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Revenue Management in the Sport Industry: an Examination of Forecasting Models and Advance Seat Section Inventory in Major League Baseball

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REVENUE MANAGEMENT IN THE SPORT INDUSTRY: AN EXAMINATION OF FORECASTING MODELS AND ADVANCE SEAT SECTION INVENTORY IN MAJOR LEAGUE BASEBALL

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ABSTRACT

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Technological advances in data storage and processing have led to more sophisticated ticket pricing strategies in professional sport. Sport organizations are beginning to adopt a form of revenue management known as dynamic ticket pricing. Effective pricing strategies such as dynamic ticket pricing require an in-depth understanding of the nature of advance ticket inventory and accurate forecasting models to predict remaining inventory at various time horizons prior to game time.

The purpose of this study was to gain an understanding of the nature of advance seat section ticket inventory. The study built on and contributed to work in sport revenue management. Although studies of sport revenue management have examined the applicability of revenue management in a sport context, there has not been a study of advance seat section ticket inventory despite the fact that sport organizations utilize price discrimination strategies at the seat section level. As such, this study provided additional insight into the applicability and potential effectiveness of a sport revenue management strategy. The methodological focus on forecasting models and accuracy enabled another contribution. A 3x3x6x7 full factorial research design examined the accuracy of various forecasting models under different data strategies, time horizons, model parameters, and levels of the values of *T* and *K* used in the moving average and exponential smoothing forecasting models. Statistically reliable differences existed between data strategies with the classical pickup data strategy providing the best forecasts of final game day inventory. Within the classical pickup strategy, no reliable differences in forecast models were detected nor were forecasts found to significantly differ when changing the value of *T* or *K*. Finally, forecast accuracy was shown to follow the theoretically predicted best to worst pattern as days out increased.

A profile analysis of seat section ticket inventory showed seat sections exhibit different slopes and changes in slope over time. The general pattern of ticket inventory followed a linear trend but with varying slopes. Steeper slopes were found at 20, 10, and 5 days out followed by a leveling out between 5 and 3 days out which was then followed by steeper slopes from 3 days to game day. This finding suggested that optimizing a sport revenue management plan should include forecasting at the seat section level.

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INTRODUCTION

In 2007 the Colorado Rockies had arguably their best season in franchise history as they shocked the Major League Baseball (MLB) world by winning 21 out of 22 games in September to force a wild card tie-breaker playoff game with the San Diego Padres on October 1. This game could be considered one of the most exciting games in Rockies history as the Rockies won in dramatic fashion in the bottom of the 13th inning. Not many could have predicted the Rockies' appearance in the playoffs, let alone a trip to the 2007 World Series. During the course of this season, attendance numbers fluctuated as the team had a winning percentage below .500 for a large portion of the season. However, in September the team went on a remarkable winning streak to finish out the season. With playoffs becoming a realistic expectation, attendance at Coors Field consistently reached near sellouts to close out the season.

As someone who witnessed a fair number of games during this unbelievable season, I was willing to pay almost any price to see the final games of the Rockies' season. I did not want to miss a Todd Helton walk-off homerun to win in dramatic fashion in the bottom of the 9th or a dramatic strikeout to close out a one-run game. I felt I was not only witnessing Rockies' history but something that rarely has happened in MLB history. I wanted to be able to say "I was there." Ticket price, with which I am normally very stingy, was not as much of a factor as being able to have the memories associated with such a unique experience. Fortunately for me and other Rockies fans, the price of the tickets sold in September were the same or very similar to the price of tickets sold in earlier months when the odds of making the playoffs looked slim to none.

However, if one would have been checking prices of hotels in Denver's lower downtown (where the Rockies play) or flights to Philadelphia (the first round playoff opponent of the Rockies) one would likely find a different pricing story. Hotel prices near Coors Field would likely have been unusually high during the Rockies playoff run. Also, trying to book a flight to Philadelphia one or two days before the playoff game would have likely revealed higher than average plane tickets than if we had known one, two, or three months in advance the Rockies would be playing the Philadelphia Phillies in the playoffs. Of course, knowing the Rockies would make the playoffs, let alone who they would be playing, could not have been predicted with much accuracy earlier in the season.

The Rockies organization could likely have made more revenue that September had they utilized a form of revenue management known as dynamic ticket pricing that the hotels and airlines had been using for years. Anyone who has traveled somewhat regularly has likely noticed rates for hotel rooms and airline tickets are generally cheaper if booked far in advance. Also, a frequent traveler may start to notice rates varying based on the day of travel. The natural question that arises is: why am I paying more or less based on when or what day I book to travel? And in my own experience with the 2007 Rockies, why did I not have to pay more for those dramatic, near sellout, games at the end of the season as opposed to the games in June when the word “playoffs” was not even used in the same sentence as Rockies? A look into the underpinnings of ticket pricing in sport, revenue management (RM), and dynamic ticket pricing may provide some of the answers I sought.

Overview of Sport Ticket Pricing

Strategies for pricing tickets have increasingly become a critical aspect of the sport manager’s job. Ticket revenue is critical for the success of a professional sport franchise and has become more important for intercollegiate athletics as well (Howard & Crompton, 2014). Despite its inclusion as one of the elements of the marketing mix, literature examining ticket pricing strategies in sport is limited (Drayer & Rascher, 2013).

Ticket pricing of sport has long been a major source of revenue for professional sport (Howard & Crompton, 2004). In 2004, Howard and Crompton reported that almost $12 billion were spent on tickets to sporting events. More recent data from Statista.com reported total ticket revenue at sporting events to be $15.6 billion in 2007 with forecasts of $19.74 billion by 2018 (Statistica, 2014). Ticket revenue accounts for a large proportion of both professional and collegiate sport total revenue and pricing of tickets is critical to the marketing mix (Howard & Crompton, 2004; Mullin, Hardy, & Sutton, 2014). Therefore, it is important for sport management practitioners and researchers to understand the various ticket pricing strategies utilized in the sport industry.

Main Types of Tickets

Sport organizations offer a variety of ticket purchase options. The main types of tickets sold include: full season, partial season, and individual games. Full season tickets allow the consumer to purchase tickets to all the games in an upcoming season and provide the organization up-front, guaranteed revenue before the season. These ticket packages are beneficial for the sport organization for several reasons.

First and most obvious, the organization collects a large lump sum from the consumer prior to the season. This revenue can then be invested or spent on needs of the organization. Second, because seasonal characteristics such as team success and weather have been shown to impact attendance (Borland & MacDonald, 2003; Coats & Harrison, 2005), selling season tickets requires the consumer to purchase before any of the variable season characteristics are known. On the consumer side, season tickets usually provide the most economical price per game ticket available from the organization. Additionally, teams will also add additional perks for season ticket holders such as free or privileged parking, special event access, rights to purchase playoff tickets, and other activities exclusive to season ticket holders.

Another type of season ticket is partial season tickets providing the consumer another option to purchase discounted seats for a portion of the regular season. These packages also provide the organization with the benefit of up-front revenue while offering flexibility to the consumer. Teams have increasingly offered this type of ticket package in a variety of forms.

The Milwaukee Brewers were one of the first teams to implement partial season tickets by offering a set of four options of 10-15 games which differed based on opponent and days. The Brewers reported a 43% increase in season ticket sales the first year offering partial season tickets (Howard & Crompton, 2004). Not surprisingly, this success led other teams to sell partial season tickets as well. Teams continually try new partial season ticket packages to attract different segments of consumers. Some teams, such as the Colorado Avalanche, now offer completely customizable “Pick-Em” plans of 20 and 10 games that allow the consumer to pick any games on the schedule (Partial Plans, 2014).

While season and partial season tickets are crucial for the financial success of a sport organization, Howard and Crompton (2004) cautioned sport managers against selling the entire season using these methods. Even if a sport franchise could sell all their seats via season ticket holders, it is advised to set aside a portion of tickets for individual sale. Reasons for reserving a certain amount of tickets for individual sale include giving potentially new fans the opportunity to attend a game and to not prevent current fans who may not be able to afford season tickets the opportunity to see a live game. Additionally, season ticket holders are less likely than single game purchasers to buy programs and merchandise every game. For many sport organizations, selling out the venue based solely on season tickets is not a luxury they have to contemplate. Especially for sports with a large inventory of games such as the MLB, finding ways to increase sales of both season (full and half) tickets and individual game tickets is critical to the financial success of the sport organization.

Pricing Strategies

Historically, sport managers have relied on suboptimal, arbitrary percentage increases or “gut” feelings of what the market will bear when deciding to change ticket prices (Howard & Crompton, 2014; Mullin et al., 2014). Technological advances have led to more complex demand-based ticket pricing strategies being implemented by at least 80% of MLB teams (Dynamic Pricing FAQ, 2015).

Sport managers have important and complex considerations when pricing tickets. With the less than optimal cost-based pricing giving way to more complex demand-based pricing, sport managers are faced with the challenge of attempting to predict advance demand and set prices to maximize revenue. Important considerations of the sport manager's decision to change prices include economic/financial, consumer behavior, and operational considerations.

Economic/financial considerations. How does a sport manager begin to form the price of an individual game ticket? Historically, sport managers have used a cost-based approach to setting initial prices (Howard & Crompton, 2014). In most cases, when pricing the sport product the sport organization has to factor production costs (e.g., salary and facility), market conditions, competitors' prices, organizational objectives, event frequency, and brand strength. Initial pricing often begins with a Break-Even Analysis that involves estimating fixed and variable costs (Mullin et al., 2014). From the Break-Even Analysis, organizations will then likely use a cost-plus pricing strategy or a market-based approach to determine ticket price. A cost-plus approach would simply determine the portion of revenue needed from ticket sales to cover costs and add a fixed amount to determine the ticket price. While a Break-Even Analysis and cost-plus pricing could provide a starting point for ticket prices, this approach should be supplemented with a market-based pricing strategy.

Market-based pricing is the most common approach to pricing the sport product (Mullin et al., 2014). However, determining what a market will bear can be a daunting task for many sport managers. The most common approach for determining market demand has been largely based on past experience and comparisons. This approach is not likely to be optimal and appears is giving way to more sophisticated price elasticity analyses based on sales data and various consumer related factors (Drayer, Shapiro, & Lee, 2012; Howard & Crompton, 2004).

Consumer behavior considerations. Knowing the minimum ticket price needed to break even is obviously an important consideration of any company. However, used in isolation, this approach has been shown to be sub-optimal for maximizing revenue (Drayer et al., 2012; Dwyer, Drayer, & Shapiro, 2013; Rascher, McEvoy, Nagel, & Brown, 2007). As more demand-based ticket models are being implemented, it is important for sport managers to have a strong understanding of ticket pricing from the consumer's perspective.

Sport consumer costs. The price of a sport ticket is a major consideration of a sport consumer's willingness to attend a game and is one of the most visible (Mullin et al., 2014). However, sport managers must also consider other costs to the consumer when setting ticket prices. A consumer is likely to consider the cost of transportation to the game, parking, concessions, programs, and merchandise when evaluating the total cost to attend a game. A common measure of total cost to attend a sporting event is given by the Fan Cost Index (FCI) provided by a leading sport industry newsletter, *Team Marketing Report*.

Fan Cost Index estimates include the total cost to attend a sporting event by assuming two adults and two children attending. For example, the average FCI to attend an MLB game in 2014 was $212.48 (FCI, 2014). This amount includes the price of four tickets, concessions, parking, program, and merchandise. According to the FCI, ticket price accounts for only about half of the total cost to attend an MLB game. Sport managers should consider the FCI when pricing tickets because consumers are likely to compare the total cost of attending a sporting event against other substitutes such as other sport teams, movie theaters, performing arts, etc. (Mullin et al., 2014). Knowing the team's current FCI and competitors' pricing can be a first step in setting initial prices but other consumer psychological factors come into play as well.

Price threshold. Consumers will purchase a product or service based on their expected range of prices. Initial price setting can be a challenge for sport managers because if priced too high, potential consumers will find it too expensive and resort to less costly alternatives. However, if the initial price is too low, this could convey poor quality to the consumer (Howard & Crompton, 2014; Mullin et al., 2014). How consumers develop a price threshold for a new product or service often depends on the initial price offering. Therefore, it is important for sport managers to carefully select an initial price as it will likely be used as a reference price by many consumers when the organization makes price changes.

Tolerance zone. Factors such as macroeconomic market conditions and organizational costs can necessitate the need to increase the price of a good or service in order for the organization to survive. The concept of a tolerance zone for pricing indicates that there are acceptable levels of price increases consumers are willing to accept (Howard & Crompton, 2004). The acceptable tolerance zone will likely depend on the initial reference price. For example, a consumer may be more willing to accept an increase from $10 to $15 than an increase from $5 to $10 even though the dollar increase is the same because the first price increase represents a 50% increase while the latter represents a 100% increase.

Along with economic and financial considerations, the three main consumer considerations discussed in this section should factor into a sport manager's initial pricing decisions. Additionally, operational aspects must also be considered. The ability to accurately forecast and control demand is an operational consideration that plays a large role in revenue management (RM) strategies (Talluri & van Ryzin, 2004).

Operational considerations. In addition to economic and consumer-related factors, sport managers should also consider operational aspects when pricing the sport product. From a RM perspective, this generally refers to the ability to forecast demand and control inventory (Talluri & van Ryzin, 2004). A balance between controlling inventory and price of tickets is important in ticket pricing. As MLB FCI calculations show, almost 50% of potential revenue is accounted for by non-ticket revenue such as concessions and parking (FCI, 2014). Because sport organizations have a fixed and perishable inventory of tickets, sport managers need to consider the tradeoffs between pricing tickets to entice more attendance which could lead to higher overall revenue or pricing tickets to maximize ticket revenue.

Sport Ticket Pricing Summary

It has been suggested that effective revenue management demand-based pricing strategies require an understanding of three major disciplines: economics, marketing, and operations (Ng, 2007; Talluri & van Ryzin, 2004). The increased implementation of demand-based pricing strategies in sport has led to recent academic research on the topic. Sport management researchers have turned to other service industry literature to find a conceptual framework for studying dynamic pricing and advance demand (Drayer & Shapiro, 2012; Dwyer et al., 2013).

Service industries such as the airline and hotel industries were at the forefront of developing revenue management and the more specific form of RM known as dynamic pricing. The literature on these and other service industries has provided an early theoretical base for this emerging sport management literature topic. However, RM researchers have called for a more complete theoretical framework than those currently utilized by sport RM literature (Ng, 2007; Talluri & van Ryzin, 2004). An understanding of consumer behavior, economics, and operations research is needed to have a thorough understanding of the potential applicability and effectiveness of a RM strategy in a sport context. More sport specific RM research is needed to understand the applicability and sustainability of a RM strategy in sport. In this dissertation I aimed to help in the understanding of this complex topic.

Statement of Problem

The purpose of this study was to investigate the utility of RM in sport through the examination of advance seat section demand and pricing. Examining seat section demand

and pricing largely falls under the economic and consumer behavior frameworks of a RM strategy. To address a major operational concern in a RM strategy (forecasting and estimation), in this study I provided an analysis of forecasting methods applicable to sport ticket pricing. Marketing expert Phillip Kotler, succinctly stated the importance of price with "Price is the only element in the marketing mix that produces revenue; the other elements produce costs" (1991, p. 474, as cited in Drayer and Rascher, 2013).

Data collection strategies utilized in my study and analytic focus at the seat section level offered another contribution. Early sport dynamic ticket pricing and advance pricing research has examined only one MLB team and one NHL team (Drayer & Shapiro, 2012; Dwyer et al., 2013). In my study I provided an analysis of a different MLB team with a different historical attendance than previous research. I collected game ticket availability and pricing data in a real time, advance demand scenario, at a more disaggregated level than prior research.

The current study built on and contributed to work transcending the three major disciplines RM comprises: sport economics, marketing, and operations. Specifically, the study was guided by the theoretical framework provided by Ng (2007) which melds the three aforementioned disciplines into a comprehensive theory of advance demand. At least two different frameworks borrowed from the service industry have already been utilized in the limited sport RM research. Yet, neither framework fully integrated the three major RM disciplines nor added the additional complexities inherent in the sport product. Thus, another contribution of this study was to examine what is believed to be a more complete RM theoretical framework.

Given the significance of ticket pricing to a sport organization's "bottom line" coupled with the increased use of demand-based pricing strategies, the following research questions were developed to guide this research:

Research Questions

RQ1 To what extent do profiles of data strategy differ in forecast errors?

RQ2 To what extent do forecast models differ from a naïve model?

RQ3 To what extent do forecast errors vary by sample size?

RQ4 To what extent do forecast errors vary by days out?

RQ5 To what extent to do seat section inventory curves differ from parallelism?

RQ6 What is the nature of differences between seat section inventory curves?

These questions were answered by collecting and analyzing seat section pricing and ticket inventory data for from the entire 2014 home season for the Kansas City Royals. Guided by forecasting and RM literature, a sequential analysis provided the answers to questions 1-4 while a profile analysis answered questions 6 and 7.

Delimitations

The forecasting methods selected for analysis were based on a review of both the forecasting and service literature. Many forecasting methods exist which may provide reasonable forecasts but the ones selected are the most prevalent in the service forecasting and RM literature. Through this study, I did not provide a comprehensive analysis of all possible forecasting methods. There has been and will likely continue to be debate over which forecasting methods to use. Further complicating this debate is the determination of which accuracy measures to use when assessing forecasting methods. I based the selection of models on the work of both prominent forecasting authors (e.g., Box & Jenkins, 1976; Makridakis & Hibon, 2003) and revenue management authors (e.g., Sun, Gauri, & Webster, 2011; Weatherford & Kimes, 2003; Wickham, 1995) to select a manageable number of forecasting methods to compare.

In this study I examined seat section data collected from one Major League Baseball (MLB) team. It cannot be assumed that the results of this study can be generalized to other MLB teams and other sports. However, the team selected was based on team characteristics (historical attendance, winning percentage, etc.) and game characteristics (day of game, time of day, etc.) which could be useful for generalizing to other MLB teams and games. The variables selected for game characteristics were based on a review of literature of determinants of demand and variable and dynamic ticket pricing. I do not imply that the selected variables are the only determinants of differences in ticket inventory.

Limitations

Due to the difficulty in obtaining pricing and demand data from professional sport organizations, this study relied on quantitative data that I manually collected. Although careful measures were taken to minimize data collection errors, accuracy of the data cannot be 100 percent guaranteed.

Ticket availability and pricing data were collected via the team's ticketing websites. These data are believed to serve as a proxy for ticket demand but industry professionals have indicated teams "hold back" inventory for various reasons. Therefore, "true demand" cannot be explained through only online data collection because it is unknown exactly how many tickets teams are holding back. However, multiple industry professionals have indicated that the data shown on team ticketing websites represent the current available tickets (R. Bennett & J. Ziegenbusch, personal communication, October 28, 2014) across all platforms (online, box office, etc.). Therefore it is believed collecting and analyzing these data can further understanding of seat section demand and pricing.

Future studies should find a way of collecting more time series data points and test the accuracy of autoregressive integrated moving average (ARIMA) models against simpler models. Nevertheless, the study provided results from two of the most common RM forecasting techniques (exponential smoothing and moving average) at six different model parameters and sample sizes as well as at seven different time horizons. Furthermore, the study provided analysis of three common data collection and organization strategies (non-pickup, classical pickup, and advance pickup).

Chapter I Summary

With sport organizations rapidly adopting a form of revenue management known as dynamic ticket pricing, it is essential for researchers to form a comprehensive understanding of the this complex strategy. While limitations in data collection and generalizability were present, this study offered what is believed to be the first examination of seat section inventory and forecasting models. Understanding how seat section inventory curves differ as well as examining accuracy of various forecasting models is critical to the development of a comprehensive revenue management strategy.

In conducting this dissertation I aimed to fill some of the gaps present in the current sport pricing and revenue management literature.

In Chapter II, I provide a comprehensive review of sport ticket pricing and revenue management literature. Much of the sport pricing literature has an economic focus but some recent work has been done with a sport marketing angle. After this review of sport pricing, I continue the review of literature to explore the complex topic of revenue management. To comprehensively explore the literature on revenue management, I organized the review into the three major disciplines subsumed within a revenue management framework: marketing and consumer behavior, economics, and operations. Major themes and theories found within this vast literature are reviewed.

Chapter III outlines the methodological strategies employed in this study. A 3x3x6x7 full factorial design was utilized to collect and analyze data while profile analysis served as the primary analytical procedure to answer research questions. Because of the difficulty in collecting pricing and inventory data directly from sport organizations, a manual data collection procedure is presented which utilized publically available online data. The nature of the advanced sport ticket selling period fits well with the use of pickup data strategies common in other service industries so these forecasting data strategies are explained in Chapter III. A simulated forecast environment was created to explore forecasting methods and replications of the design are explained.

Chapter IV provides an analysis of forecasting methods. A sequential analysis is provided to help explain what data strategies and models were found to provide the lowest forecast errors. It was found the classical pickup data strategy provided superior forecasts while no detectable differences between models were evident. Finally, the results showed the theoretically predicated best to worst forecasting abilities as predictions are made further out in time.

Finally, Chapter V provides an analysis of seat section inventory curves. This study provided a first examination of how seat section profiles differ. Statistically reliable results showed seat section profiles differ in slope and rates of change in slope at various days out. Some sections exhibited steeper slopes than others indicating potential for implementing dynamic pricing strategies. Other implications to a sport revenue management strategy are discussed.

CHAPTER II

REVIEW OF LITERATURE

The review of literature for this study is divided into two main sections. First, an examination of ticket pricing in sport is presented. The second main section focuses on the revenue management (RM) literature. The RM section is broken out into the major subtopics of RM: consumer behavior, economics, and operations research. While there is certain to be overlap of these three subtopics in the RM literature a best effort to highlight the literature which focuses on each of the three main disciplines is given.

Sport Ticket Pricing

Research is limited in the sport marketing literature regarding the pricing of sport (Drayer & Rascher, 2013). However, researchers have published research in other sport management areas such as sport economics. The following sections summarize this literature.

Ticket Pricing and Demand

An abundance of research exists regarding the determinants of attendance for sporting events (see for example, Borland and MacDonald [2003], for a review of the literature to date and more recently Soebbing and Watanabe [2014]). Rascher et al. (2007) remarked, "Unfortunately, attendance by seat location and specific price is not publicly available. If it were, one could examine how much demand changes per price point to get a sense of the nature of the shift in demand" (p. 421).

More recently, Drayer and Rascher (2013) stated:

> Despite its inclusion as one of the core Ps of the traditional marketing mix, research on sport pricing has been noticeably underrepresented in the sport marketing literature… therefore, when researchers examine consumer attitudes and behaviors, they must consider the effect of prices, particularly as more demand-based and dynamic pricing strategies emerge. (p. 123)

Shapiro and Drayer (2012) added "traditional differentiation strategies have focused on seat location; however, the utility of this strategy has not been examined in a real-time pricing environment" (p. 535). Recent technological advances now allow for public data collection of seat location demand and price. Research can now be conducted to shed light on previously elusive seat section data to help fill the gaps illuminated by sport management researchers.

Understanding seat section pricing and demand is important in the areas of sport marketing (e.g., micro target market and market segmentation; understanding optimum levels of one of the four "P"s, price), sport economics (e.g., to further examine the reason(s) for inelastic pricing in sport; the nature of consumer demand based on seat location and time), and sport operations (e.g., forecasting demand, adjusting pricing, ticket inventory control).

Although numerous studies (e.g., Borland & MacDonald, 2003; Paul & Weinbach, 2013; Shapiro & Drayer, 2012) have identified determinants of baseball demand and pricing variation, little attention has been paid to real-time price discrimination or the nature of demand shifts between sections. While sparse research exists on the impact variable ticket pricing and/or dynamic ticket pricing has on demand for tickets, research in other industries can provide some insight into this topic (e.g., Colbert, Beauregard, & Vallee, 1998; Drake & Dahl, 2003; Raghubir & Corfman, 1999).

Dynamic pricing, a demand-based pricing strategy, has emerged as a strategy to mitigate pricing inefficiencies illuminated by the secondary ticket market (Drayer & Shapiro, 2012). A dynamic ticket pricing pricing strategy is subsumed under the larger pricing and inventory management framework of RM (Talluri & van Ryzin, 2004). Historically, ticket pricing strategies have differentiated price by seat section but no known studies have examined seat section demand and pricing.

Research in sport economics has provided the most research regarding pricing and demand but the bulk of this research has taken an aggregated view despite the fact that sport organizations have widely utilized price discrimination by seat location and more recently by game characteristics. These aggregated analyses tend to overweight "cheap" seats and underweight expensive seats (Drayer & Rascher, 2013). Therefore, in this study I added to the pricing literature by examining previously elusive seat section pricing and ticket inventory data rather than only taking an aggregated view.

An analysis of forecasting methods provides an additional contribution to the literature. The study of forecasting methods is crucial to the understanding of effective RM (Ng, 2007; Talluri & van Ryzin, 2004; Weatherford & Kimes, 2003). Despite the fact that detailed forecasts serve as the major input of RM systems, no research has investigated the accuracy of sport RM forecasts. The current dissertation offers a first analysis of possible forecast methods for sport RM.

Sport Economics Literature

Much of the knowledge in sport management literature regarding ticket pricing, demand, and valuation exists in the sport economics literature (Drayer & Rascher, 2013). Within the sport economics field, there have been many studies that examine the determinants of attendance (e.g., Branvold, Pan, & Gabert, 1997; Butler, 2002; MacDonald & Rascher, 2000; Schmidt & Berri, 2001; Soebbing & Watanabe, 2014). Borland and MacDonald (2003) provided a comprehensive review of studies of determinants of demand and concluded that within the large array of factors studied, some of the most important factors impacting demand were uncertainty of outcome, quality of contest, and quality of viewing. Some major conceptual frameworks that have emerged out of the sport economics literature revolve around the ideas of inelastic ticket pricing, price discrimination, and price dispersion.

Inelastic pricing. A common tool used to analyze market demand sensitivity at various prices is the calculation of elasticity of demand given by the quotient of the percentage change in quantity demanded and percentage change in price. Pricing in the inelastic range would indicate that a change in price would not dramatically influence demand. Basic economic theory suggests that as price increases, demand decreases (Sowell, 2000). Price elasticity is a measure of the magnitude of these changes.

Price elasticity has long been studied in the sport economic literature (Fort, 2004). Two of the earliest studies included Noll (1974) and Demmert (1973) (as cited in Coates and Humprheys, 2007). What authors studying price elasticity have consistently found is that sport organizations set their prices in the inelastic range.

Several theories have been posited to explain why sport franchises would consistently price in the inelastic range.

Marburger (1997) developed a model to explain why sport franchises would price in the inelastic demand range. His model assumed that when a ticket price setter received other revenues such as concession revenue, a profit-maximizing strategy in sport would include setting ticket prices in the inelastic range. Additionally, his model assumed that the marginal cost of a seat is insignificant. Fort (2004) argued that sport franchises price in the inelastic range because pricing in this way leads to overall profit maximization. In his theoretical model, Fort posited that if television revenue was "large enough" relative to the average league marginal revenue then a team will price tickets in the inelastic region of demand (p. 91). Both models presented by Marburger and Fort are based on the theory of short-term revenue maximization with complimentary goods (Rascher et al., 2007).

Rascher et al. (2007) offered three pricing models based on different assumptions related to complementary goods. One model assumed ticket demand would be unaffected by concession demand, another model assumed teams share concessions revenue, and a third model assumed a cross-price effect between ticket and concession demand. The third model presented by Rascher et al. (2007) aligns with the belief that fans consider the total cost to attend a game and not just ticket prices when deciding to purchase a ticket.

While many studies have been published that suggest sport teams price in the inelastic range of demand, issues of data collection can make interpreting the results challenging. In particular, studies of demand and pricing typically use a simple average price across all levels of pricing and aggregate attendance data (Rascher et al., 2007). This aggregate level of data collection does not allow for comparisons of elasticity across different seat sections. Because teams commonly utilize differential pricing across sections it makes sense to study elasticity at the section level because different segments of consumers are likely to purchase at different price levels (sections). Additionally, different segments of consumers are likely to have varying levels of price tolerance (Mullin et al.,2014). This leads to the discussion of price discrimination and dispersion.

Price discrimination and dispersion. Price discrimination, or differential pricing, refers to charging different prices for the same seat based on various factors such as time of day or day of week (Howard & Crompton, 2004). One of the first known sport management works on this topic was provided by Rascher et al. (2007) in an examination of variable ticket pricing (VTP). While price discrimination refers to the different pricing of seat sections based on various quality factors, price dispersion refers to the distribution of pricing levels across all sections.

Although the concept of price dispersion is critical to a demand-based pricing strategy, few sport discipline studies have examined this topic (Watnabe, Soebbing, & Wicker, 2013). Price dispersion has been defined as "the distribution of prices of an item with the same measured characteristics across sellers, as indicated by measures such as range and standard deviation of prices" (Pan, Ratchford, & Shanker, 2002, p. 433). Watnabe et al. (2013) found that price dispersion has significantly increased in the MLB after the league's agreement with the secondary ticket provider StubHub. Ticket price dispersion can be measured across teams within a league or can be measured within teams across sections. Soebbing and Watanabe (2014) hypothesized that higher seat section price dispersion would lead to higher attendance at MLB games. Measuring price dispersion by the number of price levels the authors failed to find statistical evidence to support their hypothesis.

