS}$ , and the resulting expected revenue,  $\Pi_{NS}$ , for a given  $X_U$  are as follows:

$$p^{NS} = \begin{cases} \frac{1}{2} & \text{if } X_U \leq 2 \\ 1 - \frac{1}{\sqrt{2X_U}} & \text{if } X_U > 2 \end{cases} \quad \Pi_{NS} = \begin{cases} \frac{X_U}{8} & \text{if } X_U \leq 2 \\ 1 - \frac{2}{\sqrt{2X_U}} + \frac{1}{2X_U} & \text{if } X_U > 2 \end{cases} \quad (2.8)$$

By comparing the optimal prices and expected revenues of our standby upgrade model against this benchmark, we reach the following proposition:

**Proposition 2.1.** (i) Using standby upgrades is always beneficial as compared to the no-standby-upgrade benchmark ( $\Pi_{MY} > \Pi_{NS}$ ) for all  $X_U$ . (ii) The following order of prices always holds:  $p_S^{MY} < p^{NS} < p^{MY}$ .

Proposition 2.1 states that the hotel should increase its premium room price with the introduction of the standby upgrade program, and offer a relatively deep discount (30% to 50% for reasonable  $X_U$  values) from this new price for the standby upgrades. These changes result in additional revenue for the hotel through price discrimination and improved capacity management.

#### INDEPENDENT PRICING OF THE DIFFERENTIAL AND STANDBY UPGRADES (2S)

Our results show that the premium room differential should increase ( $p^{MY} > p^{NS}$ ) with the introduction of a standby upgrade program. However, our partner's data shows that most hotels did not change their premium room differentials when they started using standby upgrades. Convincing them to change this practice requires quantifying the additional benefit of adjusting the premium room differential when introducing a standby upgrade program.

To do so, consider a hotel which optimizes its premium room differential pricing before the introduction of standby upgrades and continues to use the same differential (i.e.,  $p^{NS}$ ) with the standby upgrade program. The optimal standby upgrade price for this hotel, denoted by  $p_S^{2S}$ , is:

$$p_S^{2S} = \begin{cases} \frac{1}{4} & \text{if } X_U \leq \frac{4}{3} \\ 1 - \frac{1}{\sqrt{4X_U - X_U^2}} & \text{if } \frac{4}{3} < X_U \leq 2 \\ 1 - \frac{1}{\sqrt[3]{2X_U}} & \text{if } X_U > 2 \end{cases} \quad (2.9)$$

While the hotel can still price discriminate using this sequential optimization, we find that the optimal prices for the premium room differential and standby upgrades are lower than those under simultaneous optimization (i.e.,  $p_S^{2S} < p_S^{MY}$  and  $p^{NS} < p^{MY}$ ).

#### FRONT-DESK UPSELLS (FDU)

Front-desk upselling is a well-known traditional technique to improve hotel revenue, where arriving guests are offered an opportunity to upgrade their room at the time of check-in. The main advantage of this technique is that the upsell is made at the end of the selling horizon, after the market size is revealed. Today, most hotels do not use formalized programs for front-desk upselling due to the lack of a centralized tool and difficulty of implementation at the front-desk. On the other hand, some hotels use decision support tools (e.g., TSA Solutions' platform and Nor1's eFDU platform) which help them decide on the front-desk upsell price for a given premium room differential. Even for these hotels, the actual application of front-desk upselling is inconsistent, as it depends on the front-desk agent to make the guest aware of the offer.<sup>4</sup>

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<sup>4</sup>Except for hotels that primarily offer an electronic check-in kiosk, the front-desk staff often finds it difficult to consistently offer upsells during busy check-in periods due to the pressure to check-in guests as quickly as possible.

Consider a hotel which offers front-desk upsells and let  $f \in [0, 1]$  be the percentage of the arriving guests who receive an upsell offer. After the market size is revealed, the hotel will have  $[1 - x(1 - p)]^+$  premium rooms available. If this number is positive, the hotel front-desk staff will make upsell offers to  $f$  of arriving guests who have booked standard rooms.

The intuition behind the pricing of upsells is straightforward; the number of upgrades available is bounded by the number of leftover premium rooms. In order to use all remaining capacity, the hotel must set the upsell price at  $\frac{fpx - px + x - 1}{fx}$ . However, selling all the remaining room capacity is only optimal when  $\frac{fpx - px + x - 1}{fx} \geq \frac{p}{2}$ ; therefore, the optimal upsell price, denoted by  $p^{FDU}$ , is:

$$p^{FDU} = \max\left[\frac{fpx - px + x - 1}{fx}, \frac{p}{2}\right] \quad (2.10)$$

We analyze two front-desk upsell policies as benchmarks. In the first benchmark (FDU1), we assume that the hotel does not factor in the possibility of front-desk upselling when setting the premium room differential (therefore using the no standby upgrade optimal differential  $p^{NS}$ ) based on our partner's implementation of front-desk upsells. We only provide results for the scenario where  $f = 1$  for FDU1 since it provides an upper bound for expected revenues. In the second benchmark (FDU2), we assume that the hotel optimizes the premium room differential  $p$  by factoring in the front-desk upselling. Note that FDU2 is beyond the common practice in the hotel industry.<sup>5</sup> We next present the benefits of standby upgrades in comparison to each of these practices.

#### MEASURING THE BENEFITS OF STANDBY UPGRADES

To demonstrate the effectiveness of standby upgrades, we conduct a numerical analysis for different  $X_U$  values. Our analysis in over 20 properties shows that  $X_U$  is

<sup>5</sup>The detailed analyses on FDU1 and FDU2 are available from the authors upon request.

unlikely to be greater than 6. Therefore, we perform our numerical analysis for  $1 \leq X_U \leq 6$ . We use the percentage improvement in revenue  $\frac{\Pi_{MY} - \Pi_C}{\Pi_C}$  as a performance metric (where  $\Pi_C$  is the expected revenue of the policy compared). Table 2.1 provides a summary of our numerical analysis.

Table 2.1 Additional % Benefit of Standby Upgrades Compared to Common Practices in Hotel Industry

	vs. NS	vs. 2S	vs. FDU1	vs. FDU2	
				$f = 0.6$	$f = 1$
$X_U = 1$	33.33	6.66	6.66	13.33	0
$X_U = 2$	29.33	10.39	8.77	10.36	-1.69
$X_U = 3$	22.10	5.99	4.26	5.30	-4.30
$X_U = 4$	19.64	5.04	3.28	3.56	-4.97
$X_U = 5$	18.42	4.83	3.06	2.82	-5.05
$X_U = 6$	17.45	4.67	2.90	2.26	-5.10

In comparison with no standby upgrades (**NS**), our results show that the revenue improvement from using standby upgrades is  $\sim 33\%$  for lower values of  $X_U$  (i.e.,  $X_U \leq \frac{3}{2}$ ) and decreases as  $X_U$  increases ( $\sim 17.5\%$  when  $X_U = 6$  in Table 2.1). Two main drivers of this benefit are as follows: First, standby upgrades increase the overall demand for the premium rooms, with an 8% to 10% increase in the expected occupancy rates (i.e.,  $\mathbb{E}[C_P + C_S]$ ). Second, standby upgrades offer better capacity utilization for premium rooms, up to a 20% increase in the full occupancy rates (i.e.,  $\mathbb{P}\{C_P + C_S = 1\}$ ) and down to a 30% decrease in the sell-out probability (i.e.,  $\mathbb{P}\{D_P > 1\}$ ) for premium rooms. These benefits decrease with higher values of  $X_U$ , as the probability of a standby upgrade not being awarded or premium room demand not being satisfied is non-decreasing in  $X_U$ .

In comparison with independent pricing (**2S**), we find that the revenue improvement ranges between 4.5% to 10.5%. Thus, the hotels which have not updated their premium room differential with the introduction of a standby upgrade program may

benefit from increasing both the premium room differential and the standby upgrade price.

In comparison with front-desk upselling (**FDU**), our results show that the revenue improvement ranges between 3% to 9% against the common front-desk upselling practice (FDU1) for  $f = 1$ , which indicates that the benefit of simultaneously optimizing the premium room price differential and standby upgrade price at the start of the selling horizon dominates the benefit of postponing the setting of the upsell price until full information on the market size is revealed. On the other hand, standby upgrades are dominated by the practice of setting the premium room differential in anticipation of front-desk upselling (FDU2) when the percentage of upsell offers made to arriving guests is high (e.g.,  $f = 1$ ). However, for hotels which cannot achieve consistent offering of upsells (e.g.,  $f = 0.6$ ), our results show that standby upgrades will often provide revenue improvements.

#### 2.3.4 EXTENSION: WHAT IF THE STANDARD ROOMS ARE OVERBOOKED?

In our base model, we assume that the standard room demand is never constrained by the standard room capacity because of the dynamic pricing techniques employed by the hotel chain for setting the standard room prices. However occasionally, there may be days where there is excess demand for standard rooms (e.g., when there is a special event such as a convention or a football game in town), and the hotel may utilize its premium rooms to accommodate oversold standard room capacity through free upgrades.

In this subsection, we consider a scenario where the hotel utilizes standby upgrades to help generate additional revenue from the premium room capacity set aside to satisfy overbooked standard room demand. Let  $w$  denote the number of premium rooms to be used to satisfy excess standard room demand. We assume that the hotel will keep the premium room bookings less than or equal to  $1 - w$  since “walking

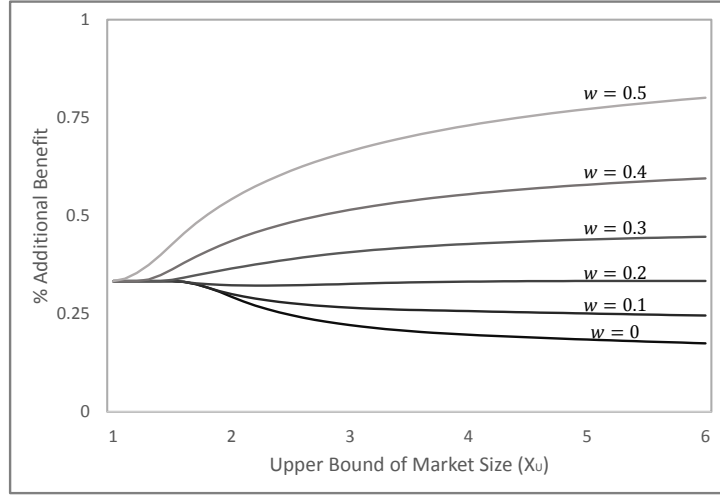


Figure 2.5 Benefit of Standby Upgrades with Overbooking

a guest” is costly. Note that this problem is not equivalent to renormalizing the premium room capacity to  $1 - w$  and applying the base model, since the total demand for premium rooms (i.e., premium room bookings and standby upgrades) is still constrained by the original premium room capacity of 1.

In our analysis, we only consider scenarios where  $w \in [0, 0.5]$ , as it is unlikely for a hotel to allocate more than 50% of the premium rooms to accommodate overbooked standard room demand. We derive the optimal premium room differential,  $p(w)$ , standby upgrade price,  $p_S(w)$  and resulting expected revenue  $\Pi(w)$ , and present the main results:<sup>6</sup>

**Proposition 2.2.** *Let  $H(w) = 4(1+w)(1-w)^2$ . (i) When  $X_U \leq H(w)$ ,  $p(w) = p^{MY}$  and  $p_S(w) = p_S^{MY}$  for any  $w \in [0, 0.5]$ . Moreover,  $\Pi(w)$  does not change in  $w$ . (ii) When  $X_U > H(w)$ ,  $p(w)$  and  $p_S(w)$  increase in  $w$ . On the other hand,  $\Pi(w)$  decreases in  $w$ .*

Proposition 2.2 indicates that the optimal pricing policy under the base model (Lemma 2.1) is robust to overbooking accommodations for small  $X_U$  values; however,

<sup>6</sup>The details of this analysis can be found in the Appendix B.



the set of these  $X_U$  values gets smaller as  $w$  increases since the threshold  $H(w)$  is a decreasing function of  $w \in [0, 0.5]$ . For  $X_U > H(w)$ , the hotel should increase its prices as  $w$  increases to control the demand.

Although the expected revenue is non-increasing in  $w$ , we show that the benefit of standby upgrades<sup>7</sup> is non-decreasing in  $w$  (see Figure 2.5). The reason is as follows: When standby upgrades are not utilized, the hotel can achieve revenue through premium room bookings only for the  $1 - w$  of its premium rooms. On the other hand, standby upgrades allow the hotel to make additional revenue from the allotted (un-bookable) premium room capacity,  $w$ . For higher values of  $w$ , i.e., when the rooms set aside for the oversold standard room capacity is high, the lost revenue opportunity due to free upgrades would be even higher; therefore, we observe an increased benefit of utilizing standby upgrades.

## 2.4 A MODEL WITH STRATEGIC GUESTS

Our hotel chain partner's data set consists of over 100 worldwide hotels using standby upgrades and contains details about guests' booking and standby upgrade decisions. Given that not all standby offers are room upgrades and guests may choose more than one room upgrade offer from the list, we divide the number of guests who were awarded a standby room upgrade by the number of guests who requested at least one standby room upgrade, and obtain an approximate *fill rate*, i.e., the likelihood of getting a premium room through standby upgrades, of 50.3% (51281 out of 101937 guests who requested a standby upgrade were awarded a premium room at the time of booking). This high fill rate suggests that some guests with valuations higher than the premium room differential may choose to opt for standby upgrade offers instead of booking premium rooms directly, in contrast to the myopic guests' case discussed

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<sup>7</sup>We use  $\frac{\Pi(w) - \Pi_{NS}(w)}{\Pi_{NS}(w)}$  as the performance metric where  $\Pi_{NS}(w)$  is the expected revenue from the no standby upgrade benchmark if the hotel offers  $w$  free upgrades to accommodate overbooked standard room demand.

in §2.3. In the hotel industry, it is commonly believed that repeat guests may form a better understanding of the hotel's premium room capacity and market characteristics for a specific stay, and thus, these guests are more likely to act strategically.

In this section, we analyze a case where all guests are strategic. We begin by defining strategic guest behavior and demonstrate the existence of an equilibrium between the guests' belief about the fill rate and the expected realization of the fill rate. We then determine the optimal pricing strategy and make comparisons with some of the strategies presented in §2.3.

#### 2.4.1 STRATEGIC GUEST BEHAVIOR

A strategic guest can make a forward-looking decision based on prices and her perception of the fill rate but cannot see the standby upgrade price before completing a booking. Note that we do not assume that strategic guests can anticipate the correct standby upgrade price before making their booking decision. Such an assumption would require that the guests are trained in advanced optimization and have access to historical demand data that is only available to the hotels. Instead, we assume that a guest can be strategic if she has a non-negative utility for a standard room booking. Accordingly, a strategic guest would always book a standard room first; then make a decision between staying with the standard room, accepting the standby upgrade offer, or booking a premium room (i.e., *upgrading*, simply changing her standard room reservation to a premium room reservation) based on her valuation  $v$ . We assume that strategic guests know the premium room capacity  $C$  and the upper bound of the market size  $X_U$  (i.e., they have full information after seeing  $p_S$ ). Similar to the existing literature, we also assume that strategic guests share a common belief about the expected fill rate,  $r'$ .

In the analysis of strategic behavior, the first step is to identify the valuation of a guest who is indifferent between booking a premium room and choosing a standby

upgrade for a given  $(p_S, p)$  and  $r'$ . This valuation,  $\tilde{v}$ , must satisfy  $r'(\tilde{v} - p_S) = \tilde{v} - p$  given  $p > p_S$ , which can be written as

$$\tilde{v} = \frac{p - r'p_S}{1 - r'} \quad (2.11)$$

Note that  $\tilde{v}$  can be in  $(p, 1]$ , but also in  $(1, \infty)$ . When  $r' = 1$ , then  $\tilde{v} = \infty$ . Since the valuation of guests in our model is in  $[0, 1]$ , there exists a guest who is indifferent between choosing a premium room and standby upgrade when  $\tilde{v} \in (p, 1]$ . On the other hand, when  $\tilde{v} \in (1, \infty)$ , there are no guests indifferent between these two products because  $r'$  is high enough that standby upgrades fully cannibalize premium room bookings. For notational simplicity, we define  $z = \min(1, \tilde{v})$ .

Figure 2.6 presents the decision making process of a strategic guest in our model: After booking a standard room and seeing  $p_S$ , a strategic guest with a valuation  $v \in [z, 1]$  directly upgrades to a premium room and one with  $v \in [p_S, z]$  chooses to accept the standby upgrade offer. A strategic guest with  $v \in [0, p_S)$  keeps the standard room booking.

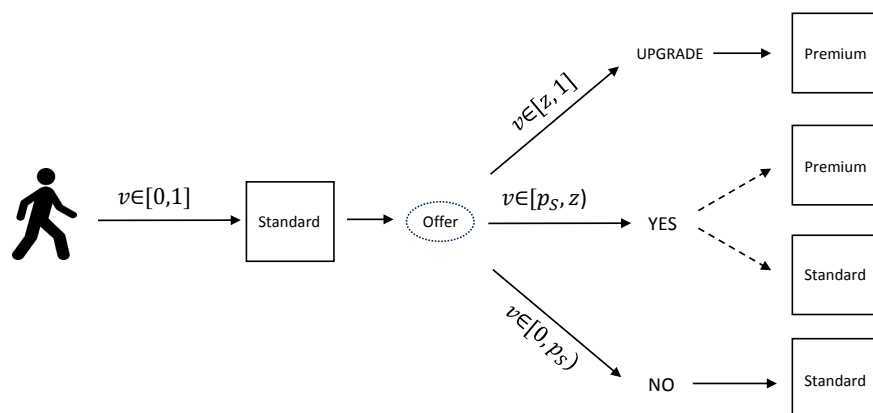


Figure 2.6 Strategic Guest's Decision Making Process

For a specific day with realized market size  $x$ , the premium room demand ( $D_P$ ) is equal to  $x(1 - z)$  and standby upgrade demand ( $D_S$ ) is equal to  $x(z - p_S)$ . The premium room capacities allocated to premium room bookings and standby upgrades,  $(C_P, C_S)$ , can be written as a function of  $D_P$  and  $D_S$  in the same way as in §2.3. The

realized fill rate, denoted by  $r$ , is equal to  $\frac{C_S}{D_S}$ . With algebraic manipulations, we can write  $r$  as a function of  $p_S, z$  and  $x$ :

$$r = \min \left[ 1, \frac{[1 - x(1 - z)]^+}{x(z - p_S)} \right] \quad (2.12)$$

As in the myopic customer case, we have three possible outcomes. For a given  $(p_S, p)$  and  $z$ , the realized market size  $x$  is the only factor that affects  $(C_P, C_S)$ . The conditions for each outcome, resulting revenues, and fill rates are as follows:

$x$	Outcome	Revenue	Fill Rate ( $r$ )
$0 \leq x \leq \frac{1}{1-p_S}$	$O_1$	$R_1 = (x(z - p_S))p_S + (x(1 - z))p$	1
$\frac{1}{1-p_S} < x < \frac{1}{1-z}$	$O_2$	$R_2 = (1 - x(1 - z))p_S + (x(1 - z))p$	$\frac{1-x(1-z)}{x(z-p_S)}$
$x \geq \frac{1}{1-z}$	$O_3$	$R_3 = p$	0

In line with the previous literature, we assume that strategic guests can correctly anticipate the expected fill rate. In a deterministic setting, the actual fraction of standby upgrade demand satisfied ( $r$ ) should be equal to the common belief of guests ( $r'$ ). For such a setting, Zhang and Cooper (2008) use a constraint where the perceived fill rate is equal to the actual fill rate, which in turn is a function of the perceived fill rate and prices (pg. 424, Eq. 23). However, the stochastic nature of our model leads to uncertainty in the fill rate. Therefore, we assume that the guests' common belief  $r'$  should be equal to the expectation of the realization of the fill rate,  $\mathbb{E}[r]$ . We know that  $r$  in our model is a function of the realized market size  $x$ , price set  $(p_S, p)$  and  $z$ . However,  $z$  is a function of  $r'$  from  $z = \min(1, \tilde{v})$  and Eq. (2.11). Therefore, we can write the relationship between  $r$  and  $r'$  using a similar approach to Zhang and Cooper (2008):

$$r' = \mathbb{E}[r(p_S, p, r', x)] \quad (2.13)$$

Next, we combine Eq. (2.12) and Eq. (2.13) to form the following lemma:

**Lemma 2.2.** (*Rational Expectations Equilibrium*) Given that strategic guests' common belief  $r'$  is a function of the fill rate  $r$ , and  $r$  is a function of  $r'$ , there must exist an equilibrium between  $r'$  and  $r$ , which is given by:

$$r' = \mathbb{E} \left[ \min \left( 1, \frac{[1 - x(1 - z)]^+}{x(z - p_S)} \right) \right] \quad (2.14)$$

#### 2.4.2 OPTIMAL PRICING PROBLEM WITH STRATEGIC GUESTS (ST)

When guests are strategic, the optimization problem becomes:

$$\max_{0 \leq p_S \leq p \leq z \leq 1} \Pi(p, p_S, z, r', X_U) = \int_0^{X_U} [pC_P(p_S, p, z, r', x) + p_S C_S(p_S, p, z, r', x)] dx \quad (2.15)$$

$$s.t. \quad r' = \mathbb{E} \left[ \min \left( 1, \frac{[1 - x(1 - z)]^+}{x(z - p_S)} \right) \right]; \quad z = \min \left[ 1, \frac{p - r' p_S}{1 - r'} \right] \quad (2.16)$$

Given the stochastic nature of the market size for premium rooms, we can show that a given price set may lead to different sets of outcomes based on  $x$ . However, we only consider the cases where the rational expectations equilibrium holds, and list these as follows:

**Strategy 1:** Choosing a price set  $(p_S, p)$  that satisfies  $X_U(1 - p_S) \leq 1$  leads to an outcome set  $\{O_1\}$  and  $r' = r = 1$ . In this strategy, none of the guests book premium rooms ( $z = 1$ ) and the standby upgrades are fully satisfied.

**Strategy 2:** Choosing a price set  $(p_S, p)$  that satisfies  $X_U(1 - p_S) > 1$  and  $X_U(1 - z) \leq 1$  leads to an outcome set  $\{O_1, O_2\}$ . In this strategy, we can observe the rational expectations equilibrium in two cases:

- *Case 1* ( $r' \geq \frac{1-p}{1-p_S}$ ): In this case, choosing a standby upgrade dominates booking a premium room even for a customer with  $v = 1$ . Therefore,  $z = 1$  and the following should hold:

$$(1 - p) \leq (1 - p_S) \left[ \int_0^{1/(1-p_S)} \frac{1}{X_U} dx + \int_{1/(1-p_S)}^{X_U} \frac{1}{x(1 - p_S)} \frac{1}{X_U} dx \right] \quad (2.17)$$

- *Case 2* ( $r' < \frac{1-p}{1-p_S}$ ): In this case, there exists a guest who is indifferent between choosing a standby upgrade and booking a premium room. Therefore,  $z < 1$  and the following should hold:

$$(z - p) = (z - p_S) \left[ \int_0^{1/(1-p_S)} \frac{1}{X_U} dx + \int_{1/(1-p_S)}^{X_U} \frac{1 - x(1 - z)}{x(z - p_S)} \frac{1}{X_U} dx \right] \quad (2.18)$$

**Strategy 3:** Choosing a price set  $(p_S, p)$  that satisfies  $X_U(1 - z) > 1$  leads to an outcome set  $\{O_1, O_2, O_3\}$  and  $z < 1$ . The following should hold:

$$(z - p) = (z - p_S) \left[ \int_0^{1/(1-p_S)} \frac{1}{X_U} dx + \int_{1/(1-p_S)}^{1/(1-z)} \frac{1 - x(1 - z)}{x(z - p_S)} \frac{1}{X_U} dx + \int_{1/(1-z)}^{X_U} \frac{0}{X_U} dx \right] \quad (2.19)$$

Because of the complicated nature of the optimization problem, there are no closed-form solutions for the optimal price set  $(p_S^{ST}, p^{ST})$  and the resulting expected revenue  $\Pi_{ST}$ . However, our model properties allow us to reach the following lemma:

**Lemma 2.3.** *When guests are strategic, the hotel should use Strategy 1 for  $X_U \leq 2$  and use Strategy 3 otherwise.*

Lemma 2.3 states that when the upper bound of the market size,  $X_U$ , for a specific day is low ( $X_U \leq 2$ ), the hotel should use a pricing strategy where all guests choose standby upgrades as the expected fill rate will be equal to 1 (or should not offer standby upgrades at all). This result is similar to the optimal solution of the fluid model in Cui (2015), where standby upgrades fully cannibalize the premium room bookings. However, we additionally find that when  $X_U$  is higher ( $X_U > 2$ ), the hotel should use a pricing strategy where some guests choose premium rooms and some choose standby upgrades, which is a new insight that suggests to hoteliers that standby upgrades can act as an effective price discrimination tool even if the guests are strategic.