In sport organizations, it is commonly known that price discrimination occurs across sections and as Watnable et al. (2013) suggested, price dispersion has also increased with the MLB's agreement with StubHub. Different quality characteristics of seats have historically led to price discrimination and now teams are increasing ticket price dispersion likely in an attempt to attract more consumers and respond to changing demand conditions. Rascher et al. (2007) provided one of the first studies on price discrimination and more recently Drayer et al. (2012) examined price changes over time. Recognizing the potential for more optimal pricing strategies, teams have implemented variable and dynamic ticket strategies that differentiate pricing based on various factors such as time of day, day of week, and opponent.

Recent Ticket Pricing Trends

Variable ticket pricing. Variable ticket pricing (VTP) in sport generally refers to the changing of the price of a single-game ticket based on expected demand (Rascher et al., 2007). Variable ticket pricing can be thought of as a static price discrimination model in which the prices are set based on *expected* demand for an event rather than the *actual* demand for the event. Price discrimination under a VTP model is applied by using historical demand knowledge based on various game characteristics such as opposing team, day of week, and time of game. Under a VTP strategy, sport organizations set ticket prices before the season and do not make subsequent changes during the season.

In 1998, the Colorado Rockies became the first team in MLB to implement a form of VTP by adjusting prices based on the time of year, day of week, holiday, quality of opponent, and the presence of a star player (Beech, 2002; Cameron, 2002; King, 2002). The Rockies applied a VTP strategy by charging more for “premium games” such as games against historically popular teams such as the New York Yankees and Chicago Cubs. Following the Rockies’ successful implementation of VTP, seven additional MLB teams including the St. Louis Cardinals, Chicago Cubs, San Francisco Giants, Cleveland Indians, New York Mets, Anaheim Angels, and the Tampa Bay Devil Rays had used some form of VTP by 2002. By 2008, nearly two-thirds of MLB teams used some form of VTP (Maich, 2008). Rascher et al.’s (2007) study showed that teams could expect additional revenues in excess of $500,000 a year when implementing a VTP strategy.

A more complex and real-time price strategy has been termed dynamic ticket pricing (DTP). Advances in technology and successful implementation of the San Francisco Giants’ utilizing of the more complex DTP pricing strategy has led to 80% of the 30 MLB teams now utilizing some form of DTP (Dynamic Pricing FAQ, 2014; Shapiro & Drayer, 2012).

Dynamic ticket pricing. Exciting times are ahead for researchers interested in understanding the potential changes the new pricing strategy of DTP will have on sport organizations. Dynamic ticket pricing is a pricing strategy that allows teams to change price as a function of inventory and time remaining (Sweeting, 2012). The secondary market, operating as a free market exchange, has provided a measuring stick to sport organizations regarding pricing inefficiencies. Research has indicated sport teams are losing out on hundreds of thousands, if not millions, of dollars in ticket revenue because secondary market prices are consistently higher than team prices (Shapiro & Drayer, 2012).

In the past decade, more teams have begun partnering with secondary ticket providers such as StubHub™ in an attempt to recapture some of the revenue they are losing on the primary ticket price. These partnerships appear to have illuminated the potential millions of dollars they are losing by using fixed pricing strategies as opposed to dynamic strategies. As a result, more teams have begun to implement their own modified ticket pricing strategies such as VTP and DTP. However, even after utilizing DTP, teams appear to still be losing out on ticket revenue when comparing prices to the secondary market (Shapiro & Drayer, 2012). While Shapiro and Drayer's (2012) study only examined one team (San Francisco Giants) and did not examine demand based on real-time data by seat location, their study provided a framework for future research on the effects of DTP.

Dynamic ticket pricing falls under the larger framework of revenue management (RM) which includes price-based and quantity-based RM. Dynamic ticket pricing would clearly fall under price-based RM (Talluri & van Ryzin, 2004). Within both of the larger RM categories (price and quantity) there are also multiple types of price-based or quantity-based RM strategies.

Despite the varying types of RM, Talluri and van Ryzin (2004) provided common elements to any RM system. An overview of RM as well as the common elements to any RM system follows.

Revenue Management: Theory and Practice

Despite its recent research interest, dynamic pricing is not a new idea. Varying prices to manage demand can be traced back to the beginnings of commerce (Talluri & van Ryzin, 2004). Businesses and individuals have generally always wanted to get the best price for selling their product and have had to make price adjustments based on consumer demand. What has changed in recent times is that technological advances have allowed for more sophisticated scientific methods for optimally applying a dynamic pricing strategy. Online retailers, such as Amazon.com, have emerged as prominent examples of dynamic pricing in practice.

Examining DTP in a sport setting is believed to require an understanding of RM and the theory of advance demand (Drayer et al., 2012; Ng, 2007). Sport studies examining either RM or advance demand are limited but the topics have recently gained attention from researchers (e.g., Dwyer et al., 2013; Shapiro & Drayer, 2014; Shapiro & Drayer, 2012). Early sport management researchers have followed the conceptual frameworks of RM provided by Kimes (1989a, 1989b) and justified the applicability of RM to sport (Drayer et al., 2012). Ng’s (2007) theory of advance demand deserves consideration when attempting to understand demand-based pricing strategies.

Talluri and van Ryzin (2004) discussed common elements of any RM system and Ng (2007) provided a conceptual framework that attempted to combine the three major disciplines RM subsumes: consumer behavior, economics, and operations (largely focusing on forecasting and estimation). The following sections offer an introduction to the literature on RM followed by a review of RM literature which focuses on each of the three major disciplines of RM.

Introduction and Basics of Revenue Management

Virtually any revenue seeking industry would like to find ways in which to maximize revenue. What one may naturally like to do is charge the highest price possible for all the units available for sale. However, any experience in a sales environment would quickly lead to the realization that not all customers are willing to pay the highest price possible and inventory subsequently goes unsold. Therefore, a strategy should be developed in order to sell the right number of units to the right customers at the right prices. The need to do this efficiently led to the development of yield (now commonly known as revenue) management.

The airline industry is credited for the advent of this revenue strategy (Belobaba, 1987a; Kimes, 1989a). Increased competition following deregulation in the 1970s forced airlines to find ways to gain a competitive advantage. Before deregulation, airlines would charge only one price for a ticket between cities. After deregulation in 1978, many startup airlines emerged that began selling discounted seats between cities. This ended up forcing the large airlines such as United, Delta, and American to respond with advance computerized systems that allowed for variable pricing to undercut the discount airlines.

Eventually, start-up discount airlines such as People's Express went out of business largely because they did not have the capability to implement a RM strategy (Belobaba, 1987a; Kimes & Chase, 1998). This need for more efficient operation and increased revenues led to the innovative strategy of yield management which is now commonly known as revenue management (Kimes, 1989a).

Definition of revenue management. What is revenue management? RM has been defined as "the process of allocating the right type of capacity to the right kind of customer at the right price so as to maximize revenue or yield" (Kimes, 1989a, p. 15). Basically, RM requires effective pricing and inventory control (Belobaba, 1987b). Revenue management addresses three basic categories of demand-management decisions: structural decisions, pricing decisions, and quantity decisions (Talluri & van Ryzin, 2004). Structural decisions include which selling format to use (e.g., posted prices or auction prices), which segmentation and differentiation mechanisms, and bundling decisions. Price decisions include setting posted prices, pricing over time, and determining how to price different product categories. Quantity decisions include how much inventory to release or hold back for sale, how to allocate inventory to different market segments, and whether to accept or reject a purchase offer.

In the case of airlines, RM helps allocate a fixed inventory of seats at various prices, at different times, to various customers (e.g., frequent business traveler versus casual traveler). One might expect an airline sales manager would prefer to sell all seats at the highest price possible. However, a tradeoff obviously exists between high prices and the risk of not selling out all the seats on the airline. RM seeks to help balance the tradeoff between high prices and high sell out percentages to increase overall revenue (Kimes, 1989b).

Kimes, Chase, Choi, Lee, and Ngonzi (1998) built upon Kimes' (1989a) definition by defining RM as managing what they called the four Cs in order to manage a fifth C, customer demand. The four Cs offered by Kimes et al. (1998) are:

- Calendar (how far in advance the reservations are made)
- Clock (the time of day service is offered)
- Capacity (the inventory of service resources)
- Cost (the price of the service)

While various researchers have attempted to define RM, others have contended there is not a satisfactory definition of RM (e.g., Jones, 1999; Weatherford & Bodily, 1992). The lack of a universally accepted definition of RM is likely because RM has evolved over its 37 year history and has been applied to an increasing body of industries which modify various aspects of previous definitions of RM to fit a particular industry mold (Ng, 2008).What is implicit in all definitions of RM is the time-perishable nature under which many service industries operate and the necessity to understand advance demand and pricing. As Ng (2007) noted "perishability and inseparability of services results in the advance pricing of services, i.e., revenue management is the management of advance revenues" (p. 533).

Contrary to a typical retail business selling tangible goods, service industries are challenged by the fact that once the service event (e.g., flight, hotel stay, ball game) takes place there is no recouping or storage of lost inventory to be sold at a later date.

Therefore, advance sales strategies must be put into place in order to sell as much inventory as possible at the right prices to maximize revenue. Talluri and van Ryzin (2004) refined the definition and knowledge base of RM by classifying RM as either "Quantity-based RM" or "Price-based RM."

Quantity-based revenue management overview. Quantity-based revenue management refers to the demand-management practices of product rationing and availability control (Talluri & van Ryzin, 2004). While pricing decisions also play a role in quantity-based RM, the primary focus of a quantity-based RM system is how much inventory to sell to which customers and when to accept or reject requests for product. Common examples of quantity-based RM can be found within the airline, hotel, and rental car industries. While inventory rationing decisions are of primary concern in a quantity-based RM system, price-based RM utilizes price as the primary factor in demand decisions.

Belobaba (1989) provided a seminal piece in the quantity-based RM literature. In his operations-focused work, Belobaba introduced the Expected Marginal Seat Revenue (EMSR) model which serves as a foundation for quantity-based RM research. The EMSR analysis was designed to help solve inventory allocation problems in the airline industry but it has also been applied to other service industries such as hotels and car rentals (Netessine & Shumsky, 2002). The EMSR model was designed to help decision makers determine the number of seats to allocate to different fare classes.

Major components of a quantity-based RM strategy include setting booking and protection levels. Booking limits refer to controls that limit the number of units that can be sold to a particular segment (class) at a particular time. Protection levels refer to the number of units to reserve or protect for a particular class (Talluri & van Ryzin, 2004). Booking limits can be expressed as a function of protection levels. That is, the booking limit, b_j for a particular class, j, can be expressed as total capacity, C, minus the j-1 protection level, y_{j-1}:

$$b_j = C - y_{j-1,} \ j = 2,3, \dots, n$$

Where n is the number of classes.

Booking limits can either be partitioned or nested. In a partitioned system, booking limits divide the available units into blocks for each class of consumer. For example, if capacity is 30 units, a partition booking limit could set booking limits for three different classes at 12, 10, and 8 for classes 1, 2, 3, respectively. Each class is essentially a segment of the population willing to pay a certain price for the product (e.g., $100, $75, or $50). The initial units allocated (i.e., the partitioned booking limits) for each class could be the result of forecasted demand based on historical data or some other form of estimation.

With partitioned booking limits, once the booking limit for a particular class has been met, that class would be closed regardless of how much inventory remained in the other classes. This is in contrast to a nested booking limit in which the higher-ranked (i.e., higher paying) classes would have access to all the lower class allocations. Using the same example as above, the nested booking limit for class 1 would be the entire capacity of 30 units. Nested booking limits are optimal when demand is uncertain which is often the case for many firms.

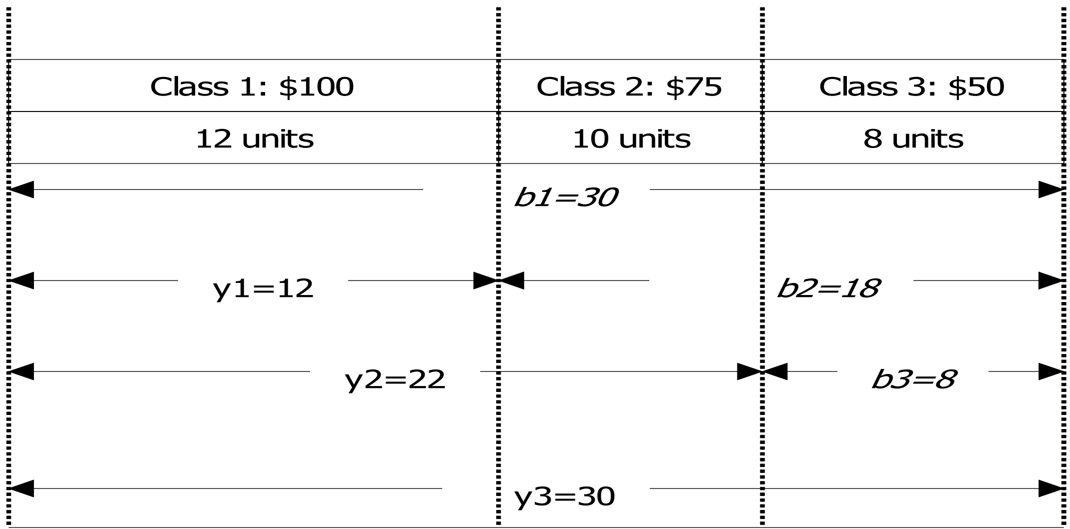

Figure 1: Example of nested booking limits and protection levels. The b_j*'s* represent the nested booking limits and the y_j*'s* represent the projection levels.

Figure 1 gives a visualization of nested booking limits and protection levels adopted from Talluri and VanRyzin, 2004, p. 29. In Figure 1, b_1, b_2, and b_3 represent the nested booking limits for the three classes and y_1, y_2, and y_3 the protection levels. In the figure it can be seen that the nested booking limits are 30, 18, and 8 for classes 1, 2, and 3, respectively. The major benefit of nested booking limits is that they allow the firm to continue to sell higher level classes until capacity is met. Contrast this with a partitioned structure where the firm would only sell at most 12 units to class 1 even if demand were higher. Furthermore, in the nested design the firm would sell at most 18 units to classes 2 and 3 combined, and at most 8 units to class 3 alone. The model can be expanded to more classes in which the notation b_j and p_j represent the booking and protection levels for the j^{th} class.

While booking limits indicate the amount a firm is willing to sell to a particular class, protection levels indicate the quantity the firm wishes to reserve or protect for a particular class *j* and all other higher ranking classes. Referring again to the example in Figure 1, the protection level for class 1, y_1, is 12 units. Of course, in a nested structure, if demand from class 1 exceeded its protection level the firm would continue to sell to class 1. The protection level simply keeps lower ranking classes from consuming certain portions of capacity from higher ranking classes. In general, given a firm has a *C* units of capacity available for sale, the firm accepts offers for booking as long as (1) there is capacity remaining and (2) the requested amount of capacity for a class *j* is below the booking limit for that class, b_j . An alternative to this process of standard nesting is what is called theft nesting.

A firm utilizing theft nesting would accept bookings for class *j* and then reduce the allocations for all lower ranking classes at the same time. So while class *j's* allocation is reduced by the booking, so are all the other lower ranking classes. In effect, theft nesting keeps allocation levels for higher ranking classes constant. Theft nesting assumes that demand is "memoryless." That is, knowing demand at a particular time does not affect estimates of future demand. To the contrary, standard nesting assumes the firm has some way of forecasting demand and the corresponding class allocations (protection levels) are based on these forecasts.

A justification for the use of standard nesting is that the allocation for the various classes is based on forecasted demand (Talluri & VanRyzin, 2004). In the example above, this would mean the protection level for class 1 (12 units) was based on some knowledge of demand for class 1. Therefore, in a standard nesting RM system, if three units were requested for purchase from class 1, the firm would reduce the protection level for class 1 from 12 to 9 units. By contrast, a theft nesting system would reduce the allocation for classes 2 and 3 by the three units sold for class 1 and keep the protection level for class 1 at 12 units. Depending on how requests are received by the firm the choice of nesting matters.

If requests for a product come in order from the lowest ranking class (e.g., class 3) to the highest ranking class (e.g., class 1) then the choice of nesting (standard versus theft) does not matter. However, in practice, this assumption is rarely the case (Talluri & van Ryzin, 2004) and requests come in random order across all classes. Therefore, a theft nesting strategy could be preferable to a standard nesting strategy because more capacity of higher ranking classes would be protected. While this may be true, standard nesting is more commonly utilized in practice (Talluri & van Ryzin, 2004). While inventory rationing decisions are of primary concern in a quantity-based RM system, price-based RM utilizes price as the primary factor in demand decisions.

Price-based revenue management overview. A price-based revenue management system attempts to optimize how to price to various consumers and how to optimally change pricing over time. Dynamic pricing and auctions are the most commonly utilized mechanisms in price-based RM (Talluri & van Ryzin, 2004). Industries providing common examples of price-based RM include manufacturing and retail. Recently, the sport industry has also appeared to have adopted a price-based RM system as teams have begun to implement dynamic ticket pricing strategies (Drayer & Shapiro, 2012; Rische, 2012).

Dynamic pricing. Common examples of dynamic pricing include retail markdown pricing and discount airline pricing. Each of these types of dynamic pricing could be useful in a sport setting. These pricing strategies are briefly described in the following sub-sections.

Retail markdown pricing. Many consumers know about or have experienced some form of retail markdown pricing. The most common retailing examples of this price-based RM strategy can be found in sporting goods, apparel, and perishable-foods (Talluri & van Ryzin, 2004). Retailers typically utilize markdown pricing to clear seasonal inventory because the inventory is either perishable or has little salvage value. Therefore, it is usually in a retailer's best interest to clear inventory at lower prices rather than try to collect negligible salvage value. Important demand information can be learned from markdown pricing.

Utilizing markdown pricing retailers can learn which products are popular with customers. It is difficult for a retailer to know which, out of hundreds if not thousands of, products will be popular with customers. Therefore, as Lazear (1986) proposed, markdown pricing can serve as a demand learning mechanism by starting prices high and marking down over time. According to Lazear, the rate at which prices fall will be a function of the number of customers, the proportion of customers who are actually buyers (as opposed to those simply shopping without purchasing), and as more is learned about the value of the good.

Another way markdown pricing informs demand knowledge is by assuming that those customers who purchase early in the selling period have higher reservation prices for the good. On the contrary, those who wait have lower reservations prices. Reasons some consumers may have higher reservation prices than others include the utility these consumers give to the good and the potential prestige for being one of the first to own a particular good (Talluri & van Ryzin, 2004). For example, it is common for lines to form outside retailers when the computer manufacturer Apple releases a new version of its popular iPhone. The prices of new releases are typically much higher immediately following the release versus a few months later. Some customers place a high utility and/or prestige to being one of the first to own the new iPhone and are willing to pay a premium while others wait sometimes as long as a year or more after release before purchasing at a much lower price. What is learned in this type of markdown pricing is that there are clearly different segments of consumers for the same product.

Discount airline pricing overview. Another common example of dynamic pricing includes discount airline pricing. While some airlines typically follow a quantity-based RM strategy to manage demand, discount airlines such as Jetblue primarily utilize price-based RM (Talluri & van Ryzin, 2004). A major difference in the pricing strategy used in airlines from retail markdown pricing is that prices typically go *up* over time as opposed to down. It is well known that the airline industry was at the forefront of implementing and improving RM strategies so it is no surprise that the industry was at the forefront of dynamic pricing strategies.

It has been suggested that the value consumers place on plane tickets increases over time (Netessine & Shumsky, 2002; Ng, 2008; Talluri & van Ryzin, 2004). Under the discount airline pricing scheme, why do prices go up as opposed to down as in retail markdown pricing? One reason given for increasing prices is that there are different segments of customers which attach different utilities or risk preferences to the value of an airline ticket (Ng, 2007; Shugan & Xie, 2000). Consumers are believed to multiply the probability of using the ticket by the price (i.e., value) of the ticket (Shugan & Xie, 2000).

Those booking far in advance typically attach a lower probability of using the ticket because of various factors that may prevent the consumer from using the ticket. As such, consumers typically expect a lower price to compensate for lower probability of consumption. While some customers prefer to get the lowest price and book early, some customers prefer to wait hours or minutes before the flight to book and subsequently subject themselves to higher prices. These consumers have a much higher probability of using the ticket and therefore are willing to accept the higher price.

A commonly cited example of why flight prices typically increase over time is the leisure traveler who tends to book earlier while the business traveler tends to book later in the selling timeframe. A leisure customer planning a vacation will likely book months in advance but could then encounter many obstacles (e.g., illness or death in family, weather, changes in employment, etc.) that could prevent the consumer from actually utilizing the ticket. Therefore, the leisure customer typically commands a lower advance price to account for the possibility of not being able to use the ticket. However, a business traveler who must attend an urgent meeting in another city will place a high value on securing a seat close to the departure date and will therefore be willing to accept a higher price for essentially the same product as the leisure traveler.

Limited research in the sport industry has suggested sport franchises utilizing dymaic pricing are following the airline model and increasing prices as game time nears (Shapiro & Drayer, 2012). More research is needed to determine if sport franchises appear to be utilizing this type of dynamic pricing strategy and understand the potential effectiveness for sport pricing. In addition to dynamic pricing strategies, some sport organizations have recently begun experimenting with the other major form of price-based RM, auction pricing.

Auction pricing overview. Traditionally, auctions have been utilized in industries such as real estate, vehicle sales, financial markets, and livestock. The Internet, and in particular eBay, has allowed auctions to be utilized for nearly anything. Talluri and van Ryzin (2004) contended that auctions are important to the study of pricing both practically and theoretically.

On the practical side, auctions are encountered in many different situations for many different industries. Auctions allow firms to achieve near-perfect first-degree price discrimination and extract nearly optimal prices without needing to estimate demand functions and consumers' willingness to pay (Talluri & van Ryzin, 2004). In contrast to other price discrimination strategies, auctions allow a firm to achieve more optimal prices without the need for as much consumer information. Theoretically, the study of auctions provides interesting opportunities to study pricing models in which consumers act strategically as opposed to the more unrealistic assumption of myopic consumers assumed in many dynamic pricing problems. Two common auction types include the open ascending (English) auction and the open descending (Dutch) auction.

In an open ascending (English) auction the firm starts with an opening price and consumers indicate their willingness to buy (typically by raising a hand or number). If the firm receives a bid, it will raise the price to determine if there are bids at the higher price. This process continues until there are no bidders at a given price and the firm awards the bidder at the last accepted price (bid) for the product.

In an open descending (Dutch) auction, a firm starts at a high price and drops the price until it receives a bid. If a firm has multiple units of an item (e.g., tickets to an event), the process of dropping prices will continue until all units have been sold. Typically, the price paid by consumers will be the lowest price at which all units have been sold. So consumers bidding at a higher price than the price that clears the inventory will end up paying less than their willingness to buy.

Auction-based pricing can be found in many industries and has even begun to surface in the sport industry. For example, Northwestern and Stanford universities have applied Dutch auction pricing to some of their more popular football games (Steinbach, 2013). The payoffs of using this pricing strategy have so far been dramatic as Northwestern reported sideline tickets selling at $195 for a home game against Ohio State. This represents a 178% increase in the highest priced ticket the year before of $70. Although the current trend in ticket pricing in the sport industry appears to be following the dynamic pricing approach, auction-based ticket pricing is an interesting avenue for research and practice.

Summary of revenue management basics. A clear dichotomy between price-based and quantity-based revenue management (RM) will rarely exist within industries or even firms within industries. For example, while many airlines would fall under the quantity-based RM strategy, discount airline companies (e.g., Southwest, Frontier) typically utilize more of a price-based RM strategy. Additionally, while retailers typically apply price-based RM they will also find creative ways to hold back inventory (quantity-based RM) in centralized warehouses and later release the inventory across their stores as opposed to allocating all inventory at one time.

Despite this blending of RM approaches, Talluri and van Ryzin (2004) suggested research classify RM into one of these categories based on whether a firm primarily utilizes capacity-allocation decisions (quantity-based RM) or price-based decisions (price-based RM) as the primary tactical tool to influence demand. These authors contended that classifying RM using this dichotomy is necessary because both the theory and practice of RM differs depending on what tactic is used to manage demand.

Recent trends in sport ticket pricing indicate that sport franchises have begun utilizing a price-based RM strategy. Dynamic pricing strategies are being applied by most teams in Major League Baseball (MLB) and efforts by MLB franchises are being made to explain their dynamic pricing policies (Dynamic Pricing FAQ, n.d.). Also, auction-based pricing has also been applied to NCAA division I football programs (Steinbach, 2013).

Based on the limited research and practice of RM in a sport setting, it is believed sport is utilizing price-based RM strategies.

Revenue Management Literature

Revenue management (RM) has now been in practice by the airlines for about 36 years. While some academic research can be found dating back earlier (e.g., Rothstein, 1971, 1974; Littlewood, 1972/2005), RM research is believed to have been fueled by the work of Peter Belobaba in 1987 and 1989 and Sheryl Kimes in 1989. Kimes' seminal piece *Yield Management: A Tool for Capacity-Constrained Service Firms* has been cited in over 400 articles and is believed to have broadened the scope and applicability of RM to virtually any service industry meeting certain criteria. Talluri and van Ryzin's (2004) comprehensive text provided a comprehensive resource for both practical and theoretical RM considerations.

Before Kimes' (1989a, 1989b) works, RM research focused almost entirely on airlines and was dominated by operations research which was heavily mathematical and related to forecasting demand (Ng, 2007). This makes sense considering the airline industry was most widely using the practice. Much of Kimes' work has been developed around the application of RM to the hotel industry but her 1989a, 2003, and 2010 pieces provided a framework to apply RM to other industries.

Kimes (1989b) credits Belobaba (1987a, 1987b, & 1989) for providing a framework for application of RM. Belobaba's (1989) seminal work has been cited by over 500 articles and propelled RM research in operations research (Ng, 2007).

Belobaba's EMSR model got the attention of researchers and practitioners by helping Western airlines increase revenue by 6.2 percent (Kimes, 1989b).

The early research on RM provided by Belobaba and Kimes helped form a foundation and propel future research and practice of RM. Kimes (2003) classified the research on RM into three broad categories: descriptive (application of RM); pricing control (development and improvement); and inventory control (management of demand patterns). Following the seminal works of Belobaba and Kimes, RM practice and research began to surface in the restaurant (Kelly, Kiefer, & Burdett, 1994), rental car (Carol & Grimes, 1995; Geraghty & Johnson, 1997), cruise lines (e.g., Maddah, Moussawi-Haidar, El-Taha, & Rida, 2010; Sun et al., 2011), and other service industries. Recently, sport management research applying the principles of RM has begun to surface (e.g., Drayer, Shapiro, & Lee, 2012; Shapiro & Drayer, 2012).

While RM research in sport management is limited, recent work applied Kimes' (1989b) RM framework to help explain sport pricing. Sport management RM literature has begun to take shape with the work of Drayer et al. (2012) and Shapiro and Drayer (2012). While there is an abundance of sport demand studies in the sport economics literature, Shapiro and Drayer's (2012) study is believed to be the first work in the sport management literature that specifically applied Kimes' (1989b) and Kimes et al.'s (1998) RM framework in a sport ticket price setting.

Early sport management RM authors provided a critical examination of the applicability to sport for each of the seven major criteria for RM: segmentable markets, perishable inventory, advance sales, low marginal costs, high marginal production costs, fluctuating demand, and predictable demand. Drayer et al. (2012) concluded that RM is a good fit for sport ticket pricing based on Kimes' criteria and added that the existence of a vibrant secondary marketplace helps confirm the need for sport organizations to develop a more efficient pricing strategy.

However, a thorough understanding of RM requires more than applying a set of criteria to a particular context. While Kimes' (1989a;1989b) works provided a framework in which RM could be applied to many service industries, much of the research on RM has been single discipline focused (Ng, 2007). Ng provided a critical analysis of RM research and provided a theoretical framework to help understand why RM practices work. To do this, Ng provided an analysis that required an in-depth understanding of three major disciplines subsumed in effective RM: consumer behavior, economics, and operations research in service firms.

An examination of the theoretical foundations of each of these three major disciplines and how each ties into effective RM is essential to advancing this topic in the sport literature (Ng, 2007; Talluri & van Ryzin, 2004). As such, the following three major sections provide an overview of the research and theory of the major RM theoretical foundations and literature from the following perspectives:

1) A marketing and consumer behavior perspective
2) An economics perspective
3) An operations perspective

RM has been mentioned as a driving force integrating pricing and operations and it is imperative that one wishing to fully understand RM has an understanding of these three major disciplines (Fleischmann, Hall, & Pyke, 2004; Ng, 2007; Talluri & van Ryzin, 2004). While overlap of the disciplines is certain to occur within RM articles, the following provides an overview of literature with an emphasis in one or the other.

Marketing/Consumer Behavior
Revenue Management
Research and Theory

In the marketing literature, Png (1989) provided an early work that stepped out of the common operationally themed revenue management (RM) literature and offered a more consumer psychology focused approach to understanding RM. While Png did not specifically use the terms yield or revenue management, the author provided a theoretical framework for understanding service consumers' purchase decisions under risk. As will be shown later, Png provided an important foundation for the theoretical work of Ng (2007) and the understanding of the risk tradeoffs consumers encounter under a RM system.

Kimes (1989a & 1989b) provided guidelines for applying RM to various service industries. Furthermore, Kimes and Chase (1998) provided two "strategic levers" for effectively controlling customer demand: pricing and duration of use. When RM researchers refer to demand, a more precise description is to refer to *advance* demand. A critical component of effectively managing a RM system is the ability to forecast advance demand and make appropriate price changes over time (Talluri & van Ryzin, 2004).

Furthermore, marketing researchers Shugan and Xie (2000) emphasized the importance of differentiating between when a product is sold versus when it is consumed. An effective RM system incorporates knowledge and theory of consumer behavior in an advance purchasing environment. The following sections provide an introduction to two theories, utility and prospect, often referred to in the economic and marketing literature to help explain consumer behavior. These theories' importance is evident in Shugan and Xie's state dependent utility framework and Ng's (2007) more recently developed RM theory of advance demand.

Utility theory. In 1947, von Neumann-Margenstern (vN-M) developed a framework to help understand consumer decisions under risky situations (Hauser & Urban, 1979). The model provides four axioms that define a "rational" decision maker. They are:

1) Completeness – the assumption that an individual has well defined preferences and can decide between two alternatives.

2) Transitivity – as an individual makes a decision in accordance with axiom 1, the individual will decide consistently.

3) Independence – assumes that when two choices are mixed with a third the consumer will rank order the choices the same way as when given only the first two.

4) Continuity – assumes when there are three choices (A, B, C) and the individual prefers A to B and B to C, then there will be some mix of A and C in which the consumer is indifferent between this mix and B.

A consumer is said to be considered "rational" when all the axioms are satisfied. Subsequently, preferences can be modeled by a utility function. Under the model, consumers are considered "risk-adverse" if they prefer a safe outcome to an uncertain but potentially more rewarding outcome, "risk-prone" if they prefer a riskier but potentially more rewarding outcome and "risk-neutral" if they have no preference of outcome.

Cook and Graham (1977) expanded utility theory to the case of irreplaceable commodities (e.g., a perishable service). Cook and Graham showed risk-adverse consumers of irreplaceable commodities will not choose to fully insure against loss (this is in contrast to fully replaceable commodities in which a risk-adverse consumer chooses to fully insure). In this work, the authors asserted that the value a consumer places on an irreplaceable commodity will not be market driven but rather driven by an individual's wealth. This work's importance to RM theory is evident in Png's (1989), Kimes' (1989a), Ng's (2007), and other RM researchers' works as perishability has been shown to be a critical component of effective RM.

Png (1989) drew upon utility theory to help explain pricing strategies for service providers. In this work, Png offered consumer decision models for spot and advance purchase under different consumer risk situations. The work provided important implications for service providers to consider how to reduce consumers' risk through insurance based on the type of reservation restrictions permitted.

While utility theory has widely been used to help explain consumer preferences under different risk situations, the theory has not been without critique. Prospect theory posits a competing model for consumer behavior under risk.

Prospect theory. Prospect theory was developed in response to flaws in utility theory when preferences systematically violate the axioms of utility theory (Kahneman & Tversky, 1979). In their seminal work, Kahneman and Tversky (1979) described how the common interpretation and application of utility theory is not adequate to describe choice under risk. In particular, these authors showed that the second axiom of transitivity is violated because people underweight probable outcomes and overweight certain outcomes: termed the certainty effect. Because the authors found empirical evidence that violated axioms of utility theory, they posited an alternative theory to explain decision making under risk called prospect theory.

Prospect theory distinguishes between an editing phase and an evaluation phase of the choice process. The editing phase occurs at the beginning of the choice process and involves:

- Coding – consumers will assess risk choices against some reference point.
- Combination – identical choices can sometimes be simplified by combining probabilities.
- Segregation – guaranteed or riskless choices will be separated in the editing phase from risky choices.
- Cancellation – if two choices share a common component, the consumer will discard the component.

The evaluation phase follows from the editing phase and is when consumers choose the option with the higher value to them. Value is treated as a function of two arguments: the reference point and the magnitude in change from that reference point.

For some time, researchers in both economics and marketing have referred to utility and prospect theory to help explain consumer decision making. Revenue management researchers such as Ng (2007), Png (1989), and Shugan and Xie (2000), have also built on these theories to produce theoretical works specifically for the service industry. These authors' works have provided important theoretical foundations for understanding RM and the pricing of inherently perishable service products. Before discussing Ng's (2007) or Shugan and Xie's (2000) conceptual models, it is important to introduce key facets of the service consumer.

The service consumer. Understanding the pricing of services involves distinguishing buyers in two basic ways (Ng, 2008). First, it is important to look at individual buyers and what motivates them to buy a certain product and how price plays a role in individual decisions to purchase. Second, it is important to examine buyers in the aggregate to understand how pricing influences market demand. Researchers studying individual buyer behavior typically rely on consumer behavior theory while a study of market demand will turn to an economic theoretical framework (Ng, 2007; Nicholson & Snyder, 2012). A thorough understanding of revenue management and the pricing of services requires an understanding of both (Ng, 2007). Indeed, it is the actions of many individual purchasers which make up the market demand curve for a product or service (Lipsey, Ragan, & Storer, 2007).

Buyer's choice. The study of consumer behavior would be much simpler if one could assume that a buyer's choice depends solely on price. Of course, the plethora of research on consumer behavior makes it obvious that buyer choice involves far more factors than price. For example, brand loyalty is one of the many factors well researched in the literature that makes it clear price is not the only influence in consumer decisions (e.g., DuWors & Hines, 1990; Krishnamurthi & Raj, 1991; Raj, 1985). Additionally, some buyers prefer to stick with one brand while others purposely seek variety (Ng, 2008).

Built on the theoretical foundations of commodity theory and the theory of psychological reactance, scarcity is another interesting factor that is believed to influence consumer choice (Brehm, 1966; Brock, 1968; Cialdini, 2009). If one considers all the possible factors that could influence consumer behavior it would almost seem futile to study this topic.

However, one accepted view of consumer behavior is that a buyer's likelihood to purchase increases when the difference in his or her willingness to pay and the associated costs increase (Ng, 2008). This difference in willingness to pay and consumer costs, commonly known as *consumer surplus*, plays a large role in consumer behavior and economic theory (Lipsey, Ragan, & Storer, 2007; Ng, 2008).

Buyer's willingness to pay. In his seminal work, Porter (1985) contended that value is a buyer's willingness to pay. So then, what is value? The answer to this question, it seems, is far from straightforward. Dodds, Monroe, and Grewal (1991) contended that research on value was limited because "value is an abstract concept that is highly interrelated and frequently confused with the concepts of quality, benefits, and price" (p. 307). Zeithaml (1988) wished to add to our understanding of value because as he stated "a major difficulty in researching value is the variety of meanings of value held by consumers" (p. 17). In Zeithaml's exploratory study, respondents described value in one of four basic ways:

1) Value is low price
2) Value is whatever I want in a product

3) Value is the quality I get for the price I pay

4) Value is what I get for what I give

According to Zeithaml (1988), these four expressions provide one overall definition of value. That is, “perceived value is the consumer’s overall assessment of the utility of a product based on the perceptions of what is received and what is given” (p. 14). Dodds et al. (1991) conceptualized value as a trade-off between perceived quality and sacrifice. Ng (2008) condensed the understanding of value into two basic definitions: gross value and net value.

Gross value refers to the expected benefits of a product or service while net value refers to gross value minus outlays (Ng, 2008). In developing the expected net value framework, Ng (2008, p. 25) provided the following definitions of perceived net value and expected net value:

- Perceived net value (PNV) – the buyer’s perception of the net gains of a good or service based on all relevant benefits and outlays *upon consumption*

- Expected net value (ENV) – the buyer’s *expectation* of the net gains of a product or service based on all relevant benefits and sacrifices *upon purchase*

Because of the advance purchasing cycle inherent with service firms, service firms’ pricing strategies are primarily concerned with expected net value (Ng, 2008).

The expected net value is high when a consumer’s expected benefits (or utility) are high and outlays are low. Both tangible and intangible attributes help increase a consumer’s expected benefits. For example, a tangible benefit of attending a particular sport event could be wider seats or more leg room while an intangible benefit could be the experience and courteousness of the ushers and staff.

Expected outlays include both monetary costs and non-monetary costs. Examples of monetary costs include the price of the service but also other costs incurred in the purchase or consumption of the service. For sport spectators, a common measure of expected monetary costs is provided in the fan cost index (FCI) which includes the cost of tickets, parking, concessions, and merchandise (FCI, 2014). Non-monetary costs to consumers include time and opportunity costs, sensory costs (e.g., discomfort from sitting or standing for long periods of time, excessive noise, etc.), and psychological costs (e.g., fear of loss of control).

The decision to purchase a service involves a dynamic and temporal mental evaluation of expected outlays for both purchase and consumption. Furthermore, outlays interact with both price and risk (Ng, 2008). If the expected net value is high enough, some buyers will decide to take the risk and purchase. By purchasing in advance the buyer minimizes some of his or her expected outlays such as search costs and risk of not being able to purchase in the future. The importance of distinguishing purchase and consumption and understanding how risk interacts with the expected net value framework becomes clearer when one examines state-dependent utility theory (Shugan & Xie, 2000) and the theory of advance demand (Ng, 2007).

State dependent utility theory. Expanding the understanding of advance purchasing and revenue management from a marketing perspective, Shugan and Xie (2000) provided implications of distinguishing between purchase and consumption. These authors suggested a model which segmented an advance purchasing market into two segments:

1) Consumers relatively disposed toward a favorable consumption state

2) Consumers relatively disposed toward an unfavorable consumption state

An underlying facet of service advance selling is risk preferences of consumers. Purchasers of most services must evaluate their expected utility of service in advance of their consumption. When buyers attach a higher expected utility to a service than the corresponding risk of non-consumption they are more likely to purchase in advance and at a higher reservation price (Shugan & Xie, 2000).

Service purchasers assume the risk of not being able to consume the product in the future. Many factors may influence any given service purchaser's risk levels. For example, an individual's risk of being able to consume a purchased ticket to an outdoor concert may be influenced by weather, illness, work conflicts, family conflicts, and many other possibilities that would inhibit consumption of the concert. The factors that can contribute to an individual's ability to consume a service lead to state-dependent utility theory (Shugan, & Xie, 2000).

State-dependent utility theory expands utility theory by modeling utility not only as a function of product attributes but also future circumstances (Shugan & Xie, 2001). Understanding that consumers have varying levels of risk prior to consumption is critical for a marketer of service providers. Marketing strategies can then be implemented at various times prior to consumption to minimize consumers' risk levels and encourage advance purchasing.

Theory of advance demand. Time of purchase is a critical factor in pricing of services and when attempting to understand advance demand (Ng, 2007; Png, 1989).

Unlike many tangible goods, consumers of services have to carefully plan the time of consumption because the service product is simultaneously produced and consumed. Therefore, the selling time for a service occurs before it is produced which creates advance demand. For service firms to price effectively they must be able to command different prices at different times during the selling period. This is essentially what revenue management is designed to do. But what contributes to different advance demand patterns? Why do some people prefer to buy early in the selling period while others choose to buy later? Examining consumers' risk preferences can help answer these questions.

Ng (2007) provided a theoretical framework to explain varying advance demand and pricing. Ng's framework focused on understanding two major risks a buyer will likely encounter when choosing when to purchase a service: acquisition risk and valuation risk. These risks are influenced by the time of purchase because it is argued that consumers' expected utility (at the consumption time) is estimated at the time of purchase (Shugan & Xie, 2000). Consumers of services must estimate their future states in order to determine their expected utility. How a buyer balances the tradeoffs of acquisition risk and valuation risk will help determine when the buyer will decide to purchase and subsequently the advance demand for the service.

Acquisition risk. Acquisition risk refers to the different values consumers attach to a service based on availability. A consumer who waits until the day of service to make a purchase runs the risk that the service may not be available. Subsequently, a consumer with high perceived acquisition risk is more likely to make an advance purchase.

Furthermore, the element of time of service can increase the value attached to the service and therefore acquisition risk is hypothesized to be heightened under the condition that a specific time is an important factor to the consumer of a service (Ng, 2007). For example, many wish to schedule a wedding on a particular month, day, and time. Therefore, a wedding is usually scheduled far in advance and a premium is paid for high demand times and days.

Valuation risk. After the advance purchase of a service, the utility of a service to a buyer could decrease to the point of zero value (Ng, 2007). For example, this can happen when a fan of a sport team such as the Denver Broncos purchases a ticket far in advance of the game and there is a blizzard on game day; then buyer decides not to consume (physically attend) the game. This is an example of what Ng (2007) termed valuation risk in which the buyer (the fan) faces uncertainty in the value of the service (game) at the time of consumption. Therefore, one would hypothesize that those consumers who face a high valuation risk (e.g., a fan worried he won't be able to attend the game) would prefer to buy close to the time of consumption (e.g., game day).

Risk tradeoff. There is an obvious tradeoff that exists between acquisition and valuation risk. Thus, a market exists for different types of consumers. A market exists for those consumers who wish to minimize acquisition risk and purchase far in advance. Additionally, a market exists for the consumer who wishes to minimize valuation risk by purchasing close to consumption time (Ng, 2007). Figure 2 is an adaptation of Ng's (2007) buyer-seller exchange of a service. The figure shows two points of sell: (a) advance sale; (b) spot sale.

Advance sale is defined to occur at any time prior to consumption whereas spot sale is defined to occur immediately before receiving the service. As is shown in Figure 2, as a consumer assumes more acquisition risk than valuation risk, he or she will tend to buy further in advance. Vice versa, as a consumer assumes more valuation risk than acquisition risk, he or she will tend to buy closer to the point of consumption.

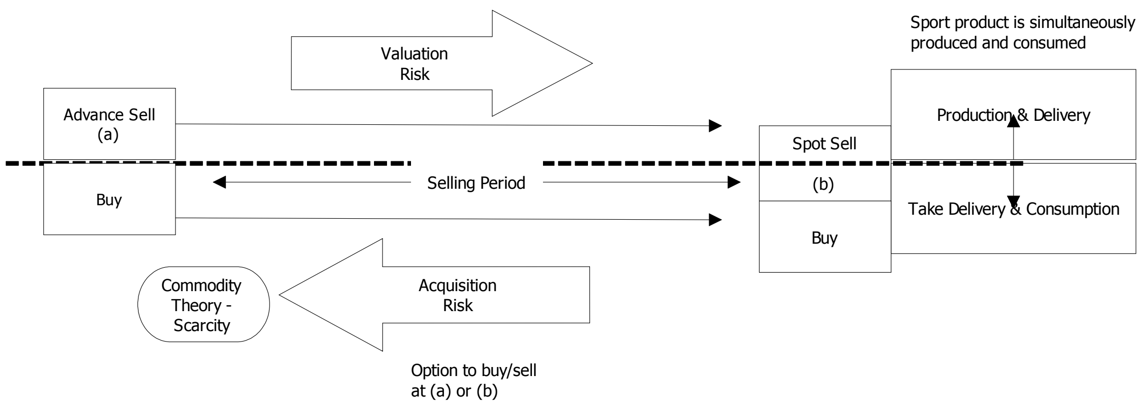

Figure 2: Buyer-Seller Exchange for service (adapted from Ng, 2007)

Ng's (2007) work provided an important bridging of the three main disciplines interconnected with revenue management (RM). Ng's work encompassing aspects of utility, prospect, and state-dependent utility theory brought together a comprehensive theory of advance demand applicable to RM. Additionally, heightened acquisition risk can be partially explained through commodity theory and the effect of scarcity on consumers' perceived acquisition risk (Brock, 1968). Another model that helps explain why advance demand RM works was presented originally by Schwartz (2000).

Schwartz's advance booking model. Another advance purchasing conceptual model that has been utilized by early sport revenue management researchers was developed by Schwartz (2000) and expanded by Schwartz in 2006 and 2008. Schwartz (2000) developed a consumer decision tree to explain consumers' decision making possibilities in an advance purchasing environment. The model followed four basic paths: book, book and search, search, and book alternative. While the work of Png (1989), Shugan and Xie (2000), and Ng (2007) illuminated the need to separate purchase and consumption when examining revenue management strategies, Schwartz (2006 & 2008) added to the theory of advance demand by considering that even after a consumer chooses to book (purchase a room, airline ticket, sport event ticket, etc.), he or she may still continue to look for "better" deals (the book and search, and search components).

Further expanding the advance booking model, Schwartz (2006) integrated standard marketing utility theory into the framework. In this work, Schwartz applied utility theory to his original model to show how various company-controlled mechanisms (e.g., pricing, promotions, etc.) are likely to influence consumer utility at each of the four advance booking decisions. The model showed that not all booking decisions are present due to high consumer costs. For example, due to high cancelation fees prevalent with airline tickets, Schwartz contended that consumer costs would be too high for a "Book and Search" utility curve to exist in the airline industry. This result can lead to recommendations for service providers to increase cancellation fees in an attempt to encourage more consumers to "book." However, caution must be exercised because too high of fees may move consumers to a state of "search" or worse "book alternative."

According to Schwartz (2006), in order to predict how consumers will respond to various revenue management strategies, one must be able to estimate the distribution of consumers on what Schwartz termed the rate/utility plane. Schwartz assumed a uniform distribution but provided no empirical evidence to support this assumption. Empirical work in RM and the theory of advance demand is needed in order to better estimate the consumer rate/utility distribution. Additionally, Schwarz's (2006) work did not assess the influence of time in the consumers' advance booking decision process. Schwartz (2008) further expanded his advance booking model by considering changes in time and the Internet on consumer booking behavior.

Technological advances have been both a blessing and curse for service industries and the practice of RM. On the one hand, advances in computer power, data storage, and decreased technological costs have allowed for the implementation of more real time pricing and inventory management systems essential to effective RM (Boyd & Bilegan, 2003; Talluri & van Ryzin, 2004). On the other hand, the Internet has allowed consumers access to substantial amounts of pricing and availability information which has closed the information gap between provider and consumer (Bair, 2003; Chen & Schwartz, 2008b; Fox, 2004).

Search costs for consumers are now relatively low because consumers can easily search multiple companies' prices and availability through aggregating service providers such as Kayak.com and Orbitz.com for travel and sites such as SeatGeek.com for sport and entertainment tickets. Schwartz's (2008) expansion of the advance booking model highlighted the importance of time and the increasing emergence of the strategic consumer brought on by search cost reductions the Internet has provided.

Major conclusions of the Schwartz (2008) piece included the need for RM systems to consider time before booking in models because customer expectations and assessment of future events is likely to change over time. Time varying variables discussed by Schwartz (2008) included the consumer's estimated probability that a discounted price will be offered in the future and probability of a sellout. Chen and Schwartz (2006) found empirical evidence to support the hypothesis that as consumers have more access to demand and pricing information they will change their willingness to book. In their work, Chen and Schwartz presented participants with visual cues of hotel demand by showing which rooms were occupied or available. This type of visual demand information is now common with airline seat selection as well as sport and event seat selection (e.g., ticketmaster.com and tickets.com allow consumers to see seats available at a baseball game and choose exact seat numbers). The results indicated that as consumers believe only a few rooms are available they are more likely to book.

Additionally, Chen and Schwartz (2008b) empirically tested whether consumers' expected lower rate and expected sellout risk changed over time and found evidence to support that expected lower rate and expected sellout risk do indeed vary over time. Dwyer, Drayer, and Shapiro (2013) examined expected lower rate and expected sellout risk in a sport setting and found both increased as the time before game decreased. However, the Dwyer et al. study did not examine the availability of demand and pricing information to consumers as the Chen and Schwartz (2006, 2008a, 2008b) studies did.

As consumers have more access to demand and pricing information, the more likely they are to make better expected lower rate and expected sellout risk assessments.

Because a firm has control of what information consumers see, it has been suggested that controlling the release and even accuracy of demand and pricing information can serve as a strategic tool in a RM system (Chen & Schwartz, 2006).

The effect of scarcity on consumers' willingness to pay has been an interesting topic of study by seminal psychological marketing authors such as Cialdini (1976). Especially under conditions of risk and uncertainty as illustrated by Kahneman and Tversky's (1979) prospect theory, the threat of potentially losing out on an opportunity to purchase can be a powerful marketing tool. However, care must be taken by revenenue management practitioners not to purposefully deceive consumers because perceived fairness of a revenue management strategy is critical to success as illustrated in the following section.

Consumer perceptions of revenue management. The implementation of a revenue management strategy must consider the perceptions developed by consumers. Consumers may evaluate the strategy and develop unique perceptions based on various factors such as price, fairness, quality, convenience, uniqueness, and substitutes. Furthermore, the unique characteristics of services such as intangibility, heterogeneity, inseparability, and perishability likely cause consumers to evaluate pricing strategies of services differently than consumer goods (Hu, Parsa, & Khan, 2006; Parsa, Naipaul, Nusair, & Yoon, 2010). The results of Parsa et al.'s (2010) study gave evidence that price framing strategies vary in effectiveness depending on the type of service (non-Hospitality vs. Hospitality). Additionally, consumers will also evaluate the product or organization based on the perceived fairness of a pricing strategy (Darke & Dahl, 2003).

Darke and Dahl's (2003) experimental study suggested consumers may be more interested in knowing they received an equal or better deal than another customer than they are about their realized savings. More recent research has also suggested consumers' perceptions of fairness play a large role in how a consumer perceives a pricing strategy (Gelbrich, 2011; McShane & Ashworth, 2012). The perceived fairness concern is exemplified by the negative backlash that Amazon.com received when randomly charging consumers different prices for identical CDs (Kannan & Kopalle, 2001).

McShane and Ashworth (2012) suggested firms employing dynamic pricing strategies take measures to prevent customers from discovering what others have paid for the same product. These authors found that when consumers discover they paid more than another consumer for the same product, this can induce feelings of disrespect and unfairness. Firms can take steps to help prevent or reduce feelings of disrespect and unfairness. Wirtz and Kimes (2007) found that price framing can be effective when respondents are not familiar with a firm's RM practice. For example, framing a price discount using a percentage can be more effective than stating a dollar discount. However, the authors found that these framing effects are minimized when consumers have knowledge of the RM strategy.

Another strategy to reduce feelings of unfairness is to make clear why prices can be different for the same product (i.e., price discrimination strategies). It is recommended that when firms implement dynamic pricing strategies they make the reasons behind the varying prices explicitly known to the consumers (McShane & Ashworth, 2012; Wirtz & Kimes, 2007). For example, an airline or sport organization could make clear that prices are likely to increase as the time of departure or game nears.

Evidence from sport organizations exists suggesting teams are attempting to educate consumers on recently implemented dynamic pricing strategies (Dynamic Pricing FAQ, n.d.) Consumers are then aware that if they wait to purchase a ticket they could likely pay more than a consumer booking months in advance. Other strategies recommended to reduce feelings of disrespect or unfairness include price matching guarantees. Kukar-Kinney, Xia, & Monroe, (2007) found that offering price matching guarantees enhances fairness perceptions of a firm's pricing policies. It may be difficult in our age of information to prevent consumers from discovering prices paid by others.

Further complicating pricing decisions, the Internet and social media now make price and service value comparisons almost effortless. Noone and McGuire (2013) examined how consumers use both price and non-price information such as consumer reviews and ratings to make purchase decisions. Their results provided evidence that while price is an important decision variable, higher prices may be acceptable when service reviews are positive while decreasing price may not have much influence when reviews are negative. The results of this Noone and McGuire's study give yet another consideration for RM managers to contemplate when changing prices.

The Drake and Dahl (2003) experiment, Amazon.com example, and the various research studies on perceived fairness of pricing strategies (e.g., Gelbrich, 2011; Kukar-Kinney et al., 2007; McShane & Ashworth, 2012) give reason for firms to be cautious when implementing dynamic pricing strategies. However, the studies listed above all examined non-perishable goods such as stereos and CDs. In service industries with perishable products such as the sport industry, dynamic pricing or other modified pricing strategies may not be met with the same backlash as consumers of non-perishable goods.

Some research has suggested that consumers of perishable goods may not have the same negative responses to dynamic pricing strategies. Airline tickets, hotel rooms, and sporting event tickets are perishables which may lead consumers to be more willing to accept a modified pricing structure in these type of industries (Kannan & Kopalle, 2001). For example, consumers of theatre attach greater value to successful plays and are willing to pay more for those plays (Colbert, Beauregard, & Vallee, 1998). Colbert et al. (1998) found that price sensitivity is related to both the product quality and segmenting consumers based on education and income. Therefore, a dynamic pricing strategy implemented in sport and entertainment settings should consider varying prices based on demand of differing games and events while also segmenting consumers. Theories aiding in the explanation of why consumer perceptions of fairness must be considered when implementing a dynamic pricing strategy include equity theory (Austin & Walster, 1974; Hatfield, Salmon, & Rapson, 2011), and the principle of distributive justice (Xia, Monroe, & Cox, 2004).

Consumer behavior aspects of revenue management summary. A thorough understanding of why RM works should include an examination of the buyer as an individual (Ng, 2008; Talluri & van Ryzin, 2004). As such, the purpose of discussing consumer behavior is to examine the RM literature and theory with a consumer behavior emphasis. Theories guiding much of the consumer behavior RM literature include early works on utility (von Nuemann Mortgenson, 1947) and prospect theory (Kahneman & Tversky, 1979) followed by state-dependent utility theory (Shugan & Xie, 2000), advance booking model (Schwartz, 2000), and a theory of advance demand (Ng, 2007). Ng's (2007) work offered a multidisciplinary approach to understanding advance demand which included consumer behavior and the subsequent topics of this literature review: economics and operations

Economic Theory of Revenue Management: The Economics of Pricing Services

While the theories of consumer choice attempt to explain the actions of the consumer as an individual, economic theory of revenue management (RM) involves aggregating the choices of individuals. Indeed, a fundamental concept of economic theory, market demand, is the summation of each individual's demand (Nicholson & Snyder, 2012). Understanding economic theory is central to understanding RM practices (Talluri & van Ryzin, 2004). In fact, the aim of RM to utilize pricing and efficient allocation of inventory to balance supply and demand is a central theme of economics. Tallury and van Ryzin (2004, p. 335-336) posed the following RM questions to be answered by economic analysis:

- How would a monopoly set the multiple prices in quantity-based RM? How do they compare to single prices?
- Is there equilibrium in capacity, allocations, and prices for two competing firms practicing RM?
- Why do firms fix prices and manipulate allocations in quantity-based RM?

- Is RM the best sale mechanism for a monopolist? For an oligopoly?
- Why do we see "price wars" or "fare sales"?
- Is dynamic pricing conducive to tactical collusion?
- Does RM increase overall welfare?
- Does RM provide the optimum number of products (variety) for customers?
- Can RM be sustained under perfect competition?
- Is RM beneficial to the consumer (by increasing total consumer surplus)?

The following sections attempt to cover the most fundamental economic theory relevant to understanding a RM strategy.

Market conditions.

Perfect competition. The first market condition that may be relevant to a RM model is perfect competition. The model assumes consumers do not care from whom they buy a particular good. Two main characteristics exist in a market under perfect competition: 1) the goods produced by firms are commodities; 2) there is a large number of firms and each only produces a small fraction of the total supply (Nicholson & Snyder, 2012; Talluri & van Ryzin, 2004). Commodities are defined as goods for which consumers have no particular preference of the source of the supply. For example, consumers may not care from whom they buy common commodities such as vehicle gas, milk, or bread; just that they can get the good for the market price. More formally, "perfect competition represents an extreme form of market competition in which the decisions of individual firms are severely constrained by market forces" (Talluri & van Ryzin, 2004, p. 336).

Under this model, in what is known as the law of one price, the firm is considered a price taker in which the firm is able to sell at market price but unable to control the market price (Nicholson & Snyder, 2012). Thus, the firm has no incentive to change prices because if it raises the price, consumers will simply buy from another supplier of the commodity. Also, the firm has no incentive to drop the price below market because buyers are willing to buy at the higher market price. Additionally, a key assumption of perfect competition is that firm's inventory decisions have no effect on market price. For example, if a gas station orders 1,000 gallons of gasoline, that station's order has minimal bearing on the market price of gasoline because millions of gallons might be sold in a single day.

The theoretical model for firm-level decisions under perfect competition assumes that firms can sell as much quantity as they wish at the market price. The limitations imposed on the firm are its own capacity constraints or costs of production. Therefore, the market price under perfect competition is equal to the marginal cost of production (Lipsey, Ragan, & Storer, 2007). In this case, the firm's decisions are entirely supply driven based only on their production costs. Therefore, under this model, RM would not be a good fit because RM relies on demand based decisions (Talluri & van Ryzin, 2004).

However, applying some modifications to the perfect competition model does make RM more applicable. In particular, when firms have to precommit to inventory and price in a market where overall demand is uncertain, then the use of RM begins to make sense. For example, airlines commit to certain flight schedules, aircraft, and pricing levels without knowing the demand for each flight. Talluri and van Ryzin (2004) showed that under the conditions of demand uncertainty and pricing and inventory commitments, the law of one price breaks down and firms may utilize RM to set capacity and pricing controls.