#### 2.4.3 BENEFITS OF STANDBY UPGRADES WITH STRATEGIC GUESTS

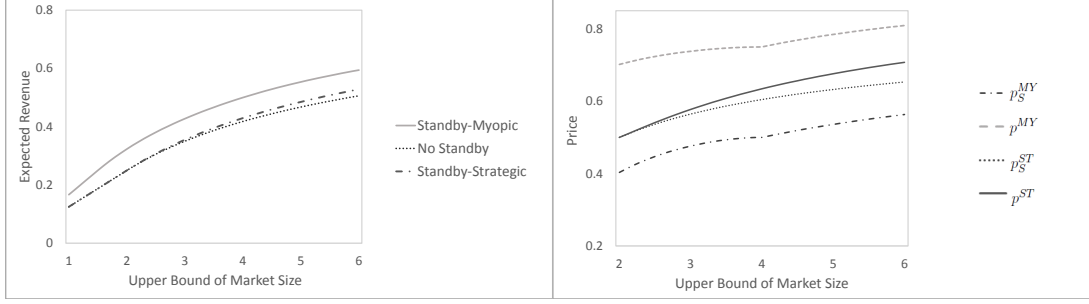
We now compare the optimal strategy under strategic customers with the two models from §2.3 to form the following proposition:

**Proposition 2.3.** *When guests are strategic, standby upgrades do not bring any benefit to the hotel if  $X_U \leq 2$  ( $\Pi_{ST} = \Pi_{NS}$ ). When  $X_U > 2$ , standby upgrades are always beneficial as compared to the no-standby-upgrade benchmark ( $\Pi_{ST} > \Pi_{NS}$ ). However, strategic guest behavior hurts the hotel revenues as compared to the myopic guest behavior ( $\Pi_{ST} < \Pi_{MY}$ ).*

In the benchmark model with no standby upgrades, all guests with a valuation  $v \geq p$  choose premium rooms. Similarly, all strategic guests with a valuation  $v \geq p_S$  choose standby upgrades for the optimal price set  $(p_S^{ST}, p^{ST})$  when  $X_U \leq 2$ ; therefore, it is straightforward to see that  $p_S^{ST} = p^{NS}$ . This leads to  $\Pi_{ST} = \Pi_{NS}$ , which implies that a standby upgrade program cannot bring additional revenue to the hotel for  $X_U \leq 2$  (see Figure 2.7a). Recall that in our benchmark model the hotel adjusts the premium room differential based on the market characteristics for a specific day of stay. Now consider a benchmark where the hotel does not adjust its premium room differential. In this case, the standby upgrade program can be used as a price correction mechanism, since the premium room differential is incorrectly priced and standby upgrades make the necessary adjustment after taking the market characteristics into account.

When  $X_U > 2$ , a standby upgrade program brings additional revenue because the expected fill rates are no longer extremely high and standby upgrades can be used to price discriminate between the high and low valuation guests (see Figure 2.7a). This additional revenue, however, decreases when the guests are strategic. To see this, consider an example using a similar performance metric  $\frac{\Pi_{ST} - \Pi_{NS}}{\Pi_{NS}}$  as in the previous sections. The revenue improvement is only 4.24% for  $X_U = 6$  when the guests are strategic compared to 17.45% when the guests were myopic. Moreover, although the revenue improvement is non-increasing in  $X_U$  when guests are myopic, the standby upgrade programs are not beneficial for low  $X_U$  values and only bring additional revenue as  $X_U$  becomes larger when the guests are strategic.

The following observation compares optimal prices based on the guest behavior:



(a) Expected Revenue

(b) Optimal Prices

Figure 2.7 Comparison of Strategic Guest Behavior Model with Previous Models

**Observation 2.1.** When  $X_U > 2$ , the following order of prices holds:  $p_S^{MY} < p_S^{ST} < p^{ST} < p^{MY}$ , and these prices increase with  $X_U$  (see Figure 2.7b).

When guests are strategic, the hotel cannot use a “high premium price - deep discount” policy as in the myopic case. The premium room differential and the standby upgrade price should be comparable so that the standby upgrades do not fully cannibalize the premium room bookings and the hotel can still price discriminate between the high and medium valuation guests.

Finally, Observation 2 suggests a counterintuitive way the hotel can price discriminate:

**Observation 2.2.** When  $2 < X_U \leq 6$ , the following order of prices holds:  $p_S^{ST} < p^{ST} < p^{NS}$ .

In contrast to our base model where the optimal policy is to increase the premium room differential and offer an aggressive discount for the standby upgrades with the introduction of standby upgrade program, this observation shows that the hotel should actually decrease the premium room differential and offer a smaller discount for the standby upgrades when guests are strategic.

## 2.5 COST OF MISSPECIFYING GUEST BEHAVIOR

All the models discussed so far assume that the hotel can correctly identify the type of guest behavior. In this section, we analyze the consequences of making incorrect



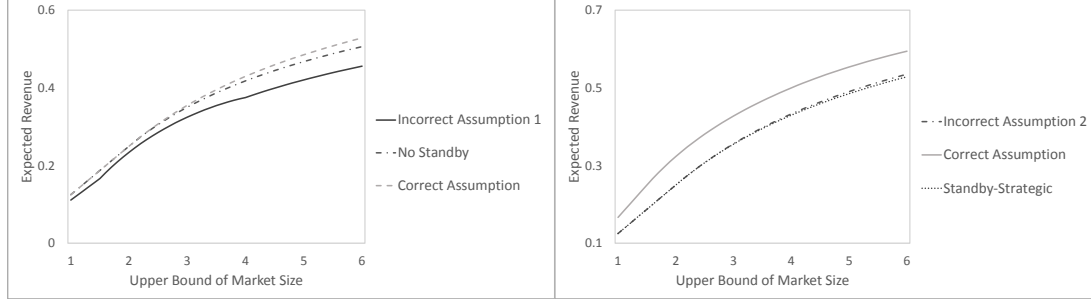
assumptions on the type of guest behavior. In doing so, we follow the literature by calculating the cost penalty of a hotel assuming myopic customers when the guests are actually strategic (Aviv and Pazgal, 2008; Zhang and Cooper, 2008; Mersereau and Zhang, 2012). Our discussions with our hotel chain partner also revealed that the property managers might be unjustifiably worried about strategic behavior (at least according to the central revenue management team), which causes suspicions about projected benefits of offering standby upgrade programs based solely on a myopic guests assumption. In response to these concerns, we add a new dimension to this common robustness test by analyzing the reverse scenario, where the hotel assumes that guests are strategic when they are actually myopic.

#### 2.5.1 INCORRECT ASSUMPTION 1: ASSUMING MYOPIC BEHAVIOR WHEN GUESTS ARE STRATEGIC

Consider a hotel using  $(p_S^{MY}, p^{MY})$  when the guests are actually strategic. Denote the expected revenue in this case as  $\Pi_{MY(ST)}$ . The following result explains the consequences of this error:

**Proposition 2.4.** *If the hotel uses the optimal price set for myopic guests when the guests are strategic, standby upgrades fully cannibalize the premium room bookings. In this case, using standby upgrades hurts revenues as compared to the no-standby-upgrade benchmark ( $\Pi_{NS} > \Pi_{MY(ST)}$ ).*

Proposition 2.4 states that when strategic guests observe a high premium room differential but a deeply discounted standby upgrade price, they all choose the standby upgrade option. When all guests choose standby upgrades, the resulting expected revenue is lower than the optimal expected revenue of the benchmark model with no standby upgrades, since  $p_S^{MY}$  is suboptimal for this model. We measure the revenue loss by using the metric  $\frac{\Pi_{MY(ST)} - \Pi_{NS}}{\Pi_{NS}}$  and see that it is between 6% and 11% (for  $X_U \leq 6$ ; see Figure 2.8a). Thus, hotels should be aware of the risks of ignoring



(a) Incorrect Assumption 1

(b) Incorrect Assumption 2

Figure 2.8 Revenue Implications of Incorrect Assumptions on Guest Behavior

strategic behavior and use the standby upgrade program cautiously if such a scenario is possible.

### 2.5.2 INCORRECT ASSUMPTION 2: ASSUMING STRATEGIC BEHAVIOR WHEN GUESTS ARE MYOPIC

Consider a hotel using  $(p_S^{ST}, p^{ST})$  when the guests are actually myopic. Denote the expected revenue in this case as  $\Pi_{ST(MY)}$ . For a given price set  $(p, p_S)$ , myopic behavior always leads to a higher expected revenue than strategic behavior since  $z > p$ . Therefore, the hotel's resulting expected revenue in this case will be higher than what the hotel expects to achieve ( $\Pi_{ST(MY)} > \Pi_{ST}$ ). While the hotel may believe that the standby upgrades bring additional revenue, the benefits could have been higher had the hotel chosen the price set  $(p_S^{MY}, p^{MY})$  as that would have led to the optimal expected revenue  $\Pi_{MY}$  under myopic guest behavior. Our analysis shows that the revenue impact of this mistake (i.e.,  $\frac{\Pi_{ST(MY)} - \Pi_{MY}}{\Pi_{MY}}$ ) ranges from 10% to 25% (for  $X_U \leq 6$ ; see Figure 2.8b).

In this scenario, the standby upgrade program still brings additional revenue, since  $\Pi_{ST(MY)} > \Pi_{ST} \geq \Pi_{NS}$ . However, the incorrect assumption has a significant negative effect since it prevents the hotel from fully taking advantage of its price discrimination opportunities. The consequences of both incorrect assumptions show us the importance of correctly identifying the guest behavior.

## 2.6 CONCLUSIONS

The question of how to best manage upsell opportunities for premium rooms at hotels has received little attention in the revenue management literature. While many hotel chains use sophisticated standard room pricing techniques, they simply add a fixed differential to the standard room price for setting premium room prices, and sometimes offer discounted upgrades at the time of check-in. A recent innovative approach aimed at improving the management of room upsell opportunities is Nor1's standby upgrade program, where discounted availability-based upgrades are offered to guests who book standard rooms and guests are only charged for the upgrade if the premium room is available once they arrive. In the current implementation of this program, however, the list price of the premium room differential remains the same as under the pre-Nor1 system.

In this paper, we offer an approach for simultaneously setting the price differential and standby upgrade price from a standard room to a premium room, based on the expected market size for premium rooms. To do so, we develop a model similar to the pre-announced pricing models used in the markdown pricing literature with necessary adjustments to capture the key characteristics of hotel standby upgrade programs. This allows us to answer our main research question:

*Which hotel properties benefit the most from offering standby upgrades?* The relative premium room capacity (premium-to-standard room capacity ratio) and the type of customer base (myopic versus strategic) are the two key factors that affect the potential revenue improvement provided by offering standby upgrades. Our analysis of booking data for our hotel chain partner's 54 US properties shows that the relative premium room capacity can be attributed to the hotel's location and brand. Particularly, upscale hotels with differentiated rooms (e.g., city/mountain/ocean/lake/river views, higher floor, corner/tower rooms, additional bed) have a higher premium-to-standard room capacity ratio (30% to 60% of the total number of standard rooms),

which leads to a lower upper bound for the premium room market size in our model. In contrast, upscale hotels with mostly standard rooms and a low premium-to-standard room capacity ratio (less than 15%) have a higher upper bound for the premium room market size. Midmarket hotels have a higher ratio of suites (generally 15% to 30%) compared to upscale hotels with mostly standard rooms. Some midmarket resort hotels have an even higher ratio of suites (40% to 50%, since these hotels mainly cater to larger families).

Similarly, the type of customer base (myopic versus strategic) can be attributed to the percentage of guests at a hotel property who are repeat customers since only repeat customers can develop a sense of the chances of being awarded a standby upgrade (a requirement for strategic behavior). Since our data does not contain any customer specific identifiers, we use the loyalty status of a customer as a proxy for repeat customers. Our analysis shows that airport hotels and hotels that primarily serve business customers near central business locations are more likely to have repeat guests (usually 55% to 65% of the customer base are loyalty guests at these hotels). Consequently, these hotels face a higher probability of strategic guest behavior than touristic downtown, resort, and roadside/small city hotels whose customers are primarily one-and-done leisure customers (only 30% to 40% loyalty guests).

Based on the reasoning described above, our analysis indicates that standby upgrade programs are more beneficial for hotels that serve non-repeat guests (see Figure 2.9). Moreover, assuming an industry average occupancy rate, mid-market resorts and upscale leisure hotels with higher premium-to-standard room capacity ratios in this group are expected to benefit more from standby upgrades. In contrast, the large premium-to-standard room capacity ratios at upscale airport or business-oriented hotels with many differentiated rooms may actually decrease the attractiveness of offering standby upgrades since the customer base is more likely to consist of strategic customers, who recognize the higher likelihood of being awarded a standby up-

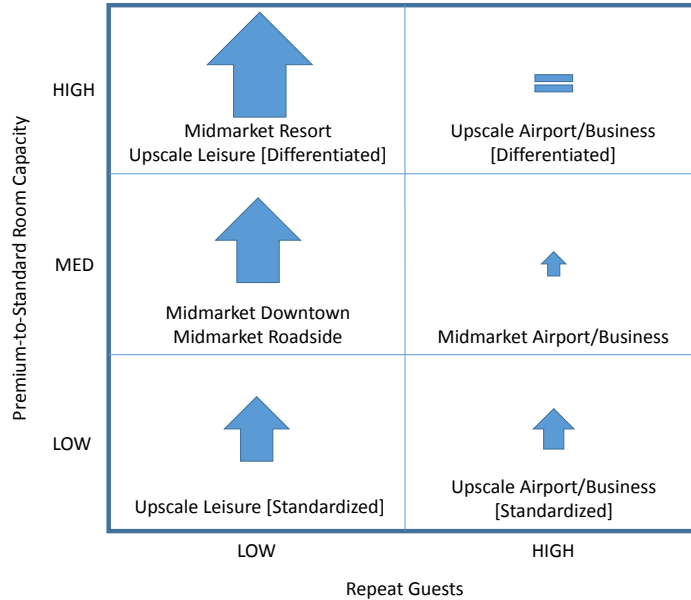


Figure 2.9 Benefits of Offering Standby Upgrades based on Market Size and Guest Behavior

grade, resulting in the cannibalization of direct sales of the premium rooms. On the other hand, the likelihood of being awarded a standby upgrade is lower in the upscale hotels with a lower premium-to-standard room capacity ratio, which makes standby upgrades beneficial even if the customer base consists of strategic customers. Thus, for hotels that cater to non-repeating (leisure) customers, standby upgrades are most attractive to upscale hotels and midmarket resort hotels with a higher premium-to-standard room capacity ratio. In contrast, for hotels that cater to repeat (business) customers, standby upgrades are most attractive to upscale hotels with a lower premium-to-standard room capacity ratio. Compared to upscale hotels with mostly standard rooms, standby upgrades always appear to be beneficial for midmarket hotels that primarily serve the leisure market. The exception is midmarket hotels near airports or major business locations, where a closer analysis of strategic guest behavior is required.

Beyond these general guidelines, our research provides the following additional insights on standby upgrade programs:

*Differentiating standard rooms can bring additional benefits to hotels using standby upgrade programs.* Our results indicate that standby upgrades are especially powerful when  $X_U$  is low (i.e. the hotel has high premium-to-standard room capacity) and guests are myopic. Based on this finding, we suggest that the hoteliers look for new and innovative ways of differentiating their standard rooms (e.g. higher floor, corner room, balcony). Doing this in the absence of offering standby upgrades may bring the hotel additional revenue but, by adding standby upgrades into their toolset, revenues can be significantly improved through further price discrimination and better overall capacity management.

*Hotels should update their premium room differential when using a standby upgrade program.* When properties included in our partner's data set began using standby upgrade programs, they continued to use the same fixed premium room price differential that was used before the program was introduced. Our results indicate that updating the premium room differential with the introduction of a standby upgrade program can significantly increase revenue for the hotel. Furthermore, the hotel should adjust its prices according to the target occupancy rates, which may be different for different days of stay.

*Replacing front-desk upsells with standby upgrade programs can be beneficial for hotels.* The advantage of a front-desk upsell program is that the market size is revealed by the time an upsell offer is made, and the hotel can set the optimal upgrade price using full information on the market size. However, inconsistent performance of the front-desk upsell program (i.e., not having a chance to offer upgrades due to a long check-in line) sometimes preclude the hotels from adjusting their premium room differentials with the consideration of front-desk upselling. In such cases, our results show that the benefit from offering standby upgrades is higher than the benefit of front-desk upsells.

*Standby upgrade programs can provide additional benefits when standard rooms*

*are overbooked.* When there is a special event at a hotel, such as a convention, the hotel may choose to overbook their standard rooms. If the hotel does not use standby upgrades, it typically has to offer free premium room upgrades to satisfy the excess standard room demand. Our analysis shows that using standby upgrades in these situations not only helps the hotel to price discriminate its customers, but also brings additional revenue from the rooms which are normally upgraded for free. Thus, offering standby upgrades becomes even more valuable for a hotel that satisfies overbooked standard room demand with free premium room upgrades.

*Correctly identifying guest behavior and adjusting prices accordingly has a significant impact on the resulting revenues.* A standby upgrade program provides a hotel with an additional way to price discriminate between guests with high and low valuations for the premium room differential. When guests are myopic, the hotel can use a higher premium room differential and a deeply discounted standby upgrade price. However, when guests are strategic, the hotel should factor in the cannibalization threat and price accordingly, leading to a smaller gap between the premium room differential and the standby upgrade price. Misidentifying strategic guests as myopic, or myopic guests as strategic, can lead to significant implications on the hotel's revenue. For example, our results suggest that an upscale hotel next to a convention center in a major business city should alternate between different pricing policies. When there is an event in the conference center, the hotel can assume that the number of repeat guests will be low and price according to myopic guest behavior. In contrast, when there is no event, most of the guests may be regular business customers who return frequently, so the hotel should price according to strategic guest behavior. Using the same pricing policy with standby upgrades for all circumstances could potentially result in an overall revenue loss for a hotel property.

We believe that standby upgrades is a promising area for future research, and may have new areas of application outside of the hospitality domain in the near future. In

fact, some airlines have already started using similar programs. This paper has taken an early attempt to examine the benefits of such upgrades analytically and suggest potential improvements. Availability of data on guests' decisions also makes this area a good candidate for empirical research on the guest decision making process.



# CHAPTER 3

## INVESTIGATING STRATEGIC CUSTOMER BEHAVIOR

### FOR HOTEL STANDBY UPGRADES

#### 3.1 INTRODUCTION

Traditional revenue management practices in airline and hotel industries use capacity control mechanisms (i.e., controlling the sale of different fare classes on a single leg of an airline and the sale of hotel rooms for a given date at different rate classes), which often leads to high prices for closer periods to the time of consumption, since customers arriving in these periods are relatively price-insensitive business travelers (Schwartz, 2000; Talluri and Van Ryzin, 2006). On the other hand, any unsold capacity at the time of consumption results in zero revenue. Therefore, if the inventory is not selling at the expected rates, airlines and hotels offer their inventory at a discount, frequently referred to as last-minute deals (Ovchinnikov and Milner, 2012).

Although last-minute efforts could generate significant revenue from the distressed inventory, revenue management teams of airline or hotels are often forced to police their policies against last-minute discounting efforts by other parts of the organization that may have more myopic views about maximizing revenues<sup>1</sup> (i.e., ignore the possibility that some high-price customers who would book anyway would shift to last-minute deals in long-term). The main reason for this is that a significant portion of customers can act strategic even facing sophisticated airline or hotel pricing algo-

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<sup>1</sup>Li et al. (2014) suggest that using a non-decreasing pricing scheme may bring up to 8% revenue improvement while facing strategic customers, in contrast to existing end-of-season discounts in the retail industry.

rithms. In fact, Li et al. (2014) show that 5% to 20% of travelers are strategic across different markets for airline fares.

A recent compromise strategy between these two opposing views has been to offer *upgrade-eligible fares* or *standby upgrades*, where the premium product capacity is used as a buffer for regular product demand (Biyalogorsky et al., 2005; Cui, 2015; Yilmaz et al., 2017). In particular, *upgrade-eligible fares* of airlines give customers a chance to get a first class seat with a higher price economy ticket provided that space is available. Nor1's *eStandby*<sup>®</sup> upgrades<sup>2</sup>, which has recently been adopted by most hotel chains and major regional/individual hotels, offer discounted, availability-based upgrades to customers. While both standby upgrades and upgradeable airline tickets typically offer a discounted premium capacity, they differ in (i) that standby upgrades are only offered for customers who have already booked standard rooms and (ii) that customers only pay if the upgrade is awarded.

These practices increase the number of paths to reach a specific flight seat or hotel room, therefore adding another dimension to a customer's decision-making. In addition, the probabilistic nature of these products make it important to understand the customers' decision-making dynamics in order to adopt the correct pricing strategies, since suboptimal pricing decisions, such as ignoring the strategic behavior or assuming that customers are strategic in settings where they are myopic, may have significant revenue implications (Yilmaz et al., 2017).

Academic interest in investigating the benefits of innovative revenue management practices with probabilistic elements<sup>3</sup> has been growing, although currently the academic literature lacks any empirical studies on the type of customer behavior in different airline and hotel settings with probabilistic products. Despite this, most of the recent analytical work in this area assumes that customers are strategic and

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<sup>2</sup>Full details on how program works can be found in §3.3.

<sup>3</sup>Popular examples are opaque selling tools such Hotwire's *Hot Rate*<sup>®</sup> *Hotels* and Priceline's *Name Your Own Price*<sup>®</sup>.

will always choose the expected-utility maximizing option. We postulate that not all customers are strategic. Instead, some customers may not be aware of these products or may not be inclined to reason through complex options based on probabilities and prices while making their decision. To the best of our knowledge, this paper represents the first attempt to empirically investigate the existence and the extent of strategic customers in a probabilistic product setting. In a standby upgrade setting, we define *strategic customers* as those who are savvy enough to initially choose a standard room over a premium room with the expectation of being offered a discounted premium room through standby upgrades. Yilmaz et al. (2017) show that it is rational for a strategic customer to do so, thus the absence of this action is an indicator of non-strategic behavior.

In order to investigate for strategic behavior, we utilize a major hotel chain's 16-month booking and standby upgrades data over a set of properties. We set out two main research goals: First, we seek to understand customer decision-making dynamics in the presence of standby upgrade programs and estimate the percentage of strategic customers. Second, we seek to identify hotel and upgrade characteristics that are more or less likely to observe strategic customer behavior.

Assuming that non-repeat customers with no loyalty program membership are an "uncontaminated" sample due to their possible lack of awareness for standby upgrades, we use these customers as a reference *myopic* group through all of our analysis. We first run a reduced-form model (a sequential application of the traditional logit model because of the step-by-step nature of decision-making) to understand the differences between non-repeat customers and repeat customers with loyalty program memberships, who are more likely to be aware of the standby upgrade program and may act strategic during the booking process.<sup>4</sup> Then, we use Maximum Likelihood

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<sup>4</sup>A strategic customer would always join the hotel's loyalty program, because joining is free and there are only positive benefits.