Perfect competition possibilities in sport. For the most part, sport organizations would not operate under perfect competition models. One reason for this is because many consumers of sport are considered "fanatics" and attach loyalty to a particular team (Funk, 2008). Therefore, a proportion of consumers (likely a majority), of an MLB team such as the Colorado Rockies, would not value watching just any other MLB game the same as watching an MLB game in which the Rockies were playing. Thus the perfect competition model would not apply to a market of only "fans" of the team.

However, most sport organizations also have consumers who are termed "casual" fans (Mullin et al., 2014). A casual fan of the Rockies will not share the same loyalty to the team as a more avid fan and will be more susceptible to influences of substitutes in the Rockies' market. Casual fans will be more influenced by other entertainment substitutes such as other sport teams, a movie, or other forms of entertainment. A main goal of the casual fan is to be entertained on a particular night and may value an MLB game the same as all other entertainment substitutes (Hong, 2009). Therefore, these fans are likely to be more influenced by the price of a MLB ticket and if the price is higher than an "equal" entertainment substitute, they will choose the substitute. It follows that there exists a market for casual fans or “casual market” and this market resembles that of a perfect competition model in which all entertainment providers would be price takers.

Although considering the consumer market on an aggregate level and not attempting to differentiate by consumer type, Alexander (2001) found that cost of other entertainment options affected demand for MLB games. An interesting question arising from the discussion of the perfect market model is do separate fan market types exist? If so, is there a fan/consumer market for professional sports that resembles that of a perfect market model? If there is a consumer market that resembles perfect competition, does a sport organization attempt to keep prices in the range of viable entertainment substitutes?

Monopoly. In contrast to perfect competition market conditions, a monopoly market occurs when a single firm supplies the entire quantity of a product and can therefore control both the inventory and prices. Like the perfect competition model, a perfect monopoly model rarely exists in practice because substitutes often exist that reduce the market power of a monopolist (Lipsey et al., 2007; Talluri & van Ryzin, 2004). However, economists have long treated professional sport franchises as relative monopolies in their respective markets (Alexander, 2001; Humphreys & Soebbing, 2012; Noll, 1974; Rascher et al., 2007).

While MLB teams can generally be thought of as monopolies, there often exist viable substitutes such as other professional and collegiate sport organizations to prevent a “perfect monopoly” situation (Alexander, 2001). The extent of monopoly power depends on the availability and quality of substitutes (Lipsey, Ragan, & Storer, 2008; Nicholson & Snyder, 2012; Talluri & van Ryzin, 2004).

Monopoly possibilities in sport. Professional sport organizations have long been considered to operate as relative monopolies (Brown, Rascher, Nagel, & McEvoy, 2010). In the famous case of *Federal Baseball Club v. National League* (1922) the Supreme Court ruled that the MLB was a monopoly exempt from anti-trust laws. As such, sport franchises have provided an avenue for economists to study pricing and quantity decisions under monopolistic assumptions. The assumption of monopoly markets is important in the study of the RM pricing problem in which firms are seeking higher profits by using more complex pricing strategies (Dana, 2001). The pricing theory related to monopoly markets is further examined in the discussion of price discrimination and dispersion.

Oligopoly. This market conditions exist when there is a limited number of firms which influence the supply of the same or similar good. Because there is only a limited number of firms, when firms in an oligopoly change prices or quantities, they influence the market demand (Lipsey et al., 2007). Oligopoly markets interest RM researchers because they are often the type of market that exists where RM is practiced (Talluri & van Ryzin, 2004). While in a monopoly firms operate in isolation, the actions of a firm in an oligopoly influence the firm's competitors as well. This feature of an oligopoly market creates a strategic interaction between firms.

Oligopoly possibilities in sport. While individual professional sport franchises operate as monopolies in their respective cities (Humphreys & Soebbing, 2012), the leagues to which franchises belong (e.g., NFL, NBA, NHL, MLB) are considered by some to operate as an oligopoly (Noll, 1974; Worstal, 2013). While in some respects this is certainly true (e.g., there are few franchises that make up each professional sport, barriers to entry are high, interdependence, etc.), no evidence could be found that the pricing and capacity decisions of sport franchises in different cities influence the demand at other franchises. Could it also be conceivable that the *collection* of professional sport franchises within a city or region behave as an oligopoly market for professional sport? If so, does this then mean that the actions of, for example, an NLH team, influcence the market of an NBA, MLB, and NFL team in the same city? No research could be found that examines the possibility but it could be an interesting avenue for further research.

The demand function. As was discussed in the consumer behavior section, each buyer of a product or service has a certain willingness to pay (or outlay as Ng [2008] termed it) based on his or her perceived value. Assuming there are many potential buyers for a given product, the economics of pricing is concerned with the actions of buyers as a whole. The demand function gives us a way of modeling consumers in the aggregate and responses to varying prices.

Assumptions of the demand function. The demand function relies on several assumptions.

1) There exists many buyers for a product or service.
2) The buyer must believe he or she has no influence over price (i.e., the buyer is a “price taker”)
3) The relationship between price and quantity assumes that all other factors are constant.

Graphically, the basic linear demand function is decreasing in quantity as illustrated by Figure 3 (i). Figure 3 illustrates some of the basic theory of pricing using one price versus multiple prices (price discrimination). The shaded area shown in 3 (i) indicates the maximum revenue generated by selling at a single price where $p*$ indicates the price that maximizes revenue. The graphs illustrate an important point when examining buyers in the aggregate as opposed to individually.

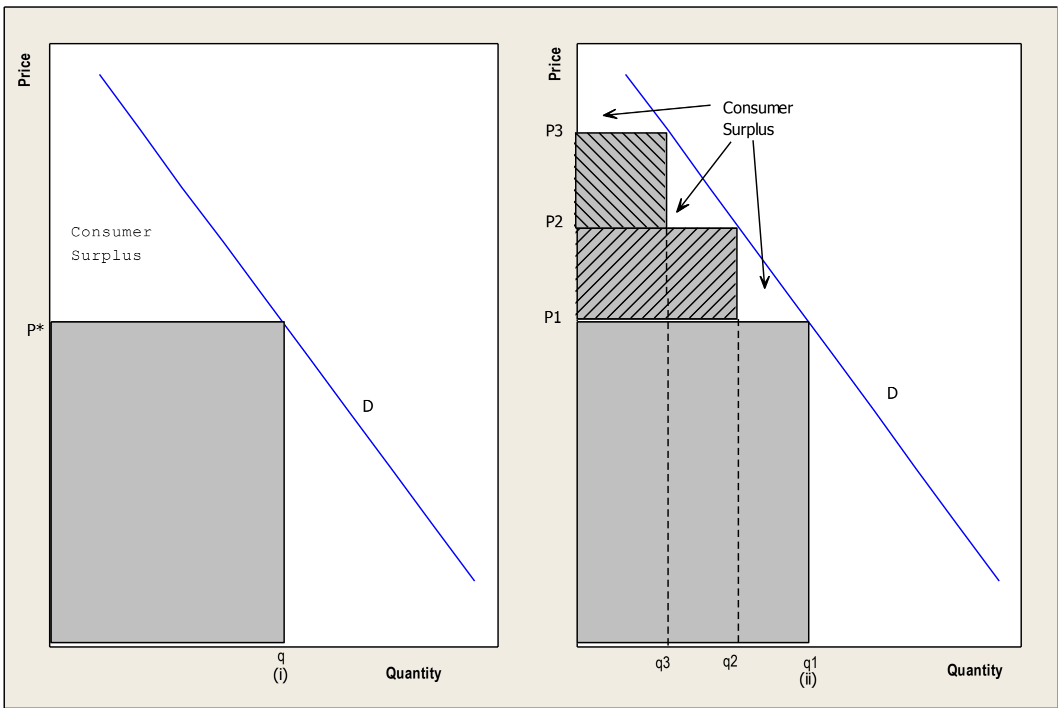

Figure 3: Demand curve without (i) and with price discrimination (ii)

If companies knew exactly how much each buyer in the market were willing to pay, they could theoretically charge an infinite number of prices which would reflect the maximum price each buyer is willing to pay. However, in reality it is nearly impossible for firms to price this way and therefore they must attempt to discover the revenue-maximizing price, $p*$, that finds the most buyers in aggregate who are willing to pay that price. This inevitably leads to *consumer surplus* which is represented by the area below the demand curve, *D*, and above the horizontal line at *p**.

Consumer surplus occurs when buyers are charged a price that is lower than their reservation price (Lipsey et al., 2007; Nicholson & Snyder, 2012). When the firm chooses a price, *p**, the demand curve indicates that there is a certain number of buyers, *q*, who are willing to pay *p**. However, because the firm is only charging one price in Figure 3 (i), it can be seen that there is a certain number of buyers less than *q* who would have been willing to pay more than *p** which results in the consumer surplus shown. Figure 3 (ii) illustrates that when a firm employs a multi price strategy the shaded area under the demand curve (maximum revenue) increases while consumer surplus decreases. This concept is the crux of price discrimination (discussed in detail a later section).

The basic demand models above help illustrate the potential benefit for firms to utilize a multi-pricing strategy. However, an important assumption to further investigate is the assumption that all other factors (e.g., marketing efforts) are held constant. When this assumption is relaxed, shifts in the demand function occur.

Demand shifts. The section on consumer behavior theory indicated that firms can employ different tactics to influence a consumer's willingness to buy (or outlay). When a firm engages in marketing or other strategies it is doing so to influence buyers to buy when they may have not previously been inclined (Lipsey et al., 2007). These activities influence the demand by shifting the original demand curve (D1) to the right (D2) as shown in Figure 4.

Figure 4 helps illustrate the firm's pricing decisions when the demand curve shifts from *D1* to *D2*. Point A on the graph shows the maximum revenue at price *P2* under the original demand curve for quantity *Q1*, point B illustrates the price *P1* which maximizes revenue under the shifted demand curve for quantity *Q1*, and point C is the point where *P2* maximizes revenue for quantity *Q2*. Because the firm's demand curve has shifted to *D2*, the firm must decide whether to increase price to *P1* and take the revenue generated for *Q1* consumers (point B) or to keep the price at *P2* and take the revenue generated for *Q2* consumers (point C). The firm will choose the price which generates the most revenue between points B and C.

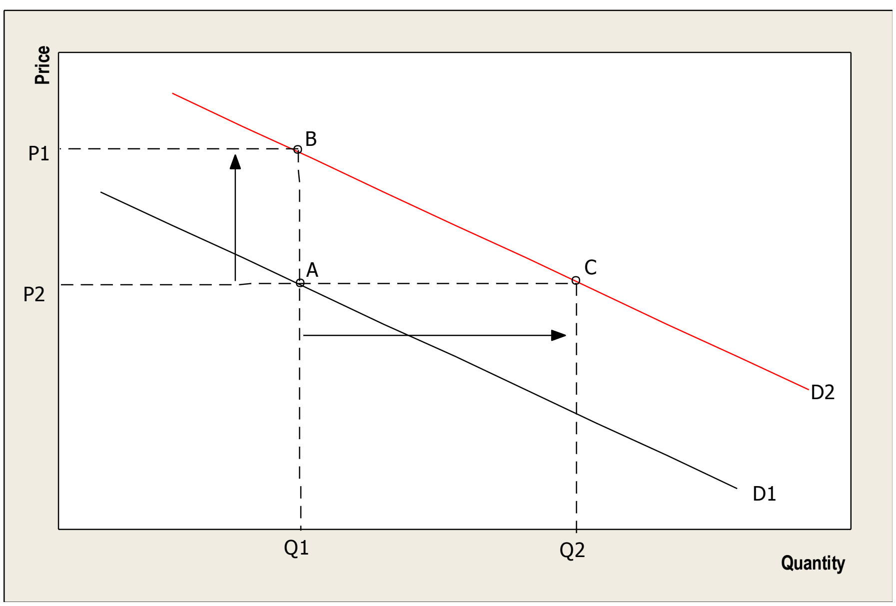

Figure 4: Shifts in the demand curve.

A numerical example. To help further illustrate a firm's pricing decision when the demand curve shifts consider a firm that sells tickets to events. Suppose *P2=$7* is the firm's initial price and *Q1=10* is the demand at that price. Now suppose the firm implements a marketing strategy aimed at increasing demand to an event. If the marketing strategy is successful, it will shift the demand curve to the right so that with the original price of $7, now the demand has increased to 15 (*Q2*). Furthermore, the firm is considering increasing the price from $7 to $10 (*P2 to P1*). At $10, the demand for the event is the same under the new demand curve as it was under the old demand curve at the lower price (*Q1*). In this example, the new revenue at point A would be $70 (*P1*Q1=$7*10=$70*), point B would be $100, and point C would be $105. Therefore, ceteris paribus, under the shifted demand curve the firm should maintain its original price of $7 and take the revenue generated from the increased demand at *Q2*.

Supply and capacity. While the demand curve is essentially constructed based on how much quantity consumers demand at each possible price, the supply curve is essentially what firms will provide at each possible price. In contrast to the demand curve, the supply curve will slope upward because as prices rise, firms will generally produce more of a product (Lipsey et al., 2007). The interaction of demand and supply forms the foundation of standard economic theory that is used to study pricing effects and find optimal pricing solutions (Nicholson & Snyder, 2005). Figure 5 displays how demand and supply interact to form the equilibrium price (E) in which the quantity demanded equals the quantity supplied.

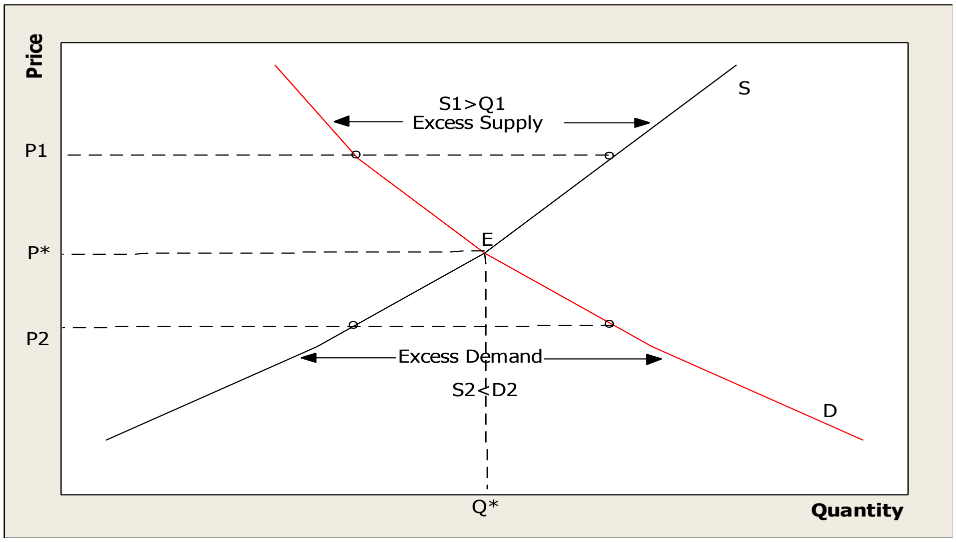

Figure 5: Interaction of Supply and Demand

Economic theory development has led to the four laws of demand and supply (Lipsey et al., 2007). These laws are given below and illustrated in Figure 6:

1) An increase in demand causes an increase in both the equilibrium price and the equilibrium quantity exchanged. This can be seen in Figure 6 (i) as the equilibrium price increases from E_o to E_1, quantity increases from Q_o to Q_1 as the demand is shifted from D_o to D_1.

2) A decrease in demand causes a decrease in both the equilibrium price and the equilibrium quantity exchanged.

3) An increase in supply causes a decrease in the equilibrium price and increase in the equilibrium quantity exchanged. This can be seen in Figure 6 (ii) as the equilibrium price decreases from E_o to E_1, quantity increases from Q_o to Q_1 as the supply is shifted from S_o to S_1.

4) A decrease in supply causes an increase in the equilibrium price and a decrease in the equilibrium quantity exchanged.

Thus far the discussion of supply and demand and the economic theory developed around them has assumed a free market that allows for prices to fluctuate to meet the equilibrium point where supply equals demand. However, various price and/or quantity restrictions are common in practice which prevents equilibrium. Examined in the following sections are the important pricing concepts of price ceilings and floors as well as capacity constraints.

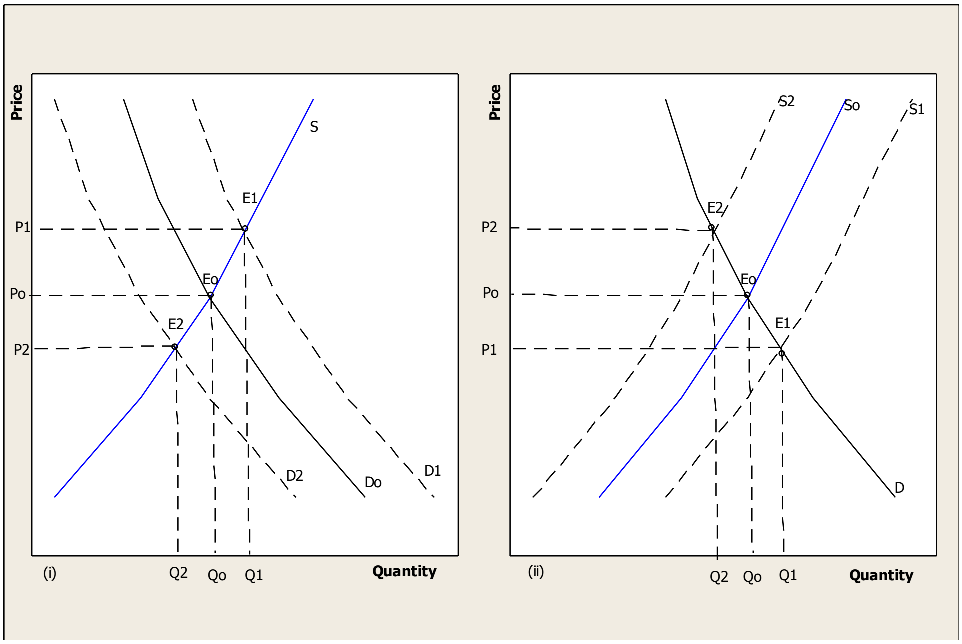

Figure 6: Illustration of the four laws of demand and supply.

Price ceilings and floors. It has been suggested that price ceiling and floors are applied when a sport organization sets ticket prices (Drayer et al., 2012; Howard & Crompton, 2004). Thus far, the theoretical discussion of demand, supply, and equilibrium prices assumed prices are allowed to flow toward the equilibrium point. However, when price restrictions such as ceilings and floors are introduced to a market, prices are not always allowed to reach the equilibrium point and either shortages or surpluses occur (Nicholson & Snyder, 2012).

A price floor is the minimum permissible price a firm can charge for a good or service and a price ceiling is the maximum. If a price floor is set above the equilibrium price as show in Figure 7 (i) a surplus will occur. If a price ceiling is set below the equilibrium price as shown in Figure 7 (ii) a shortage occurs and creates a black market (Lipsey et al., 2007). Price restrictions are therefore important to consider in a study of ticket pricing in sport.

An example of a potential price floor for sport event tickets would be the price of season tickets (Salant, 1992). Some of the most important consumers of sport firms are season ticket holders because they commit a large guaranteed revenue source for the firm before the season (Howard & Crompton, 2004). Therefore, it is believed sport organizations employing a variable or dynamic ticket pricing strategy would implement ticket price floors to ensure single game ticket prices do not fall below season ticket prices. Additionally, sport organizations may implement price ceilings.

Some ceilings may be a result of organizational policy and some may be a result of governmental policy. Because of the high visibility of sport in American society, sport organizations may implement a ticket price ceiling to maintain good public relations (Drayer et al., 2012; Howard & Crompton, 2014). It is important to examine the theory behind the potential effects of such ceilings and floors on the ability to implement a dynamic ticket pricing strategy.

The results of setting prices below market equilibrium can be seen with the booming secondary ticket market with firms such as StubHub, Ticketmaster, eBay, and others essentially acting as a legal black market for the resale of tickets (Brown et al., 2010; Drayer et al., 2012). Indeed, recent studies have suggested that sport firms are pricing below the secondary market which has illuminated ticket pricing inefficiencies (Shapiro & Drayer, 2012). Sport organizations are responding to previously rigid price setting policies by implementing demand based pricing. Conceptually, demand based pricing should allow sport firms to price more fluidly in an attempt to meet market equilibrium and diminish the opportunities for arbitrage in the secondary market.

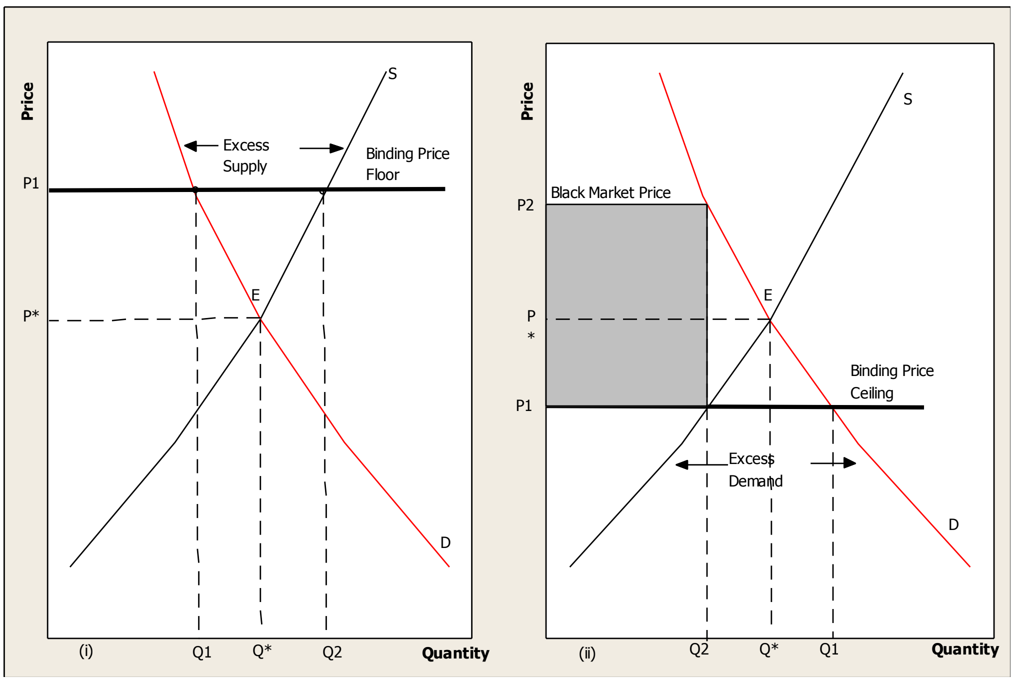

Figure 7: Price ceilings (i) and floors (ii)

Capacity constraints. Because most service firms cannot supply an infinite amount of their product, they have to be conscious of their capacity constraint. Sport stadiums only have so many seats, hotels so many rooms, restaurants so many tables, etc. Because of the perishable nature of service inventory, managing capacity to match a firm's supply and demand is a critical component for service providers (Ng, Wirtz, & Lee, 1999). Capacity constraints are an important consideration when examining the demand curve for service firms because economic theory often makes the assumption of no capacity constraints (Ng, 2008).

To illustrate this point, let P^* and Q^* represent the profit-maximizing price and quantity, respectively, and consider a firm with capacity constraint, $K_2 < Q^*$. Also, assume $P_1 > P^* > P_2$ represent three prices the firm could charge. Ignoring capacity constraints, the theoretical demand curve would indicate the firm should set the price at P^* and sell Q^* units to maximize revenue. However, because of the capacity constraint, the firm can sell at most K_2 units and therefore "misses out" on the revenue from Q^*-K_2 consumers. Therefore, based on the demand curve and capacity constraint the firm should now price at P_1 instead of P^* to meet demand and obtain higher revenues.

Now suppose the firm had capacity $K_1 > Q^*$. The firm could choose to price at P_2 to fill capacity but this would be suboptimal because Q^* represents the profit maximizing quantity. Therefore, as can be seen in Figure 8, conventional economic wisdom would suggest the firm price at P^* and "waste" some of the capacity represented by K_1-Q^*. However, service firms rarely adopt this one-price economic convention but rather utilize price discrimination strategies in an attempt to fill capacity (Ng, 2008). In addition to utilizing price discrimination to use more capacity, Ng et al. (1999) suggested service firms could utilize unused capacity as a strategic tool.

Price elasticity. Krishnamurthi and Raj (1991) gave an example of how consumer behavior research and economics blended together in their study of consumer brand preference and price elasticity. In their work, Krishnamurthi and Raj showed that consumers with higher brand loyalty were less sensitive to price when choosing to buy but *more* sensitive to quantity decisions. The implications of this work indicated that pricing and promotion strategies are more effective on non-loyal customers but a reduction in price does not influence loyal consumers to buy more quantity.

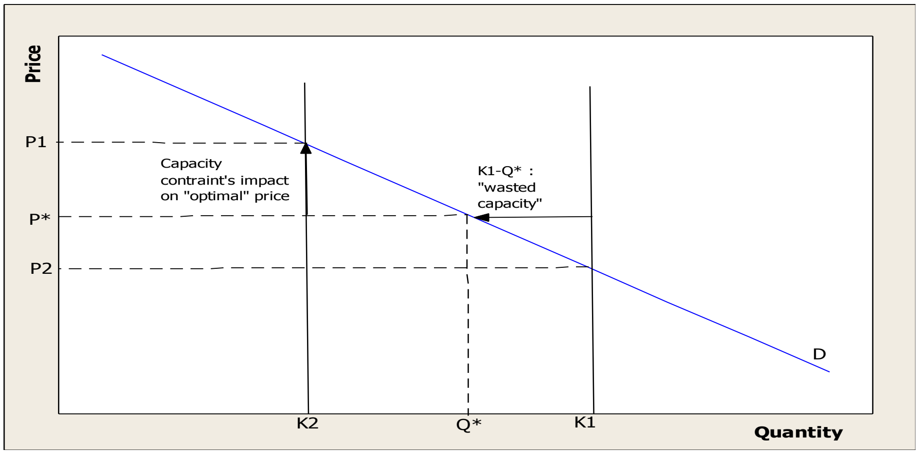

Figure 8. The impact of capacity constraints on the demand curve.

Examining demand and supply models is useful in determining whether quantities rise or fall with changes in price but perhaps the more important question is by *how much* does a change in price influence demand. Price elasticity of demand is one of the most important concepts studied in microeconomics because it provides a convenient way of summarizing how people react to price and how firms react to demand curves (Nicholson & Snyder, 2012). Price elasticity gives a measurement of the sensitivity of demand to changes in price (Lipsey et al., 2007) and is given by:

$$\eta = \frac{\text{Percentage change in quantity demanded}}{\text{Perentage chage in price}} = \frac{\Delta Q/\overline{Q}}{\Delta \mathrm{P}/\overline{\mathrm{P}}} = \frac{(Q1 - Qo)/\overline{Q}}{(P1 - Po)/\overline{P}}$$

Where $\overline{Q}$ and $\overline{P}$ represent the mean quantity and price, respectively. Given the assumption of a negative sloped demand curve elasticity will be a negative number.

However, it is not uncommon for the absolute value of elasticity to be reported (Nicholson & Snyder, 2012; Rascher et al., 2007).

Demand is said to be *inelastic* if 0< η<1 (i.e., percentage change in quantity demanded is less than percentage change in price). If demand is inelastic the effect of price on quantity is small. When η>1 demand is said to be *elastic* and price affects quantity demanded significantly. When percent change in quantity demanded equals percentage change in price (i.e., η=1) demand is said to be *unit elastic*.

Figure 9 illustrates an important result that occurs when demand is unit elastic. The graph shows a linear demand curve, *D,* and total revenue (bold blue curve) produced at each price and quantity along the curve.

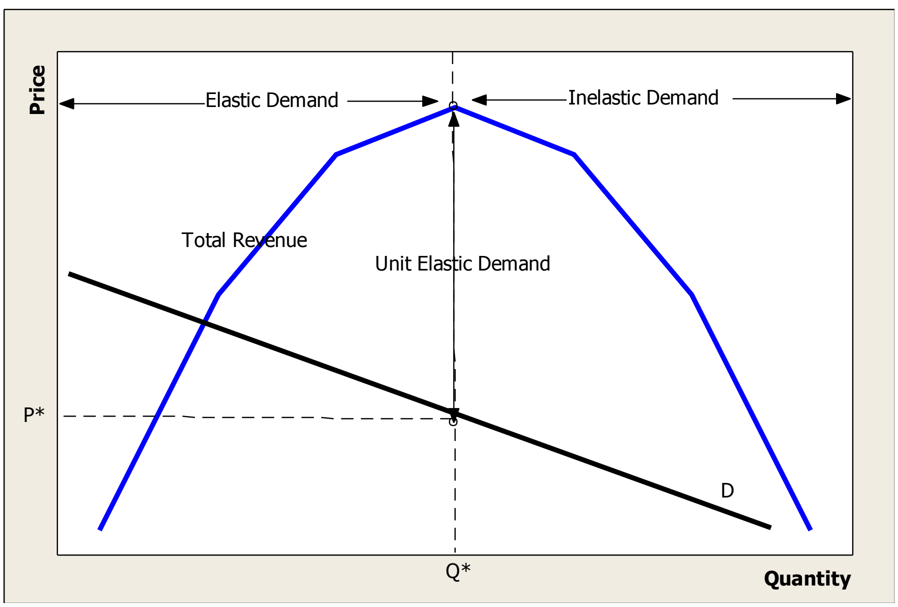

Figure 9: Interaction of Total Revenue and Price Elasticity

For quantities less than *Q**, demand is elastic and total revenue increases with decreases in price. For quantities greater than *Q**, demand is inelastic and total revenues decrease with decreases in price. Maximum revenue is obtained at unit elasticity when quantity is Q^* and price is P^*. This result leads to the examination of marginal analysis.