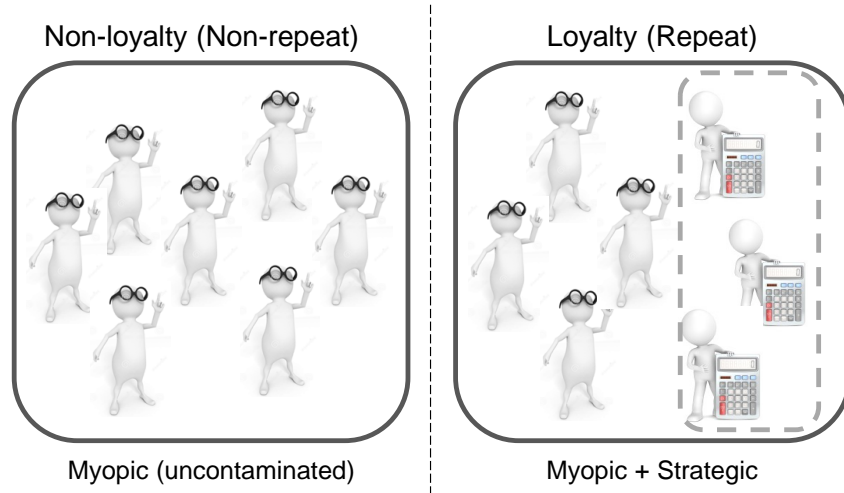


Figure 3.1 Postulated Behaviors for Non-loyalty and Loyalty Groups

Estimation (MLE) techniques to estimate an actual percentage of the *non-myopic*<sup>5</sup> customers within the loyalty program members and test if this group is actually strategic (see Figure 3.1 for a representation of the customer population if the test provides evidence for strategic behavior).

We find evidence for strategic behavior in three (out of 8) hotel properties that we study. Our estimation results suggest that 22% to 42% of the loyalty program members (10% to 22% of the total customers) are strategic in these upper mid-scale brand properties near major expressways or business areas. On the other hand, we cannot find any evidence for strategic behavior in other properties, upper midscale or upscale hotels near attractions (e.g., golf course, theme park), and upper midscale hotels near convention centers and hospital complexes.

The remainder of this paper is structured as follows: The next section reviews related work and positions our contribution to the empirical literature on the existence and the extent of strategic behavior. §3.3 briefly discusses the heterogeneity in the decision-making process for different types of customers. §3.4 provides the details

<sup>5</sup>We do not force the condition of being strategic for the customers in this group, i.e., they may not show characteristics set by a strategic behavior model.

of our data. §3.5 explains our reduced-form analysis and preliminary results. §3.6 presents our MLE analysis and main results. §3.7 concludes with the limitations and future work.

## 3.2 LITERATURE REVIEW

In the operations management literature, strategic customer behavior, in particular, strategic timing of a purchase, has been extensively investigated through analytical models for different settings such as pre-announced discounts, contingent discounts, capacity rationing, and reservations. Optimal pricing policies for a firm facing strategic customers and negative consequences of ignoring such behavior have also been examined in detail (for a review, see Netessine and Tang, 2009). Most of this work makes the assumption that customer population is fully strategic. Although this assumption may hold for the retail industry where customers can make sophisticated decisions because of the availability of historical data, it is not clear whether it may hold in a hospitality setting, especially for a program as recent as standby upgrades. Thus, it is important to investigate the existence and extent of the strategic behavior in the standby upgrades context.

In the economics and marketing literature, there is a stream of research that takes strategic behavior into account in empirical models. Erdem and Keane (1996) model customer behavior in an environment when there is uncertainty about brand attributes. They compare a dynamic model with immediate utility maximizing customers and a dynamic model with forward-looking customers who maximize the expected present value. They estimate the likelihood functions for these models using Nielsen scanner data for detergent. Nair (2007) provides a framework to investigate the optimal pricing for strategic customers with an empirical study in the market for video-games in the US. These two papers are based on the assumption that the customers are forward-looking. On the contrary, Chevalier and Goolsbee (2009) test

whether textbook customers are forward-looking by using a large data set on textbooks sold in college bookstores and find evidence of the forward-looking behavior. Additionally, Hendel and Nevo (2013) estimate the fraction of customers, who can store for future consumption needs, at a market level using the sales data of two-liter bottles of Coke, Pepsi, and store brands. Through different behavioral models, they show that 59% to 90% of the customers are storers.<sup>6</sup>

On the other hand, very little research provides evidence for strategic customer behavior in the operations management literature. Li et al. (2014) use a structural model to estimate the fraction of strategic customers by using airline fares and booking data and show that 5.2% to 19.2% of the customers act strategic. Through a lab experiment, Osadchiy and Bendoly (2015) provide insights for the forward-looking nature of decision-makers faced with buy-now vs. buy-later decisions and how dependent that nature is on the presence of information regarding future product availability. Their results show that 77% of subjects are forward-looking, and 36% of them correctly perceive the future availability risk. In our setting with standby upgrades, the form of strategic behavior is significantly different: Customers do not strategize the time of their purchase, instead they have an option to request a standby upgrade at a discounted rate and get a premium room only if it is available at the time of check-in. Therefore, the strategic behavior is in the choice rather than timing.

Our paper is based on the connection between the loyalty status and customer behavior. The marketing literature defines loyalty as an irrational and emotional attachment to a product, service, or business (Taylor et al., 2004). To the best of our knowledge, Meyer-Waarden (2008) is the only empirical work on the relationship between loyalty programs and customers' purchases. Using a supermarket scanner data, the author shows that purchase intensity and frequency of cardholders is sig-

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<sup>6</sup>Note that these papers focus on different forms of strategic behavior, compared to the operations management literature.

nificantly higher than that of non-members. Shugan et al. (2005), on the other hand, claims that many so-called loyalty programs are shams because they produce liabilities (e.g. promises of future rewards) rather than assets. Related to this discussion, we provide mixed results for hotel standby upgrades: We show that the loyalty customers have a higher willingness-to-pay for a premium room in some hotels, but may act strategic (and partially cannibalize the premium room bookings) in others. Our findings for different hotels provide evidence supporting both arguments, and show the importance of identifying the type of customers that a hotel property has.

Dealing with supply and demand mismatch through upgrades has been recently gaining interest in the operations management literature. Gallego and Stefanescu (2009) and Yu et al. (2015) work on the capacity management problem with such upgrades. Cui (2015) show that the probabilistic element of standby upgrade program can be used as a price correction mechanism in the presence of strategic customers when the hotel is a price taker for standard and premium room prices. Yılmaz et al. (2017), on the other hand, provide insights about how to optimally price standby upgrades and premium room prices to price discriminate while facing different types of customer behavior.<sup>7</sup> The authors also measure the negative consequences of ignoring the strategic behavior and the lost opportunity in case of assuming customers are strategic when they are actually myopic.

Discussions with our hotel chain partner's central revenue management team revealed that property managers are overly concerned about the customer behavior when using standby upgrades. In particular, they do not have a means for estimating the percentage of strategic customers and are confused about the correct pricing strategy. This paper aims to take a first step toward filling this gap by empirically

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<sup>7</sup>They show that the hotels observing myopic behavior can use standby upgrades as an aggressive price discrimination tool by setting a higher premium room price and applying a deep discount for the standby upgrades. On the other hand, the hotels observing strategic behavior can continue using their current premium room price and apply a mild discount for standby upgrades.

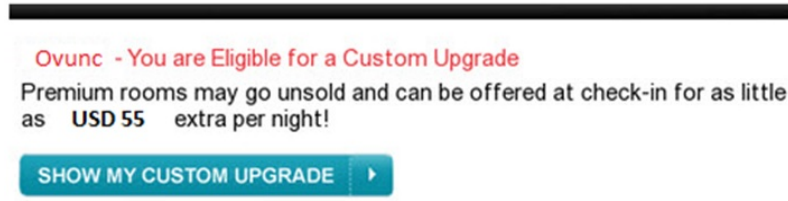


Figure 3.2 Reservation Confirmation Window Showing that Standby Upgrades are Available

investigating the existence and the extent of strategic behavior for different hotel environments. Our methodology and empirical results, connected with analytical results of Yilmaz et al. (2017), provide guidance for hoteliers to use standby upgrade programs more effectively based on the hotel type and customer behavior.

### 3.3 BEHAVIORAL MODELS FOR CUSTOMERS' DECISION-MAKING PROCESS

In this section, we focus on the customer decision-making process through an analytical explanation. Before going into details, let us present how standby upgrade program works in detail:

The guest (she) first makes a choice between booking a standard room and premium room (or do not purchase). When she completes the reservation, she receives a banner ad indicating that customized upgrade offers are available via email or on brand.com confirmation page (see Figure 3.2). After clicking the banner ad, she receives a list of discounted upgrade offers (see Figure 3.3). These offers include room upgrades (e.g. standard guestroom to a suite), room features (e.g. city view), amenities (e.g. internet), early check-in/late check-out, parking, spa services, etc. If she requests an upgrade, she learns whether the upgrade(s) is awarded at the time of check-in. If awarded, she is automatically charged the discounted price, otherwise she keeps the original booking and pays nothing extra.

For simplicity, consider a hotel with one standard and one premium room type. A customer makes a set of decisions based on her valuation for the standard room and



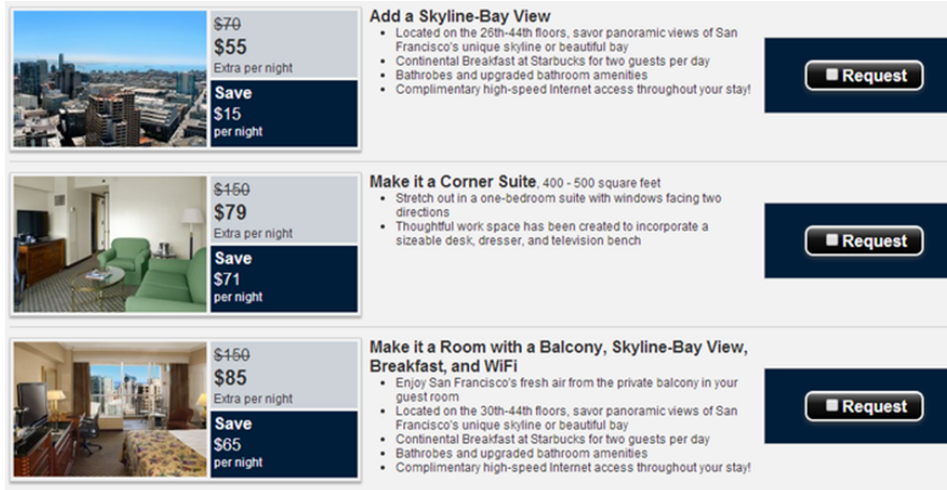


Figure 3.3 Standby Upgrade Offers

premium room, the standard and premium room prices, her awareness of standby upgrades, and the standby upgrade price. Figure 3.4 illustrates this process. Following Yilmaz et al. (2017), we approach this problem using the customer valuation for the differential, i.e., the difference between her premium and standard room valuations, instead of using a two-dimensional valuation for standard room and premium rooms.

We postulate that customers are heterogeneous in their valuations for the premium room differential, and their loyalty status has a direct effect on their capabilities of being strategic. The customers without loyalty membership are assumed to be non-repeat customers, therefore not aware of standby upgrade programs. On the other hand, loyalty program members are mainly repeat customers who potentially know about the standby upgrade program based on their experience. Note that there are some high-tier loyalty members who accumulate points above a certain threshold and qualify for additional benefits such as free upgrades. Since these customers are not targeted by standby upgrades, we only focus on the basic-tier loyalty customers in this paper.

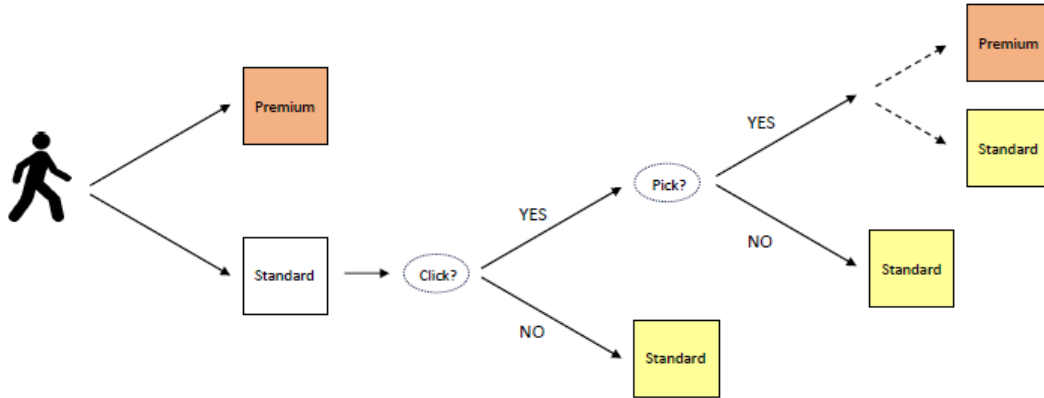


Figure 3.4 Steps of Customer Decision-making Process

### 3.3.1 CUSTOMERS WITH NO LOYALTY PROGRAM MEMBERSHIP

Customers with no loyalty membership are likely to be unaware of the standby upgrade program prior to booking a room since most of them are not repeat customers. Therefore, they are unlikely to act strategically: They make a decision between a standard and premium room initially without considering the possibility of receiving a standby upgrade offer after booking. If they book a standard room, they then make a decision on the standby upgrade offer based on their valuation on the differential between two rooms,  $v$ : For a price set<sup>8</sup>  $(p_S, p)$ , a customer without loyalty membership books the premium room initially if her valuation is  $v \geq p$ . If  $v < p$ , she books a standard room and sees the standby upgrade offer. If  $v \in [p_S, p)$ , she accepts the offer, otherwise she rejects.<sup>9</sup>

<sup>8</sup>Today, most hotels use state-of-the-art tools to price their standard rooms. On the other hand, they use a fixed premium differential,  $p$ , and standby upgrade price,  $p_S$ , pegged to standard room price.

<sup>9</sup>Our data shows that some of these customers do not click the banner ad. They may be missing the banner ad, or may have very low valuations for standby upgrades and do not want to see the offer. We cannot distinguish between customers who do not see the offer and who do see the offer but have low valuations.

We use the group of customers without loyalty membership as an uncontaminated myopic reference group in our analysis for investigating the strategic behavior of customers with loyalty memberships.

### 3.3.2 LOYALTY PROGRAM MEMBERS

Our data set shows the award rate, i.e., the likelihood of getting a premium room through standby upgrades, for customers requesting the standby upgrade offers as around 50%. We postulate that at least a portion of loyalty program members may be aware of this high award rate and choose to opt for a standby upgrade offer even if they have high valuations for the differential and would, in the absence of a standby upgrade program, book a premium room directly.

Consider such a customer with a belief on award rate,  $r' \in [0, 1]$ . There exist two threshold values for this customer at a given  $r'$ : (i) The indifference point between keeping the standard room and requesting standby upgrade,  $v_1 = p_S$ . (ii) The indifference point between requesting standby upgrade and booking a premium room,  $v_2 = \frac{p-r'p_S}{1-r'}$ . Thus, for a price set  $(p_S, p)$ , a strategic customer books the premium room initially if her valuation is  $v \geq v_2$ . If  $v \in [v_1, v_2)$ , she books a standard room and chooses the standby upgrade offer. Otherwise, she books a standard room and rejects the offer. Note that  $v_2 = \infty$  if  $r' = 1$ . Figure 3.5 illustrates the utility-maximizing actions for a strategic customer on an example with  $r' \in [0, 1]$ ,  $v \in [0, 1]$  and  $(p_S, p) = (0.5, 0.7)$ .

Given our explanations, we expect strategic customers to be less likely to book premium rooms at the onset, but more likely to click the banner ad to see the standby upgrade offers compared to myopic customers. We also expect these customers to be more likely to request an upgrade.<sup>10</sup>

<sup>10</sup>We assume that customers who consider standby upgrades do not differ in their valuations for the differential based on their type, myopic or strategic.

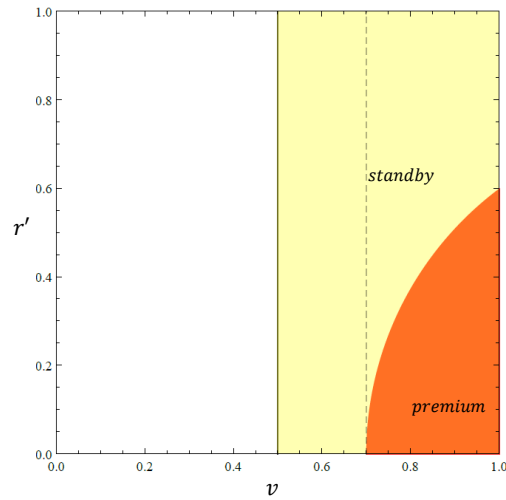


Figure 3.5 Optimal Actions for a Strategic Customer based on  $v$  and  $r'$

### 3.4 DATA

The data for this study is from a major hotel chain (with more than 100 properties in the United States). The data set contains reservation information and standby upgrade decisions of customers over 16 months between January 2013 and April 2014.

#### BOOKING DATA:

The booking data contains complete reservation information except for the name of the customer: Hotel brand, property name, reservation number, booking date, arrival and departure dates, rate code, booked room type, booked room rate, loyalty status, exposure to the standby upgrade.

#### STANDBY UPGRADE DATA:

For each customer who completed the booking process and received the banner ad, the standby upgrade data set contains: the action on the banner ad (clicked or not); if clicked then the date of the click, standby upgrade offers presented with information

Hotel	ID	Book	Arrive	Depart	Room	Rate	Loyalty	Banner	Standby	Price	Offer	Request
CHI	1	1-3-13	1-3-13	2-3-13	STD	89	1	1	PRE	20	8	0
CHI	2	2-2-13	1-3-13	3-3-13	STD	89	0	1	PRE	20	10	1
CHI	3	1-2-13	1-3-13	2-3-13	PRE	109	1	-	-	-	-	-
CHI	4	1-3-13	1-3-13	2-3-13	STD	89	1	0	-	-	-	-
CHI	5	11-3-13	1-3-13	3-3-13	STD	89	0	1	PRE	20	12	0
CHI	6	1-2-13	1-3-13	2-3-13	STD	89	1	0	-	-	-	-
CHI	7	1-2-13	1-3-13	2-3-13	PRE	109	0	-	-	-	-	-

Figure 3.6 A Snapshot of the Final Data Set

on the type of the offer (room upgrades, amenity, parking etc.), actual price of the offer ( $p$ ), discounted price of the offer ( $p_S$ ), the customer's action on the offer (requested or not), and if requested, then the outcome (awarded by the hotel or not).

### 3.4.1 DATA PREPARATION

We integrate the two main data sets mentioned above with our hotel chain's property database and room type mapping. We remove standby upgrade offers for ancillary products, since these often have unconstrained capacity. In addition, the decision-making process becomes much more complex when there are more than a single room upgrade, therefore we only focus on the hotels with two main room types, one standard and one premium.<sup>11</sup> As a result, we use a subset of 8 hotel properties for our data set, resulting in 15,222 bookings. A snapshot of the final data set is given in Figure 3.6.<sup>12</sup>

<sup>11</sup>Some hotels in the final data set have more than two room types. For these hotels, we omit the luxury upgrades (e.g., presidential suite) which are extremely rarely requested and also have a very low likelihood of being awarded. Following Yilmaz et al. (2017), we focus on incremental room upgrades (e.g., mountain view room, a standard suite).

<sup>12</sup>As mentioned earlier, we only focus on basic-tier loyalty customers, therefore we dropped all customers with high-tier loyalty status.

Table 3.1 Variable Descriptions

Names	Definitions	Detail
<i>LOS</i>	Length-of-stay	$Min(DepartureDate - ArrivalDate, 3)$
<i>ADV</i>	Advanced-booking time	0 if booked within last week, 1 if 7 to 13 days, 2 if 14 to 20 days, 3 o.w.
<i>SAT</i>	Saturday-night-stay	1 if stay includes Saturday night, 0 o.w.
<i>LOYAL</i>	Loyalty membership	1 if loyalty program member, 0 o.w.
<i>PRICE</i>	Standby upgrade price	Discounted offer price
<i>Premium</i>	Initial booking choice	1 if premium room, 0 o.w.
<i>Interest</i>	Interest on the banner ad	1 if clicked, 0 o.w.
<i>Upgrade</i>	Action on standby upgrade	1 if requested, 0 o.w.

Because of the sequential nature of the decision-making process, we create three data sets from the resulting data set: The first data set (DS1) contains the initial decision of the customers, i.e., whether they book a standard room or a premium room. The second data set (DS2) has the customers' action on the banner ad, i.e., whether they click the banner ad or not. Note that customers who initially choose a premium room (e.g., customers #3 and #7 in Figure 3.6) are not in this data set, because they would not see a room upgrade offer in the standby upgrade list. The final data set (DS3) is for the standby upgrade decision, i.e., whether they request the offer or not, and it only includes the customers who clicked the banner ad (e.g., customers #1, #2, and #5 in Figure 3.6).

### 3.4.2 VARIABLES

Table 3.1 presents our independent variables that are expected to influence customers' decision-making, and dependent variables that represent customers' sequential decisions. Note that for the *length-of-stay* variable, we categorize bookings as one-night, two-night and 3+ night stays. For the *advanced-booking time* variable, we categorize

Table 3.2 Statistical Summary

Names	Values				Between-hotel variation	
	0	1	2	3	Min-Max	Std.Dev.
<i>LOS</i>	-	60.3%	22.1%	17.6%	35.8% - 88.6%	16.1%
<i>ADV</i>	46.9%	15.7%	8.7%	28.7%	39.0% - 59.3%	7.2%
<i>SAT</i>	62.9%	37.1%	-	-	48.7% - 72.8%	7.1%
<i>LOYAL</i>	46.8%	49.9%	-	-	30.3% - 67.7%	12.2%
<i>Premium</i>	76.3%	23.7%	-	-	51.7% - 90.4%	13.0%
<i>Interest</i>	58.5%	39.9%	-	-	52.6% - 66.3%	4.8%
<i>Upgrade</i>	82.8%	17.2%	-	-	70.8% - 87.0%	5.1%

bookings as within one-week, one-to-two-weeks, two-to-three-weeks, and 3<sup>+</sup> weeks from the arrival date (instead of using a continuous booking time variable).

The basic composition of the customer base can be seen in Table 3.2. For each variable, we present the percentages for each value in the entire customer population at the left hand side. In order to show the between-hotel variation, we share the min-max range and the standard deviation information.<sup>13</sup> For example, 62.9% of the entire population are customers who did not include Saturday in their bookings. This number is as low as 48.7% in hotel property A and as high as 72.8% in hotel property D, with a standard deviation of 7.1%. Note that the statistics related to *Interest* and *Upgrade* are based on DS2 (customers who booked a standard room initially) and DS3 (customers who clicked on the banner ad), respectively.

<sup>13</sup>For variables with more than two possible values (*LOS* and *ADV*), we share the between-hotel variation information with respect to the reference value (1 for *LOS* and 0 for *ADV*).

### 3.5 REDUCED-FORM ANALYSIS: SEQUENTIAL LOGIT MODEL

#### 3.5.1 MODEL DISCUSSION

While a Multinomial Logit Model (MNL) with a choice set of premium room, standby upgrade and standard room is one option to investigate the existence of loyalty customers' strategic behavior, we choose a model which accounts for the fact that decisions are made in a sequence of stages. We estimate the effect of loyalty status on decision-making using a Sequential Logit Model (Tutz, 1991), i.e., a sequential application of the traditional logit model. This model makes it easier to estimate the effect of an independent variable across transitions. We use STATA 14 for our analysis as follows:<sup>14</sup>

First, we estimate the coefficients for the initial booking decision using

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0^1 + \beta_L^1 LOYAL_i + \beta_C^1 CONTROLS_i \quad (3.1)$$

on DS1 where  $p_i = \Pr(Premium_i = 1|x_i)$  for each customer  $i$  with regressors  $x_i$ . Our variable of interest is *LOYAL*, but we have a set of control variables: *LOS*, *ADV*, and *SAT*.

Second, we estimate the coefficients for the action on the banner ad using

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0^2 + \beta_L^2 LOYAL_i + \beta_C^2 CONTROLS_i \quad (3.2)$$

on DS2 where  $p_i = \Pr(Interest_i = 1|x_i)$  for each customer  $i$ . Our variable of interest and the set of control variables are same.

Finally, we estimate the coefficients for the standby upgrade request using

$$\log\left(\frac{p_i}{1-p_i}\right) = \beta_0^3 + \beta_L^3 LOYAL_i + \beta_{price}^3 PRICE_i + \beta_C^3 CONTROLS_i \quad (3.3)$$

on DS3 where  $p_i = \Pr(Upgrade_i = 1|x_i)$  for each customer  $i$ . Given that Nor1 offers the same standby upgrade for different prices to different customers and the

<sup>14</sup>Note that we do this analysis for each hotel separately.



customers see the price as they make their decision at this stage, we add *PRICE* as an independent variable.

### 3.5.2 PRELIMINARY RESULTS

Our estimations provide coefficients for loyalty status in each step of the decision-making for each hotel. We observe three main patterns for the loyalty coefficients of each step: In the first group of hotels (2 out of 8), we find that loyalty customers are more likely to book premium rooms initially ( $\beta_L^1 > 0$ ), more likely to click the banner ad ( $\beta_L^2 > 0$ ) and more likely to request an upgrade ( $\beta_L^3 > 0$ ). This suggests that the loyalty customers in these hotels have a higher valuation for the premium rooms.<sup>15</sup> In the second group of hotels (3 out of 8), we find that loyalty customers are only more likely to click the banner ad ( $\beta_L^2 > 0$ ), which suggests higher awareness of the standby upgrade program. Finally, in the third group of hotels (3 out of 8), we see that loyalty customers are less likely to book premium rooms initially ( $\beta_L^1 < 0$ ), but more likely to click the banner ad ( $\beta_L^2 > 0$ ) and more likely to request an upgrade ( $\beta_L^3 > 0$ ).<sup>16</sup> These coefficients are consistent with our expectations for the strategic customer behavior. In Table 3.3, we report the loyalty coefficients (for the three steps) and price coefficients (only for the last step) for three representative hotels, each following a different pattern.

In summary, our reduced-form analysis shows that loyalty membership does appear to have an effect on the decision-making, but this effect is not consistent across all hotels. In addition, we assume a fixed loyalty effect in this analysis, however it is not clear whether the loyalty membership has an effect on all loyalty customers, therefore we take a detailed look in the loyalty customers' behavior in the next section.

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<sup>15</sup>Remember that our analytical explanation was based on the assumption that customers who consider standby upgrades do not differ in their valuations for the differential based on their type, myopic or strategic.

<sup>16</sup>Note that *PRICE* has a negative coefficient (which is statistically significant except for two of the properties) in each hotel as one can expect.

Table 3.3 Sequential Logit Results for Three Example Hotels

	Hotel B	Hotel D	Hotel F
$\beta_L^1$	0.193**	-0.169	-0.258**
$\beta_L^2$	0.495***	0.549***	0.820***
$\beta_L^3$	0.423**	0.148	0.877*
$\beta_{price}^3$	-0.187***	-0.179***	-0.216**

\*:  $p < 0.1$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$

### 3.6 MAXIMUM LIKELIHOOD ESTIMATION: PERCENTAGE OF STRATEGIC CUSTOMERS

#### 3.6.1 MODEL DISCUSSION

While it is interesting to know that some customers may act strategically, it is perhaps more useful to know what percentage of customers do so. Therefore, we take another step and use a Maximum Likelihood Estimation (MLE) approach to estimate the actual percentage of strategic customers in the loyalty member population, based on the assumption that this group is a combination of both myopic and strategic customers. We use the *ml* routine in STATA 14 for the analysis.

We start with the assumption that  $\alpha$  percentage of loyalty members are non-myopic.<sup>17</sup> An important challenge here is that we have three decision-making steps, but we need a single  $\alpha$  value to represent the non-myopic group. In other words, we need a procedure which can combine all three steps into one and estimate a single  $\alpha$ . Therefore, we take the following approach:

1. We use the sequential logit model shown in (3.1), (3.2), and (3.3) only on the non-loyalty group to estimate three sets of coefficients  $\hat{\beta} = [\hat{\beta}_1 \hat{\beta}_2 \hat{\beta}_3]$  for the set of control variables (*LOS*, *ADV*, *SAT* for each step, and *PRICE* only for

<sup>17</sup>We do not force the condition of being strategic.

- the last step). Note that we do not estimate a coefficient for loyalty, since all customers in this group are customers without loyalty program membership.
2. Using the sets of estimated coefficients  $\hat{\beta}$  in Step 1, we find the predicted conditional probabilities  $\hat{p}_{ik}$  for each customer in the loyalty group for each step  $k = 1, 2, 3$ . Given the step-by-step nature of the decision-making, we focus on the probabilities for a customer at a specific step. For example,  $\hat{p}_{i2}$  represents the probability of a customer clicking on the banner ad given that she chooses a standard room at the onset. Note that these probabilities represent the scenario where all loyalty members are myopic.
  3. We define four possible decision paths for a customer,  $j$ : (1) booking a premium room, (2) booking a standard room, but not clicking the banner ad, (3) booking a standard room and clicking the banner ad, but not requesting a standby upgrade, and (4) booking a standard room and clicking the banner ad, also requesting a standby upgrade. We calculate the predicted probabilities for each decision path-customer combination ( $j = 1, 2, 3, 4$ ),  $\hat{t}_{ij}$ , using  $\hat{p}_{ik}$ 's.
  4. We estimate a single  $\hat{\alpha}$  and three set of coefficients  $\hat{\theta} = [\hat{\theta}_1 \hat{\theta}_2 \hat{\theta}_3]$ , i.e., coefficients for non-myopic loyalty members, for the same set of control variables maximizing the log-likelihood function

$$\ln \mathcal{L} = \sum_{i=1}^n \sum_{j=1}^4 y_{ij} \ln [\alpha F_j(x_i, \theta) + (1 - \alpha) \hat{t}_{ij}(x_i, \hat{\beta})] \quad (3.4)$$

where  $y_{ij}$  represents the binary outcome for the decision path-customer combination (1 if realized, 0 otherwise),  $F(\cdot)$  is the c.d.f. of the logistic distribution, and  $x_i$  is the set of regressors.

We now interpret  $\hat{\alpha}$  as the proportion of non-myopic customers in the loyalty member population, which is essentially the probability that a customer is non-myopic.

5. Using the new sets of estimated coefficients  $\hat{\theta}$ , we find the predicted conditional probabilities  $\hat{q}_{ik}$  for each customer in the loyalty group for each step  $k = 1, 2, 3$ . In order to understand the differences between the two groups, we compare the two set of predicted conditional probabilities:  $\hat{p}_{ik}$  vs.  $\hat{q}_{ik}$ .

Given the nature of our approach, our non-myopic group can be considered as a group following a different behavior than the myopic group, which may or may not be consistent with the strategic customer behavior described before. Therefore, we call  $\hat{\alpha}$  of loyalty members strategic only if the predicted conditional probabilities for the non-myopic group (compared to the myopic group) follow the patterns expected from strategic customers. The next section explains this process in detail.

### 3.6.2 RESULTS

Using the model explained above, we estimate a single  $\hat{\alpha}$  for each hotel in our data set and calculate the predicted conditional probabilities for each loyalty member for both scenarios, myopic and non-myopic. We use two statistics (for each step) to make the comparison between the two sets of predicted probabilities: (i) the mean of the difference between the predicted probabilities for the non-myopic group and the myopic group, i.e.,  $\frac{\sum_{i=1}^n \hat{q}_{ik} - \hat{p}_{ik}}{n}$  for  $k = 1, 2, 3$  and (ii) the percentage of times the probability for the non-myopic group is higher than the predicted probability for the myopic group, i.e.,  $\frac{\sum_{i=1}^n \mathbb{1}\{\hat{q}_{ik} > \hat{p}_{ik}\}}{n}$  for  $k = 1, 2, 3$ .

We summarize the estimation results<sup>18</sup> across different hotels in Table 3.4. For hotels A, B, C, and H, we see that the non-myopic group is more likely to book premium rooms initially (e.g., by 8% for Hotel B on average), more likely to click on the banner ad (e.g., by 15.6% for Hotel B on average, given that the customer booked a standard room) and more likely to request an upgrade (e.g., by 8.2% for Hotel B on

<sup>18</sup>We use the paired t-test to determine whether the mean of the differences between two samples (non-myopic group and myopic group) differs from 0. We find strong evidence ( $p < 0.001$ ) that the mean of the differences differs from 0 for each hotel.

Table 3.4 Estimation Results for Strategic Behavior

Hotel	$\frac{\sum_{i=1}^n \hat{q}_{ik} - \hat{p}_{ik}}{n}$			$\frac{\sum_{i=1}^n \mathbb{1}\{\hat{q}_{ik} > \hat{p}_{ik}\}}{n}$			$\hat{\alpha}$	Strategic?
	$k = 1$	$k = 2$	$k = 3$	$k = 1$	$k = 2$	$k = 3$		
A	4.54%	12.99%	7.20%	100%	100%	72.3%	100%	No
B	7.99%	15.62%	8.17%	84.6%	96.9%	77.71%	67.6%	No
C	5.79%	53.67%	25.02%	65.3%	100%	100%	26.1%	No
D	-0.72%	11.09%	2.26%	33.8%	89.4%	56.0%	100%	Not clear
E	-15.65%	9.00%	17.02%	18.6%	73.2%	69.2%	42.4%	Yes
F	-8.96%	43.34%	13.87%	15.5%	100%	80.2%	42.2%	Yes
G	-8.63%	36.70%	11.07%	20.8%	63.5%	58.6%	22.1%	Yes
H	11.81%	33.93%	3.17%	55.7%	83.6%	55.5%	31.6%	No

average, given that the customer clicked on the banner ad) compared to the myopic group. This is not parallel to our expectations for strategic customers, therefore we cannot call the non-myopic group strategic for these properties. These non-myopic groups must be composed of customers who have a higher willingness-to-pay for the premium rooms.

On the other hand, for hotels E, F, and G, we find out that the non-myopic group is less likely to book a premium room at the onset (e.g., by 9% for Hotel F on average), but more likely to click on the banner ad (e.g., by 43.3% for Hotel F on average, given that the customer booked a standard room), and more likely to request an upgrade (e.g., by 13.9% for Hotel F on average, given that the customer clicked on the banner ad) compared to the myopic group. This is consistent with our expectations for strategic behavior, providing evidence for strategic behavior in these properties.

For hotel D, although statistics suggest the existence of strategic behavior (and paired t-test supports this), the mean of the differences between non-myopic and myopic groups is very small (0.7%) for the first step of the decision-making, which

may be practically insignificant. In addition,  $\hat{\alpha}$  is 100%, which makes us think that a more detailed analysis is needed (potentially with more data).

### 3.7 CONCLUSIONS AND DISCUSSIONS

The academic interest in investigating customers' strategic behavior, i.e., delaying a purchase strategically anticipating that prices might decrease, has been growing. On the other hand, recent probabilistic products in airline and hotel industries create opportunities for a new form of strategic behavior, i.e. choosing a probabilistic product with an expectation of receiving a high-utility product, for travelers. One example of a probabilistic product is Nor1's standby upgrade program, where discounted availability-based upgrades are offered to customers who book standard rooms and customers are only charged for the upgrade if the premium room is available once they arrive.

In this paper, we investigate the existence and extent of strategic behavior in a hotel setting with standby upgrades. Based on the assumption that non-repeat customers are unaware of these upgrades before the booking (i.e., they are myopic), we investigate how loyalty program members, who are likely to be familiar with these upgrades, make their decisions differently than non-repeat customers. We provide evidence of strategic customer behavior, i.e., choosing a standard room initially and requesting a standby upgrade with the expectation of receiving a premium room through standby upgrades, in three out of 8 hotel properties. We obtain an estimate of 10% to 22% of the customer population to consist of strategic customers (22% to 42% of the loyalty program members) in these properties. On the other hand, we show that loyalty program members in some other properties may actually have higher willingness-to-pay for premium rooms, compared to customers with no loyalty program membership.

Combining our empirical results with detailed information on the hotel properties,

Table 3.5 Comparison of Customer Dynamics

	All		Loyalty		Non-loyalty	
	E,F,G	Other	E,F,G	Other	E,F,G	Other
$LOS = 1$	65.1%	53.2%	70.5%	57.2%	60.0%	48.6%
$ADV = 0$	49.1%	44.8%	48.2%	43.7%	50.0%	46.2%
$SAT = 0$	64.2%	60.5%	64.1%	63.4%	64.3%	57.2%
$LOS = 1, ADV = 0, SAT = 0$	27.1%	21.0%	28.2%	22.0%	26.0%	20.0%
$LOS = 3, ADV = 4, SAT = 1$	2.3%	6.3%	2.1%	5.7%	2.4%	7.0%

we provide two important insights for the hoteliers:

*Strategic behavior is prevalent in the upper midscale hotels near major expressways or business areas.* According to STR reports, the largest chain scale in the United States is made up of the upper-midscale segment (around 20% of all the hotel rooms), i.e., reasonably-priced quality hotels located in major cities or suburban areas, often near major expressways, business areas, shopping areas, and attractions.

Our data set includes seven of these upper midscale brand properties and one upscale brand property. We find that loyalty program members staying in upper midscale hotels near major expressways or business areas (properties E, F, and G in our data) are more likely to be strategic, compared to loyalty program members staying in upper midscale or upscale hotels near attractions (e.g. golf course, theme park), and upper midscale hotels near convention centers and hospital complexes.

We next compare the customer dynamics for properties that exhibit strategic behavior (properties E, F, G) with properties we cannot find evidence for strategic behavior (“Other”).<sup>19</sup> Table 3.5 provides important statistics for this comparison, first for all customers, then for loyalty and non-loyalty customers.

We observe that hotels E, F, and G observe a higher percentage of shorter stays, a higher percentage of customers booking within the last week, but a smaller percentage

<sup>19</sup>Hotel D is omitted in this analysis.

of Saturday stays. Although the largest customer segment in all properties is the customers who stay only one night, book within the last week and do not stay on a Saturday night, hotels E, F, and G have significantly higher percentage of these customers (27.1%) compared to other hotels (21.0%). On the other hand, we observe a completely opposite scenario for one of the other major customer segments, i.e., customers who stay 3 or more nights, book in advance, and stay on a Saturday night. The number for this segment is only 2.3% in hotels E, F, G, although it is 6.3% for the other hotels. Parallel to Yılmaz et al. (2017), these statistics show that strategic customer behavior is prevalent in business-oriented hotels. Note that these statistics are similar in both loyalty and non-loyalty groups, which suggests that the main reason for the strategic behavior is not the differences between loyalty and non-loyalty segments, but the differences in the customer dynamics.

*Hotels should customize the premium room and standby upgrade prices.* Hotels have full control over the standby upgrade prices and also can offer discounts for loyalty program members for premium rooms. Our methodology and results provide guidance to the hotel properties for a better pricing strategy, i.e., how to set standby upgrade prices and when to offer discounts for the premium rooms. When our methodology provides evidence for strategic behavior for a hotel property, a simple but efficient pricing strategy is to offer loyalty program members a discount for the premium rooms, but keep their standby upgrade prices higher (Yılmaz et al., 2017). In the extreme scenario, the hotel property may choose to offer individual premium room and standby upgrade prices to their loyalty program members, based on our model's predicted probabilities.

Note that there are some limitations of our study which suggest future directions to be explored. First, we only have a small set of properties in our complete data set, because many properties offer more than one room upgrade to their customers. Analyzing customers' decision-making process becomes much more complex in this



setting, i.e., requesting multiple room upgrades decreases the customer's chance of getting a specific type of room through standby upgrades compared to requesting a single room upgrade (when both of the requested premium rooms are available at the time of check-in, the hotel assigns one through the system without asking the customer). A choice model considering this scenario may be a good addition to our methodology. Second, we cannot enforce strategic behavior in our analysis, since we do not have any information on the market competition and we do not consider any capacity related issues because we only have booking information for the hotel brand website. When such data is available, a model which takes the competition and capacity (e.g., group bookings etc.) into account may offer an in-depth analysis for the potential equilibrium between the actual award rates and customers' beliefs. Third, we only focus on the basic-tier loyalty customers in this paper, because high-tier loyalty members may qualify for free upgrade eligibility. Although the literature on the hotel and airline loyalty programs has been growing, we believe that an empirical study using a similar data to ours may provide interesting insights on the differences between basic-tier and high-tier loyalty customer decision-making.

## CHAPTER 4

### TEAM-SPECIFIC TICKET OPTIONS

#### 4.1 INTRODUCTION

The North American sports market was worth \$60.5 billion in 2014. Gate revenues is the industry's largest segment, accounting for \$17.7 billion. Revenue management applications such as variable and dynamic pricing have gained popularity over the last few years where most teams enjoy significant revenue improvements.<sup>1</sup> These applications help teams recapture their ticket value from secondary markets, which is a \$5 billion industry by itself.<sup>2</sup>

One reason that the secondary market for tickets is so large is that for many mega sporting events, the two teams that will play in the final game (or four teams in a final-four) are not known until a short period before the game. The NBA Finals, NHL Stanley Cup, and MLB World Series consists of best-of- series (i.e., a head-to-head competition where the two competitors compete to first win the majority of the games), where the competing teams host the games in a pre-set order. However, the NFL Super Bowl, NCAA Men's Basketball Final-Four, and College Football Playoff National Championship are played in a single-game format at a neutral site. The ticketing market for these events starts months (or even years) in advance, which makes matching demand with supply and dealing with the resale market a real challenge for the event organizers.

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<sup>1</sup>Around 50% of all major pro league clubs used variable or dynamic pricing techniques in 2016.

<sup>2</sup>The figures are from PricewaterhouseCoopers Sports Outlook issued in October 2015 ([pwc.com/us/en/industry/entertainment-media/publications/sports-outlook-north-america.html](http://pwc.com/us/en/industry/entertainment-media/publications/sports-outlook-north-america.html))

Table 4.1 Ticket Information for Major Tournaments

Name	Ticket Allocation and Resale Options
Super Bowl (2018)	35% to teams playing, 6.5% to host team, 33.6% to remaining teams, and 25% to NFL Lottery (1000), <i>On Location Experiences</i> packages (9000) Resale market exists (not for public lottery tickets)
NCAA Men's Basketball Final-Four (2016)	26% to four teams playing, 4% to host venue, 30% to lottery, 40% to NCAA, sponsors, media & organizing committee Significant number to <i>PrimeSport</i> packages Resale via <i>NCAA Ticket Exchange</i> or other
College Football Playoff National Championship (2016)	50% to teams playing, 15% to host team, 10% TeamTix team reservations, 25% to College Football Playoff Lottery, significant number to <i>Playoff Premium</i> packages Resale via <i>Fan-to-Fan Ticket Marketplace</i> or other

In these events, a significant portion of the tickets are allocated to teams playing the games while another significant portion is frequently allocated to the fans of hosting team (or city). These allocations are usually made through lotteries where the priority is given to season ticket holders. The organizer then keeps some of the tickets for the organization, players, coaches etc., and allocates the remainder to sponsors, media, hospitality rights holder, and other fans. For details of the allocation of tickets for a sample of major sporting events, see Table 4.1.

The customer base for these mega sporting events is typically more heterogeneous than for a regular season game. There are fans who want to watch the game regardless of the teams playing, just for the experience. On the other hand, there are fans who only want to see the team that they support and therefore face a dilemma: They may buy tickets before the teams are known and risk watching other teams, or they may choose to wait until the teams are known and pay potentially higher prices in

the secondary market (or possibly not even find tickets for the event at any price).

In this paper, we focus on the tickets for the College Football Playoff National Championship game. College Football has a regular season (13 weeks, usually from the first week of September to the last week of November) where teams play a regular season, and Top-4 ranked teams make it to the semi-finals for the national title game. The selection of these four teams is made by a committee (i.e., the Selection Committee) which announces rankings weekly, starting five weeks before the official decision.<sup>3</sup> Fans can use various polls (the AP Poll, Coaches' Poll etc.) during the season, in addition to the Selection Committee's weekly rankings to help predict a given team's probability of being selected. However, over the last 10 years only six (13) of the pre-season Top-2 (Top-5) ranked teams and only eight (16) of the November Top-2 (Top-5) ranked teams made it to the championship game.<sup>4</sup> Although rankings, standings, and the odds provided by the betting market can be used as a proxy, these numbers show that there is a high level of uncertainty about which teams will play in the championship game. In this setting, satisfying the team-fan demand and maximizing ticket revenues is difficult for the organizer, because the finalist teams are known only 9 to 11 days before the final, and the resale market is significant.

Event organizers in similar settings have been working on several solutions in order to solve this demand-supply matching problem, including using conditional tickets/packages and ticket options.<sup>5</sup> Over the last two seasons, a significant portion of College Football Playoff National Championship tickets (around 10%) were allocated to Forward Market Media (FMM), which sold them using TeamTix, i.e., team-specific ticket options for the National Championship game. Here is how these options work: A fan (she) can purchase a ticket option for her favorite team. If the

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<sup>3</sup>This has been the format since the 2014 season.

<sup>4</sup>The AP Poll rankings is used when the Selection Committee rankings are not available.

<sup>5</sup>We provide information in Appendix C about other sports leagues that follow a similar format.

team qualifies to play in the National Championship game, she is obliged to purchase a ticket at face-value to the game. Thus, the total amount she pays is equal to the sum of the option price and the face-value amount. If the team does not qualify, she only pays the option price.

FMM uses a sophisticated approach for the price/capacity decisions for TeamTix, which works similar to a simple revenue management tool with capacity-controls, i.e., price levels rise and fall based on the demand, and ignores how fans react to their teams' performance. Such an algorithm can only passively respond to demand changes, however a successful algorithm should be optimizing prices by updating its demand expectation based on important events such as the game results, ranking changes, etc. We also observe that the algorithm does not respond to the trades in the marketplace, another interesting feature of the TeamTix market.

In this paper, we seek to better understand how customers make their purchasing and reselling decisions in this market. Using a unique data set, we investigate the main drivers of volume changes for market transactions and trade offers. We first show how game results (e.g., win against a top opponent, loss etc.) and rankings can change the market dynamics. In addition, we share our observations for the team market size heterogeneity and fans' game day reaction. Finally, we present evidence of speculative behavior in the market. Thus, our results provide guidance for an event organizer on how to price team-specific ticket options and how to deal with the marketplace.

The remainder of this paper is structured as follows: The next section reviews the literature on the ticket options. §4.3 provides details on TeamTix and its marketplace. §4.4 discusses the customer decision-making process and describes the market dynamics. §4.5 presents our data and empirical approach. §4.6 and §4.7 demonstrate our empirical results on the market transactions and trade offers, respectively. §4.8 concludes with some important managerial insights.

## 4.2 LITERATURE REVIEW

In this paper, we address a new revenue management practice named “team-specific ticket options”. Happel and Jennings (2001) suggest that a potential futures market for major event tickets may be beneficial. Sainam et al. (2010) study the ticket options that can be used in the sports industry. Using a stylized two-fan model (one team-based fan who is interested in watching her team only and one game-based fan who is interested in the game regardless of the teams playing) with a known probability for the occurrence of preferred game, they show that consumer options may result in revenues at least as high as those from advance selling (before finalists are known) and full information pricing (after finalists are known). Additionally, they conduct an empirical study with 155 undergraduate students and show that team-based fans are willing to pay more for the consumer options compared to the tickets. Cui et al. (2014) discuss the pricing strategies for a single game with known teams (or a concert), and show when resale may be beneficial for event organizers who face die-hard fans that arrive early and busy professionals that decide later. The authors show through a stylized two-period model that resale is always beneficial for an organizer using fixed pricing and may also be good for an event organizer using multi-period pricing when the capacity is small. Finally, they offer a revenue improving solution where consumers initially buy an option, which they can exercise at a later date if still interested in the game. Note that in their setting, there is no uncertainty involved about the game to be played, since the teams are known and the main source of uncertainty is the consumer’s valuation for the game.

The team-specific ticket options concept is also discussed in several papers. Balseiro et al. (2011) consider a setup with a knockout tournament where the event organizer sells advance tickets and “tournament options” for each team. The authors focus on the joint problem of pricing and capacity allocation, and using a deterministic approximation they show that options are beneficial only if the demand is high

and fans strictly prefer their own team. Their analysis, however, is limited to the symmetric case (i.e., all teams have equal chances of making it to the final game, equal arrival rates for arrival of fans of different teams, and identical fan valuations). While the previously described work offers some analytical insights, it is important to empirically measure the market response to team performance and rankings/standings, as well as the team-level heterogeneities to correctly price the team-specific ticket options. In this paper, we provide a detailed analysis for market dynamics (with fan and team-level heterogeneities) using a unique data set, which will be described in the next section.