Marginal analysis. To determine how much a firm should sell requires an understanding of marginal revenue, marginal cost, and elasticity. A firm can then utilize marginal analysis to determine the price and quantity to sell. The definitions of key components to marginal analysis include:

- Total revenue: the price multiplied by the quantity sold.
- Average revenue: total revenue divided by quantity
- Marginal revenue: the revenue generated from selling one more unit of capacity
- Marginal cost: the cost of selling one more unit of capacity

Two general rules apply to profit-maximizing firms (Lipsey et al., 2007):

1) The firm should not produce at all unless its revenues exceed its costs.
2) If the firm does produce, it should produce a level of output such that its marginal revenue equals its marginal cost.

Assuming a firm satisfies rule (1), marginal analysis helps the firm decide how much and at what price to sell by applying rule (2). Furthermore, an important distinction of service firms is that most costs are already committed and marginal cost is negligible (Ng, 2008). Therefore, a profit maximizing service firm should set price where marginal revenue and marginal cost are both zero (i.e., marginal revenue=marginal cost=0). As illustrated in Figure 10 the profit maximizing price (P^*) will correspond to a quantity (Q^*) that maximizes total revenue when marginal revenue equals zero and demand is unit elastic.

In his discussion of the theory of price setting of professional sport, Salant (1992) expressed this classic result of economic theory mathematically using the following expression:

$$p\left(1 - {}^{1}\!/_{\varepsilon}\right) = marginal\ cost$$

This expression as well as Figure 10 have long been used to show that profit maximizing firms with negligible or zero marginal cost should set prices at unit elasticity $\varepsilon = 1$ (Salant, 1992). Thus, in studies examining pricing of service firms, one can calculate elasticity from demand and pricing information in an effort to determine if the firm is in fact pricing to maximize profits.

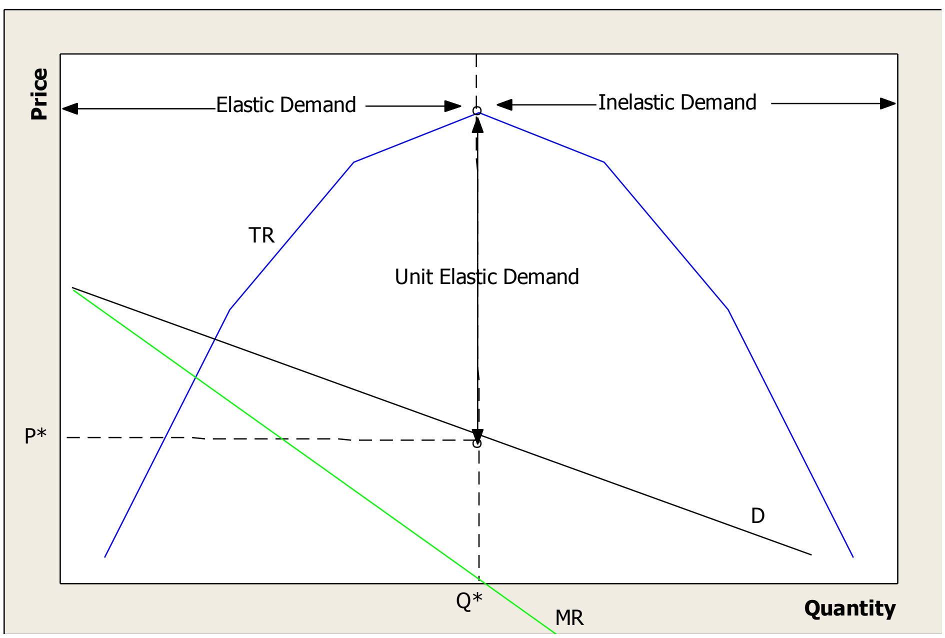

Figure 10: Revenue Functions and Marginal Analysis.

Price discrimination. Dana (1999) described RM as increasing a firm's profits by implementing the following two price discriminating practices:

- Peak-Load Pricing

- Third-degree price discrimination that screens customers and segments them based on their price sensitivity.

Although the term “price discrimination” seems to have a negative connotation, price discrimination is simply charging different prices to different customers. It is important to understand when and how price discrimination practices work because it serves as the foundation for practicing RM (Ng, 2008; Talluri & van Ryzin, 2004). The main types of price discrimination include peak-load pricing, first, second, and third degree price discrimination.

Peak-load pricing. A common form of price discrimination is what is known as peak-load pricing. It is particularly relevant to the service industry because of the perishable nature of services. Crew, Fernando, and Klendorger (1995) defined peak-load pricing as “the pricing of economically non-storable commodities whose demand varies periodically” (p. 216). Basically, peak-load pricing attempts to “level out demand by pricing differently in peak and off-peak periods, thereby achieving more efficient capacity allocation” (Talluri & van Ryzin, 2004, p. 341). Bergstrom and MacKie-Mason (1991) provided a simple two period peak-load pricing model. One period is termed the peak period and one the off-peak period.

An example of peak-load pricing in a sport context can be found by examining demand for weekend games versus weekday games. A Saturday night MLB game may be considered a peak period while a Tuesday day game an off-peak period. Therefore the team could utilize peak-load pricing and charge a higher price for the Saturday game.

***First-degree price discrimination*.** First-degree price discrimination refers to the ability to charge different prices for the same product to different consumers based on willingness to pay. In theory, this form of price discrimination provides the firm the most efficient way of pricing because it effectively extracts all consumer surplus from the buyer (Lipsey et al., 2007; Nicholoson & Snyder, 2012).This is because every buyer in the market reveals to the firm exactly how much they are willing to pay for a product.

For many firms, first-degree discrimination is impossible or impractical (Talluri & van Ryzin, 2004). However, this form of price discrimination can be found in auction practices where buyers must reveal to the firm exactly what they are willing to pay for a product. An example of the use of this type of price discrimination is utilized on the online auction site, eBay, in which buyers reveal through bidding how much they are willing to pay for a product.

Second-degree price discrimination. Second-degree price discrimination infers that firms are not able to tell the difference between different types of buyers (Ng, 2008). The most common use of second degree price discrimination involves pricing based on quantity (Nicholson & Snyder, 2012). For example, a firm may offer unit discounts if buyers buy in bulk (e.g., two units for $2, one unit for $1.59). The key characteristic of second-degree price discrimination is that consumers self-select into segments (e.g., one segment that wishes to pay a higher total but receive unit discounts and those consumers who wish to pay less total but higher per unit costs). This form of price discrimination can be found in a sport setting with the use of bundled ticket packages such as season tickets or mini-plans.

Third-degree price discrimination. The most common form of price-discrimination is third-degree (Ng, 2008). In this case, the firm chooses to charge different prices for the same product based on different segments of the market. Some common strategies include segmenting based on time (e.g., time of purchase, time of event), location (e.g., charging international students higher tuition than local residents, different pricing based on location of seats in a sport venue), and age (e.g., senior discounts). The major goal of third-degree price discrimination is to sell more inventory when price elasticity is high and to extract more consumer surplus when price elasticity is low.

For example, sport franchises may feel people are more sensitive to ticket prices during the week for various reasons (i.e., price elasticity is higher during the week) but people seem to be willing to pay more for weekend games (price elasticity is lower during the weekend). If these assumptions hold true, a sport franchise could utilize third-degree price discrimination to charge lower ticket prices during the week to sell more tickets (inventory) but charge higher prices during the weekend to extract more consumer surplus (willingness to pay).

Conditions for price discrimination. Economic theory requires the following conditions necessary for effectively practicing price discrimination:

1) Variance in customer preference: consumers must exhibit some differences in preference for a product or there is little room for price discrimination to work. In sport, consumer preferences include location of seat, time of day, day of week, and opponent to name a few.

2) No resale (arbitrage): if consumers are allowed to resell the product or service then arbitrage is possible if not likely. For example, a person could buy a ticket to a ballgame for a low price early in the sale period and then resell closer to game time for a higher price (i.e., scalp the ticket). Sport franchises and municipalities have attempted to control scalping but the legitimization of secondary ticket market providers such as StubHub and eBay have made the requirement of no resale nearly impossible.
3) Monopoly power: as mentioned previously, absolute monopoly power is more of a theoretical abstraction than reality. However, to practice price discrimination effectively, firms should have some monopoly power. Competition is likely to exist for any firm, but as long as the number of competitors remains relatively low, price discrimination can be practiced. However, as competition increases or the ability to differentiate the product decreases, the effectiveness of a price discrimination strategy decreases.

Price discrimination in sport. It is well known that sport franchises have practiced third-degree price discrimination based on seat location for some time. Additionally, sport franchises have practiced bundled ticket pricing (a form of second-degree price discrimination) for some time (Howard & Crompton, 2004). Recently, collegiate athletic departments have begun to experiment with first degree price discrimination by utilizing reverse auction pricing (Steinbach, 2013). An examination of Talluri and van Ryzin's (2004) criteria for price discrimination raises some questions as to how effective price discrimination strategies can be in a sport context:

1) Variance in customer preference: Research exists showing that sport consumers have varying preferences for the sport product (e.g., Funk, 2008; Madrigal, 2008; Mullin et al, 2014). Sport consumers have varying levels of "fan avidity," preferences of what opponents to watch, and from what seat locations they prefer to watch a live game. Sport teams clearly satisfy the first criterion of price discrimination.
2) No resale (arbitrage): Sport franchises and municipalities have historically placed restrictions of ticket resale (Brown et al., 2010; Noll, 1974). These restrictions would appear to help satisfy the second criterion for second-degree price discrimination. However, the practice of scalping tickets is well known in the sporting industry. Recent trends indicate a growing acceptance of the practice of reselling tickets via the secondary market. Indeed, the Internet and secondary ticket market providers such as StubHub have provided a legitimized opportunity for the practice of arbitrage. In fact, in 2007, StubHub signed a contract with the MLB to become the exclusive secondary ticket provider (Brown et al., 2010). With this legitimization of a secondary market to resell tickets, the second criterion for price discrimination no longer appears to hold for sport franchises. As such, questions arise as to how effective price discrimination strategies would be in sport.
3) Monopoly power: The four most prominent professional leagues in the United States (NFL, MLB, NHL, NBA) are essentially monopolies (Brown et al., 2010). In fact, the U.S. Supreme Court ruled that the MLB was a legal

monopoly exempt from anti-trust laws (*Federal Baseball Club v. National League,* 1922). Of course the leagues do not enjoy perfect monopoly status because substitutes for entertainment such as other sports (e.g., collegiate, semi-professional) or movie theaters exist in the markets where professional sport franchises are located. Nevertheless, these leagues still represent relative monopolies in their cities because there are no other similar professional football, baseball, hockey, or basketball leagues. For example, a person living in Denver, Colorado has but one choice to watch a professional baseball game (Colorado Rockies), football game (Denver Broncos), hockey game (Colorado Avalanche), or basketball game (Denver Nuggets). In this respect, professional sport franchises enjoy relative monopoly status. Therefore, it appears the third criterion for sport price discrimination holds. However, as the Denver example illuminates, while competition may not exist within the sports, it does exist across leagues and across other sport and entertainment substitutes. Thus, the ability to price discriminate in sport is weakened. This helps explain why sport marketers spend so much of their resources attempting to differentiate their product in order to be able to lessen the effect of substitutes on price discrimination practices (Mullin et al., 2014).

Despite the violation of the second criterion for price discrimination, teams continue to practice price discrimination by seat location and ticket bundles. One of the reasons for the continued use of price discrimination could lie in a sport franchise's marketing department.

Sport organizations spend a reasonable amount of resources on marketing and differentiating their sport so as to shift the demand curve and be able to price discriminate (Mullin et al., 2014). Furthermore, teams appear to be trying to control some of the ticket reselling activities by partnering with secondary ticket providers (Brown et al., 2010). Additionally, teams are beginning to utilize dynamic ticket pricing so their single game price discrimination strategies are no longer fixed as they were in years past (Drayer et al, 2012; Rascher et al., 2007). These reasons explain why sport franchises may still be able to effectively utilize price discrimination despite failing to fit Talluri and van Ryzin's (2004) criteria perfectly.

Advance selling, demand, and price discrimination. The integration of consumer behavior and economic theory can be seen when one examines the advance selling period inherent with service firms. As discussed in the consumer behavior section, distinguishing between time of purchase and time of consumption is critical to the pricing of services. The nature of service providers to price in advance leads to time of purchase being the most utilized factor in service firm price discrimination strategies (Ng, 2008). The theory of advance demand presented by Ng (2007) helps illuminate the complex nature of service firm demand.

Advance demand can be considered to have three major components (Ng, 2008). First, there is a deterministic component in which a pricing policy may influence the quantity demanded. Next, there is a stochastic aspect of advance demand brought by varying buyer arrival times (i.e., consumers "arrive" at random times unpredictable by the firm). Finally, there is a probabilistic component to advance demand because even after a consumer has "arrived" at a particular time, there is still a probabilistic choice set the consumers goes through. Schwartz's (2000, 2006, 2008) advance booking model attempted to explain the probabilistic choice set for a service consumer with the options of book, book and search, search, and book alternatives.

At each point in time, service providers are likely to encounter different demand curves based on consumers' acquisition and valuation risks (Ng, 2008). Not only are firms likely to encounter differing demand distributions across time but variances in price elasticity across time are also likely to occur. Theoretically, there exists an infinite number of demand curves and price elasticities across the selling period which makes optimal pricing of services challenging. This difficulty in pricing services, along with advancement in technology, gives rise to dynamic pricing.

Dynamic pricing. Dynamic pricing "refers to prices that are updated in real time, as a response to changing buyer/demand information and conditions" (Ng, 2008, p. 106). Although dynamic pricing has recently received increased attention in the literature, dynamic pricing is not a new concept. Forms of dynamic pricing can be traced back thousands of years with traders in bazaars bargaining with consumers (Talluri & van Ryzin, 2004). As long as there has been free trade, one can find some form of dynamic pricing as traders attempt to find the highest prices consumers are willing to accept. The basics of dynamic pricing are rooted in free trade and economic principals of supply and demand (Christ, 2011).

Changing prices are often the most common and natural business practice for RM. Some common examples of price changing found in business practices include clearance sales, display and trade promotions, personalized pricing, coupons, discounts, etc. Dynamic pricing as a RM strategy is concerned with how best to utilize various price changing techniques to optimize revenue. Technological advancements in data collection, storage, and analysis have allowed dynamic pricing to achieve new levels of sophistication and accuracy.

Dynamic pricing application. Industries providing insight and innovations of dynamic pricing include: retailing, manufacturers, and E-business. The use of dynamic pricing in retailing has been reported to have increased gross margins as high as 24% for ShopKo with other retailers reporting gains anywhere from 5% to 15% (Friend & Walker, 2001). Technological advances have allowed for the construction of demand models utilizing historical point-of-sale (POS) and inventory data as inputs to predict timing and magnitude of price change (Talluri & van Ryzin, 2004).

Manufacturers such as Ford Motor Company have also implemented scientific approaches to pricing and have reported beating profit targets by $1 billion after implementation (Coy, 2000). Coy (2000) stated “the new strategy of smart pricing draws on microeconomics, buyer psychology, and the computer power to sift through lots of data on spending patterns” (para. 3). This aligns with Ng’s (2007), Talluri and van Ryzin’s (2004), and Desiraju and Shugans’ (1999) works that a thorough understanding of a RM system requires a blending of knowledge from economics, consumer behavior, and operations.

The recent surge in interest in dynamic pricing models can be attributed to several factors (Ng, 2008, p. 105):

1) The Internet has created a critical mass of buyers whom sellers can reach without going through conventional channels.
2) Increased electronic purchasing allows for greater availability of demand data.
3) Technological advances have made it easier and less costly to change prices.

Being able to forecast demand across the advance selling period is critical to the success of a RM dynamic pricing strategy (Ng, 2008; Talluri & van Ryzin, 2004). This leads to the discussion of the operational component of RM.

Operations Revenue Management Research and Theory: Estimation and Forecasting

One wishing to understand revenue management (RM) from an operations research perspective would be inclined to review Belobaba's seminal works (1987a, 1987b, & 1989). Some ten years after Belobaba's works, Botimer and Belobaba (1999) provided a new theoretical framework for pricing and differentiation in the airline industry. Additionally, Bitran and Caldentey (2003) provided an overview of different pricing models for RM including dynamic pricing.

Much of the literature on RM from an operational research perspective focuses on a firm's ability to estimate and forecast demand. Indeed, Littlewood's (1972/2005) classic piece focused on mathematical models to forecast demand and Belobaba's (1987a, 1987b) development and implementation of the expected marginal seat revenue (EMSR) model garnered the attention of academics and practitioners alike with reported increases in airline revenue of 4-6%. Estimation and forecasting is key to the understanding and proper implementation of a revenue management system (Ng, 2008; Talluri & van Ryzin, 2004; Weatherford & Kimes, 2003).

In the following sections I attempt to address some of the most salient topics and methods on these topics related to RM. In particular, the focus of this section is on the role of forecasting in RM including: surveying available data sources, designing a forecasting system, forecasting strategies and methodologies, and factors involved in operationalizing a RM forecasting system (Talluri & van Ryzin, 2004).

Surveying available data sources. Of the many challenges faced by a RM system designer, data collection, management, and storage obviously serve as a foundation for forecasting (Talluri & van Ryzin, 2004). Without a way to collect, store, and manipulate data into useable formats, forecasting and estimation would be nearly impossible. It is imperative to a RM forecasting system to develop a solid database design due to the immense number of records that have to be retrieved, stored, updated, and added in relatively small time windows.

The recent surge in the practice and research of RM can largely be attributable to advances in technology allowing for improved data collection and storage capabilities. Improvements to computing power and data storage have made the once daunting and expensive task of data collection and analysis practical for many firms. Without these improvements and subsequent reductions in the costs of data collection and storage, forecasting and other forms of analysis were simply not an option for all but the largest firms (Kimes, 2010; Ng, 2008).

Data are obviously the life-blood of a forecasting system because, without data, there are no forecasts. Thus, finding and selecting appropriate data sources is imperative to a successful RM system. Most RM systems rely on historical sales data to generate forecasts (Talluri & van Ryzin, 2004). In the following sections I discuss the most common data sources.

Sales-transaction data sources. Most RM systems rely on transactional databases such as property management systems, customer-relationship management, and point-of-sale. Quantity-based RM data sources typically include reservation databases that store information in the aggregate (such as total bookings in a particular class) and at the individual booking level. The individual data are called customer booking records or passenger name records and typically contain customer information such as name, address, booking time, number of units booked, price paid, etc.

Retail firms, which typically utilize price-based RM, store information such as store-level scanner, consumer-panel, regional demographics, advertising, and promotion data. Additionally, marketing firms often provide panel-data services which allow firms to track purchase behavior over time. Panel data are obtained from tracking a group of panelists over time and can provide valuable purchase behavior information. Such panel data allow firms to make connections between purchase behavior and marketing strategies employed over time information (Talluri & van Ryzin, 2004).

Controls-data sources. Another form of data collection important to a RM system involves collecting and storing data on the RM process itself. Past prices, when a booking class was closed, and promotion activities are examples of the type of data collected in controls databases. An example of controls-data source would be the booking and consumption data gathered for hotels (Weatherford & Kimes, 2003). Another potentially valuable data source for forecasting includes industry-wide databases.

These databases can provide data on competitor bookings, prices of competing products, and market share.

Auxiliary data sources. These data sources can also be beneficial to a RM forecasting system. Some forecasting models may take into account the state of the economy, employment rates, income, and savings rates, etc. For some time, economists have utilized economic data such as per capita income, population size, rate of unemployment, gross domestic product, and working hours, to understand factors influencing attendance of sporting events (e.g., Borland & MacDonald, 2003; Noll, 1974). Weather data may be included in forecasting models in order to help with discounting decisions if, for example, a large storm were predicted to hit the area. Because many sporting events are held in open air stadiums, collection of weather data prior to game time could help improve attendance forecast.

Partial-bookings data. Because of the advance demand and purchase inherent in services, demand data are collected at many times leading up to consumption. Partial-bookings data capture bookings over the advance selling period and can be useful for forecasting (Lee, 1990; Talluri & van Ryzin, 2004; Weatherford & Kimes, 2003). Daily booking data can be used to forecast increments in demand as opposed to aggregate demand (Lee, 1990; Wickham, 1995). For example, one could use historical daily data from the 10th day prior to consumption of one event to forecast demand ten days prior to a similar event. Such information could be useful to marketers to plan the timing of promotions and other marketing strategies.

Designing a forecasting system. Once the data sources have been identified there are a number of other considerations a firm wishing to implement a RM forecasting system must consider. Two main questions need to be answered:

- How is the distribution of future demand going to be estimated?
- How will data and forecasts be aggregated?

The following two sections explore the choices arising from these questions.

Demand distributions. Most RM forecasting problems involve estimating future demand. One key decision that needs to be made is what type of estimation should be used. The parametric approach involves assuming demand data follow a specific functional form and then estimating the parameters of this function form. Early RM researchers claimed probabilistic demand to be central to airline inventory control problems (Belobaba, 1987a). Some of the first work on RM forecasting by Beckman and Bobkowski (1958, as cited in McGill & van Ryzin, 1999) compared Poisson, Negative Binomial, and Gamma distributions for airline passenger demand data and found that the Gamma distribution provided a reasonable fit for the data. Belobaba (1987b) assumed demand for flights followed a normal distribution and offered empirical support to justify this assumption. An alternative to the parametric approach, non-parametric approach, does not assume an *a priori* functional form but rather relies on estimating the demand distribution directly based on historical data. The parametric approach is the most widely used choice of method in RM practice (Talluri & van Ryzin, 2004).

Levels of aggregation. After deciding on the type of estimation approach, another critical decision is how to aggregate data and subsequently make forecasts. The choice of level of aggregation largely depends on data availability and purpose of forecast. Research has shown that disaggregated forecasts outperform aggregated forecasts in hotel forecasting (Weatherford, Kimes, & Scott, 2001) but errors have been high for disaggregated forecasts in airlines application (Weathford & Kimes, 2003). More research is needed to understand what level of data produces the best forecasts in a sport setting.

For example, if one wishes to forecast overall demand for a MLB game, then aggregated attendance data from previous years (or similar games in same year) may be used to develop overall game attendance forecasts for future games. However, because professional sport teams (e.g., MLB, NFL, NBA, etc) have historically price discriminated based on seat location, one may wish to forecast demand for specific seat sections as price for seat sections can vary considerably in any given venue. In this case, demand and pricing data would need to be collected for each seat section.

To date, sport demand studies have only been able to estimate demand based on aggregate game data (Borland & MacDonald, 2003; Rascher et. al, 2007; Soebbing & Watanabe, 2014). This is attributed to the difficulty (if not impossibility) of obtaining section level data directly from sport franchises (Soebbing & Watanabe, 2014). This limitation on data collection makes forecasting demand and other important measures such as elasticity of demand difficult. Those who produce estimates of elasticity of demand in sport have been forced to use aggregate demand and revenue to calculate average ticket price. This poses problems in the calculation of elasticity of demand because most of the average price data do not weight based on the number of seats sold in particular sections (Noll, 1974; Rascher et al., 2007; Salant, 1991). To further the understanding of demand and pricing in sport, disaggregated section level data is needed.

Forecasting strategies and methodologies. Much of statistical methodology focuses on models where error terms are assumed to vary independently. With many statistical methods, dependence between observations is undesirable and randomization is often utilized to validate analysis as if observations were independent (Box, Hunter, & Hunter, 1978). However, there are many instances in business, economics, engineering and natural sciences in which dependent observations are collected repeatedly over time and the nature of the dependence is of interest (Box & Jenkins, 1976). A wide range of forecasting methods are available and range from simple methods (such as using the most recent observations as a forecast) to highly complex econometric systems (Makridakis, Wheelright, & McGee, 1983). Revenue management forecasting is primarily interested in predicting future values of demand and the success of a RM system lies in a firm's ability to forecast demand (Kimes, 1999; McGill & van Ryzin, 1999; Pak & Piersma, 2002).

Forecasting methods are utilized in a vast number of industries and fields including statistics, computer science, engineering, economics, and weather. Box and Jenkins (1976) provided a seminal text on the subject of time series analysis. The Box and Jenkins text is said to have popularized time series applications and has led to new developments in time series research. In particular, "the importance of diagnostic checking in modeling has become even more critical in this data-rich environment for all statistical analyses" (Mills, Tsay, & Young, 2011, p. 1).

As with any statistical methodology, models can be simple or complex. However, according to Talluri and van Ryzin (2004) most forecasting algorithms in RM practice are not complicated. Rather, the focus of RM forecasting methods is on speed, simplicity, and robustness. The following sections provide an overview of forecasting notation and the mathematics behind certain techniques that can potentially be utilized in a RM forecasting strategy.

Forecasting notation. Before presenting some of the most common RM forecasting techniques and models it is helpful to define common time series analysis notation. Notation for representing time series data involves defining t as the current time in a list of observations and l as lead times such that $t+l$ represents some future time in which forecasts are desired (Box & Jenkins, 1976). Then we can define z_t as the demand at time t and $z_{t-1}, z_{t-2}, z_{t-3}, \ldots$ as the demand at previous times. These previous observations of demand can then be used to forecast demand at future lead times $l=1,2\ldots,l,$ denoted $\hat{z}_{t-1,}\hat{z}_{t-2}, \hat{z}_{t-3} \ldots$. The function, $\hat{z}_t(l)$, represents what is called the forecast function and provides forecasts at time origin t and for future lead times $l=1,2,\ldots$. The error term for the i'th observation, e_i, is the difference in the observed demand and the forecasted demand, $e_i = z_i - \hat{z}_i$.

Stationarity and autocorrelation. Two important concepts in time-series forecasting are stationarity and autocorrelation. Time-series data are said to be stationary if the data vary about a constant mean value and the variance around the mean is constant over time (Makridakis et al., 1983). More formally, if $z_t, z_{t2}, z_{t3}, \ldots z_{tm},$ is a set of m observations made at times $t_1, t_2, \ldots, t_m$ and $z_{t+k}, z_{t2+k}, \ldots z_{tm+k}, \ldots z_{tm}$ is another set of m observations made at times $t_{1+k}, t_{2+k}, \ldots, t_{m+k}$, the process is said to be strictly stationary if the joint probability distributions are the same at all choices of t and all pairs of values k and m (Box & Jenkins, 1976).

Determining whether data are stationary is an important part of the forecasting model identification process. For example, in forecasting methods that utilize the simple mean as a forecasting tool, the forecasts will not be accurate if the data are not stationary (e.g., a trend or seasonal component exists). In practice, many time series data or not stationary but can be made stationary through simple transformations (e.g., differencing successive values) (Box & Jenkins, 1976; Talluri & van Ryzin, 2004). The transformed series can then be modeled and forecasts generated for the original series.

Another key concept when deciding an appropriate forecasting method is autocorrelation (denoted r_k). As stated by Makridakis et al. (1983):

> Success in time-series analysis depends in large part on interpreting the results from autocorrelation analysis and being able to distinguish what is pattern and what is randomness in the data. (p. 369)

This key time-series statistic measures the correlation between a time series with itself at various lags. Statistical tests for r_k provide information on the randomness of the data and provide information helpful in identifying appropriate models. The autocorrelation function (ACF) and partial autocorrelation function (PACF) are critical components in a methodological selection of time series methods which are discussed in greater detail in subsequent sections.

Smoothing and decomposition forecasting methods. Sometimes referred to as structural forecasting methods, smoothing and decomposition forecasting methods are largely heuristic in nature (Makridakis et al., 1983; Talluri & van Ryzin, 2004). These methods have garnered wide appeal from practitioners because their development has been mainly empirically based rather than theoretical (Makrikakis et al., 1983). Despite the lack of strong statistical and theoretical development these methods have been shown to provide accurate forecasts in certain situations (Makridakis et al., 1982; Talluri & van Ryzin, 2004; Weatherford & Kimes, 2003; Wickham, 1995). Some evidence exists which suggests these simple methods provide significantly more accurate forecasts than more complex forecasting methods such as autoregressive integrated moving average (ARIMA) models (Carbone, Anderson, Corriveau, & Corson, 1983).

Sometimes termed "ad-hoc" forecasting methods, these methods are more commonly known as smoothing and decomposition by time series authors (e.g., Bowerman & O'Connel, 1993; Box & Jenkins, 1978; Makridakis et al., 1983). Authors claim these methods have good theoretical properties despite their largely heuristic origins (Talluri & van Ryzin, 2004). Decomposition methods typically involve breaking up the data and composing the time series data into hypothesized patterns using three types of components: level, trend, and seasonality.