Sainam et al. (2015) take a first cut at understanding fans' decision-making in the "consumer forwards" market. Using a data set for the 2006 NCAA Men's Basketball Final-Four forwards, they analyze the purchase and resale transactions in a team-forward market to understand the drivers of a "good purchase", i.e., if the consumer buys the forward and the team makes it to the Final-Four, and a "good resale", i.e., if the consumer sells the forward and her team does not make it to the Final-Four. After identifying team-based fans, game-based fans, and speculators, they show the factors influencing the likelihood of ending up with a forward on a team that makes it to the Final-Four, and of reselling a forward on a team that does not make it to the Final-Four. Although this paper is an important step to understand the fans' decision-making process, it focuses on the individuals, not the organization in charge of selling the team-specific options. Taking an operations perspective, we focus on the drivers of transaction and offer volumes in the team-specific options market. Through our empirical results, we provide key insights on pricing for an organizer that uses team-specific ticket options.

### 4.3 TEAMTIX

FMM, the provider of TeamTix team-specific ticket options, was the official partner of College Football Playoff during 2015 and 2016 seasons.<sup>6</sup> Other than selling team-specific ticket options for the National Championship game, the company also offered a marketplace through their website for fans to trade these options. The initial option prices were set by the College Football Playoff at the beginning of the season, but prices were then dictated by the demand changes in the market, described as follows.

Fans can buy options directly from the main channel at the market price. Fans who own options can place them for sale (called an *offer*) at any price in the marketplace. These options can be purchased by other fans until the market is closed. In addition, fans who are not willing to pay the current market price or the lowest offer price can also *bid* in the marketplace. In order for a bid to become an actual option, it should be matched to the market price or the lowest offer price in the future. In the marketplace, fans can modify or withdraw their offers and bids at any time (unless a transaction occurs). Note that FMM gets a transaction fee of 10% from buyers and 15% from sellers with \$5 being the minimum.

For marketing purposes, the company tweets transactions as well as announcements for offers and bids for marketing purposes (Figure 4.1). There are three types of tweets: (i) “Market Update”, announcement for an actual transaction, (ii) “Lowest Offer”, announcement of an offer which is higher than the current market price, but lower than all other offer prices, and (iii) “Highest Bid”, announcement of a bid (for the market) which is lower than the current market price, but higher than all other bid prices.<sup>7</sup>

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<sup>6</sup>FMM encountered some legal issues which were not related to TeamTix, and is no longer able to sell TeamTix. A new company, ShooWin, signed a licensing deal and will use FMM’s technology starting with the 2017 season.

<sup>7</sup>The number of options involved (1 to 6 seats), team name, stadium seating level (Zone 400 vs. Zone 100, standard and end zone respectively), and price information are also posted.



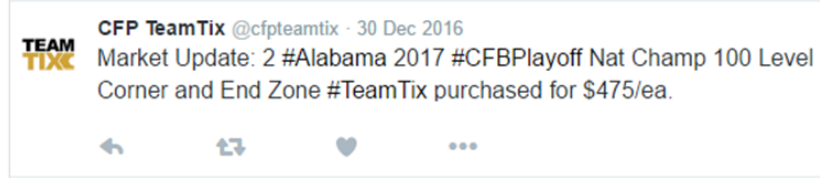


Figure 4.1 TeamTix Tweet for a Market Update

#### 4.4 FANS' DECISION-MAKING PROCESS

Before going into empirical analysis, we create a stylized model to understand the decision-making of a fan and dynamics of TeamTix market.

##### 4.4.1 MODEL SETUP

We define a stylized model using the following setup:

**Timeline:** The season consists of two parts before the final game: Early season ( $T = 1$  to  $T = 2$ ) and late season ( $T = 2$  to  $T = 3$ ).<sup>8</sup> All fans are present in the system at  $T = 1$ .

**Pricing:** (i) A team-specific ticket option for team  $i$  is priced at  $p_1^i$  at  $T = 1$  and  $p_2^i$  at  $T = 2$ .  $p_2^i$ 's are announced at  $T = 2$ .

(ii) A fan with an option for team  $i$  can sell her option from  $p_2^i$  at  $T = 2$ , but has to pay a transaction fee of  $\theta$  (a percentage based on the option price).

(iii) If team  $i$  makes it to the final game, a fan with an option has to exercise the option at  $T = 3$  and pay an additional  $p_f$ , the face value of the ticket.

**Fans' Belief:** (i) At  $T = 1$ , each fan  $j$  of team  $i$  has a belief on the probability that team  $i$  makes it safely to the late season<sup>9</sup>,  $q_{1j}^i$ . (ii) At  $T = 1$ , fan  $j$  of team  $i$  has a

<sup>8</sup>One can think of early season as a certain part of the regular season, and late season as the rest of the regular season and the semi-final game for College Football.

<sup>9</sup>Most College Football teams play 12 games in the regular season, while the teams considered for the semi finals have at most one loss. Therefore, a loss or two in the early season make it almost impossible for the team to make it to the final game.

belief on the probability that team  $i$  makes it to the final game (conditional on the team successfully making it to the late season),  $q_{2j}^i$ , which can be updated at  $T = 2$ .

**Fan Valuations:** (i) Fan  $j$  of team  $i$  has a valuation  $V_{ij}$  for the final game, if team  $i$  plays in the final. If the team does not make it to the final, the fan has a zero valuation.

(ii) Fan  $j$  of team  $i$  has an expectation for  $p_{2j}^i$  at  $T = 1$ , denoted by  $\hat{p}_{2j}^i$ .

#### 4.4.2 OPTIMAL DECISION-MAKING PATH

As shown in Figure 4.2, a fan  $j$  of team  $i$  chooses one of four decision paths to follow:<sup>10</sup>

1. Buy an option at  $T = 1$  and keep it.
2. Buy an option at  $T = 1$  and try to sell it at  $T = 2$ .
3. Do not buy the option in period 1, but buy it in period 2.
4. Do not buy the option.

In order to find the optimal decision path for each fan, we use backward induction starting with  $T = 2$ . If the fan has the option at  $T = 2$ , then she can (i) keep the option with an expected utility of  $q_2(V - p_f)$ , or (ii) sell the option with a utility of  $p_2(1 - \theta)$ . Therefore, a fan would keep the option only if:

$$q_2 \geq K_1 = \frac{p_2(1 - \theta)}{(V - p_f)} \quad (4.1)$$

and try to sell it otherwise. On the other hand, if the fan does not have the option at  $T = 2$ , then she can (i) buy an option with an expected utility of  $-p_2 + q_2(V - p_f)$ , or (ii) do not buy the option with a utility of 0. In this scenario, a fan would buy an option only if:

$$q_2 \geq K_2 = \frac{p_2}{V - p_f} \quad (4.2)$$

<sup>10</sup>For simplicity, we omit the  $i$  and  $j$ 's in the following notation.

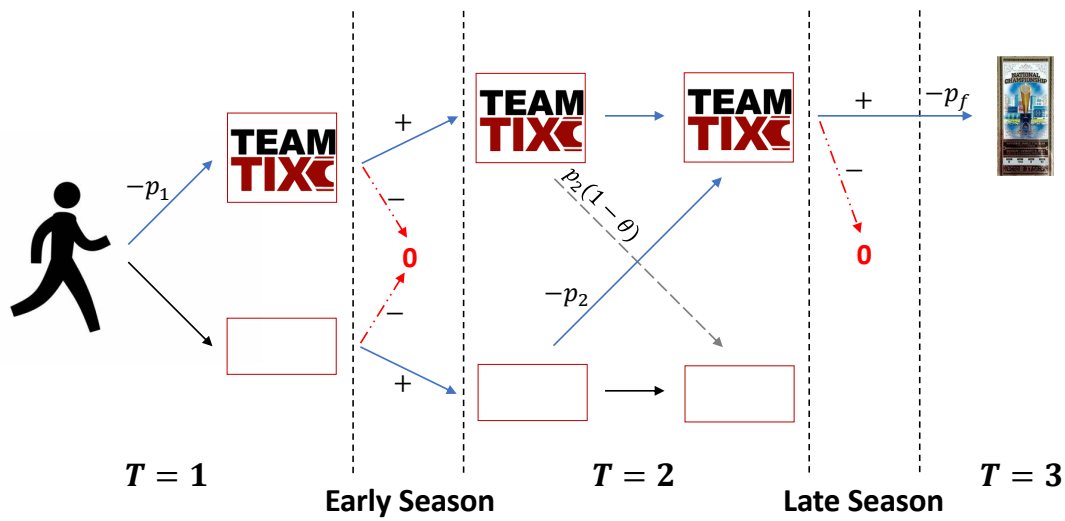


Figure 4.2 Fans' Decision-making Process

The values on each arrow represent the net utility of the actions taken. “+” represents that the team is still “alive” in the competition, “-” represents that team will not make it to the final game.

and would not buy otherwise. We show that a fan’s belief on the probability that team  $i$  makes it to the final game (conditional on the team successfully making it to the late season),  $q_2$ , falls into one of three regions:

- $q_2 \leq K_1$ : The fan should try to sell (if bought at  $T = 1$ ) or should not buy (if not bought at  $T = 1$ ).
- $K_1 \leq q_2 \leq K_2$ : The fan should keep (if bought at  $T = 1$ ) or should not buy (if not bought at  $T = 1$ ).
- $q_2 \geq K_2$ : The fan should keep (if bought at  $T = 1$ ) or buy (if not bought at  $T = 1$ ).

Figure 4.3 represents the decision thresholds for a fan at  $T = 2$ , depending on her  $q_2$ . Note that we have used the wording “try to sell” so far, because a fan may not be able to sell her option at  $T = 2$  if the market demand is less than the total supply. Denote  $\hat{s}$  as a fan’s belief for the chance of selling the option at  $T = 2$ . Note that a fan does not know the true  $p_2$  at  $T = 1$  (but has an expected value  $\hat{p}_2$ ) and may update

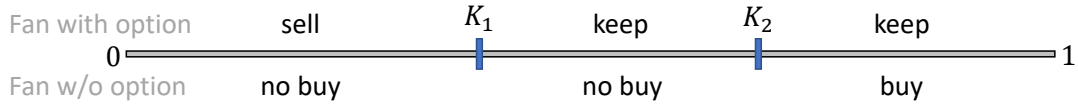


Figure 4.3 Fans' Optimal Decisions at  $T = 2$

$q_2$  at  $T = 2$ . Working backwards, we now present the analysis of decision-making at  $T = 1$ :

- $q_2 \leq K_1$ : If the fan buys an option and then tries to sell, then her expected utility is  $U_{bs} = -p_1 + q_1 \hat{s} \hat{p}_2 (1 - \theta) + q_1 (1 - \hat{s}) q_2 (V - p_f)$ . If she does not buy at all, then the utility is  $U_{nn} = 0$ . Therefore, a fan should buy an option at  $T = 1$  to sell at  $T = 2$  only if:

$$q_1 \geq \frac{p_1}{\hat{s} \hat{p}_2 (1 - \theta) + q_2 (1 - \hat{s}) (V - p_f)} \quad (4.3)$$

and should not buy (at any point) otherwise.

- $K_1 \leq q_2 \leq K_2$ : If the fan buys an option and then keeps it, then her expected utility is  $U_{bk} = -p_1 + q_1 q_2 (V - p_f)$ . If she does not buy at all, then  $U_{nn} = 0$ . Therefore, a fan should buy an option to keep at  $T = 1$  only if:

$$q_1 \geq \frac{p_1}{q_2 (V - p_f)} \quad (4.4)$$

and should not buy (at any point) otherwise.

- $q_2 \geq K_2$ : If the fan buys an option to keep, then  $U_{bk} = -p_1 + q_1 q_2 (V - p_f)$ . If she does not buy at  $T = 1$ , but buys at  $T = 2$ , then her expected utility is  $U_{nb} = q_1 [-\hat{p}_2 + q_2 (V - p_f)]$ . Therefore, a fan should buy an option to keep later only if:

$$q_1 \geq \frac{p_1}{\hat{p}_2} \quad (4.5)$$

and should wait to buy at  $T = 2$  otherwise.

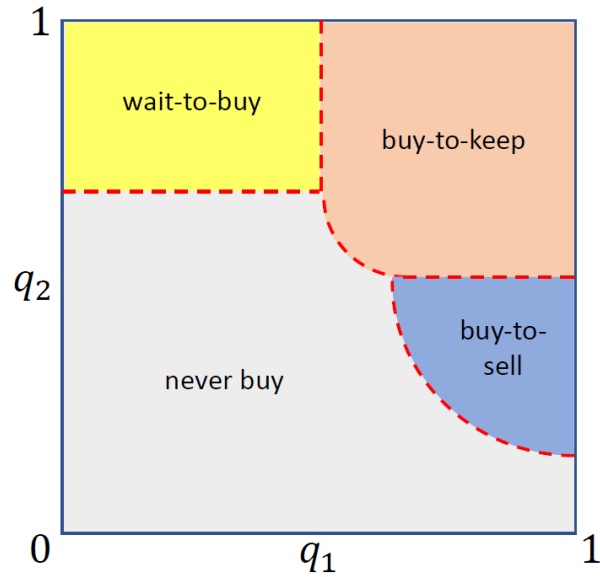


Figure 4.4 Market Segmentation based on  $q_1$  and  $q_2$  for the Numerical Example

#### 4.4.3 EXPECTED FAN BEHAVIOR AND MARKET DYNAMICS

Consider the following example (team  $i$ ) for a given set of market parameters,  $p_1 = 100$ ,  $p_f = 700$ ,  $\theta = 0.25$ , common fan valuation  $V = 1000$ , common belief on the chance of being able to sell  $\hat{s} = 0.5$ , and expectation for the price at  $T = 2$ ,  $\hat{p}_2 = 200$ . We show the market segmentation for team  $i$  based on the optimal actions for  $q_1, q_2 \in (0, 1)$  in Figure 4.4. We see four segments mentioned earlier: (i) Buy-to-keepers with high  $q_1$  and  $q_2$ , (ii) Buy-to-sellers with high  $q_1$  and low  $q_2$ , (iii) wait-to-buyers with low  $q_1$  and high  $q_2$ , and (iv) no buyers. We discuss two potential deviations that may be observed in the market:

*Deviation of  $p_2$ :* We noted earlier that fans have only an expectation on  $p_2$  at  $T = 1$ . However, they may alter their original action if they observe a different  $p_2$  than what they expect. For a fan base who under- or over-estimates  $p_2$ , we provide the changes in the size of the market segments in Table 4.2. Remember that we observe that FMM's algorithm does not change the prices based on the game results or team rankings, but

changes them based on the demand. In this setting, the prices may be cheaper than fan's expectations immediately after an important win, i.e., fans have overestimated  $p_2$ . When this happens, some fans who originally did not plan to buy the option at  $T = 2$  may actually buy. In addition, fans who bought the option at  $T = 1$  to sell may find selling unprofitable and decide to keep. Note that this decrease in the "buy-to-sellers" will be equal to the increase in the "buy-to-keepers". Therefore, we expect an important win to give a positive demand shock to the market. However, this demand shock may increase the prices into a high level, which may lead some "buy-to-keepers" to turn to "buy-to-sellers".

Table 4.2 Potential Changes in the Market Segments after  $p_2$  is Observed

Case	Wait-to-buy	Buy-to-keep	Buy-to-sell
$p_2 > \hat{p}_2$	↓	↓	↑
$p_2 < \hat{p}_2$	↑	↑	↓

*Deviation of  $q_2$ :* If the fan base increases their  $q_2$  for a team after watching the early season ( $T = 1$  to  $T = 2$ ), we would observe more "buy-to-keepers" (i.e., some "buy-to-sellers" become interested in keeping their options) and buyers than expected at  $T = 2$ . Therefore, we expect to see a positive demand shock if the a team does much better than expected. On the other hand, if the team does worse than expectations, e.g., has an unexpected loss, fans may lower their  $q_2$ , which leads to more "buy-to-sellers". In this scenario, we expect to see more offers in the marketplace. Note that a change in  $q_2$  does not change the boundaries of the regions, but the densities for  $(q_1, q_2)$  beliefs.

#### 4.4.4 SPECULATORS

In this subsection, we discuss the case of speculators whose goal is to make profit through buying an option at  $T = 1$  and selling at  $T = 2$ . These speculators have a

zero valuation for the game, regardless of the teams. A speculator basically compares her utility between not buying (with  $U_{nn} = 0$ ) and buying to sell (with  $U_{bs} = -p_1 + q_1 \hat{s} \hat{p}_2 (1 - \theta)$ ). Therefore, a speculator should buy an option to sell at  $T = 1$  only if:

$$q_1 \geq \frac{p_1}{\hat{s} \hat{p}_2 (1 - \theta)} \quad (4.6)$$

and should not get into the market otherwise.

For rational speculators to enter the market, their  $\hat{p}_2$  and  $\hat{s}$  should be high enough. Note that  $\hat{s}$  can be high enough only if there is an expectation for a significant wait-to-buy segment, i.e., fans who have a low  $q_1$  and high  $q_2$ . Given (4.6), we see that an equilibrium with rational speculators can exist only if the fans under-estimate or speculators over-estimate the true  $q_1$ . Note that if some of the fans are not present in the market at  $T = 1$ , speculators will have a higher chance to sell to these late-comers, therefore we expect to see more speculators.

## 4.5 DATA AND EMPIRICAL METHODOLOGY

### 4.5.1 DATA PREPARATION AND VARIABLES

We have collected the following data for the 2015 season of College Football (September 1st to December 31st): Tweets from *@cfpteamtix*,<sup>11</sup> detailed game information (i.e., day/time, location, rivalry, conference game, final score, betting market odds), and rankings (i.e., AP Poll and Selection Committee rankings).<sup>12</sup>

The regular season was 13 week-long (from September 3rd to November 29th). After it ended, the conference championship games were played within the next week. On December 6th, the Selection Committee announced the semi-finals (i.e., Clemson vs. Oklahoma and Alabama vs. Michigan State), which were to be played on

<sup>11</sup>Twitter's Advanced Search feature does not allow us to reach all tweets of an account although it goes until the date of account opening. Therefore, we use *twimemachine.com*, which displays all tweets up to a certain point in the past, to periodically scrape the *@cfpteamtix* feed.

<sup>12</sup>As mentioned earlier, Selection Committee announces rankings starting on November 3rd. We use Selection Committee rankings when available, but use AP Poll rankings for the earlier period.

Table 4.3 Number of Tweets and Related Seat Capacity by Team, Zone, and Tweet Type

Team	Transactions				Offers			
	Zone100		Zone400		Zone100		Zone400	
	Tweets	Seats	Tweets	Seats	Tweets	Seats	Tweets	Seats
Alabama	78	193	70	166	53	188	37	123
Baylor	37	86	40	117	21	51	19	60
Clemson	94	249	93	252	55	164	38	87
Iowa	30	90	38	104	5	17	19	52
Louisiana St	82	233	76	247	23	58	24	89
Michigan St	4	4	69	214	15	48	23	77
Mississippi	18	67	29	99	16	43	18	75
Notre Dame	76	208	88	235	49	154	59	188
Ohio State	57	150	66	184	53	174	47	135
Oklahoma	45	132	39	124	3	7	16	59
TOTAL	521	1412	608	1742	293	904	300	945

December 31st.<sup>13</sup> Our data spans the period from September 1st to December 31st; however, we note that TeamTix were not sold during the conference championship week (from November 30th to December 5th) based on College Football Playoff's decision.

After combining these different data sources, we choose 10 teams with high tweet volumes: Alabama, Baylor, Clemson, Iowa, Louisiana State, Michigan State, Mississippi, Notre Dame, Ohio State, and Oklahoma. Table 4.3 presents the number of tweets and related seat capacities (we call this *volume*) for each team, seating zone and tweet type (transactions vs. offers). For market transactions, we have a total of 1129 tweets for a seat volume of 3154 (Clemson leads with 501 seats). For trade offers, we have a total of 593 tweets for a seat volume of 1849 (Notre Dame leads with 342 seats). We share a weekly snapshot for Alabama's regular season in Appendix C.

We use daily volume (i.e., actual capacity, not the number of tweets) for market

<sup>13</sup>Winners of the semi-final match-ups, Clemson and Alabama, faced each other in the National Championship game on January 11th (2016), and Alabama won the title.



Table 4.4 Variable Descriptions

Name	Detail
$TopWin_{it}$	1 if team $i$ won against a top-10 opponent in the last match, 0 o.w.
$QualWin_{it}$	1 if team $i$ won against an opponent ranked 11-25 in the last match, 0 o.w.
$Loss_{it}$	1 if team $i$ lost the last match, 0 o.w.
$RivalWin_{it}$	1 if team $i$ won against a rival in the last match, 0 o.w.
$WinAO_{it}$	1 if team $i$ won against the odds in the last match, 0 o.w.
$Bye_{it}$	1 if team $i$ had a bye (i.e., did not play a game) in the last week
$Rank_{it}$	Team $i$ 's CFP ranking for a given day (AP Poll ranking when not available)
$RankMom_{it}$	Last change in the ranking of team $i$
$EnterTop4_{it}$	1 if team $i$ entered Top 4 in the last ranking announcement, 0 o.w.
$LeaveTop4_{it}$	1 if the team $i$ left Top 4 in the last ranking announcement, 0 o.w.
$SALES_{ikt}$	The number of seats involved in transactions for team $i$ in zone $k$ on day $t$
$OFFERS_{ikt}$	The number of seats involved in offers for team $i$ in zone $k$ on day $t$

transactions and trade offers (for each team and zone) as our dependent variables. All variables are defined in Table 4.4. Although our variables are at the daily level, the value of our independent variables change only after games or ranking announcements.

#### 4.5.2 COUNT-DATA MODELS: POISSON AND NEGATIVE BINOMIAL

In this section, we explain two count-data models used in our analysis. Our natural starting point is the Poisson model. The Poisson model has a probability mass function (where  $\mu$  is the rate parameter):

$$Pr(Y = y) = \frac{e^{-\mu} \mu^y}{y!}, \quad y = 0, 1, 2, \dots \quad (4.7)$$

with  $E(Y) = Var(Y) = \mu$  (equidispersion property, i.e., mean-variance equality).

We use the following mean parametrization:

$$\mu = e^{x'\beta} \quad (4.8)$$

When the equidispersion property is violated, we use the Negative Binomial distribution whose probability mass function is (where  $\Gamma(\cdot)$  denotes the gamma integral and  $\alpha$  denotes its variance parameter):

$$Pr(Y = y|\mu, \alpha) = \frac{\Gamma(\alpha^{-1} + y)}{\Gamma(\alpha^{-1}\Gamma(y + 1))} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu}\right)^{\alpha^{-1}} \left(\frac{\mu}{\alpha^{-1} + \mu}\right)^y, \quad y = 0, 1, 2, \dots \quad (4.9)$$

with  $E(Y|\mu, \alpha) = \mu$  and  $Var(Y|\mu, \alpha) = \mu(1 + \alpha\mu)$ . The Negative Binomial model allows the use of the same mean parametrization,  $\mu = e^{x'\beta}$ , and leaves  $\alpha$  as a constant.

#### 4.5.3 EMPIRICAL METHODOLOGY

As for our empirical approach, we start with the simple Poisson model. We next use the Poisson Maximum Likelihood Estimator to relax the equidispersion assumption to obtain a robust estimate of the variance-covariance matrix of the estimator. Then, we test for equidispersion  $Var(y|x) = E(y|x)$ . To do this, we follow Cameron and Trivedi (2009) and implement an auxiliary regression of the generated dependent variable,  $\{(y - \hat{\mu}) - y\}/\hat{\mu}$  on  $\hat{\mu}$ , without an intercept term and perform a  $t$  test of whether the coefficient of  $\hat{\mu}$  is zero. If the coefficient of  $\hat{\mu}$  is significantly different than zero, the test suggests the presence of overdispersion. Then, we use the Negative Binomial model, which explicitly models the overdispersion. Finally, we use a Likelihood Ratio test for the hypothesis  $H_0 : \alpha = 0$ .

While using these models in *STATA 14*, we try models with different sets of independent variables in our analyses, from a model with only control variables to a full model:

- Model 1 (base model) includes team and week fixed effects, and the number days of since the last match (or the bye-day of team  $i$ ):  $Team_i, Week_t, Lag_{it}$
- Model 2: Model 1 and game result variables ( $TopWin_{it}, QualWin_{it}, Loss_{it}, RivalWin_{it}, WinAO_{it}, Bye_{it}$ )
- Model 3: Model 1 and ranking variables ( $Rank_{it}, RankMom_{it}$ )

- Model 4: Model 1 and Top 4 related variables ( $EnterTop4_{it}$ ,  $LeaveTop4_{it}$ )
- Model 5: Model 1, game result and ranking variables
- Model 6: Model 1, game result, ranking and Top 4 related variables

## 4.6 SALES IN THE MARKET

In this section, we first present the results of our empirical estimation and discuss the main drivers of the TeamTix sales volume. Then, we discuss the team-level heterogeneity and game day effect on the sales.

### 4.6.1 EMPIRICAL RESULTS

Since all the Poisson models fail the equidispersion test ( $p < 0.001$ ), we use the Negative Binomial model. A Likelihood Ratio test shows that  $\alpha$  is significantly different than 0.

We report the Negative Binomial results for total volume, volume for Zone 400 (standard seats) and Zone 100 (end zone seats) using Model 5 (controls, game result variables and ranking variables) in Table 4.5, because the Top 4 related variables ( $EnterTop4_{it}$ ,  $LeaveTop4_{it}$ ) do not make any improvement in the model fit. Although we share the actual coefficients of the models in Table 4.5, we use *incident rate ratios* for the discussion.<sup>14</sup> Based on our final models, a win against a top-10 ranked opponent is expected to increase the sales by 167% for Zone 400 (191% for Zone 100) for the following week. On the other hand, a team ranked  $n + 1$  receives 14% less Zone 400 (and 15% less Zone 100) sales compared to a team ranked  $n$  for a given week. These results are consistent with our expectations from our stylized model. In addition to these two consistently significant independent variables, our results show

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<sup>14</sup>This is the estimated rate ratio for a unit change in an independent variable, given that the other variables are held constant in the model. For example, an incident rate ratio of 1.5 can be translated to having a rate 1.5 times greater for the dependent variable for a unit change in the independent variable.

Table 4.5 Models on Sale Volume

	Total	Zone 400	Zone 100
TopWin	0.992***	0.982***	1.069***
QualWin	0.145	-0.228	0.555**
Loss	-0.045	-0.448*	0.298
RivalWin	0.238	0.294*	0.374*
WinAO	0.247	0.313	0.448
Bye	-0.416*	-0.464*	-0.265
Rank	-0.153***	-0.157***	-0.150***
RankMom	-0.005	0.024	-0.030
Team Dummies	Yes	Yes	Yes
Week Dummies	Yes	Yes	Yes
Lag	Yes	Yes	Yes
<i>N</i>	860	860	860
<i>R</i> <sup>2</sup>	0.0952	0.111	0.1045

\*:  $p < 0.1$ , \*\*:  $p < 0.05$ , \*\*\*:  $p < 0.01$

that a win against a team ranked 11-25 has a smaller positive effect on Zone 100 sales (by 74%).

Figure 4.5 shows two examples of the predicted outcomes and actual outcomes for Alabama (Zone 400) and Iowa (Zone 400).<sup>15</sup>

#### 4.6.2 TEAM-LEVEL HETEROGENEITY

Including team fixed effects in our model allows us to compare market sizes of teams for a hypothetical scenario with teams having identical performance throughout the season. Using incident rate ratios, we provide the expected percentage of sales for each team compared to the reference team, Alabama (100%), in Figure 4.6. “Big football” schools, Louisiana State and Notre Dame have much larger markets for TeamTix. Interestingly, Clemson’s market size was also significantly larger than Alabama’s. This may be due to the fact that before the 2015 season Clemson had not won a national title or played a title game since 1981. Note that for all these

<sup>15</sup>Because the zero values issue, we cannot provide meaningful prediction fit statistics here.

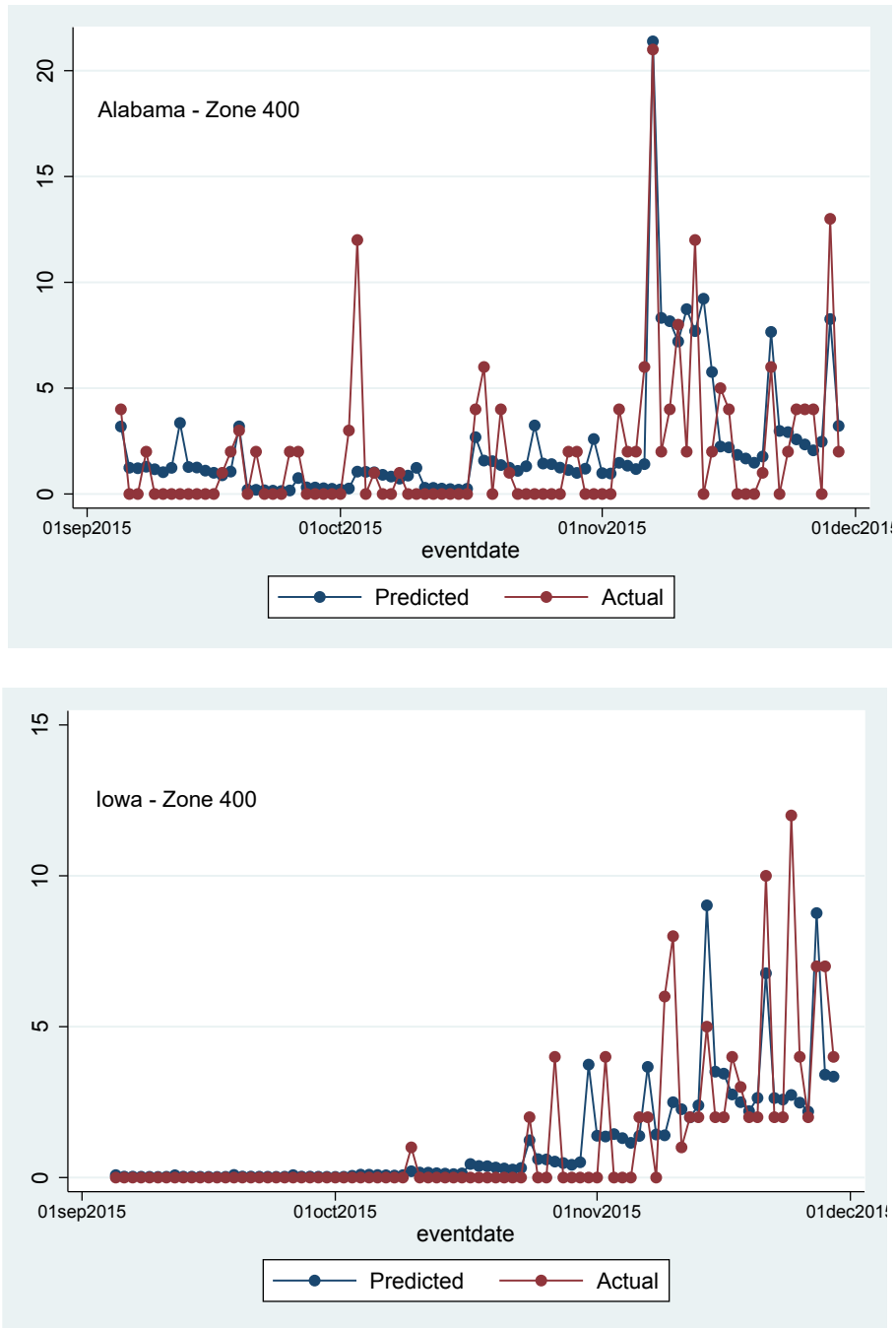


Figure 4.5 Examples of Predicted and Actual Outcomes

teams, the difference for Zone 400 options is larger than that for Zone 100 options. On the other hand, Michigan State and Ohio State market sizes are significantly

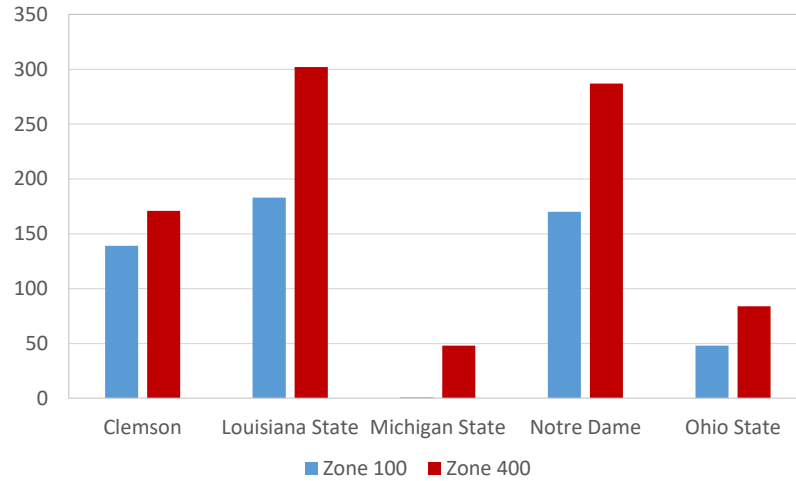


Figure 4.6 Expected Percentage of Sales for an Example Set of Teams

smaller than Alabama.<sup>16</sup> Our results do not show any significant differences between Alabama and the rest of the teams, Iowa, Mississippi, and Oklahoma.

#### 4.6.3 DAILY DIFFERENCES IN THE SALES: IMMEDIATE REACTION TO GAME

Our controls also include week fixed effects and the number of days after the last match (or the “bye day”). Using incident rate ratios, we provide the expected percentage of sales for each day following the game day, compared to the reference day, i.e., game day, in Table 4.6. Our results show that the TeamTix market has significantly more visitors on the game day compared to other days. Note that the other days do not follow a specific pattern (i.e., increase, decrease, U-shape etc.). There are two possible explanations for this. First, fans may only care about the college football (and National Championship Game) while their team is playing a game. Second, fans usually do not get any information (except player injuries etc.) throughout the week, thus there is little benefit on purchasing options until the game day. We discuss the pricing implications of this phenomena in §4.8.

<sup>16</sup>The interestingly low 1% for Michigan’s Zone 100 sales is somewhat expected, because only 4 Zone 100 seats were sold throughout the regular season.

Table 4.6 Expected Percentage of Sales for Each Day Following the Game Day

Day	Zone 100	Zone 400
1	32%	39%
2	32%	38%
3	43%	34%
4	31%	30%
5	28%	27%
6	52%	32%

#### 4.7 DRIVERS OF THE OFFER VOLUME

In this section, we first present the results of our empirical models and discuss the main drivers leading TeamTix owners to offer their options to the market. Then, we share an interesting finding about potential speculators in the market.

##### 4.7.1 EMPIRICAL RESULTS

Similar to the models in the previous section, all Poisson models fail the equidispersion test ( $p < 0.001$ ). Therefore, we additionally use the Negative Binomial model. The Likelihood Ratio test shows that  $\alpha$  is significantly different than 0.

##### 4.7.2 OFFER VOLUME

We report the Negative Binomial results for total volume, volume for Zone 400 and Zone 100 using Model 6 (controls, game result variables, ranking variables, and Top 4 related variables) in Table 4.7, since it provides the best fit. Based on our final models, a game loss is expected to increase the number of selling offers in the market by 220% for Zone 400 (158% for Zone 100). This is parallel to the analytical explanation based on our stylized model. Interestingly, we find that the number of selling offers for a team ranked  $n + 1$  is 12% less for Zone 400 (and 6% less for Zone 100) compared to a team ranked  $n$  for a given week. This is counter-intuitive, because one may expect

Table 4.7 Models On Offer Volume

	Total	Zone 400	Zone 100
TopWin	-0.024	0.947*	-1.332**
QualWin	0.249	0.665	-0.547
Loss	1.012***	1.164***	0.948*
RivalWin	-0.253	-0.493	0.034
WinAO	-0.174	-1.241	1.166
Bye	-0.741*	-1.247**	-0.510
Rank	-0.109***	-0.127***	-0.063*
RankMom	-0.054	0.003	-0.094*
EnterTop4	0.204	0.387	-0.164
LeaveTop4	0.667*	0.631	0.829*
Team Dummies	Yes	Yes	Yes
Week Dummies	Yes	Yes	Yes
Lag	Yes	Yes	Yes
$N$	860	860	860
$R^2$	0.131	0.134	0.1408

that a team's fans try to sell their TeamTix if they lose their hope for their team making it to the National Championship Game.

#### 4.7.3 SPECULATORS IN THE MARKET

Although a team-fan is likely to buy TeamTix for only one team, the current system allows customers to buy TeamTix for multiple teams. We do not have any personal identifiers in our data set, however we suspect that our unexpected finding on the effect of rankings may be due to customers who purchase ticket options to sell if the team performs well, i.e., speculators. Sainam et al. (2015) shows that a significant portion of customers bought options for two to five teams and a small portion bought options for six or more teams in the 2006 College Basketball season, which supports our suspicion.

In order to formally investigate the existence of speculators, we introduce two new variables:  $FinalEnterTop4_{it}$  and  $FinalLeaveTop4_{it}$ , which is equal to 1 if team  $i$  en-



Table 4.8 Models on Offer Volume Considering Speculators

	Total	Zone 400	Zone 100
TopWin	0.067	0.889	-1.137*
QualWin	0.018	0.434	-0.716
Loss	1.044***	1.101***	1.057**
RivalWin	-0.222	-0.471	0.090
WinAO	0.175	-0.842	1.342
Bye	-0.707*	-1.244*	-0.453
Rank	-0.085***	-0.094***	-0.051
RankMom	-0.027	0.037	-0.075
EnterTop4	-1.104**	-0.673	-1.228*
LeaveTop4	1.315***	1.459**	1.462**
FinalEnterTop4	3.918***	3.500***	3.155**
FinalLeaveTop4	-1.102*	-1.135	-1.062
Team Dummies	Yes	Yes	Yes
Week Dummies	Yes	Yes	Yes
Lag	Yes	Yes	Yes
<i>N</i>	860	860	860
<i>R</i> <sup>2</sup>	0.1412	0.1419	0.1463

tered and left respectively, the Top 4 after a Selection Committee ranking announcement during last 25 days of the regular season. We run a similar set of Negative Binomial models and present our results in Table 4.8. We observe an interesting case here: Although entering the Top 4 has a negative effect on the number of seats offered in the market before November, entering the Top 4 in November actually increases the number of seats offered.<sup>17</sup> This is parallel to our analytical explanation for the speculators and suggests that there are speculators in the market who buy options early in the season and sell later when the team climbs in the rankings.

<sup>17</sup>In order to show this, we test if the sum of the coefficients for *EnterTop4* and *FinalEnterTop4* is different than zero. Our tests show the sum is significantly higher than zero ( $p < 0.001$  for Zone 400,  $p < 0.05$  for Zone 100).

## 4.8 CONCLUSIONS AND MANAGERIAL INSIGHTS

In this paper, we focus on an innovative revenue management practice for the sports industry, named team-specific ticket options. This product gives a fan the chance to buy an option for sporting events where the two teams that will play are not known in advance and the fan only pays the ticket face value if his/her team makes it to the final. It reduces the risk for fans (i.e., ending up with a ticket in hand to watch other teams or trying to find a ticket through highly overpriced resale market), and also helps the organizer to match demand and supply during the short time between the announcement of the finalists and the game day.

College Football Playoff, the organizer of the College Football National Championship game, partnered with Forward Market Media (FMM), who offers team-specific options called TeamTix, in the last two years and allocated a significant portion of the stadium capacity to TeamTix. On the other hand, the implementation was not a success because of several reasons. In this paper, we take a look at the TeamTix market combining behavioral dynamics and a unique data set we created for 2015 season.

We provide the following insights for event organizers and team-specific ticket option platforms:

*Pricing of team-specific ticket options:* As mentioned earlier, the price of TeamTix is dictated by the market demand. In addition to the significant team, rank and week effects, we show that a win against a Top 10 ranked opponent increases the sale volume during the week. We also observe significantly more sales on the day the team plays a game.

The traditional revenue management approach used by FMM's algorithm naturally increases the price when the demand rate gets higher than expected, by closing cheap fare classes. Therefore, when the team wins against a Top 10 ranked opponent, a sudden increase in the demand rate is observed as suggested by our model in

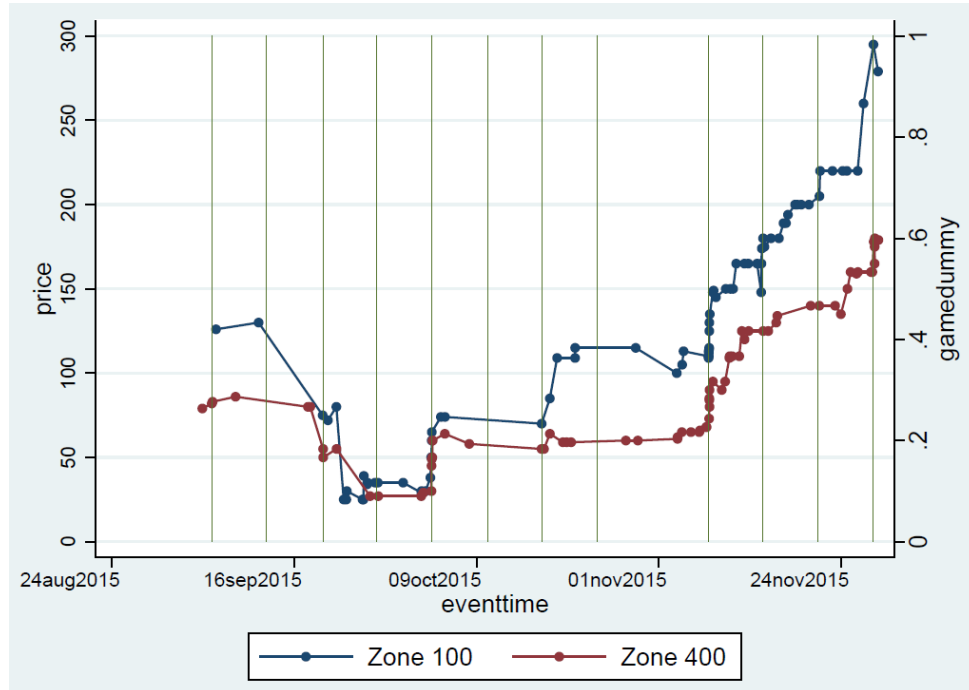


Figure 4.7 Price for Alabama TeamTix (Regular Season)

§4.6 and the prices increase. See the price changes for Alabama Zone 100 and Zone 400 options in Figure 4.7 for the 5th, 7th and 9th games<sup>18</sup> where Alabama had wins against the top 10 opponents.

On the other hand, we observe that the algorithm spends a significant amount of time to detect the demand increase. However, a better Revenue Management system should effectively respond to a top win by updating the demand expectation (as predicted by our model) and increase the price into a higher level immediately. Since the price optimization is beyond the scope of our paper, we only provide some general guidelines for the organizers:

- While setting base prices at the beginning of the season, the platform should consider not only the team's chance of making it to the final game, but also the market size.

<sup>18</sup>Note that game times are marked by vertical lines.

- Since fans can only update the probabilities of their team making it to the final after observing the result of the last match and team performance (and the corresponding rank change), prices should be updated immediately after each match is over, and adjusted only if demand deviates from the predicted.
- Given we observe more market movements on the game days, the platform should monitor the changes very closely.

*Marketplace and Speculators:* Although team-specific options is a way to deal with issues related to the resale market, the existence of a marketplace for TeamTix creates its own problems.<sup>19</sup> Our analysis shows that there are speculators in the market who buy the options from a cheaper price and sell at the end of the season if the team does well. This may be happening because of the following reasons: (i) Most fans do not form strong expectations for their team at the beginning of the season, but then may highly inflate their expectations after seeing their team performing. (ii) Speculators are aware of the TeamTix market and buy TeamTix earlier than most of the fans.

The current marketplace allows people to offer for trade from the price of their choice. Therefore, we observe many occurrences where a fan (or a speculator) sells its TeamTix a little bit cheaper than the main channel. The pricing algorithm should be able to respond this by using some type of matching strategy, especially for the teams with low market sizes because the chance of selling team-specific ticket options equal to the allocated capacity is really low and each trade directly decreases the platform profits (i.e., platform can only get a transaction fee). We do not present an analysis on this, however we believe that it is an interesting future research direction.

There are several limitations in our study. First, we specifically focus on the seat capacities, and ignore the number of tweets which may be helpful in several cases. For example, two people offering two seats each is identical to one person offering

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<sup>19</sup>We have anecdotal evidence that marketplace has a positive effect on people who are indecisive about buying TeamTix.

four seats in our models. Combining tweet volume and seat capacity may be a good step for extending our analysis. Second, we do not have personal identifiers in the data, therefore we cannot really know if there are any fans who bought for multiple teams, and offered their TeamTix to the market at different times. Finally, we do not consider the final location in our study. We believe that the pricing system must adjust the team market bases for the location of the final site. For example, the 2016 Championship game (of 2015 season) was played in Phoenix, AZ. The location was quite far for all 10 teams of analysis and the resulting resale market prices were cheaper than expected. On the other hand, the 2017 Championship game (of 2016 season) featured the same two teams, Alabama and Clemson, although the resale market prices were much more expensive (around three to five times more) compared to the previous season, because the game was in Tampa, FL. Given that the fans have a side option to wait for the resale market, the pricing algorithm should make the necessary adjustments for the teams which are close to the final game site.

We believe that team-specific tickets is a promising area of future research for the Operations Management field, and may have potential areas of application outside of the current domain. For example, hotels near the final game site can easily allocate some rooms for team fans and sell team-specific options. This actually works better than regular options where fans have the flexibility not to exercise the option (which creates a high-level of uncertainty), because team-specific options are automatically exercised when a team makes it to the final. Although the related airline problem would be too complicated because the origin-team combinations can be too many, we believe that team-specific options can be useful for the origin cities with a high density fan base for a specific team.

## CHAPTER 5

### CONCLUSION AND FUTURE RESEARCH

In this dissertation, we discuss two Revenue Management practices with probabilistic elements (i.e., standby upgrades and team-specific ticket options). While using such practices, hotels and event organizers are susceptible to strategic customer behavior. We use both analytical and econometric approaches to investigate our research questions.

Chapter 2 and 3 of this dissertation are on standby upgrades, which is a fairly new innovative practice in the hotel industry, while Chapter 4 studies team-specific ticket options, an innovative practice used in sporting events. In particular, Chapter 2 discusses how to optimally price standby upgrades (i.e., a practice where the guest is only charged if the discounted upgrade is available at the time of arrival) and evaluates their benefits through an analytical model. Chapter 3 uses a major hotel chain's booking and standby upgrades data to investigate the extent of strategic guest behavior through empirical analysis. Chapter 4 studies fans' decision-making process for team-specific ticket options for the College Football Championship game using a unique data set.

Chapter 2 has been already published in *Manufacturing & Service Operations Management*. For Chapter 3, our next step would be to increase the number of the hotel properties analyzed. In order to do this, we will work on the complex problem of multiple standby upgrade offers. In addition, instead of searching for strategic behavior, we may create several different strategic behavior models and estimate the percentage of strategic customers based on these different models. Free upgrade

eligibility is another interesting issue we can focus on.

For Chapter 4, our next step would be to prepare a similar 2016 College Football season, which may help us generalize our results and offer new insights. We also expect to see the importance of the location of the final match. Empirically, although our current model provides a reasonable fit, we plan working on a hurdle-like model which takes tweets and seats into account at two different steps and potentially provides a much better fit. Finally, we may revisit our stylized model in order to focus on the price optimization problem. Then, we can use our data sets to test how good our suggestions work in real life scenarios.

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## APPENDIX A

### SUPPLEMENT FOR CHAPTER 2

#### **Analysis on Assumption 4:**

An alternative approach for setting  $p$  and  $p_S$  would be to use a set of two valuations ( $v_S, v_P$ ) for the standard and premium rooms, respectively (priced at  $s$  and  $s + p$ ). When the standard room price ( $s$ ) is fixed throughout the selling horizon, this approach can provide closed-form solutions for the optimal prices, within certain distributional assumptions on the valuations of standard and premium rooms. It is difficult to implement this approach in practice, however, for two main reasons: First, hotels already use sophisticated techniques for setting the standard room prices, which leads to dynamically changing prices over the selling horizon. Second, hotels have historically pegged the price of their premium rooms to the price of their standard room prices, providing little to no variability in the pricing differential between these two types of room. This makes the estimation of the joint distribution of the customers' valuations for the standard and premium rooms extremely difficult. We avoid these problems by only focusing on the valuation for the premium room differential,  $v = v_P - v_S$ . Note that this approach is identical to the two-valuation approach for customers with  $v_S \geq s(t)$ , where  $s(t)$  is the standard room price at time  $t$  of the selling horizon. Since a guest searching for a hotel in an online travel agency (e.g., Expedia) or the hotel brand website will first be exposed to the standard room prices at different hotels<sup>1</sup>, it is reasonable to assume that guests of interest in our

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<sup>1</sup>The common practice is to show the lowest rate of the hotel for online travel agencies and to show the best available rate (BAR) of the different brand hotels in the area for the hotel chains. Therefore, guests can see different room types only after choosing a specific hotel.

analysis have  $v_S \geq s(t)$ , i.e., a guest who finds the standard room price to be too high at a specific property would not search for premium rooms in the same hotel.