Denoted A_t, level refers to the typical average value of the data. Trend, T_t, refers to a predictable increase or decrease in the data and seasonality (S_t) refers to a periodic or repeating pattern in the data over time. An example of a seasonality pattern would be expected increases or decreases in sales during a weekday versus weekend or during summer or winter months. According to Talluri and van Ryzin (2004) “Ad-hoc forecasting methods are intuitive, are simple to program, and maintain and perform well in practice. For these reasons, they are prevalent in RM practice” (p. 434). The following sections explain the most common smoothing and decomposition methods.

Moving average. Denoted *MA(T)* for moving average of order *T*, this method assumes that the most recent observations provide the best predictors of future data. As opposed to taking the average of all historical data, this technique simply takes the average of the *T* most recent observations and uses this average to forecast future values. In RM practice, *T* is typically between 3 and 15 (Talluri & van Ryzin, 2004). Mathematically, the simple *T*-period moving-average forecast is given by:

$$\frac{\hat{z}_{t+1} = z_t + z_{t+1} \dots + z_{t-T+1}}{T}$$

While this technique allows for simple calculations of forecasts, if the data trend upward or downward the moving average will systematically under- or over-forecast, respectively (Makridakis et al., 1983). To account for trends, one technique utilized is exponential smoothing.

Exponential smoothing. Because of their simplicity and robustness, exponential smoothing techniques are commonly utilized in RM practice (Talluri & van Ryzin, 2004; Weatherford & Kimes, 2003). In fact, because of their practical usefulness, exponentially weighted averages were being used prior to theoretical justification (Winters, 1960; Box, Hunter, & Hunter, 1978). Three main exponential smoothing techniques include:

- Simple exponential smoothing
- Exponential smoothing with linear trend
- Exponential smoothing with trend and seasonality

Single exponential smoothing is the simplest version of exponential smoothing and includes a smoothing constant, $0 < \alpha < 1$, for the level, A_t. The model for simple exponential smoothing takes on the form:

$$\hat{z}_{t+1} = A_t = \alpha z_t + (1-\alpha)\hat{z}_t \qquad (1)$$

Equation 1 provides a simple and convenient way to update forecasts as new data are recorded (Holt, 1957/2004; Box, Hunter, & Hunter, 1978). However, as is evident in Equation 1 the forecasting process must begin with an initial estimate of $\hat{z}_t$ which can be obtained with the following equation:

$$\hat{z}_t = \alpha \sum_{n=0}^{M}(1-\alpha)^n z_{t-n} + (1-\alpha)^{M+1}\widehat{z_b} \qquad (2)$$

where z_b is the first observed value of demand and M is the number of observations up to and including the current period, t. Even in cases where α is small, if M is large, the last term is typically negligible and can be ignored (Winters, 1960).

The value of α changes how quickly forecasts respond to the most recent data. By setting α in the higher range (e.g., α=.9) forecasts will respond quickly to current conditions because higher weights are assigned to the most recent data with a rapid decrease in weights on data further back. In contrast, setting α in the lower range of values (e.g., α=.1) will result in forecasts being less responsive to change because more weight is applied to older data (Makridakis et al., 1983; Winters, 1960). Determining the "best" value of α differs based on the particular data under study and is best determined following a structured modeling process such as those outlined by Box and Jenkins (1976).

Choosing the value for α is a RM design decision with values usually ranging from .05 to .3 in RM applications (Talluri & van Ryzin, 2004). In a study of the accuracy of various airline forecasting techniques, Wickham (1995) used values of .2 and .4 for α. Weatherford and Kimes (2003) tested α levels between .05 and .95 and found the "best" performance (based on mean absolute error(MAE)) for various hotel rate categories was found when α was .05, .15, .35, .45, .55, and .65. Sun, Gauri, and Webster (2011) tested α values between .05 and .95 in increments of .05 and found the range of .05 to .3 the best.

Exponential smoothing with linear trend. Exponential smoothing with linear trend introduces another parameter, $0 < \beta < 1$, which is a smoothing factor for the underlying trend (T_t). The forecast for the period, $t+1$, is given by,

$$\hat{z}_{t+1} = A_t + T_t \text{ where,}$$

$$A_t = \alpha z_t + (1-\alpha)(\hat{z}_t + T_t) \text{ and,}$$

$$T_t = \beta(\hat{z}_t - \hat{z}_{t-1}) + (1-\beta)T_{t-1}.$$

Exponential smoothing with trend and seasonality. Finally, exponential smoothing with trend and seasonality, introduces a third parameter, $0 < \gamma < 1$, which is used to control the smoothing of a seasonality (S_t). The seasonal effect has a periodicity (L) which indicates the number of periods before a season repeats. For example, if one is forecasting monthly and the seasonality is by month, L=12. Then, the forecast for period, t+1, is given by:

$$\hat{z}_{t+1} = (A_t + lT_t)S_{t+l-L} \quad \text{where,}$$

$$A_t = \alpha(\frac{z_t}{S_{t-L}}) + (1-\alpha)(\widehat{z}_t + T_t) \text{ and,}$$

$$T_t = \beta(\hat{z}_t - \hat{z}_{t-1}) + (1-\beta)T_{t-1} \text{ and,}$$

$$S_t = \gamma(\frac{Z_t}{S_t}) + (1-\gamma)S_{t-L}.$$

Time-series analysis forecasting methods. While exponential smoothing and decomposition forecasting methods are largely heuristic, time-series forecasting methods are based on well-specified classes of models with more mathematically sophisticated approaches and wide applicability (Makridakis et al., 1983). Some common applications of time series analysis include: economic and business planning, production planning, inventory and production control, control, and optimization of industrial processes (Box & Jenkins, 1976). It should be no surprise that time-series methods have long been utilized in RM applications and research (e.g., Belobaba, 1987a; Kimes, 1999; Sun et al., 2011, etc.).

Comprehensively developed by Box and Jenkins (1976) the autoregressive-integrated moving-average (ARIMA) models form a general and wide reaching class of forecasting models (Markidakis et al., 1983). Essentially, an infinite number of models can be constructed from the general ARIMA (*p,d,q*) model with the following components:

AR: p = order of the autoregressive process

I: d = degree of differencing involved

MA: q= order of the moving average process.

While *p, d, q,* can theoretically take on any value, in practice most models are constructed with values of 0, 1 or 2 (Matridakis et al., 1983; Sun et al., 2011; Talluri & van Ryzin, 2004). To determine appropriate values for *p, d,* and *q* requires a systematic approach to model building. One commonly and widely accepted approach is termed the Box-Jenkins Identification Process (Bowerman & O'Connell, 1993; Box & Jenkins, 1976; Matridakis et al., 1983; Talluri & van Ryzin, 2004).

Box-Jenkins stochastic model building process. Selecting an appropriate forecasting model can be a time consuming and arduous task. To help find an appropriate model, Box and Jenkins (1976) provided a systematic, iterative way to help identify and build stochastic time series models. The Box-Jenkins iterative stages of model selection are:

1. Identification
2. Estimation
3. Diagnostic checking
4. Forecasting

Identification. In the identification stage, statistical and graphical approaches are employed to narrow the list of potential models. First, it is important to know that ARIMA models are assumed to be based on stationary data. However, because most time series in practice are non-stationary, transformations are typically required. Graphical plots are a good first step in the identification process and are often all a forecaster needs to determine if a time series is stationary (Box, Hunter, & Hunter, 1978; Makridakis et al., 1983). Additionally, plots and significance tests of autocorrelation coefficients can show whether a time series is stationary or not.

An unstationary series will have autocorrelation coefficients that are statistically significant for many lags while stationary series typically only have at most three significant autocorrelations at lags 1, 2, and 3 (Makridokis et al., 1983; Talluri & van Ryzin, 2004). Graphically, the ACF will show only a few large spikes followed by quickly decreasing spikes for a stationary series while an unstationary series will show many large spikes which slowly decrease (Bowerman & O'Connell, 1993). If the original data are not stationary, often the first difference (particularly of sales data) will provide a set of stationary data (Box, Hunter, & Hunter, 1978). Second, differences can also be applied if the first differenced series is still unstationary.

In practice, it is uncommon to difference more than two times so the value of d in the ARIMA (p, d, q) is typically either 0, 1, or 2 (Box & Jenkins, 1976). If first or second differences do not make the series stationary other transformations such as the logarithm of the series may be more appropriate (Talluri & van Ryzin, 2004). For example, if the percentage changes between successive observations are stationary, a logarithm transformation would likely make series stationary.

Once a value for d is tentatively chosen, the ACF and PACF plots of the transformed series can then be evaluated to provide clues for the values of p and q. Table 1 provides a summary of the theoretical properties of the ACF and PACF for common ARIMA models (Box & Jenkins, 1976).

In practice, the ACF and PACF will rarely, if ever, behave exactly as the theoretical models presented above. However, one can still utilize the ACF and PACF to get a broad idea as to what the underlying models may be. It is possible for several models to be identified in this stage but further investigation via estimation and diagnostic checking can shed more light as to the best model (Box & Jenkins, 1976; Makridakis et al., 1983).

Table 1

Theoretical ACF and PACF properties for common ARIMA models.

ARIMA Model	ACF	PACF
(1,d,0)	decays exponentially	only first r_k nonzero
(0, d,1)	only first r_k nonzero	exponential dominates decay
(2, d,0)	mix of exponentials or damped sine waves	only first two r_k nonzero
(0, d,2)	only first two r_k nonzero	dominated by mix of exponentials or damped sine waves
(1, d,1)	decays exponentially after first lag	dominated by exponential decay after first lag

Note. ACF=autocorrelation function; PACF=partial autocorrelation function.

Estimation. Having tentatively identified a model(s) the next step is to estimate the model parameters from the data. Makridakis et al. (1983, p. 441) provided the following two fundamental ways of estimating time-series model parameters:

1. Trial and error – examine many values of the parameters and find the one (or set) that minimizes the sum of squared residuals.
2. Iterative improvement – choose an initial estimate and let a computer program iteratively refine the estimate.

Trial and error could take a considerable amount of time and therefore the iterative approach is recommended (Makridakis et al., 1983). The iterative approach has significantly improved and become relatively efficient with advances in technology and early algorithms developed by Marquardt (1963) for FORTRAN and Meeker (1977, as cited in Minitab 17 Statistical Software, 2010) for Minitab. Minitab's and SAS's ARIMA function provide an iterative process for finding optimal parameter values. With either Minitab or SAS the user can define starting parameter values or accept the default starting value of 0.1 (Bowerman & O'Connell, 1993; Minitab 17 Statistical Software, 2010). Additionally, Box and Jenkins (1976, p.517-520) provided a collection of tables to help with identifying starting parameter values.

If possible, it is recommended to narrow the choices of starting parameters. However, in practice the process of finding starting parameters can be complicated and time-consuming. Tables provided by Box and Jenkins (1976) can help with starting values but algorithms programmed into statistical software such as Minitab and SAS will often efficiently find the optimal parameters as long as the starting values are reasonable (Bowerman & O'Connell, 1993; Makridakis et al., 1983). In Minitab, even if the optimal solution is not reached after the maximum 25 iterations allowed by the program, one can store the first 25 estimates and use them as starting values for a subsequent fit as often as necessary (Minitab 17 Statistical Software, 2010).

Diagnostic checking. Once a potential model has been identified and parameters found, it is necessary to conduct diagnostic checks to verify the chosen model is adequate. Test statistics for checking the adequacy of the model include the Box-Pierce and Ljung-Box statistics. Theory has indicated that the Ljung-Box statistic is the "better" of the two statistics (Bowerman & O'Connell, 1993). If the test for model adequacy indicates that the model is adequate, Bowerman and O'Connell (1993) recommended that only the individual residual autocorrelations and partial autocorrelations with *t*-values greater than 2 be further investigated.

An examination of the ACF and PACF of the residuals provides further diagnostic checking. If the model is adequate the ACF and PACF of the residuals will show no significant autocorrelations or partial autocorrelations (Makridakis et al., 1983). Finally, in order to check for overfitting of the model, it is recommended to conduct tests of the coefficients in the model (Box & Jenkins, 1976; Makridakis et al., 1983). Tests of coefficients can help indicate whether a particular model has been overfitted. If the coefficients are not found to be significantly different than zero, then it is generally recommended to drop them from the model and reexamine (Makridakis et al., 1983).

Forecasting. If diagnostic checking implies an adequate model, the model can then be used to generate forecasts. Statistical software packages such as Minitab and SAS make the task of forecasting relatively straightforward. If one utilizes the rigorous model building procedure outlined by Box and Jenkins (1976) and described in previous sections, the forecasting functions built into statistical programs such as SAS or Minitab make the task of forecasting simple and efficient. For example, if the model building process suggested an ARIMA (0,1,1) model was adequate for making forecasts, Minitab's ARIMA function involves entering 1 in the "Difference" and "Moving Average" dialog boxes. Then Minitab will provide forecasts for user entered origin and lead times including 95% confidence limits for forecasts.

Pickup forecasting methods. More of a strategy for data organization than separate forecasting techniques, pick-up forecasting has widely been used in RM applications (Talluri & van Ryzin, 2004). Pickup forecasting methods may utilize any of a number of the forecasting techniques illustrated in previous sections to forecast final and/or incremental demand (e.g., exponential smoothing, moving averages, ARIMA, etc.). The design of a pickup data strategy is mostly simple and heuristic. However, despite the relatively simple design, these forecasting methods have been widely used and reported to perform well in RM applications (Lee, 1990; Talluri & van Ryzin, 2004; Weatherford & Kimes, 2003; Wickham, 1995; Zakhary, Atiya, el-Shishiny, & Gayar, 2011).

Pickup in this sense means the number of reservations or demand that is forecasted to be "picked up" over intervals of time across the selling period (Sun et al., 2011). Classical pick-up (CP) and advance pick-up (AP) define the two broad categories of pickup strategies (Lee, 1990; Sun et al., 2011). The main difference in CP and AP strategies is the applicable data set used to make forecasts. CP and AP strategies are further subdivided into additive and multiplicative models. Additive models assume current demand on a day prior to consumption is independent of final demand while multiplicative models assume final demand is dependent on current demand (Weatherford & Kimes, 2003).

To facilitate the discussion of pick-up methods, the following notation is utilized in the development of data tables and mathematical models:

- $D_{gs}(t)$: Cumulative demand, *D*, *t* days before service consumption where *g* is the game number and *s* is the section name.
- Let *M* represent the last day of data collected in the database for an event (e.g., if 20 days from service consumption were the furthest back in time the database includes records, *M*=20 days).
- $PU_{day(t,0)}$: Represents the demand "picked up" between *t* days before consumption and the day of consumption (*t*=0). For examples, if the demand at 10 days before game day was 100 and the demand on game day was 120, the demand picked up would be 120-100=20.
- $PU_{day(t,t-x)} = PU_{day(t-x)} - PU_{day(t)}$: Represents the demand "picked up" between *t* days before consumption and *t-x* days before consumption where *x* is the number of days between reading days.

The general form of demand data can be constructed as in Figure 11. For simplicity the game and section subscripts are removed because each section requires a separate data table similar to the generalized table. The "?"s in the lower right corner of Figure 11 indicate unknown demand at the time of forecast.

Because of the heuristic and computational nature of pick-up forecasting methods it is beneficial to utilize a sample data set to help illustrate the generalized mathematical models. Figure 12 provides a sample dataset for a particular section of various MLB games that will be referred to in subsequent sections:

Consumption Date	Day(M)	Day(M-1)	Day(M-2)	<-----*Time Before Service* ----->			Day2	Day1	Day0
d	$D_{d}(M)$	$D_{d}(M-1)$	$D_{d}(M-2)$	…	…	…	$D_{d}(2)$	$D_{d}(1)$	$D_{d}(0)$
d-1	$D_{d-1}(M)$	$D_{d-1}(M-1)$	$D_{d-1}(M-2)$	…	…	…	$D_{d-1}(2)$	$D_{d-1}(1)$	$D_{d-1}(0)$
d-2	$D_{d-2}(M)$	$D_{d-2}(M-1)$	$D_{d-2}(M-2)$	…	…	…	$D_{d-2}(2)$	$D_{d-2}(1)$	$D_{d-2}(0)$
d-3	$D_{d-3}(M)$	$D_{d-3}(M-1)$	$D_{d-3}(M-2)$	…	…	…	$D_{d-3}(2)$	$D_{d-3}(1)$	$D_{d-3}(0)$
d-4	$D_{d-4}(M)$	$D_{d-4}(M-1)$	$D_{d-4}(M-2)$	…	…	…	$D_{d-4}(2)$	$D_{d-4}(1)$	$D_{d-4}(0)$
d-5	$D_{d-5}(M)$	$D_{d-5}(M-1)$	$D_{d-5}(M-2)$	…	…	…	$D_{d-5}(2)$	$D_{d-5}(1)$	$D_{d-5}(0)$
d-6	$D_{d-6}(M)$	$D_{d-6}(M-1)$	$D_{d-6}(M-2)$	…	…	…	$D_{d-6}(2)$	$D_{d-6}(1)$	?
d-7	$D_{d-7}(M)$	$D_{d-7}(M-1)$	$D_{d-7}(M-2)$	…	…	…	$D_{d-7}(2)$	?	?
d-8	$D_{d-8}(M)$	$D_{d-8}(M-1)$	$D_{d-8}(M-2)$	…	…	$D_{d-8}(.)$	?	?	?
d-9	$D_{d-9}(M)$	$D_{d-9}(M-1)$	$D_{d-9}(M-2)$	…	$D_{d-9}(.)$	?	?	?	?
d-10	$D_{d-10}(M)$	$D_{d-10}(M-1)$	$D_{d-10}(M-2)$	$D_{d-10}(.)$	?	?	?	?	?

Figure 11: Generalized Pick-Up Data Structure Matrix

Figure 12 refers to the section level cumulative demand of various games (GameNo) for an MLB team. The *Day(t)* columns refer to the number of *t* days before the game takes place and each cell refers to the cumulative demand for a particular section at *Day(t)* prior to the game. The rows of the table represent what Lee (1990) termed "advance data," and the columns represent "historical data."

Cumulative Demand Leading Up to Consumption

GameNo	GameDate	Day20	Day10	Day5	Day4	Day3	Day2	Day1	Day0
1	23-May	1	8	23	43	53	62	72	84
2	30-May	2	17	24	36	53	63	98	109
3	6-Jun	1	13	18	26	35	55	70	80
4	13-Jun	2	14	20	31	47	77	87	107
5	20-Jun	11	24	32	45	57	77	89	104
6	27-Jun	1	7	13	23	28	48	81	91
7	4-Jul	0	3	8	14	32	42	67	?
8	11-Jul	1	11	18	30	48	63	?	?
9	18-Jul	1	18	26	35	50	?	?	?
10	25-Jul	0	5	12	23	?	?	?	?
11	1-Aug	2	15	24	?	?	?	?	?

Figure 12: Sample cumulative demand data set.

The rows of data represent the development of the demand curves for individual games while the columns represent the historical demand at various times of similar games (e.g., "similar" could be all Saturday games). The shaded cells highlight the demand data for completed games while the non-shaded demand cells show future game data to date. It is the goal of pick-up methods (as with all forecasting methods) to fill in the "?"s with forecasts that minimize forecast error given by:

$$Forecast\ Error = e_{gst} = \widehat{D_{gs}(t)} - D_{gs}(t)$$

Where $\widehat{D_{gs}(t)}$ is the forecasted final demand for game *g*, section *s*, at time *t* before game day and $D_{gs}(t)$ is the observed demand.

CP additive pick-up forecasting (CP_a). A classical pickup method utilizes only the data from completed similar events to generate forecasts (shaded cells of data in Figure 11). For flights, a similar flight could be a flight from Denver to Dallas that leaves at 8:00am every day. In a sporting context, similar games could be all MLB games played on a Saturday afternoon. The classical pick-up commonly utilizes an average (or weighted average) of demand "picked up" from a particular point in time until the date of service but other forecasting methods may also be used (e.g., exponential smoothing, ARIMA, etc.).

The pickup demand, $PU_{gs(t,t\text{-}x)}$, is estimated by:

$$PU_{\mathrm{gs}(t,t-x)} = D_{gs}(t' - x) - D_{gs}'(t) \tag{3}$$

Where $D_{gs}(t' - x)$ and $D_{gs}'(t)$ represent the estimates of demand at various days for a selected number of games. Finally, the forecasted demand for a particular game is given by:

$$\widehat{D_{gs}(t)} = D_{gs}(t) + PU_{\mathrm{gs}(t,t-x)} \tag{4}$$

Pickup demand (PU) can be estimated incrementally (at each future reading day) or cumulatively depending on the data structure (cumulative demand or incremental demand between days).

To illustrate an example using cumulative demand data, refer to Figure 12 which shows six games with complete demand data (games 1-6) and five future games with incomplete data (games 7-11). Suppose a forecaster wished to estimate the total demand for game 9 utilizing a classical additive pickup method. To do this, the forecaster must estimate the demand that will be picked up from *Day3* (the current cumulative demand for game 9) to *Day0* (game day).

First, the forecaster must decide how many games, *n*, to include in the forecasts for game 9. Assuming the forecaster wishes to utilize all six completed games (*n*=6), a simple average (or other forecasting method) of demand is calculated for games 1-6 on *Day3* and *Day0* data and then subtracted to come up with the estimated demand pick-up given by:

$$\mathrm{PU}_{9(3,0)} = \overline{\mathrm{D}_{1-6}(0)} - \overline{\mathrm{D}_{1-6}(3)} = 96 - 46 = 50$$

Then apply Equation 4 to calculate the forecasted demand for game 9:

$$\widehat{\mathrm{D}_9(3)} = \mathrm{D}_9(3) + \mathrm{PU}_{\mathrm{day}(3,0)} = 50 + 50 = 100$$

While other forecasting methods can be used to estimate $\mathrm{PU}_{\mathrm{day}(t,t-x)}$ the general process is carried out using Equations 3 and 4.

CP multiplicative pick-up forecasting (CP_m). While additive pickup models assume final demand is independent of current demand *t* days before the event, multiplicative pickup models assume final demand is dependent on the current demand *t* days before the event (Weatherford & Kimes, 2003). The method is based on determining a pick-up ratio from the final demand and the demand at time *t* days before the service day. The ratio is given mathematically by Equation 5.

$$MR_{gs}(t) = \frac{\overline{D_{gs}(0)}}{\overline{D_{gs}(t)}} \tag{5}$$

Where $MR_{gs}(t)$ is the multiplicative factor for the demand to come from day *t* until game day, $\overline{D_{gs}(0)}$ is the average final demand for completed games, and $\overline{D_{gs}(t)}$ is the average demand at day *t* days before the future game being estimated.

To illustrate this CP_m method, refer again to game 9 from the data in Figure 12. Again choosing *n*=6 games and *t*=3 days before the event the calculations are carried out as follows:

$$MR_9(3) = \frac{\overline{D_9(0)}}{\overline{D_9(3)}} = \frac{96}{46} = 2.087 \tag{6}$$

Where $\overline{\mathrm{D}_9(0)}$ is the simple average of final demand for games 1-6 on game day (*t=0*) and $\overline{\mathrm{D}_9(3)}$ is the simple average of known demand on *Day3* for games 1-6. Now, to calculate a forecasted final demand for game 9 we multiply $\mathrm{MR}_9(3)$ by the current demand of 50 to get 2.087*50=104.35. As with additive pickup methods, other methods of computing the multiplicative ratio (weighted averages, exponential smoothing, etc.) can be used to calculate the estimated demands.

AP additive pick-up forecasting (AP_a). While forecasting demand using the CP_a method utilizes only games with complete data (shaded area from Figure 12), AP_a utilizes all the data available. Another key difference between *AP* and *CP* methods is that the demand picked up from *Dayt* to *Day0* is calculated using a sum of incremental demand data at each unknown time. Figure 13 shows the incremental demand data at each time interval.

Returning again to the game 9 example, we wish to calculate incremental demand forecasts for *Day2, Day1,* and *Day0*. Once we estimate these values, the estimated demand to be picked up will be the sum of these incremental values. That is:

$$PU_{9(3,0)} = \acute{D_9(2)} + \acute{D_9(1)} + \acute{D_9(0)} \tag{7}$$

Once we have $PU_{9(3,0)}$ we apply Equation 4 to find the estimated total demand for game 9. A simple average is used again in this example with *n*=6 to estimate the values of $\acute{D_9(2)}$, $\acute{D_9(1)}$, and $\acute{D_9(0)}$. The difference in the *AP* versus *CP* methods is seen from the sample used to calculate the values $\acute{D_9(2)}$, $\acute{D_9(1)}$, and $\acute{D_9(0)}$. The highlighted numbers in each day column in Figure 13 indicate the sample utilized to calculate the forecasted incremental demand picked up while the shaded cells with italicized numbers indicate the simple average for each day. The sum of the estimated incremental demand picked up is then added to the last known cumulative demand (50) to get the final forecasted demand:

$$\widehat{D_9(3)} = D_9(3) + PU_{9(3,0)} = 50 + 19.17 + 21.67 + 13 = 103.84$$

Note this estimate is slightly different from the estimate using the CP_a approach.

AP multiplicative pick-up forecasting (AP_m). As with the AP_a method, the main difference between CP_m and AP_m is the use of incremental demand estimates and incomplete demand data to estimate $\widehat{\mathrm{D_{gs}(t)}}$. AP_m uses the average (or other forecasting method) of incremental percent changes to estimate final demand. Figure 14 shows the incremental percent changes from each time, t+1, and t.

Incremental Demand Leading up to Game

GameNo	GameDate	Day20	Day10	Day5	Day4	Day3	Day2	Day1	Day0
1	23-May	1	5	15	20	10	9	10	12
2	30-May	2	5	7	12	17	10	35	11
3	6-Jun	1	10	5	8	9	20	15	10
4	13-Jun	2	7	6	11	16	30	10	20
5	20-Jun	11	3	8	13	12	20	12	15
6	27-Jun	1	4	6	10	5	20	33	10
7	4-Jul	0	3	5	6	18	10	25	
8	11-Jul	1	8	7	12	18	15		
9	18-Jul	1	7	8	9	15	*19.17*	*21.67*	*13*
10	25-Jul	0	3	7	11				
11	1-Aug	2	8	9					

Figure 13: Incremental demand leading up to MLB Game.

The highlighted numbers in the *Day2, Day1, Day0* columns indicate the sample of percent changes used to calculate the mean percent change for game 9. The final forecasted demand for game 9 can be represented as a product of the current demand and the three incremental percent changes shown:

$$\widehat{D_9(3)} = 50 * (1.48) * (1.40) * (1.16) = 120.18$$

Percent Change

GameNo	GameDate	Day20	Day10	Day5	Day4	Day3	Day2	Day1	Day0
1	23-May	*	7.00	1.88	0.87	0.23	0.17	0.16	0.17
2	30-May	*	7.50	0.41	0.50	0.47	0.19	0.56	0.11
3	6-Jun	*	12.00	0.38	0.44	0.35	0.57	0.27	0.14
4	13-Jun	*	6.00	0.43	0.55	0.52	0.64	0.13	0.23
5	20-Jun	*	1.18	0.33	0.41	0.27	0.35	0.16	0.17
6	27-Jun	*	6.00	0.86	0.77	0.22	0.71	0.69	0.12
7	4-Jul	*	*	1.67	0.75	1.29	0.31	0.60	?
8	11-Jul	*	10.00	0.64	0.67	0.60	0.31	?	?
9	18-Jul	*	17.00	0.44	0.35	0.43	*0.48*	*0.40*	*0.16*
10	25-Jul	*	*	1.40	0.92	?	?	?	?
11	1-Aug	*	6.50	0.60	?	?	?	?	?

Figure 14: Percent change in demand between reading days t and t+1.

In general, the mathematical formula for this AP_m method is given by:

$$\widehat{D_g(t)} = D_g(t) * \prod_{t=0}^{t-1} (1 + R_g\,(t))$$

Where $R_g(t)$ is the estimated incremental percent change for game g at times t-1 through t=0.

The multiplicative assumption that future demand is positively correlated with current demand is seen with the higher forecasts under the AP_m (120.18) versus AP_a (103.84) and the CP_m (104.35) versus CP_a (100) methods. Additionally, differences in forecasts will be found if one applies each approach using different demand data structures (cumulative versus incremental). For example, if incremental data had been used in the CP_m example instead of cumulative data the demand forecast would be 111.08. Therefore, it is important to test multiple strategies and evaluate the accuracy of strategies and models under different forecasting situations.

Adding to the possible ways of utilizing a pick-up strategy would be to utilize estimating methods other than the mean (e.g., exponential smoothing, ARIMA, etc.). Wickham (1995) applied exponential smoothing with parameters of .2 and .4 to estimate the pick-up demand while Lee (1990) utilized an ARIMA model. The examples of the four approaches given were provided to give the reader a basic understanding of pick-up methods; not attempt the nearly impossible task of illustrating all pick-up methods. The vast number of possible ways of utilizing pick-up methods is to be expected with this mostly heuristic strategy. The advantage of the heuristic nature of pick-up methods is researchers and practitioners can experiment and test the methods most applicable given their data structures and associated costs of forecasting.