Next, we show the equivalence of the two-valuation and differential-valuation approaches. A myopic guest first chooses the utility maximizing action among the following options: No booking (utility of 0), booking a standard room (utility of  $v_S - s(t)$ ) and booking a premium room (utility of  $v_P - [s(t) + p]$ ). She books the standard room if  $v_S \geq s(t)$  and  $v_S - s(t) \geq v_P - [s(t) + p]$ . Note that the second condition is identical to  $v \leq p$ . When she sees the standby upgrade offer, she then chooses the utility maximizing action between rejecting the offer (utility of  $v_S - s(t)$ ) and accepting the offer (utility of  $v_P - [s(t) + p_S]$ ). The second utility can be written as  $(v_S + v) - [s(t) + p_S]$ . She accepts the offer if and only if  $v_S - s(t) \leq (v_S + v) - [s(t) + p_S]$ , which is identical to the condition  $v \geq p_S$ . Here is a numerical example: Consider our partner's property in New Orleans, LA with  $p = 45$  and  $p_S = 20$ . Assume that Guest A has a valuation set  $(v_S, v_P) = (220, 250)$  and visits the hotel website 20 days before her day of stay and sees a standard room price of  $s(t_1) = 189$  (and a premium room price of  $s(t_1) + p = 234$ ). In this scenario, she books the standard room because her utility from the standard room is higher than her utility from booking the premium room ( $220 - 189 = 31 > 250 - 234 = 16$ ). After booking the standard room, she receives and accepts the standby upgrade offer, because she has a chance to gain an additional utility of  $[250 - (189 + 20)] - 31 = 10$  if the premium room is awarded. Using our notation, since  $v = 250 - 220 = 30$ , the customer first books a standard room ( $v < p$ ) and then chooses the standby upgrade ( $v > p_S$ ). Now consider Customer B with the same valuation set but who visits the hotel website only 3 days before the day of stay and sees a standard room price of  $s(t_2) = 279$  (and a premium price of  $s(t_2) + p = 324$ ). Since her utility is negative for the standard room and the premium room ( $220 - 279 = -59$ ,  $324 - 250 = -74$ ) at the time of booking, she does not book a room.

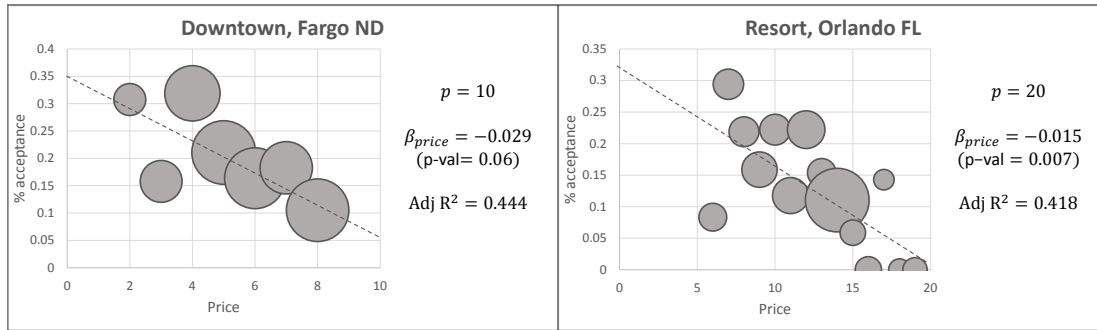


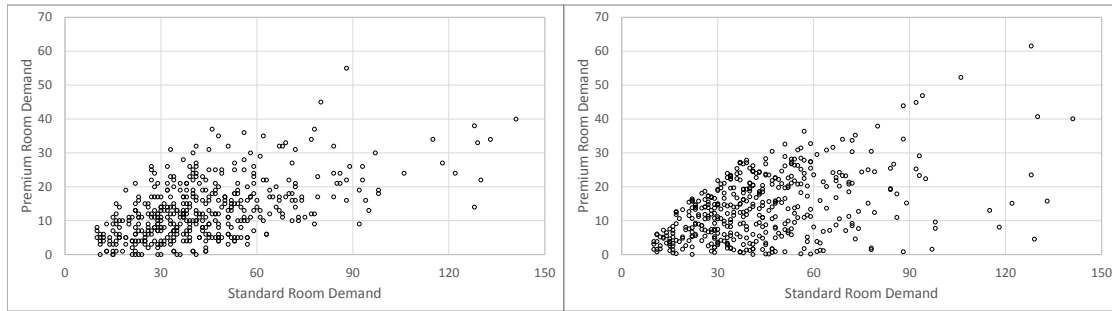
Figure A.1 WLS Estimation on Two Properties to Test for the Uniform Pricing Assumption

$p$ : Fixed differential,  $\beta_{price}$ : coefficient of price, Bubble size: weight of the data point in WLS

To help validate our linear price-demand model assumption, we utilize our partner's data on the booking and standby upgrade decisions. Note that the data does not allow for a price sensitivity analysis of the differential since the hotels use fixed price differentials. However, Nor1 changes the standby upgrade prices over time even though they do not have access to a hotel's remaining room capacity. This variability in standby upgrade prices allows us to analyze the price sensitivity of guests to the standby upgrade offers. To do so, we measure the association between the standby upgrade price offered and the customers' acceptance ratio by using a linear regression approach. Since some prices are offered more than others, we use a weighted-least-squares (WLS) estimation, where we use the square root of the number of guests offered each price point as the weights. Our analysis of 8 different properties shows that the coefficient for the standby upgrade price is negative and significant for all the properties. Figure A.1 illustrates the results for two of these properties. In order to test any nonlinear relationships between the standby upgrade price and the acceptance ratio, we also tried fitting the natural logarithm of price and the price-squared as independent variables, but the linear relationship provided the best fit.

#### Analysis on Assumption 5:

In the dynamic pricing literature, there are two common approaches for modeling the potential market size: Stochastic arrivals which can capture changing product



(a) Realized Demand

(b) Modeled Demand

Figure A.2 Standard vs. Premium Room Demand at a New Orleans Hotel

valuations and perceptions on the probability of a product being available over time (Aviv and Pazgal, 2008; Elmaghraby et al., 2009; Yin et al., 2009; Osadchiy and Vulcano, 2010), and simultaneous arrivals with a deterministic market size (Liu and van Ryzin, 2008; Gallego et al., 2008). In the latter, the total number of customers is assumed to be known by the seller, and when the customers arrive, they make their decision based on the prices of the buy-now vs. wait options.

Our analysis of 16 months of hotel booking data shows that standard room demand and premium demand are positively correlated, however the correlation is not as strong as one may expect. There are many days where the standard room demand is high while the premium room demand is relatively low (see Figure A.2a for an example from a hotel property in New Orleans, LA where the correlation coefficient between the standard room demand and premium room demand is only 0.55). We think the reason as follows: For our guests, the ones who look for the cheapest deal in the market have  $v = 0$ . These guests book standard rooms (or do not buy if a competitor has a better deal), and are irrelevant for the premium room market. On the other hand, other guests (with  $v > 0$ ) make a decision between purchasing a standard room with or without a standby upgrade and a premium room. The partitioning of these two groups is based on market dynamics such as standard room price paths, competitors' price paths, existence of group reservations, etc. Therefore, we choose the simultaneous arrivals approach since guest valuations for the premium



room differential do not change over time, but assume a stochastic market size to capture the uncertainty. For validation purposes, we simulate premium demand as a function of standard room demand and find that the modeled outcomes are quite close to the realized outcomes (see Figure A.2b).

## APPENDIX B

### PROOFS FOR CHAPTER 2

#### Proof of Lemma 1:

In this proof, we derive the optimal prices and expected revenues in the myopic case for a given  $X_U$ .

For each  $X_U$  value, we have three candidate pricing strategies for the optimal price set. These strategies have different expected revenue functions and constraints. We first analyze Strategy 1 and Strategy 3 and show the optimal price sets under these, and then use them to construct a solution for Strategy 2.

- For Strategy 1, the expected revenue function can be written as:

$$\Pi_{MY1} = \frac{X_U}{2} [p_S p - p_S^2 + p - p^2] \quad \text{where } X_U(1 - p_S) \leq 1$$

We solve the unconstrained problem first. First order conditions (FOC) give us (the constant is ignored):

$$\frac{\partial \Pi_{MY1}}{\partial p} = p_S + 1 - 2p = 0 \quad \frac{\partial \Pi_{MY1}}{\partial p_S} = p - 2p_S = 0$$

The optimal price set is  $(p_S, p) = (\frac{1}{3}, \frac{2}{3})$  for the unconstrained problem (the objective function is concave as its Hessian is negative definite). We have two possibilities:

$\Rightarrow$  The constraint is satisfied when  $X_U \leq \frac{3}{2}$ ; therefore, the optimal price set for the unconstrained problem is the optimal price set for the constrained problem in this range.

$\Rightarrow$  The constraint is violated when  $X_U > \frac{3}{2}$ . Because of the concavity of the expected revenue function,  $X_U(1 - p_S) = 1$  must be binding at optimality. Since the constraint is not a function of  $p$ , we can show (through the Lagrange method) that  $p_S + 1 - 2p = 0$  must be satisfied. Therefore,  $p_S = \frac{X_U - 1}{X_U}$  and  $p = \frac{2X_U - 1}{2X_U}$ .

For Strategy 1, the optimal price set and resulting expected revenue for different  $X_U$  values are as follows:

$$(p_S, p) = \begin{cases} (\frac{1}{3}, \frac{2}{3}) & \text{if } X_U \leq \frac{3}{2} \\ (\frac{X_U - 1}{X_U}, \frac{2X_U - 1}{2X_U}) & \text{if } X_U \geq \frac{3}{2} \end{cases} \quad \Pi_{MY1} = \begin{cases} \frac{X_U}{6} & \text{if } X_U \leq \frac{3}{2} \\ \frac{4X_U - 3}{8X_U} & \text{if } X_U \geq \frac{3}{2} \end{cases}$$

- For Strategy 3, the expected revenue function can be written as:

$$\Pi_{MY3} = \frac{1}{X_U} \left[ pX_U - \frac{p - p_S}{2 - 2p} - \frac{p_S}{2 - 2p_S} \right] \quad \text{where } X_U(1 - p) \geq 1$$

We solve the unconstrained problem first. FOC give us (the constant is ignored):

$$\frac{\partial \Pi_{MY3}}{\partial p} = X_U - \frac{1 - p_S}{2(1 - p)^2} = 0 \quad \frac{\partial \Pi_{MY3}}{\partial p_S} = \frac{1}{2 - 2p} - \frac{1}{2(1 - p_S)^2} = 0$$

The optimal price set is  $(p_S, p) = \left( 1 - \frac{1}{\sqrt[3]{2X_U}}, 1 - \frac{1}{\sqrt[3]{(2X_U)^2}} \right)$  for the unconstrained problem (the objective function is concave as its Hessian is negative definite).

We have two possibilities:

$\Rightarrow$  The constraint is satisfied when  $X_U \geq 4$ ; therefore, the optimal price set for the unconstrained problem is the optimal price set for the constrained problem in this range.

$\Rightarrow$  The constraint is violated when  $X_U < 4$ . Because of the concavity of the expected revenue function,  $X_U(1 - p) = 1$  must be binding. Since the constraint is not a function of  $p_S$ , we can show (through Lagrange method) that  $\frac{1}{2 - 2p} - \frac{1}{2(1 - p_S)^2} = 0$  must be satisfied. Therefore,  $p_S = \frac{\sqrt{X_U - 1}}{\sqrt{X_U}}$  and  $p = \frac{X_U - 1}{X_U}$ .

For Strategy 3, the optimal price set and resulting expected revenue for different  $X_U$  values are as follows:

$$(p_S, p) = \begin{cases} \left( \frac{\sqrt{X_U}-1}{\sqrt{X_U}}, \frac{X_U-1}{X_U} \right) & \text{if } X_U \leq 4 \\ \left( 1 - \frac{1}{\sqrt[3]{2X_U}}, 1 - \frac{1}{\sqrt[3]{(2X_U)^2}} \right) & \text{if } X_U \geq 4 \end{cases}$$

$$\Pi_{MY3} = \begin{cases} \frac{\sqrt{X_U}-1}{\sqrt{X_U}} & \text{if } X_U \leq 4 \\ 1 - \frac{3}{\sqrt[3]{(2X_U)^2}} + \frac{1}{X_U} & \text{if } X_U \geq 4 \end{cases}$$

- We have found two boundary points so far:  $X_U = \frac{3}{2}$  and  $X_U = 4$ . Our expected revenue function for Strategy 2 was as follows:

$$\Pi_{MY2} = \int_0^{1/(1-p_S)} \frac{R_1}{X_U} dx + \int_{1/(1-p_S)}^{X_U} \frac{R_2}{X_U} dx$$

where  $X_U(1-p_S) \geq 1$  and  $X_U(1-p) \leq 1$

1) When  $X_U \geq \frac{3}{2}$ , the optimal price set of Strategy 1 is an asymptotically feasible price set for Strategy 2 since the constraint  $X_U(1-p_S) = 1$  is binding.

2) When  $X_U \leq 4$ , the optimal price set of Strategy 3 is an asymptotically feasible price set for Strategy 2 since the constraint  $X_U(1-p) = 1$  is binding.

By definition, the optimal price set under Strategy 2 is the one with the maximum expected revenue of all feasible price sets. Thus, Strategy 2 cannot be worse than Strategies 1 and 3 in the range of  $1.5 \leq X_U \leq 4$ .

After noting these, the expected revenue function can be written as:

$$\Pi_{MY2} = \frac{1}{X_U} \left[ p_S X_U + \frac{X_U^2}{2} (p_S p - p_S + p - p^2) - \frac{p_S}{2 - 2p_S} \right]$$

We solve the unconstrained problem first. FOC give us:

$$\frac{\partial \Pi_{MY2}}{\partial p} = X_U(p_S + 1 - 2p) = 0 \quad \frac{\partial \Pi_{MY2}}{\partial p_S} = 1 - \frac{X_U(1-p)}{2} - \frac{1}{2X_U(1-p_S)^2} = 0$$

The optimal price set must satisfy:

$$p = \frac{p_s + 1}{2} \quad \text{and} \quad p_s = 1 - \frac{4}{X_U} + \frac{2}{X_U^2(1 - p_s)^2}$$

We discard the solutions violating  $0 \leq p_s \leq p \leq 1$ . Our analysis shows that the optimal price set for the unconstrained problem violates  $X_U(1 - p_s) \geq 1$  and  $X_U(1 - p) \leq 1$  when  $X_U < \frac{3}{2}$  and  $X_U > 4$ . Moreover,  $X_U(1 - p_s) = 1$  must be binding for  $X_U < \frac{3}{2}$ ; therefore,  $p_s = \frac{X_U - 1}{X_U}$ . Through Lagrange method, we know that  $\frac{\partial \Pi_{MY2}}{\partial p} = 0$  must be satisfied in this scenario. Therefore  $p = \frac{2X_U - 1}{2X_U}$ . With the same approach,  $X_U(1 - p) = 1$  must be binding for  $X_U > 4$ ; therefore,  $p = \frac{X_U - 1}{X_U}$ . Through Lagrange method, we know that  $\frac{\partial \Pi_{MY2}}{\partial p_s} = 0$  must be satisfied in this scenario. Therefore,  $p_s = \frac{\sqrt{X_U - 1}}{\sqrt{X_U}}$ .

For Strategy 2, the optimal price set and resulting expected revenue for different  $X_U$  values are as follows:

$$(p_s, p) = \begin{cases} \left( \frac{X_U - 1}{X_U}, \frac{2X_U - 1}{2X_U} \right) & \text{if } X_U \leq \frac{3}{2} \\ \left( \frac{3X_U - 4}{3X_U} - \frac{8(1 - i\sqrt{3})}{3\kappa} - \frac{\kappa(1 + i\sqrt{3})}{6X_U^2}, \right. \\ \left. \frac{3X_U - 2}{3X_U} - \frac{4(1 - i\sqrt{3})}{3\kappa} - \frac{\kappa(1 + i\sqrt{3})}{12X_U^2} \right) & \text{if } \frac{3}{2} < X_U < 4 \\ \left( \frac{\sqrt{X_U - 1}}{\sqrt{X_U}}, \frac{X_U - 1}{X_U} \right) & \text{if } X_U \geq 4 \end{cases}$$

$$\text{where } \kappa = \sqrt[3]{27X_U^4 - 64X_U^3 + 3\sqrt{3}\sqrt{27X_U^8 - 128X_U^7}}.$$

Let  $\kappa = a + ib$ , and its complex conjugate  $\bar{\kappa} = a - ib$ . Our analysis shows that  $\kappa\bar{\kappa} = 16X_U^2$  when  $\frac{3}{2} \leq X_U \leq 4$ . Multiplying the second term of  $p_s$  in the second row with  $\bar{\kappa}$  gives  $p_s = \frac{3X_U - 4}{3X_U} - \frac{\bar{\kappa}(1 - i\sqrt{3})}{6X_U^2} - \frac{\kappa(1 + i\sqrt{3})}{6X_U^2}$ . The complex parts of the second and third terms cancel out and we have  $p_s = \frac{3X_U - 4}{3X_U} - \frac{2b\sqrt{3} - 2a}{6X_U^2}$ . Using the same iterations for  $p$ , we can show that  $p = \frac{3X_U - 2}{3X_U} - \frac{b\sqrt{3} - a}{6X_U^2}$ . In order to make it easier to follow, we use  $\Upsilon = \frac{b\sqrt{3} - a}{6X_U^2}$ .

Based on the prices given above, the resulting expected revenue for different  $X_U$  values are as follows:

$$\Pi_{MY2} = \begin{cases} \frac{4X_U-3}{8X_U} & \text{if } X_U \leq \frac{3}{2} \\ \frac{9X_U(6\Upsilon(X_U(\Upsilon(X_U\Upsilon-2)+2)-3)+5)-44}{36X_U(3X_U\Upsilon+2)} & \text{if } \frac{3}{2} \leq X_U \leq 4 \\ \frac{\sqrt{X_U}-1}{\sqrt{X_U}} & \text{if } X_U \geq 4 \end{cases}$$

We compare  $\Pi_{MY1}$ ,  $\Pi_{MY2}$  and  $\Pi_{MY3}$  for a given  $X_U$ , which leads to Eq (3) and Eq (4).  $\square$

### Derivation of Eq.(5):

In this proof, we derive the optimal price and expected revenues for the no-standby case for a given  $X_U$ .

Two possible strategies exist based on  $X_U$  values:  $X_U(1-p) \leq 1$  and  $X_U(1-p) \geq 1$

- For Strategy 1, the expected revenue function can be written as:

$$\Pi_{NS1} = \int_0^{X_U} \frac{x(1-p)p}{X_U} dx = \frac{X_U}{2} p(1-p) \quad \text{where } X_U(1-p) \leq 1$$

We solve the unconstrained problem first. FOC give us (the constant is ignored)

$$\frac{\partial \Pi_{NS1}}{\partial p} = 1 - 2p = 0.$$

Using a similar approach as in Strategy 1 of the myopic case gives:

$$p = \begin{cases} \frac{1}{2} & \text{if } X_U \leq 2 \\ \frac{X_U-1}{X_U} & \text{if } X_U \geq 2 \end{cases} \quad \Pi_{NS1} = \begin{cases} \frac{X_U}{8} & \text{if } X_U \leq 2 \\ \frac{X_U-1}{2X_U} & \text{if } X_U \geq 2 \end{cases}$$

- For Strategy 2, the expected revenue function can be written as:

$$\Pi_{NS2} = \int_0^{1/(1-p)} \frac{x(1-p)p}{X_U} dx + \int_{1/(1-p)}^{X_U} \frac{p}{X_U} dx = \frac{1}{X_U} \left( pX_U - \frac{p}{2-2p} \right)$$

$$\text{where } X_U(1-p) \geq 1$$

We solve the unconstrained problem first. FOC give  $\frac{\partial \Pi_{NS2}}{\partial p} = X_U - \frac{1}{2(1-p)^2} = 0.$

Using a similar approach as in Strategy 3 of the base model gives:

$$p = \begin{cases} \frac{X_U - 1}{X_U} & \text{if } X_U \leq 2 \\ \frac{\sqrt{2X_U} - 1}{\sqrt{2X_U}} & \text{if } X_U \geq 2 \end{cases} \quad \Pi_{NS2} = \begin{cases} \frac{X_U - 1}{2X_U} & \text{if } X_U \leq 2 \\ 1 - \frac{2}{\sqrt{2X_U}} + \frac{1}{2X_U} & \text{if } X_U \geq 2 \end{cases}$$

We compare  $\Pi_{NS1}$  and  $\Pi_{NS2}$  for a given  $X_U$  and choose the optimal price, leading us to Eq (5).  $\square$

### Proof of Proposition 1:

Comparison of the expected revenue functions and optimal price sets in Eq (3), Eq (4) and Eq (5) leads to  $\Pi_{MY} > \Pi_{NS}$  and  $p_S^{MY} < p^{NS} < p^{MY}$ .  $\square$

### Derivation of the Model Extension for Overbooking:

With the new booking constraint on the premium rooms, there are four different sets of possible outcomes (instead of the three in the base model) for a given price set  $(p_S, p)$  and a realized market size  $x$ : In  $O_1^W$ , the hotel can fully satisfy the premium room and standby upgrade demand ( $D_P \leq 1 - w$  and  $D_S + D_P \leq 1$ ). In  $O_2^W$ , the hotel can fully satisfy the premium room demand ( $D_P \leq 1 - w$ ), but can only partially satisfy the standby upgrade demand ( $D_S + D_P > 1$ ). In  $O_3^W$ , the premium room demand exceeds the new booking constraint ( $D_P > 1 - w$ ), but the standby upgrade demand is fully satisfied ( $D_S \leq w$ ). In  $O_4^W$ , the premium room demand exceeds the booking constraint and the hotel can only partially satisfy standby upgrade demand ( $D_S > w$ ).<sup>1</sup> Using a similar approach as in the base model, we can write the premium room capacity allocated to premium room bookings and standby upgrades, and resulting revenue as follows:

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<sup>1</sup>Note that as  $w \rightarrow 0$ ,  $O_4^W$  converges to  $O_3$  in our base model with  $(C_P, C_S) = (1, 0)$ .

Outcome	$(C_P, C_S)$	Revenue
$O_1^W$	$(D_P, D_S)$	$R_1^W = (x(1-p))p + (x(p-p_S))p_S$
$O_2^W$	$(D_P, 1-D_P)$	$R_2^W = (x(1-p))p + (1-x(1-p))p_S$
$O_3^W$	$(1-w, D_S)$	$R_3^W = (1-w)p + (x(p-p_S))p_S$
$O_4^W$	$(1-w, w)$	$R_4^W = (1-w)p + wp_S$

Note that no strategy can lead to both  $O_2^W$  and  $O_3^W$  for the given conditions. Therefore, we can show that five possible strategies exist:

**Strategy 1:** Choosing a price set  $(p_S, p)$  leading to an outcome set  $\{O_1^W\}$  where the hotel's expected revenue is  $\Pi_{W1} = \int_0^{X_U} \frac{R_1^W}{X_U} dx$ .

**Strategy 2:** Choosing a price set  $(p_S, p)$  leading to an outcome set  $\{O_1^W, O_2^W\}$  where the hotel's expected revenue is  $\Pi_{W2} = \int_0^{1/(1-p_S)} \frac{R_1^W}{X_U} dx + \int_{1/(1-p_S)}^{X_U} \frac{R_2^W}{X_U} dx$ .

**Strategy 3:** Choosing a price set  $(p_S, p)$  leading to an outcome set  $\{O_1^W, O_3^W\}$  where the hotel's expected revenue is  $\Pi_{W3} = \int_0^{(1-w)/(1-p)} \frac{R_1^W}{X_U} dx + \int_{(1-w)/(1-p)}^{X_U} \frac{R_3^W}{X_U} dx$ .

**Strategy 4:** Choosing a price set  $(p_S, p)$  leading to an outcome set  $\{O_1^W, O_3^W, O_4^W\}$  where the hotel's expected revenue is  $\Pi_{W4} = \int_0^{(1-w)/(1-p)} \frac{R_1^W}{X_U} dx + \int_{(1-w)/(1-p)}^{w/(p-p_S)} \frac{R_3^W}{X_U} dx + \int_{w/(p-p_S)}^{X_U} \frac{R_4^W}{X_U} dx$ .

**Strategy 5:** Choosing a price set  $(p_S, p)$  leading to an outcome set  $\{O_1^W, O_2^W, O_4^W\}$  where the hotel's expected revenue is  $\Pi_{W5} = \int_0^{1/(1-p_S)} \frac{R_1^W}{X_U} dx + \int_{1/(1-p_S)}^{(1-w)/(1-p)} \frac{R_2^W}{X_U} dx + \int_{(1-w)/(1-p)}^{X_U} \frac{R_4^W}{X_U} dx$ .

The following lemma presents the optimal strategies for a given set of  $X_U$  and  $w$ .

**Lemma:** When the hotel allocates  $w \in [0, 0.5]$  of its premium room capacity to satisfy the excess standard room demand and utilizes standby upgrades, the hotel should follow Strategy 1 when  $X_U \leq L(w) = \frac{3}{2}$ , Strategy 5 for  $X_U \geq H(w) = 4(1+w)(1-w)^2$ , and Strategy 2 otherwise. (see Figure B.1 for  $L(w)$  and  $H(w)$ ).

**Proof of Lemma 4:**



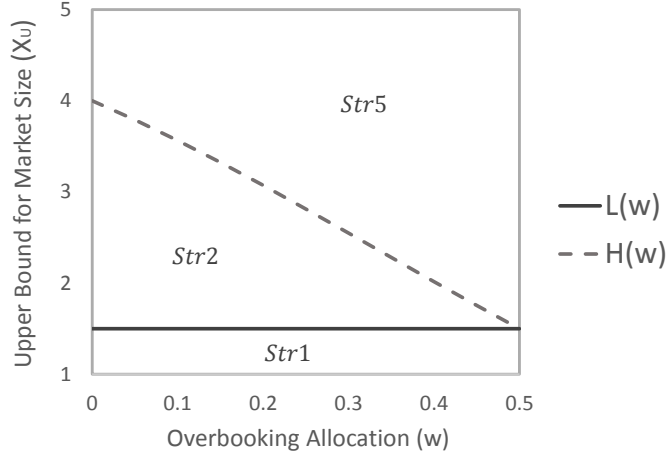


Figure B.1 Bounds of the Optimal Strategies for Different  $w$  and  $X_U$  values

For Strategy 1, the expected revenue function can be written as:

$$\Pi_{W1} = \frac{X_U}{2} [p_S p - p_S^2 + p - p^2] \quad \text{where } X_U(1 - p_S) \leq 1 \quad \text{and} \quad X_U(1 - p) \leq 1 - w$$

Note that this function is identical to  $\Pi_{MY1}$  in Lemma 1. Therefore, the optimal price set is  $(p_S, p) = (\frac{1}{3}, \frac{2}{3})$  for the unconstrained problem. The constraints can be rewritten as  $X_U \leq 3(1 - w)$  and  $X_U \leq \frac{3}{2}$ . Since we only consider  $w \in [0, 0.5]$ , the optimal price set for the unconstrained problem is the optimal price set for the constrained problem only if  $X_U \leq \frac{3}{2}$ . Parallel to Lemma 1, Strategy 1 is the optimal strategy for the maximization problem only when  $X_U \leq \frac{3}{2}$ . Let  $L(w) = \frac{3}{2}$  denote the upper bound of  $X_U$  for Strategy 1.

For Strategy 5, the expected revenue function can be written as:

$$\Pi_{W5} = \frac{-2p^2(1 - p_S - 1)(1 - w)X_U + p(2p_S^2 w X_U + p_S((w - 2)w - 2X_U + 2))}{2(1 - p)(1 - p_S)X_U} - \frac{(w - 1)(w + 2X_U - 1) + p_S(p_S(2wX_U + (1 - w)^2) + w(w + 2X_U - 2))}{2(1 - p)(1 - p_S)X_U}$$

$$\text{where } X_U(1 - p) \geq 1 - w \quad \text{and} \quad X_U(p - p_S) \geq w$$

FOC give us (the constant is ignored):

$$\frac{\partial \Pi_{W5}}{\partial p} = \frac{(p_S - 1)(1 - w)^2}{2(1 - p)^2 X_U} - w + 1 = 0$$

$$\begin{aligned} \frac{\partial \Pi_{W5}}{\partial p_S} &= \frac{p(2(1-p_S)^2 w X_U - 1) + p_S^2(-2w X_U + (1-w)^2)}{2(p-1)(1-p_S)^2 X_U} \\ &+ \frac{2p_S(2w X_U + (1-w)^2) - w(w + 2X_U - 2)}{2(p-1)(1-p_S)^2 X_U} = 0 \end{aligned}$$

Note that Strategy 3 in Lemma 1 is a special case of Strategy 5 when  $w = 0$ . Using a similar approach as in Lemma 1, the constraints are satisfied when  $X_U$  is greater than some lower bound  $H(w)$  for the optimal price set for the unconstrained problem. Similarly, the constraint  $X_U(1-p) = 1-w$  must be binding for  $X_U \leq H(w)$ . Solving the binding constraint and FOC gives us  $H(w) = 4(1+w)(1-w)^2$ . Parallel to Lemma 1, Strategy 5 is the optimal strategy for the maximization problem only when  $X_U \geq 4(1+w)(1-w)^2$ . The proof on the suboptimality of Strategy 3 and Strategy 4 when  $w \leq 0.5$  is available from authors upon request.  $\square$

### Proof of Proposition 2:

For the first part of the proposition, it is easy to see  $\Pi_{W1} = \Pi_{MY1}$  and  $\Pi_{W2} = \Pi_{MY2}$ . The optimal price sets are identical for the two unconstrained problems with the same objective function. Following the lemma above,  $p(w) = p^{MY}$  and  $p_S(w) = p_S^{MY}$  when  $X_U \leq H(w)$  (when Strategy 1 or 2 is optimal). Given  $X_U(1-p) \leq 1-w$  is not violated,  $C_P$  and  $C_S$  are the same for both problems resulting in no change in the expected revenues.

The proof of the price comparisons in the second part of the proposition is straightforward but lengthy, therefore available from the authors upon request. For the expected revenue comparisons, let  $\Pi(p_S, p, w)$  denote the expected revenue of a price set  $(p_S, p)$  for a given  $w$ . Consider a hotel using a price set  $(p_S^*(w), p^*(w))$  which is optimal for a given  $X_U$  and  $w$  when Strategy 5 is used. When  $O_1$  or  $O_2$  is observed,  $C_P$  and  $C_S$  do not change in  $w$ . On the other hand, recall that  $(C_P, C_S) = (1-w, w)$  when  $O_4$  is observed. In this outcome,  $C_P$  decreases in  $w$  while  $C_S$  increases. Given  $p > p_S$  and  $R_4^W = (1-w)p + wp_S$ ,  $\Pi(p_S^*(w), p^*(w), w) < \Pi(p_S^*(w), p^*(w), w - \Delta)$  where  $\Delta$  is a very small positive number. Since we have  $\Pi(p_S^*(w), p^*(w), w - \Delta) \leq$

$\Pi(p_S^*(w - \Delta), p^*(w - \Delta), w - \Delta)$  given that the latter is the optimal expected revenue for  $\theta + \Delta$ , we can deduce  $\Pi(p_S^*(w), p^*(w), w) < \Pi(p_S^*(w - \Delta), p^*(w - \Delta), w - \Delta)$ . Thus, we conclude that  $\Pi(w)$  decreases in  $w$ .  $\square$

### Proof of Lemma 3:

In this proof, we show the optimal strategy for strategic guests for a given  $X_U$ .

For each  $X_U$  value, we have three candidate pricing strategies for the optimal price set. These strategies have different expected revenue functions and constraints.

- For Strategy 1 where  $X_U(1 - p_S) \leq 1$ , the expected revenue function is  $\Pi_{ST1} = \int_0^{X_U} \frac{R_1}{X_U} dx$ .

Since premium room bookings and standby upgrade demand are fully satisfied in this strategy,  $r' = 1$  ( $v^* = \infty$ ) and  $z = 1$ . Therefore,  $R_1$  simplifies to  $(x(1 - p_S))p_S$ , and  $\Pi_{ST1} = \Pi_{NS1}$ .

- For Strategy 2 where  $X_U(1 - p_S) > 1$  and  $X_U(1 - z) \leq 1$ , the expected revenue function is:

$$\Pi_{ST2} = \int_0^{1/(1-p_S)} \frac{R_1}{X_U} dx + \int_{1/(1-p_S)}^{X_U} \frac{R_2}{X_U} dx$$

There are two cases:

- $r' \geq \frac{1-p}{1-p_S}$ . This results in  $z = 1$  and the following constraint holds:

$$(1 - p) \leq (1 - p_S) \left[ \int_0^{1/(1-p_S)} \frac{1}{X_U} dx + \int_{1/(1-p_S)}^{X_U} \frac{1}{x(1 - p_S)} \frac{1}{X_U} dx \right]$$

In this case,  $R_1$  simplifies to  $(x(1 - p_S))p_S$  and  $R_2$  simplifies to  $p_S$ , therefore

$$\Pi_{ST2a} = \Pi_{NS2}.$$

- $r' < \frac{1-p}{1-p_S}$ . This results in  $z < 1$  and the following constraint holds:

$$(z - p) = (z - p_S) \left[ \int_0^{1/(1-p_S)} \frac{1}{X_U} dx + \int_{1/(1-p_S)}^{X_U} \frac{1 - x(1 - z)}{x(z - p_S)} \frac{1}{X_U} dx \right]$$

Note that the constraint can be simplified to  $X_U(1 - p) = 1 + \log(X_U(1 - p_S))$ . Through this constraint and the condition  $X_U(1 - p_S) > 1$ , we get  $p < \frac{X_U - 1}{X_U}$  and  $p_S < \frac{X_U - 1}{X_U}$ . Since  $z$  disappears from the constraint, the equilibrium is not unique. However, the smallest possible  $z$  results in the highest expected revenue, as it implies that more people will directly book the premium rooms. Given  $p_S < \frac{X_U - 1}{X_U}$ , the expected revenue for a given price set  $(p_S, p)$  reaches its upper bound at  $z = \frac{X_U - 1}{X_U}$  (i.e. the  $X_U(1 - z) \leq 1$  constraint is binding).

- For Strategy 3 where  $X_U(1 - z) > 1$ , the expected revenue function is:

$$\Pi_{ST3} = \int_0^{1/(1-p_S)} \frac{R_1}{X_U} dx + \int_{1/(1-p_S)}^{1/(1-z)} \frac{R_2}{X_U} dx + \int_{1/(1-z)}^{X_U} \frac{R_3}{X_U} dx$$

The following constraint holds:

$$(z - p) = (z - p_S) \left[ \int_0^{1/(1-p_S)} \frac{1}{X_U} dx + \int_{1/(1-p_S)}^{1/(1-z)} \frac{1 - x(1 - z)}{x(z - p_S)} \frac{1}{X_U} dx \right]$$

which can be simplified to  $X_U(z - p) = \log\left(\frac{1-p_S}{1-z}\right)$ .

Let  $\Pi_{ST3}(p_S, p, z)$  and  $\Pi_{ST2b}(p_S, p, z)$  denote the expected revenues of a price set  $(p_S, p)$  and a  $z$  value satisfying the constraints of Strategy 3 and the second case of Strategy 2, respectively. For a given  $X_U$ , the upper bound for  $\Pi_{ST2b}(p_S, p, z)$  is  $\Pi_{ST2b}\left(p_S^*, p^*, \frac{X_U - 1}{X_U}\right)$  where  $(p_S^*, p^*)$  is the optimal price set of the second scenario of Strategy 2. The set  $(p_S^*, p^*, z)$  asymptotically satisfies the constraints of Strategy 3, therefore  $\Pi_{ST3}\left(p_S^*, p^*, \frac{X_U - 1}{X_U}\right) = \Pi_{ST2b}\left(p_S^*, p^*, \frac{X_U - 1}{X_U}\right)$ . Given  $\Pi_{ST3}\left(p_S^*, p^*, \frac{X_U - 1}{X_U}\right) \leq \Pi_{ST3}(p_S^{**}, p^{**}, z^{**})$  where the left-hand side is the expected revenue of a feasible price set under Strategy 3 while the right-hand-side is the optimal expected revenue under Strategy 3,  $\Pi_{ST2b} \leq \Pi_{ST3}$ . Thus, Strategy 2 is weakly dominated by Strategy 3, and we ignore Strategy 2 from further consideration.

Now, we can compare Strategy 1, the first scenario of Strategy 2 and Strategy 3 under two cases of  $X_U$ :

- $X_U \leq 2$ : In this range,  $\Pi_{NS2} \leq \Pi_{NS1}$ ; therefore, Strategy 1 (with the optimal  $p_S = \frac{X_U-1}{X_U}$ ) dominates the first scenario of Strategy 2. Consider a hotel trying to implement Strategy 3. Given a low  $X_U$  and its resulting high  $r'$  values in this range, the asymptotic upper bound of the expected revenue under Strategy 3 is the expected revenue under  $(p, p_S, z) = \left(\frac{X_U-1}{X_U}, \frac{X_U-1}{X_U}, \frac{X_U-1}{X_U}\right)$ , which is also the optimal expected revenue under Strategy 2. Therefore, Strategy 1 is the optimal strategy in this range.
- $X_U > 2$ : In this range,  $\Pi_{NS2} > \Pi_{NS1}$ ; therefore, the first scenario of Strategy 2 (with an optimal  $p_S = \frac{\sqrt{2X_U-1}}{\sqrt{2X_U}}$ ) dominates Strategy 1. Consider a hotel that chooses a price set  $\left(\frac{\sqrt{2X_U-1}}{\sqrt{2X_U}}, \frac{\sqrt{2X_U-1}}{\sqrt{2X_U}} + \Delta\right)$ , where  $\Delta$  is a very small positive number. In this case, we can have  $z < 1$ , i.e., some of the guests with  $v > \frac{\sqrt{2X_U-1}}{\sqrt{2X_U}} + \Delta$  book a premium room, therefore  $\Pi_{NS2} < \Pi_{ST3}\left(\frac{\sqrt{2X_U-1}}{\sqrt{2X_U}}, \frac{\sqrt{2X_U-1}}{\sqrt{2X_U}} + \Delta, z\right)$ . Given  $\Pi_{ST3}\left(\frac{\sqrt{2X_U-1}}{\sqrt{2X_U}}, \frac{\sqrt{2X_U-1}}{\sqrt{2X_U}} + \Delta, z\right) \leq \Pi_{ST3}(p_S^{**}, p_S^{**}, z^{**})$  where the left-hand side is the expected revenue of a feasible price set under Strategy 3 while the right-hand-side is the optimal expected revenue under Strategy 3,  $\Pi_{NS2} < \Pi_{ST3}(p_S^{**}, p_S^{**}, z^{**})$ . Thus, Strategy 3 is the optimal strategy in this range.  $\square$

### Proof of Proposition 3:

In this proof, we compare the expected revenues of the strategic case with the no-standby benchmark and the myopic case for a given  $X_U$ .

Let  $\tilde{\Pi}(p_S, p)$  denote the expected revenue of the price set  $(p_S, p)$  when guests are myopic and  $\hat{\Pi}(p_S, p)$  denote the expected revenue of the price set  $(p_S, p)$  when guests are strategic.

- $X_U \leq 2$ : In this case, we know from Lemma 3 that a hotel facing strategic guests should use Strategy 1, i.e., a price set where all guests choose standby upgrades, and  $\Pi_{ST1} = \Pi_{NS1}$ . Given  $\Pi_{NS} < \tilde{\Pi}(p_S^{MY}, p^{MY})$ , we deduce  $\Pi_{ST1} < \tilde{\Pi}(p_S^{MY}, p^{MY})$ .

- $X_U > 2$ : In this case, we know from Lemma 3 that the hotel's optimal strategy is to choose a price set that leads to  $z < 1$ . We make two comparisons for this range of  $X_U$  values:

⇒ Comparison of  $\Pi_{ST}$  and  $\Pi_{NS}$ : Given  $z < 1$ , standby upgrade program price discriminates. Consider a hotel facing strategic guests that uses a standby upgrade program and chooses a price set  $(p^{NS}, p^{NS} + \Delta)$  where  $\Delta$  is a very small positive number.  $\hat{\Pi}(p^{NS}, p^{NS} + \Delta) > \Pi_{NS}$ , since some of the guests with  $v > p^{NS} + \Delta$  book a premium room. Given  $\hat{\Pi}(p^{NS}, p^{NS} + \Delta) \leq \hat{\Pi}(p_S^{ST}, p^{ST})$ , we find  $\hat{\Pi}(p_S^{ST}, p^{ST}) > \Pi_{NS}$ .

⇒ Comparison of  $\Pi_{ST}$  and  $\Pi_{MY}$ : Consider a hotel using the optimal price set for the strategic case, i.e.,  $(p_S^{ST}, p^{ST})$ . Given  $1 - z < 1 - p^{ST}$ , the number of premium room bookings when guests are myopic is greater than the number of premium room bookings when guests are strategic. Therefore,  $\hat{\Pi}(p_S^{ST}, p^{ST}) < \tilde{\Pi}(p_S^{ST}, p^{ST})$ . Since  $\tilde{\Pi}(p_S^{ST}, p^{ST}) \leq \tilde{\Pi}(p_S^{MY}, p^{MY})$  as the latter is the optimal profit for the strategic customer case, we find  $\tilde{\Pi}(p_S^{MY}, p^{MY}) > \hat{\Pi}(p_S^{ST}, p^{ST})$ . □

#### Proof of Proposition 4:

In this proof, we show that strategic guests never book premium rooms if the hotel uses the optimal price set in the myopic case for a given  $X_U$ . Let us evaluate  $X_U \leq 1.5$  and  $X_U > 1.5$  separately:

- $X_U \leq 1.5$ : In this case, the hotel uses Strategy 1, i.e., fully satisfies the premium room and standby upgrade demand. Therefore,  $r' = r = 1$  and all strategic guests choose standby upgrades.

- $X_U > 1.5$ : In this case, the hotel uses Strategy 2 or Strategy 3. For a given  $X_U$ , we need to show that the price set  $(p_S^{MY}, p^{MY})$  always leads to  $z = 1$ . In order to show this, we test whether the utility of choosing a standby upgrade dominates booking a premium room for all guests. For a given  $(p_S^{MY}, p^{MY}, X_U)$  set, the following inequality always holds:

$$(1 - p^{MY}) \leq (1 - p_S^{MY}) \left[ \int_0^{1/(1-p_S^{MY})} \frac{1}{X_U} dx + \int_{1/(1-p_S^{MY})}^{X_U} \frac{1}{X_U(1 - p_S^{MY})x} dx \right]$$

where the left-hand side of the inequality is the utility of booking a premium room for a guest with  $v = 1$  and the right hand side of the inequality is the utility of choosing a standby upgrade for a guest with  $v = 1$  times her expectation on the fill rate. Given that this inequality always holds, even a guest with  $v = 1$  would choose the standby upgrade offer. Therefore, standby upgrades fully cannibalize the premium room bookings.  $\square$

## APPENDIX C

### SUPPLEMENT FOR CHAPTER 4

#### **Information About Other Sports Leagues/Tournaments:**

NFL Super Bowl:

*Tournament structure:* 32 teams compete in two conferences during the regular season and top six from each conference make it to playoffs (single-game knockout) and get match-ups based on their standings. In last 10 years (including 2017), No.1 seeds in each conference played in Super Bowl only 11 times.

*Ticket allocation and resale market:* For Super Bowl, NFL makes a pre-season lottery to send out 1000 tickets to public from the face value, which winners are not allowed to pick up their tickets until the game day, and only after they already have entered the game site. In addition, NFL gives selling rights of more than 5000 packages (9000 for Super Bowl 2018) to *On Location Experiences*. The company sells packages in two ways: (i) Standard packages where the customer is confirmed immediately, (ii) conditional packages where the customer reserves a package and has to buy only if his/her team advances to final (for last 8 teams). The resale market is not controlled, therefore tickets in this market may get extremely expensive.

FIFA World Cup:

*Tournament structure:* 32 teams (coming from different zonal qualifications) compete in eight groups and then top two from each group make it to playoffs (single-game knockout). There is no official standing or ranking system, the playoff bracket is announced before the tournament and matchups are based on the group standing.



*Ticket allocation and resale market:* For World Cup, because of the size of the tournament, FIFA sells a lot of different types of tickets. Therefore, one can get into the final match through different channels: (i) Buying an individual match ticket, (ii) buying venue-specific match tickets for the stadium of the final, (iii) buying a regular team-specific ticket for all rounds <sup>1</sup>, and (iv) buying optional team-specific tickets for all rounds where the customer basically reserves a ticket and has to pay for the ticket only if his/her team advances to final. When the demand exceeds the supply for a game, FIFA uses a random drawing procedure where priority is given to advanced reservations. Note that FIFA does not allow customers to resell tickets from a different price than face value, but provides a channel for resale. FIFA also allocates a significant number of its capacity to *MATCH Hospitality* to sell hospitality packages for the whole tournament or individual games.

NCAA Men's Basketball:

*Tournament structure:* Teams play a regular season where 68 teams make it to playoffs (single-game knockout), where 32 Division I conference champions receive an automatic bid. Rest of the teams are decided by selection committee which also decides on the seeding. There are several polls announced weekly for top-25 teams (e.g. AP Poll, Coaches Poll) which give fans an idea about their team's strength. Note that Selection Committee gave a preview of top-16 seeds a month before the official announcement of their decision, first time in 2017. Last 10 years (up to 2016) show that only 17 of Preseason Top-4 ranked teams make it to the Final-Four. Interestingly, this number is only 16 for four No. 1 seeds of the playoffs.<sup>2</sup>

*Ticket allocation and resale market:* The College Basketball use a similar structure to the College Football where there is a pre-season lottery and a significant number

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<sup>1</sup>This ticket guarantees the customer tickets for each round of the tournament, regardless of whether the team itself qualifies.

<sup>2</sup>27 of Preseason Top-10 ranked teams make it to the Final-Four. This number is 25 for No.1 and No.2 seeds of the playoffs.

of tickets are given to hospitality rights holders, *PrimeSport*. It also has an official channel for resale, where customers can resell tickets from any price.

### Alabama's Regular Season Snapshot:

Figure C.1 displays Alabama's weekly bid, offer, and transaction volumes in the 2015 season with the weekly performance.

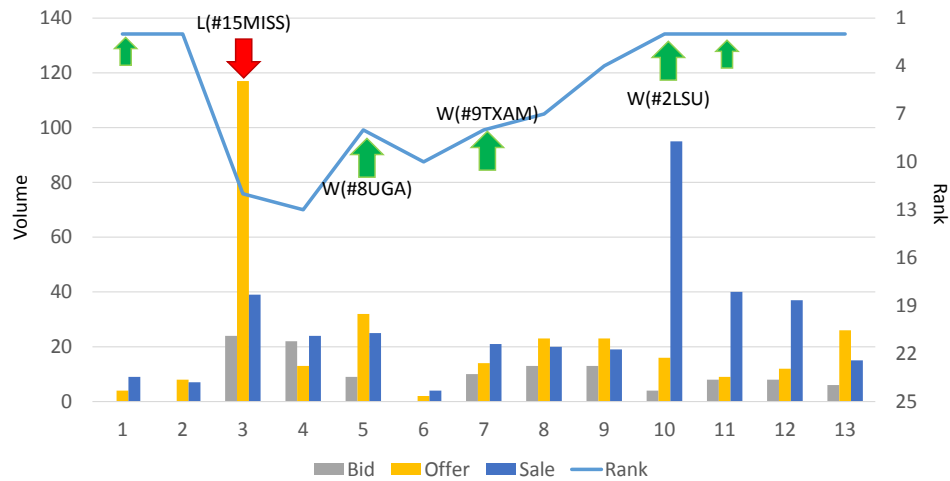


Figure C.1 Alabama in the 2015 Regular Season

*Blue tracker displays Alabama's weekly ranking. Big and small green arrows represent important wins, versus Top-10 and Top-25 ranked teams respectively. Red arrow represents a loss.*