Combining forecasting methods. The aim of this chapter was to present the most prevalent forecasting methods in the current revenue management literature. In addition to the methods presented in this chapter, there are other forecasting techniques available (e.g., Bayesian, State-Space and Kalman Filtering, Delphi Method, and Machine-Learning/Neural-Network). Furthermore, researchers have suggested combining methods to improve forecasts (e.g., Bates & Granger, 1969; Makridakis et al., 1993; Winkler & Makridakis, 1983). Combining forecasts is based around the idea that if the error terms between two or more forecasting methods are negatively correlated, then combining the methods will result in a lower overall forecast error (Talluri & van Ryzin, 2004). Not only has finding the "best" individual forecasting method been extensively researched but how best to combine forecasting methods has been a topic of research for some time.

Bates and Granger (1969) offered one of the first pieces to provide guidance on how to select appropriate weights for combining forecasts through linear combinations. These authors combined exponential smoothing with ARIMA forecasts and found that a combination approach offered better forecasts than either individual approach alone. The appropriate weights are those which minimize the mean-squared error (MSE) of the combined forecast. One way to compute a combined forecast between two forecasts is expressed by:

$$\hat{Z} = \alpha\hat{Z}_1 + (1-\alpha)\hat{Z}_2$$

Where $\hat{Z}_1$ is the forecast from method 1 and $\hat{Z}_2$ is the forecast from method 2. Bates and Granger (1969) offered several different possibilities for the calculation of the weighting factor, α, and RM researchers Talluri and van Ryzin (2004) discussed the following:

$$\alpha = \frac{MSE_2 - \rho\sqrt{MSE_1}\sqrt{MSE_2}}{MSE_1 - MSE_2 - 2 - \rho\sqrt{MSE_1}\sqrt{MSE_2}}$$

where ρ is the correlation coefficient between the errors of the forecasts of the two models.

In general, Bates and Granger (1969) suggested more weight be given to individual forecast methods that performed best in the recent past and the weight should be allowed to adapt to account for the possibility of non-stationary series. A time adaptive combination scheme provided by Bates and Granger (1969) is to define $\alpha = \alpha(t)$, where

$$\alpha(t) = \sum_{i=1}^{t} \frac{MSE_{i+1}(t)}{MSE_i(t) + MSE_{i+1}(t)}$$

where $MSE_i(t)$ is the mean squared error of forecast model *i* at time *t.*

Newbold and Granger (1974) provided empirical evidence supporting the use of combined forecast methods when they examined 80 monthly time series. Winkler and Makridakis (1983) found that combined forecast methods were more accurate for most conditions. In fact, Winkle and Makridakis found that even the worst combined forecasting methods performed better than 7 of 10 individual methods. Additionally, while weighted averages provided the best results when combining methods, Winkler and

Makridakis stated that the differences in forecast errors between weighted and simple averages were not large. Therefore, depending on time and costs, a "better" combination technique may be to use a simple average of individual methods (Makridakis, 1989).

In the RM literature, Weatherford and Kimes (2003) suggested forecasting methods of exponential smoothing, pickup, moving average, Holt's method, and linear regression provided the most robust methods for forecasting hotel room demand. They also recommended combination approaches be applied in "some way" (p. 414) but did not provide specific combination approaches.

Choosing forecasting methods. With so many possible forecasting techniques as well as the combinations of various techniques, how does a forecaster decide what to use? As with many statistical techniques, the answer is often "it depends" and different methods will generally produce different forecasts (Makridakis & Winkler, 1983). Newbold and Granger (1974) provided a set of guidelines for selecting forecasting methods but followed their set of guidelines with this cautionary quote:

> Never follow blindly the guidelines (a)-(e)! In many practical situations one knows something of value about the series under consideration. This information should, if possible, be employed in any decision as to how the series should be forecast. (p. 145)

Newbold and Granger (1974) suggested for time series with fewer than 30 observations there is little a forecaster can do but utilize averaging and exponential smoothing techniques. Makridakis, Wheelwright, and McGee (1983) stated that smoothing methods are generally best for immediate or short term forecasting, decomposition and ARIMA methods for short to medium, and regression techniques are best suited for medium to long usage. The "M-competitions" (named after Spyros Makridakis) have become notorious in the forecasting literature for helping answer the questions regarding best forecasting methods.

The M-competitions were largely developed in response to criticism of Makridakis and Hibon’s (1979) conclusion that simpler methods (e.g., averaging, exponential smoothing) provided more accurate forecasts than more sophisticated approaches such as ARIMA (Fildes & Makridakis, 1995; Makridakis & Hibon, 2000). Forecasting competitions are argued to provide important empirical tests of various forecasting methods (Fildes & Makridakis, 1995). There have been three published M-competitions to date: Makridakis et al. (1982); Makridakis et al. (1993); and Makridakis & Hibon, 2000).

The three replications of the M-competitions and extensions which included more researchers, more and different types of time series data, and more methods all reached the same general conclusion: statistically sophisticated or more complex methods did not provide significantly more accurate forecasts than simpler ones. This did not mean that more sophisticated approaches such as ARIMA did not perform well; rather that they just did not provide significant improvement in comparison to simpler methods.

A disappointing note on the M3 competition conclusions can be found by closer examination of the results provided by private forecasting company Forecast Pro. Forecast Pro forecasts were provided using an algorithm which selects the best forecasting method between multiple methods such as exponential smoothing, ARIMA, and simple moving averages. While Makridakis and Hibon (2000) pointed out that Forecast Pro forecasts performed well they did not mention what method(s) the Forecast

Pro algorithm ultimately selected. The information regarding which method the Forecast Pro algorithm selected is important considering not all practitioners or researches will have access to the Forecast Pro software. Did the algorithm tend to select one method more than the other? The answer to this question could help researchers and practitioners alike in the selection of forecasting methods.

In the first forecasting competition since the M3, Athanasopoulos, Hyndman, Song, and Wu (2011) evaluated the performance of various forecasting methods using tourism time series data. According to these authors, this was the first published work in the empirical forecasting literature since 1974 which found that ARIMA models performed as well as, if not better than, other methods. These authors found further evidence of the good performance of Forecast Pro forecasts. However, like Makridakis and Hibon (2000) they do not provide the models that the Forecast Pro algorithm ultimately selected to generate forecasts. Additionally, in contrast to the wide variety of business and economic time series data sets that the M-competitions utilized, Athanasopoulos et al. (2011) only examined tourism data, limiting the generalizeability of their results.

While it would be much easier on researchers and practicing forecasters if the literature had produced a best forecasting method to use, it is clear this is not the case. Selecting a forecasting method is obviously dependent on the situation. Makridaks et al. (1982) summarized the situation by stating “It is important to understand that there is no such thing as the best approach or methods as there is no such thing as the best car or best hi-fi system" (p. 112). Nevertheless, researchers and practitioners do not have to steer the forecasting ship rudderless.

Bowerman and O'Connell (1993, p. 17), Makridakis et al. (1983), Newbold and Granger (1974), and others have provided guidelines to consider when selecting a forecasting method:

1. The accuracy desired
2. The time frame
3. The pattern of data (trend, cycle, seasonal)
4. The cost of forecasting (time, storage, complexity, etc)
5. The forecast form desired (point or internal)
6. The availability of the data (accuracy, timeliness)
7. The ease of operation and understanding

Accuracy desired. Arguably the most important decision a forecaster must make is the level of acceptable accuracy desired (Bowerman & O'Connell, 1993; Makridakis et al., 1983)**.** In some instances, forecasts within 20% of observed values may be acceptable whereas in other citations a 1% error may disastrous. Makridakis et al. (1983) provided the following questions to ask when assessing the accuracy of forecasting methods:

1. For a given situation, how much improvement can be obtained in the accuracy of the forecasts?
2. What additional accuracy can be achieved in a given situation through use of formal forecasting techniques?

3. What is the role of judgment in forecasting accuracy? When can subjective assessments help improve the accuracy of forecasting?

A difficulty in assessing these questions is that there lacks a universally accepted measure of forecast accuracy. However, one way of comparing forecasting methods is to compare them to a naïve forecasts. Naïve forecasts are simple forecasts in which various measures of accuracy can be compared to more sophisticated forecast methods. Common forecasting measures of accuracy include:

- Percentage error: $PE_t = \left(\frac{X_t - F_t}{F_t}\right) * 100$
- Mean percentage error: $MPE = \frac{1}{n}\sum_{i=1}^{n} PE_i$
- Mean absolute percentage error: $MAPE = \frac{1}{n}\sum_{i=1}^{n}|PE_i|$
- Mean absolute deviation (MAD): $MAD = \frac{1}{N}\sum_{t=1}^{n}|X_t - F_t|$
- Theil's *U*-Statistics: $U = \sqrt{\frac{\sum_{i=1}^{n-1}(\frac{F_{i+1} - X_{i+1}}{X_i})^2}{\sum_{i=1}^{n-1}(\frac{X_{i+1} - X_i}{X_i})^2}}$

Two naïve forecasts offered by Makridakis et al. (1983) are given as NF1 and NF2. An NF1 forecast is simply the most recent value of the variable used as the forecast whereas an NF2 is a seasonally adjusted forecast of the most recent value of the variable. A simple way of calculating NF1 in statistical software programs is to use a moving average procedure of length one, MA(1). NF2 is calculated in the same way as NF1 on deseasonalized data.

NF1 and NF2 provide a basis from which to compare other forecasting methods. By comparing the forecasts of more sophisticated forecasting methods to naïve forecasts, one can assess whether the potential improvement in accuracy is worth the extra time and costs involved. Unfortunately, the limited RM literature assessing various forecasting methods does not compare formal methods to naïve forecasts but only to the various accuracy measures. Makridakis et al. (1983) suggested the difference between accuracy measures (MAPE, MSE, etc.) obtained from naïve forecasts and more formal methods provides more meaningful comparisons than a comparison of only accuracy statistics.

The MAPE, MAD, and *U* error terms are frequently utilized in RM forecasting studies to compare forecasting methods. MAPE provides an intuitive comparison of forecasts' error because its value represents the percentage of error. For example, MAPE=10 means the forecast is 10% off for a particular method. Theil's *U* perhaps provides the best metric to measure competing methods (Makridakis et al., 1983; Wickham, 1995). This is because *U* essentially provides a comparison of a forecast from a model to that of NF1. The value of *U* can quickly tell the forecaster if his or her methods produce results better, the same as, or worse than the simple NF1 forecast based on the following:

- $U<1$: the forecasting method produces a better forecast than NF1
- $U=1$: the forecasting method performs exactly as the NF1
- $U>1$: the forecasting method performs worse than the NF1

As it can be seen, the *U* metric can provide a quick comparison of various methods.

Time frame. Methods are likely to perform differently over different time horizons (e.g., days, weeks, months, years). Length of time frame is categorized by the following:

- Immediate term – less than one month
- Short Term – one to three months
- Medium Term – three months to two years
- Long Term – more than two years.

It is no surprise that as the forecasting period increases it is more difficult to accurately forecast. As such, qualitative methods utilizing the experience of a forecaster and/or practitioner are usually recommended for long term forecasts (Bowerman & O'Connell, 1993; Makridakis et al., 1983). Smoothing methods are suggested for immediate and short term, decomposition and ARIMA methods for short to medium term, and regression methods for medium to long term.

Pattern of data. An examination of the data pattern is essential to selecting forecasting methods. The data could exhibit patterns in trend, seasonality, and cycle which make certain methods inapplicable. For example, if the data exhibit a trend, mean and simple smoothing methods would not be appropriate but linear or higher forms of smoothing (quadratic, cubic, etc.) can handle different types of trends in the data.

Cost of forecasting. Four main costs should be considered when selecting a forecast method: development costs, data storage costs, maintenance costs, and repeated applications costs. An organization will either need to program its own forecasting methods for its situation or purchase prepackaged statistical software such as SAS or Minitab.

Once a forecasting program is developed or purchased data storage is obviously critical to producing forecasts. Recent technological advances have made data storage less expensive and are a significant factor in the increased use of RM strategies and dynamic pricing which rely on forecasting methods. Maintenance costs are costs associated with the readjustments or modifications to existing forecasting models.

Modifications to existing forecasting models are necessary when new data become available, changes in the pattern of data occur, or when additional runs of the model are required. Finally, repeated application costs refer to the costs associated with generating the forecast. Some of these costs are in the time it takes the computer program to run while some of the costs are in the human resources needed to run the program.

Fortunately, technological advances in computer speed and power have minimized the run times for even the most sophisticated ARIMA models. However, training or hiring an employee who knows how to develop these models properly is likely where most of the repeated applications costs will be invested. Less sophisticated models such as exponential smoothing will require less training while ARIMA and econometric models will require both longer development times and more training of personnel to develop and run the appropriate models.

Forecast form. The forecaster must choose whether a point or interval forecast is desired. Depending on the situation a point forecast may be acceptable and in others an interval (e.g., 95% CI) is more appropriate. The choice of point or interval has theoretical implications as certain methods (e.g., decomposition, exponential smoothing) are not based on statistical theory but rather intuitive empirical methods (Bowerman & O'Connell, 1993). Therefore statistical assumptions behind the construction of confidence and prediction intervals do not apply to decomposition and exponential smoothing methods. Nevertheless, Bowerman and O'Connell provided empirical methods of constructing prediction intervals that they contend provide reasonably accurate intervals if enough historical data are available. Thus, the choice of point or interval may come down to whether the forecaster wishes for a theoretically developed statistical approach or more intuitive empirical approaches.

Availability of data. Clearly the availability of data will be an important factor in choosing a forecasting method. Some methods (e.g., ARIMA) are reported to need more historical data in order to construct an accurate forecasting model while others (e.g., exponential smoothing) require much less data. Furthermore, the accuracy and timeliness of historical data is of clear concern when forecasting. If historical data are not accurate it is likely no forecasting method will be able to provide accurate forecasts. If needed historical data are not available, other methods of data collection must be employed.

Ease of operation and understanding. Despite the rigorous development of sophisticated forecasting models and algorithms, the sophistication offers little value if the person attempting to produce the forecasts cannot apply the methods with understanding. A manager responsible for making decisions will not be confident in the predictions made by a forecasting method he or she does not understand. Indeed, Wheelwright and Clarke (1976) found that companies utilizing the often more accurate yet significantly more complex ARIMA methods abandoned these more complex methods because users did not have a conceptual understanding of them and therefore did not feel confident in the forecasts they produced.

Operations revenue management literature summary. The importance of forecasting in a RM strategy is clear as Lee (1990) showed that a ten percent improvement in airline demand forecasting could contribute up to a three percent increase in revenue. Despite the fact that accurate forecasts are crucial to good revenue management, few empirical RM forecasting studies testing the accuracy of methods exist and no sport specific forecasting methodological works could be found.

Weatherford and Kimes (2003) provided one of the first methodological RM forecasting works and found exponential smoothing, pickup methods, and moving average models to be the most robust hotel booking forecasting methods. Chen and Kachani (2007) also studied hotel demand forecasting and found exponential smoothing with α=.35 performed well. However, although discussed in their methodology, these authors did not provide results or discussion of the accuracy of more sophisticated methods. Furthermore, neither Sun et al. (2011), Weatherford and Kimes (2003), nor the Chen and Kachani (2007) works included forecasts for naïve methods. Including naïve forecasts is essential to forming comparisons between other forecast methods' relative performance over the simplistic naïve forecasts (Makridakis et al., 1983). If forecast methods do not significantly outperform naïve forecasts then there is little justification for the extra work and cost of a more sophisticated forecasting method.

The majority of empirical forecasting literature has suggested that simpler methods perform as well as, if not better than, more sophisticated approaches such as ARIMA. In the RM forecasting literature, the tendency appears to be toward simple models as well (Sun, Gauri, & Webster, 2011; Talluri & van Ryzin, 2004; Weatherford &

Kimes, 2003; Wickham, 1995). The pickup methods illustrated by Lee (1990), Wickham (1995), and Talluri and van Ryzin (2004) all used relatively simple forecasting methods (e.g., simple/weighted average, exponential smoothing, etc.) to forecast the estimated demand to be "picked" up.

The empirical forecasting works provided by seminal forecasting authors such as Makridakis have provided a solid foundation for forecasting researchers and practitioners. Additionally, strong theoretical works such as Box and Jenkins (1976) provide step by step model identification and diagnostic checking for creating more sophisticated ARIMA models. In general, it appears from the empirical works that simpler methods outperform more complicated.

However, the recent research by Athanasopoulos et al. (2011) suggested ARIMA models may provide better forecasts in certain situations. In RM research, simple methods such as exponential smoothing, moving average, and pickup methods appear to be the methods of choice. Although pickup methods are more of a forecasting strategy for aggregating or disaggregating data as opposed to separate forecasting methods they are reported to be utilized frequently in RM practice with good results (Talluri & van Ryzin, 2004).

Selecting an appropriate forecasting model is a blend science and art. The research listed in this section provided a foundation for future researchers to begin but as Bowerman and O'Connell (1993) discussed:

> Choosing the forecasting method to be used in a particular situation involves finding a technique that balances the factors just discussed. It is obvious that the "best" forecasting method for a given situation is not always the "most accurate". Instead, *the forecasting method that should be used is one that meets the needs of the situation at the least cost and with the least inconvenience.* (p. 19)

Revenue management research in the sport industry is still in its infancy and no sport specific RM forecasting research can be found. As dynamic pricing strategies become common in sport organizations, a methodological study examining the accuracy of various forecasting methods could provide valuable insight for both the sport and RM literature base.

Chapter II Summary

The sport management literature on revenue management has only begun to scratch the surface of this complex topic. Early sport management literature would be described by what Kimes (2003) called descriptive because the early focus has been on justifying the applicability of RM in sport (see for example, Shapiro & Drayer, 2012). Additionally, some sport management literature would be classified under what Kimes called pricing control (e.g., Drayer et al., 2012; Dwyer et al., 2013). However, no sport management research could be found that examines the other critical facet of revenue management: inventory control. Sport specific RM research is needed to understand the applicability and sustainability of a RM strategy in sport. In this dissertation I aimed to help in the understanding of this complex topic by taking an inventory control angle and examining inventory curves over time.

The forecasting literature has suggested that exponential smoothing and moving average models are the most appropriate in a short term forecasting environment.

However, testing of these models in a sport context could not be found. Furthermore, much of the existing revenue management forecasting literature does not test the statistical reliability of results. Research on forecasting models in a revenue management context needs to not only test which models produce the lowest mean errors but also the reliability of results.

Finally, research in the sport economic literature has only be able to examine aggregate attendance data after a season has been completed. These aggregate data do not provide information about demand curves at the seat section level even though sport organizations have historically price discriminated based on seat location. To form a more complete understanding of pricing and demand models, research needs to be conducted at the seat section level over time.

CHAPTER III

METHODOLOGY

Research Design

Study one utilized a 3x3x6x7 factorial research design to examine the application and accuracy of various forecasting methods in a sport revenue management (RM) context. This methodological study tested various forecasting data strategies, models, sample sizes, over a 20 day selling period. Forecasting errors were compared to naïve forecasts which are the equivalent to control groups under each data strategy. Essentially, study one was aimed at forming an understanding of the third major component of an effective RM strategy: operational research and specifically estimation and forecasting. As such, much of the theoretical development of forecasting models was discussed in Chapter II under the heading "Operations Revenue Management Research and Theory: Estimation and Forecasting" beginning on page 92.

The research design followed to answer research questions five and six was a longitudinal observational design to examine potential differences in seat section demand. It is believed to be the first study of its kind because of the proprietary nature of seat section demand data. To date, seat section demand data can only be attained if the researcher has a working relationship with a sport organization. The main goal was to provide an initial understanding of advance seat section ticket inventory curves using a manual data collection strategy through online ticketing of teams' official websites.

The nonexperimental design used to answer RQs five through seven was unavoidable in the given circumstances because I was unable to randomize or manipulate demand or price changes over time (Pedhazur & Schmelkin, 1991, p. 304). However, it could be possible the design does resemble a quasi-experimental design by arguing that some decision maker (or DTP algorithm) is likely manipulating price changes in an effort to change demand over time.

Due to the varying designs and research questions this chapter was structured to describe the methods utilized for each study with appropriate research questions clearly labeled. The following subsections are addressed for each study: research design, description of variables, sampling strategy, data collection procedures, and data analysis.

Factorial Sequential Design to Assess Forecasting Methods

A key component to any RM system is the ability to forecast demand. As such, it is important to investigate various forecasting methods' performance. Forecast method performance is unique to each situation and therefore tests of accuracy between various methods and model parameters should be applied to specific contexts (Bowerman & O'Connell, 1993; Makridakis et al., 1983). The following subsections describe the factors analyzed in the sequential factorial design to assess data strategies, models, model parameters, sample size and forecast horizon.

The study followed a sequential analysis by first identifying the exponential smoothing parameters which minimized absolute forecast error in a training set of data.

Then, the exponential parameters which minimized error in the training set were held constant for the remainder of the study. Next, data strategies were tested for reliable differences between strategies. After a superior data strategy was identified, the next phase of the study examined the model, sample size, and time horizon combinations to determine if reliable differences between models existed within the superior data strategy. The following sections describe the various factors examined.

Forecasting data strategies. Three forecasting data strategies were examined in this study. First, a non-pickup (NP) data strategy utilized the final game day forecasts of completed games to generate forecasts of future games. The applicable data set in this strategy was ticket inventory on game day (Day0). Next, a classical pickup (CP) data strategy utilized the booking curves of completed games to generate estimates of the pickup row used to generate forecasts of future games. Finally, an advanced pickup (AP) data strategy utilized all available data from both completed and future games. Details of these data strategies can be found in the subsection labeled "Pickup forecasting methods" starting on page 111 of the literature review.

Forecasting models. The data for this study were classified as immediate time series data. Additionally, due to the difficulty in collecting MLB seat section demand data, limitations in test set data sample size restricted the possible models. Therefore, the most appropriate methods and models of forecasting were simple forecasting techniques **a**nd pickup data organization methods (Bowerman & O'Connell, 1993; Makridakis et al., 1983; Talluri & van Ryzin, 2004).

As such, for study one I followed the work of previous RM forecasting studies (e.g., Lee, 1990; Sun et al., 2011; Weatherford & Kimes, 2003; Wickham, 1995) and studied exponential smoothing, moving average, and pickup data strategies. These models were chosen because of their prevalence in the RM forecasting literature, their relatively simple procedures, and because of the time series data available. Each model and various parameters were tested under each data collection strategy (non-pickup, classical pickup, and advance pickup). Table 2 provides a condensed list of the models and the tested parameters under each data collection strategy.

Although discussed in the theoretical section of forecasting models in Chapter II, ARIMA models are not included in the model set because these models require at least 30 observations of the dependent variable and have not been included in previous RM studies (Makridakis et al., 1983; Tabachnick & Fidell, 2001). It is believed this combination of data strategies, models, parameters, and time horizons provides a strong set of potential data strategies and models to be tested and applied in a sport RM context. As more data become available, more statistically sophisticated models may be tested in future studies.

Model parameters. Effective forecasting systems require the examination and calibration of forecasting models on a recurrent basis (Makridakis et al., 1983). Because the number of experimental runs exponentially increases with each factor and level of factors, I constrained the number of parameters tested for each model explained below.

Table 2

Selected forecast models by data collection strategy and parameters.

Model Type	Data Collection Strategy	Forecasting Class	Description	Parameters
NF1	Non-pickup	Baseline	Naive forecasting using MA(1), uses most recent data value as forecast	
NF2	Advanced Pickup	Baseline	Naive forecast using last known demand to generate pickup row	
NF3	Classical Pickup	Baseline	Naïve forecast using the last complete game to generate the pickup row	
MA	Non-pickup	Smoothing	Moving average of final demand	2-12 by 2
ES	Non-pickup	Smoothing	Exponential smoothing of final demand	.05-.3 by .05
MA	Pickup	Classical Pickup	Moving average of demand picked up for completed games	2-12 by 2
ES	Pickup	Classical Pickup	Exponential smoothing of demand picked up for completed games	.05-.3 by .05
MA	Pickup	Advance Pickup	Moving average of demand picked up for completed and non-completed games	2-12 by 2
ES	Pickup	Advance Pickup	Exponential smoothing of demand picked up for completed and non-completed games	.05-.3 by .05

Note. NF1=naïve forecast under non-pickup; NF2=naïve forecast under advanced pickup; NF3=naïve forecast under classical pickup; MA=moving average; ES=exponential smoothing.

Moving average. Moving average models were tested at six different lengths, T. The lengths of T were constrained to values between 2 to 12 in increments of two games. Of course, the value of T is further constrained by sample size because historical data included in the test set limits how many data points, T, can be utilized. For example, if the test sample size of games is set at two, only MA(2) can be estimated from this test set. The values of T were chosen because most RM applications of MA(T) use values between 2 and 15 (Talluri & van Ryzin, 2004) and because published RM forecasting research has empirically tested these values (e.g., Sun et al., 2011; Weatherford & Kimes, 2003).

Exponential smoothing. As mentioned in Chapter II, the parameter values of an exponential smoothing (ES) approach refer to the smoothing constant, α, utilized in the model. Most RM applications have utilized values between .05 < α < .30 (Talluri & van

Ryzin, 2004). Sun et al. (2011) and Weathford and Kimes (2003) empirically validated this range of α in their studies. As such, for the current study I constrained the values of α to this range and test values in increments of .05.

Naïve forecast models. Naïve forecast methods essentially form a control group against which to compare relative performance of forecasting methods. In this study, because three data strategies were utilized, three different naïve forecasts were generated within each data strategy. In most forecasting literature the naïve forecast utilized is simply the last known value as the forecast for the next. This study examined a different naive forecast within each revenue management data strategy.

Types of naïve forecasts. This study utilized three forms of naïve forecasts to form baseline comparisons within each data strategy. In a non-pickup (NP) strategy, the naïve forecast is the traditional naïve forecast found in forecasting literature. The NP naïve forecast simply uses the previous game's final ticket inventory to predict the next game's final inventory. Within a classical pickup (CP) strategy, the naïve forecast utilizes the inventory curve of the last known complete game to generate the estimated pickups for future games. The naïve pickup line is then utilized in the standard CP data strategy to produce forecasts. Finally, within an advanced pickup (AP) data strategy, the naïve forecast utilizes the last known final demand to forecast all future games.

Sample size. One research design consideration when evaluating forecast methods is how much data to use in generating forecasts. In this study, this amounted to how many games should be included to generate the moving average and what number of games should be used to start the exponential smoothing process. Wickham (1995) examined test set sizes from 4-10 flights while Weatherford and Kimes (2003) tested hotel room set sizes from 1-6, 8, 10, and 12. In the current study I examined game sample sizes from 2-12 in increments of two for a total of six different sample sizes. The type of question that sample size can answer is: how many games does a forecaster need to generate accurate forecasts? The answer to this question will be of value to sport ticket forecasters because it will allow them to identify at what point in the season they can expect forecasts to be accurate.

Forecasting horizon. Another consideration in selecting the best forecast method is to consider the forecasting horizon. A forecaster will have demand data at various points in time prior to an event and it is of value to know if forecast methods differ based on forecasting horizon. The question to be asked is: at which time horizon are forecast errors the smallest? For this study, the available time horizons are 20, 10, 5 to 1 days prior to an MLB game. The selected time horizons were based on 1) time and feasibility constraints of this study and 2) prior literature regarding dynamic ticket pricing (DTP) in sport over time has examined 20, 10, and 5 days out from game day (see for example, Shapiro & Drayer, 2012).

Factorial runs. Based on the varying levels of data strategy (3 levels), models (3 levels), game sample size (6 levels), and forecasting horizon (7 levels), a multilevel factorial design was created to generate forecasts for all data strategies and models at each of the varying levels of sample size and forecasting horizon. As such, 378 base runs were needed to measure forecast errors at each level of the factors.

Based on the design presented, I sought answers to the following research questions:

RQ1 To what extent do profiles of data strategy differ in forecast errors?

RQ2 To what extent do forecast models differ from a naïve model?

RQ3 To what extent do forecast errors vary by sample size?

RQ4 To what extent do forecast errors vary by days out?

Advance Seat Section Demand

The goal of study two was to understand the nature of seat section demand over time. As Ng (2007) pointed out the pricing of services is concerned with advance demand and pricing. To form an understanding of potential sport RM strategies utilizing DTP, one must first gain an understanding of the nature of the seat section demand curves over time. Study two of this dissertation attempted to shed light on the nature of seat section inventory curves for MLB games.

Armed with this information, researchers and practitioners can begin to understand the potential benefits of a RM strategy such as DTP. For example, if one has an understanding of the nature of the ticket inventory curve over time, a question a business decision maker may ask is: to what extent could we expect inventory to change if we implemented a 20% price increase/decrease at various times leading up to game time? Unfortunately, there is no known published research which examines seat section demand patterns over time for MLB despite the fact that most teams are now implementing DTP strategies.

This study used a nonexperimental, longitudinal research design to answer the research questions related to demand for MLB games over time. Profile analysis procedures were utilized to examine potential differences in ticket inventory based on time before game and seat section.

In this study the observations were recorded as ticket availability at eight different time points prior to an MLB game. The design is nonexperimental because I had no ability to manipulate any of the variables studied or randomize observations to different conditions.

Study two answered the following research questions:

> RQ5 To what extent do seat section inventory curves differ from parallelism?
>
> RQ6 What is the nature of differences between seat section inventory curves?

Description of Variables

Forecast Method Accuracy

Dependent variable. The dependent variable in study one was the forecast error produced by the various models and conditions. Forecast error was measured by the mean absolute deviation (MAD) (see page 126 for a mathematical description). As was described in Chapter II, the MAD provides an intuitive method of comparison in the same units as the original variable.

Independent variables. The independent variables for study one are the various data strategies, models, sample size, and time horizons prior to game. Data strategies are a categorical variable with the values of non-pickup (NP), classical pickup (CP), and advanced pickup (AP). Models are measured as a categorical variable with three values: naïve (i.e., control), moving average (MA), and exponential smoothing (ES). The time horizon to game was a discrete variable taking on the values 20, 10, and 5-1 days prior to a game. The sample size was a discrete variable taking on the values 2, 4, 6, 8, 10, and 12. The model parameters were also discrete variables taking on various values based on moving average or exponential forecasting methods.

Advance Seat Section Demand

Dependent variable. The dependent variable for study two as the ticket availability as recorded from MLB teams' official websites. Ticket availability was a continuous variable and was collected for 11 seat sections at eight different times before the game. An estimate of ticket demand can be calculated by differencing the ticket availability at adjacent data recording days. For example, to calculate ticket demand between four days prior to a game and three days prior, one would simply take the difference of ticket availability on day four and day three. Because some data collection days are not equidistant apart, it may be necessary to calculate an average per day ticket availability and/or demand by dividing by the total number of days between reading days. For example, it may be necessary to calculate average ticket availability between days 20 and 10 by dividing by 10 days.

Independent variables. The independent variables included in the study of ticket availability over time were seat sections, price changes, and MLB game profiles. The primary goal of study two was to gain an understanding of seat section demand over time. As such, seat sections were the primary grouping independent variable (IV) with 11 levels. The 11 seat sections represented seat sections at every price level the Royal's offer. The Royals classify seat sections as Premium, Field/Plaza Level, Fountain, Loge Level, and Hy-Vee Level. The range of single game prices for each of the 11 seat sections examined in this study are displayed in Table 3. As can be seen, the sections vary considerably in the range of prices. Therefore, it was important to collect inventory at each section level.

Table 3

Seat Descriptions and Price Ranges

Team	SectionName	SectionCategory	MinP	MaxP
Royals	KiaDiamondClubSeats	Premium	83	126
Royals	Loge	Loge Level	23	71
Royals	HyVeeInfield	Hy-Vee Level	5	27
Royals	HyVeeOutfield	Hy-Vee Level	8	26
Royals	HyVeeBox	Hy-Vee Level	18	33
Royals	FoutainSeats	Fountain	17	69
Royals	FieldPlaza	Field/Plaza Level	10	69
Royals	OutfieldBox	Field/Plaza Level	23	53
Royals	FieldBox	Field/Plaza Level	36	82
Royals	DugoutPlaza	Field/Plaza Level	39	109
Royals	DugoutBox	Field/Plaza Level	52	140

Note. Sections are classified by name and a broader category based on seat location and pricing. MinP=minimum single game price, in dollars, observed over the season; MaxP=maximum price, in dollars, observed over the season.

MLB game profiles served as blocking variables because it is believed differences in demand and pricing exist based on the characteristics that define a profile (day of week, time of day, opponent). Eight different MLB game profiles were initially constructed but adjustments were necessary based on sample size of each profile.

Similar type games can be categorized into game profiles based on various characteristics. These profiles can then serve as blocking variables in various research designs. Sport teams have historically priced games differently based on day of week (weekday or weekend), quality of opponent (usually based on winning percentage), time of day (day or night), time of year (summer, spring, fall), holidays, opponent type (Division, interleague, Non-Division, marketable), etc. As mentioned in the literature review, the sport economics literature examining determinants of demand is extensive but variables used in models are inconsistent across studies. The lack of cohesion in these studies makes it difficult if not impossible to identify a common set of variables to include in demand and pricing models.

The few known sport DTP studies examining changes in price over time (Shapiro & Drayer, 2012, 2014) collected a sample of 12 San Francisco Giant games which varied by divisional opponent (2 levels), interleague opponent (2 levels), month (7 levels), day (7 levels), time of day (2 levels), game number of series (3 levels), whether the game was broadcast on television (2 levels), and whether there was a promotion offered for the game (2 levels). If game profiles were created using these factors and levels it would result in a possible 4,704 game profiles (2^5*7^2*3). Given only 81 home games in an MLB season it is unrealistic and impractical to study this many factors at this many levels. For the current study I offered a condensed set of profile conditions as described below.

Eight profiles of game types were identified based on what is believed to be the most straightforward and common factors distinguishing variance in demand and pricing. It is recognized that many other constructions of profiles can be created based on other factors and levels of factors. However, as shown above, the number of factors and levels of each factor considered, exponentially increases the number of profiles to be compared and it is not realistic or feasible to construct a profile for every possible factor. As such, game profiles were created using the following three factors:

- DayType: 2 levels - weekday (Monday-Thursday), weekend (Friday-Sunday)
- StartType: 2 levels - day or night
- OpponentType: 2 levels – marketable or other

The main purpose of the given factors for game profile construction was for blocking purposes rather than to answer focal RQs of the study. It is commonly accepted in MLB that demand for sporting events typically varies by type of day and starting time. Games are played all days of the week and are played during the day (typically starting between 1:00-3:00pm) and night (typically starting from 6:00-8:00pm). Additionally, each MLB team will play games within their five-team division, within their 15 team league but outside the division, and against teams from the other league. MLB games can be categorized by game profiles which attempt to group games with these similar characteristics. The construction of game profiles is discussed in the data collection procedures section.

Opponent type is a less discussed game characteristic but some trade journal literature has suggested teams price "marketable" teams such as the New York Yankees, San Francisco Giants, Boston Red Sox, St. Louis Cardinals, and Los Angeles Dodgers differently than other teams (Cameron, 2002; King, 2002). These teams have a long history of success and fan following and were therefore coded as marketable while all other teams were coded as other for the creation of game profiles.

Minitab 17 was utilized to create profiles using the software's design of experiments procedure. Table 4 provides profile numbering, description, and frequency statistics for the 81 Royals home games. An unequal number of games within profiles is to be expected as there are more weekdays than weekend days and more "Other" type teams than "Marketable."

Table 4

Description and number of 2014 Royal game profiles.

Profile	DayType	DayTime	Opponent	Count	Percent
1	Weekday	Day	Other	5	6.17
2	Weekday	Night	Other	30	37.04
3	Weekday	Day	Marketable	0	0
4	Weekend	Night	Other	15	18.52
5	Weekend	Night	Marketable	6	7.41
6	Weekend	Day	Marketable	3	3.7
7	Weekday	Night	Marketable	7	8.64
8	Weekend	Day	Other	15	18.52

Note. Games were classified based on factors commonly believed to possibly influence demand and pricing of games. Note that even limiting the classifying factors to three still resulted in one profile (3) not represented in the Royal's home schedule.

Profile frequency data from the 81 Royals games reveals the difficulty in obtaining at least one game in every profile even from a small set of factors at two levels. As shown in Table 4, profile three (a weekday, day game, against marketable opponent) was not represented in the sample of Royal games. Once the general profile table was created, Access data tables were created in order to relate the various profiles to actual 2014 Royals games.

Table 5 provides a sample of Royal games representing each profile. As can be seen, the game profiles provide a clear and convenient way of grouping similar games. In RM studies examining cruise line forecasting (Sun et al., 2011), hotel forecasting

(Weatherford & Kimes, 2003), and airline forecasting (Lee, 1990; Wickham, 1995) similarity characteristics were used to group cruise lines (by cruise line, port, duration), hotel (by day of arrival), and airlines (day of departures). These authors chose to only study one particular day for either hotel arrivals or airline departures. Sun et al. (2011) examined weekly bookings data for cruise line departures for six cabin types but tested their forecasting methods on only one cabin type. The current study took a similar approach and examined only one game profile which contained the largest proportion of games.

Table 5

Sample of games with various profiles.

Team	Profile	GameNo	START_DATE	Opponent	DayType	StartType	OpponentType
Royals	1	6	4/9/2014	Rays	Weekday	Day	Other
Royals	2	16	5/13/2014	Rockies	Weekday	Night	Other
Royals	4	7	4/18/2014	Twins	Weekend	Night	Other
Royals	5	31	6/7/2014	Yankees	Weekend	Night	Marketable
Royals	6	75	9/14/2014	Red Sox	Weekend	Day	Marketable
Royals	7	29	6/5/2014	Cardinals	Weekday	Night	Marketable
Royals	8	68	8/31/2014	Indians	Weekend	Day	Other

Note. GameNo=the chronological order in which the game occurred during the season.

Sampling Strategy

Target Population

The target population for this study was all MLB regular season home games. As mentioned previously, the majority of MLB teams are utilizing some form of DTP and as such it was hoped the results of this study can be generalized to some extent to all MLB teams and games.

Sampling Frame

There are currently 30 MLB teams. MLB teams are divided into two leagues (American and National) each with 15 teams and subdivided into three divisions (East, Central, and West) each with five teams. Starting in April and ending in October, each team plays a total of 162 games (81 home, 81 away). Teams historically have had differing levels of home attendance throughout a season. For the purpose of this study, these attendance numbers were categorized into three tiers (high, mid, and low). These levels were constructed based on 2013 attendance figures collected from espn.com (MLB Attendance, 2015). To be classified as “high” attendance, a team’s attendance had to be in the top quartile of percentage of capacity, “mid” in the interquartile range, and “low” in the first quartile.

Sample

The sample for this study was all 81 home games for the Kansas City Royals. Kansas City was purposefully chosen as the sample team because in 2013 the Royals were in the “mid” attendance category and they contracted with tickets.com allowing for ticket price and availability data collection.

A “mid” attendance team is believed to be important for this study because the only other known DTP study of price over time (Shapiro & Drayer, 2012) examined the San Francisco Giants. Not only are the Giants in the “high” attendance category but they have been in the top three in attendance since 2011 (MLB Attendance, 2015). To contribute further to the understanding of DTP strategies, it is important for researchers to examine more teams and with differing levels of attendance. It is reasonable to believe DTP strategies will perform differently for teams with varying levels of attendance.

Furthermore, Kansas City was chosen due to data availability from their official website. The majority of teams in the MLB contract with either tickets.com or ticketmaster.com to offer online ticket purchasing. Teams utilizing tickets.com offer a more convenient way of collecting ticket pricing and availability data and thus provide another reason for the selection of the Royals for this study. The intricacies of this data collection are described in the data collection procedures section.

Power and Sample Size

Because it was decided to focus on one game profile (profile 2) for this study on forecasting errors, limitations in sample size are expected to influence power of statistical tests. Due to the nature of the simulated forecast environment to create artificial completed and future games, as well as the desire to test parameter and sample size values up to 12 games, only 10 replications of the forecast environment were possible for this study. Because no known studies have examined forecast method performance in a sport context, estimating power and minimum sample size for this study was challenging. The approach to estimating required sample size (replications of the forecast environment) was to rely on estimates from prior RM literature and utilize Minitab 17's power and sample size procedure for full factorial designs.

Recall that Lee (1990) stated that a 10% improvement in forecast error can lead to substantial increases in revenue. Therefore, a minimum meaningful difference of 10% in forecast errors was used in the power analysis. Additionally, Wickham (1995) suggested the standard deviation of short term forecast errors was 35%. This information was enough to calculate an estimate of the required number of replications required to achieve a minimum power of .8. With the full factorial design entered into Minitab's power and sample size tool, as well as values for a maximum difference between main effect means of .1, desired power of .8, and standard deviation of .35, the required number of replications of the simulated forecast environment was 7.

Because the maximum number of replications using the forecasting environment data split for this study was 10, I decided to replicate the forecast 10 times which would produce a power of .96 under the aforementioned assumptions. Because of the higher expected power levels with 10 replications, special attention was paid to effect sizes of statistically significant findings. In the post-hoc analyses I discussed effect sizes both in terms of the percent of variance explained by factors through partial η^2 as well percent changes in forecast errors between the levels of the various factors. Any difference of forecast errors of 10% or greater between groups was considered a practically significant effect size for the purposes of this study.

Significance levels. As with effect size, little discussion of significance levels can be found in the RM forecasting methodology literature. Wickham (1995) utilized an alpha level of .05 which was used as the significance level when comparing forecasts in study one.

When comparing price and demand over time, once again discussion of a priori significance levels is absent in the sport DTP limited literature. Shapiro and Drayer (2012) listed their calculated p-values for various tests and mentioned they were "significant" but did not explicitly list to what level of significance they were comparing their calculated p-values. As with effect size, a discussion of a priori significance level is absent in the sport DTP literature. As such, a conventional alpha level of .05 was utilized.

Sample size summary. This study offered another contribution to the literature by explicitly discussing the necessary factors of calculating appropriate sample sizes so further research methods can be improved. The critical substantive question to ask for this topic is: What differences in mean inventory and/or pricing strategies will provide a "meaningful" result? Hints to the answer of this question can be found in some sport pricing studies. For example, Rascher et al. (2007) showed a variable pricing strategy resulted in an average 2.8% increase in revenue above a non-varying strategy. Depending on the team, revenue increases were as high as 6.7% or $1.01 million for the New York Yankees.

In studying advance demand and dynamic pricing, a relevant question would revolve around potential revenue increases given a percent increase in price. If a team increases a price by 20% at some point prior to game day, what can they reasonably expect their revenue change to be? The answer to this question would revolve around the relevant effect size in mean change in demand given the price change. For example, assuming a current price of $20 has a demand of 100, a team may wish to know the expected revenue change from a 20% increase in price. Now assume the forecasted demand at the new price of $24 is 90. Is the difference in 10 units of demand a small, medium, or large effect? If no action is taken the revenue is $2,000 but if the price is increased to $24 the forecasted revenue is $2,160. The $160 increase in revenue represents an 8% increase. Based on results of Rascher et al.'s (2007) study, an 8% increase in revenue would be substantial. Therefore, one could argue the difference in demand in this example represents a "large" effect. Clearly, more research is needed on this topic to define what represents small, medium, and large effects.

Data Collection Procedures

A gap in the literature is how seat section inventory and pricing change over time. No studies could be found that examine ticket inventory and pricing by section and this is important to understanding demand based pricing strategies (Drayer et al., 2012; Rascher et al., 2007). Critical advance pricing decisions such as how and when to make price changes cannot be thoroughly understood without examining ticket inventory and price variance between sections over time.

Understanding the effectiveness of a revenue management system in sport requires both an examination of advance inventory and pricing. The sport literature to date has been unable to capture seat section inventory and pricing data. While Shapiro and Drayer (2012) examined price variance over time the authors did not examine how ticket inventory varied with price differences. The majority, if not entirety, of sport studies have used some form of average ticket price and aggregate game attendance. This poses problems when examining demand-based pricing strategies because these strategies inherently differentiate price by seat section.

Previous research on demand and pricing in sport has largely relied on secondary data collection techniques. Recent research has utilized average season attendance data provided from the *Red Book* and *Green Book* to study price dispersion in the MLB

(Soebbing & Watanabe, 2014). Additionally, Dwyer et al. (2013), guided by Schwartz's (2000) advance-booking model, utilized survey data collection methods to assess time's influence on consumers' estimation of ticket availability and price. However, no data collection on ticket availability and pricing could be found at the seat section level. This level of detail is typically only available to researchers with a relationship with an organization (Shapiro & Drayer, 2014). The current study offered a ticket availability and pricing data collection strategy that does not require a relationship with a particular organization.

Seat Section Data Collection Procedures

Due to the proprietary nature of pricing and demand information it is difficult to obtain seat section pricing and demand data directly from professional baseball teams. As such, the data collection strategy for this study was to manually collect data from the team's ticketing websites. As shown in Figure 15, ticket price and availability can be viewed by scrolling over each section number. In the example shown in Figure 15 it can be seen that a seat section number (139) in section name "Dugout Box" has a ticket price of $82.00 and there are 11 seats available for purchase.

A Microsoft Access database was created to collect and store seat section pricing (11 section names), ticket availability (157 section numbers), date of game, time of game, opponent, section name, and number. The data were recorded for all 81, 2014 Kansas City Royal home games at eight different lead times before game day (20 days, 10 days, 5-0 days). This resulted in 7,128 (11 sections by 81 games by 8 lead times) records for seat section pricing and 101,736 (157 section numbers by 81 games by 8 lead times) records for seat section ticket availability.

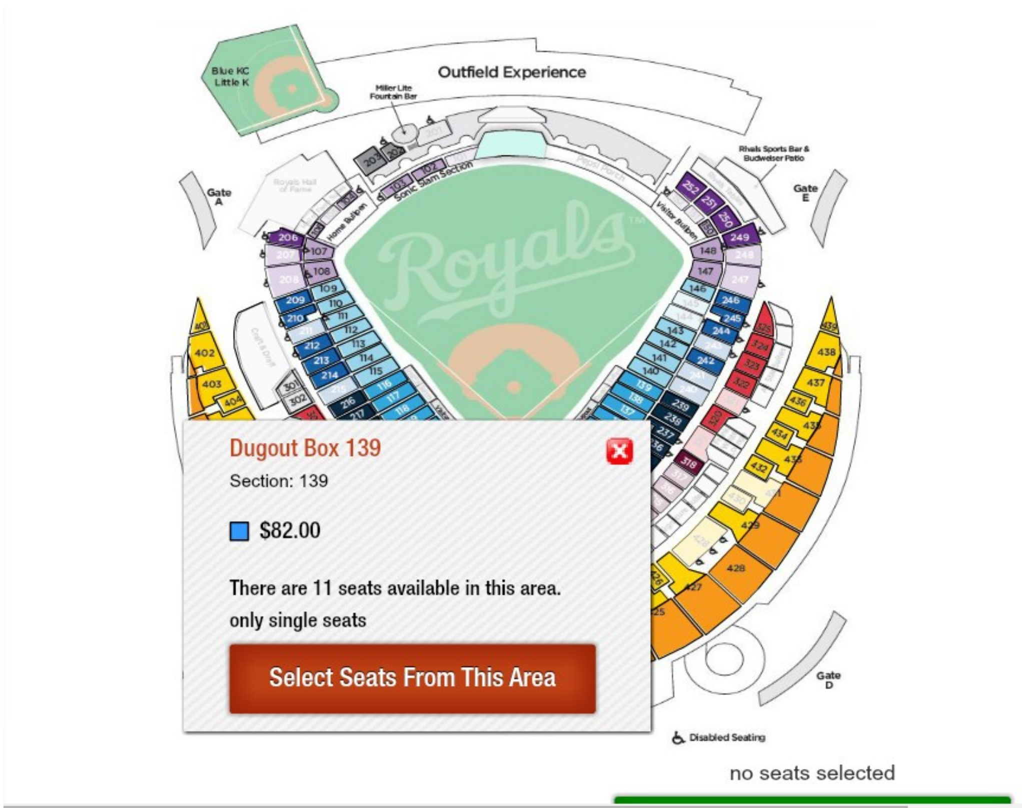

Figure 15: Ticket price and availability data collection example. The data collected was the price and ticket availability as shown. A MS Access Database was utilized to collect and store ticket price and availability data across 11 different seat sections indicated by the colors scheme seen in the stadium map.

Creation of the General Forecasting Data Matrix

In order to utilize the data collected for forecasting method analysis, a data matrix was constructed. Lee (1990), Talluri and van Ryzin (2004) as well as Wickham (1995) provided the guidelines for this type of RM forecasting data collection and organization. Table 6 shows the general forecasting data matrix for a particular game profile, *4*, seat section *A*.

Because of evidence suggesting different game profiles have different pricing and demand curves, separate data matrices need to be constructed for each game profile. Each game profile matrix was subdivided into a test set and holdout set of games. In the first phase of analysis, the test set was utilized to discover the forecasting models and parameters which provide the most accurate forecasts. Then, in the second phase of analysis, the models identified in the first phase were applied to the holdout set to test the robustness of the models to produce accurate forecasts.

Table 6

Sample Seat Availability Matrix for Section A, Profile 4

				Days out							
Game	Pr.	Sect.	Date	20	10	5	4	3	2	1	0
10	4	A	23-May	1	8	23	43	53	62	72	84
22	4	A	30-May	2	17	24	36	53	63	98	109
35	4	A	6-Jun	1	13	18	26	35	55	70	80
46	4	A	13-Jun	2	14	20	31	47	77	87	107
50	4	A	20-Jun	11	24	32	45	57	77	89	104
55	4	A	27-Jun	1	7	13	23	28	48	81	?
62	4	A	4-Jul	0	3	8	14	32	42	?	?
65	4	A	11-Jul	1	11	18	30	48	?	?	?
71	4	A	18-Jul	1	18	26	35	?	?	?	?
77	4	A	25-Jul	0	5	12	?	?	?	?	?
81	4	A	1-Aug	2	15	?	?	?	?	?	?

Note. The example of a data split between completed games and future games to be forecasted is indicated by the shaded line at game 50. This represents the current forecasting environment where games 10-50 have been played and games 55-81 can have inventory forecasted. The “?”’s in the matrix show the unknown values at the current time. Pr. = game profile; Sect.=seat section.

The dark shaded row at game 50 gives an example of the data split. Essentially, the idea behind this process was to create a historical data set (games 10, 22, 35, 46, and 50) to be used for foresting an artificial future data set (games 55, 62, 65, 71, 77, 81). The “?”s in the matrix indicate artificial unknown values to be estimated by various forecasting models. Once the model parameters were estimated, the various forecasting models were used to generate forecasts for missing values in the games in the holdout set (artificial future games). Because it is unknown how many games should be included in the historical data set to produce optimal parameter values, this was included as a methodological question of study one.

Creation of Forecast Environment

Figure 16 displays an example of the simulated forecasting environment used in study 1. Cells highlighted in red denote unknown values in the simulated forecasting environment. Notice that the data split displayed in Figure 16 meant that game 78 has no known inventory values in this simulation meaning forecasts cannot be generated for this game. As shown in the last column of the figure, this leaves 7 completed games and 7 future games in the forecast simulation.

Replications of the forecast simulation were possible by shifting the last known “complete” game down one row. For example, the first simulation in Figure 16 shows game 63 as they last completed game. A second simulation would occur by shifting the matrix down one row for which game 64 would be the last completed game. The forecast environment was utilized for each data strategy to generate forecasts from the best model parameter combinations identified in phase 1 of the analysis. Once the best model parameter combinations were determined in phase 1, parameters remained fixed for each model in the forecasting phase in order to answer the primary research questions of study one.

GameNo	Profile	Day20	Day10	Day5	Day4	Day3	Day2	Day1	Day0	Simulated Game Type
53	2	19876	17767	16829	16433	15866	15624	14924	13532	Complete game
54	2	23223	22063	21817	21708	21638	21397	20992	20251	Complete game
55	2	21624	19931	19338	19251	18967	18661	18066	17311	Complete game
59	2	23174	21873	22786	22514	22251	21848	21538	20815	Complete game
60	2	24007	22795	22400	22037	21474	20929	20144	17754	Complete game
61	2	24060	23622	23886	23688	23588	23349	22468	20937	Complete game
63	2	24862	24461	24649	23820	24207	24125	24093	23498	Complete game
64	2	23873	22585	21783	21442	21378	21333	20997	20624	Future game
65	2	24022	23537	22593	22176	22368	22140	21915	21485	Future game
69	2	23688	20637	20374	19939	19379	18749	18088	17240	Future game
70	2	24029	22316	20638	19888	19469	19320	19108	18725	Future game
71	2	24666	24137	23630	23514	23426	23321	23165	22742	Future game
76	2	22325	19541	18630	18308	17813	17447	17271	17085	Future game
77	2	20422	15976	14746	14064	13430	13157	12587	11995	Future game
78	2	20885	18260	16864	16021	15805	15588	14862	13516	Future game

Figure 16: Simulated forecasting environment. Data in table represent total ticket inventory. Cells highlighted in red indicate unknown values in the forecasting simulation. Replications of the forecasting environment are possible by shifting the last known completed game row down.

Data Analysis

The major goal of study one was to test the accuracy of various forecasting strategies and methods to forecast final game demand at various time horizons. To the consumer of forecasts, it is the accuracy of forecasts that is of most concern while a modeler wishes to examine goodness-of-fit for a model to known facts (Makridakis, et al., 1983). Because the limited research examining DTP and advance demand in sport uses data classified as immediate time series data, in this study I collected immediate data. Therefore, pickup strategies utilizing averaging techniques and exponential smoothing were the focus of comparison but ARIMA and regression techniques should be considered in future studies. The structure of this section begins with the basic data screening, descriptive statistics, and diagnostic checking common to both studies. Following descriptions of the basic data analysis, the statistical procedures pertinent to each study are discussed.

Data Screening and Verification

The first step was to run frequencies on the dependent and independent variables. Outliers were defined as those data values three standard deviations from the mean forecast error (study 1) and ticket availability (study 2). Outliers were expected for both ticket availability and pricing of special MLB games such as Opening Day and holiday games (Memorial Day, Independence Day, Labor Day). One option was to group these “special” games together in an attempt to identify common trends in the data and the other was to not analyze these games as they represent only 3.7% of all possible home games. As my hope for this study is to provide generalizations to a majority of games, the latter option was exercised. Analyses were conducted both with and without outliers.

The data were screened for what appeared to be obvious data entry errors. As the data collection for this study involved manual data entry of ticket availability and prices, data entry errors were likely to occur. The data were screened for obvious departures from adjacent cells and no obvious data entry errors were detected.

Data Transformations

The data collection for this study involved collecting pricing by seat section name (11 prices per game, per time) and collecting ticket availability for each seat section number (157). Because each seat section number is nested within a unique seat section name, each section number does not have a unique price. Therefore, after the data were collected, the ticket availability data per section number was summed to the seat section name level. Because of departures in normality and detection of many outliers, the decision was made to apply transformations to the data in order to conform the data to assumptions of statistical analysis.

Descriptive and Basic Graphical Analysis

Useful descriptive statistics in time series data include the mean, standard deviation, variance, autocovariance, and autocorrelation. Prior to applying forecast methods, these descriptive statistics were analyzed for each of the game profile data matrices. Furthermore, box plots of seat section ticket availability and pricing plotted at each time before game added an initial graphical analysis of demand and pricing patterns. After screening, transformations and descriptive analysis, various statistical procedures were utilized for the two proposed studies.

Verification of Statistical Assumptions

As discussed in detail in Chapter II, stationarity and autocorrelation are two important concepts when verifying assumptions in time series analysis. A time series plot of untransformed seat section demand over time provided an initial examination of stationarity. Plots of the autocorrelation coefficient function and partial autocorrelation function plots and tests of autocorrelation coefficients provided more rigorous examination as to the pattern of data.

Profile and graphical analysis were the primary statistical techniques utilized in both studies. Important considerations in a profile analysis include equal sample sizes in cells and missing data, normality of sampling distributions, outliers, homogeneity of variance-covariance matrices, linearity, multicollinearity, and singularity (Tabachnick &

Fiddell, 2001a, p. 440). Residual plots were constructed to provide evidence of skewness and outliers. Frequency statistics revealed if there were more research units (games) in the smallest group (seat section) than dependent variables (DV). Profile analysis is robust to the violation of normality (Tabachnick & Fiddell, 2001a) so unless there are fewer research units in the smallest group, deviation from normality is not expected to change the conclusions of the statistical tests. Linearity was examined through scatterplots between all pairs of DVs. Because the DVs are forecast errors and ticket availability repeatedly measured over time, it was expected that correlations among the DVs would be high. Therefore, according to Tabachnick and Fiddell (2001a) only statistical multicollinearity poses problems in profile analysis. Homogeneity of variance was assessed through residual plots and F_{max} values generated from the ratio of the largest to smallest group standard deviations. Because cell samples sizes were equal in both studies, F_{max} values as large as 10 could be tolerated.

Statistical Procedures: Study One
Sequential Profile Analysis

The following data analysis procedures were used to answer the research questions related to forecasting methods. While the selection of potential models, factorial design, data collection and organization, and data manipulation can become complex in studies of forecasting methods, the analytic procedures utilized to assess forecast methods have been relatively simple (e.g., Makridakies & Hibbon, 2000; Sun et al., 2011; Weatherford & Kimes, 2003). The following data analysis for this study was consistent with previous literature.

A sequential analysis was followed to systemically answer the research questions. In order to limit the number of parameter combinations utilized for the exponential smoothing (ES) model, it was decided to conduct forecasts on a small test data set of games. The parameters tested ranged from .05 to .3 in increments of .05. Parameter combinations that minimized mean absolute deviation (MAD) in the test set were then held constant in the main data collection and analysis.

After model parameters were determined and fixed from the test sample, profile analysis was utilized to answer the main research questions of the study. The within-subjects IV treated multivariately was seven days out (time horizon) before game day. The between subjects grouping variable followed the sequential process by first treating the data strategies as the grouping variable to determine how data strategies differed (RQ1). A trend analysis was planned and conducted to test for linear, quadratic, and cubic trend differences between data strategies. Post-hoc analyses utilizing a confidence interval contrast procedure was used to determine what model by data strategy combinations produced statically reliable differences at each day out. An adjusted error rate of .0008 was used to adjust for the 63 comparisons in the construction of 99.9% confidence intervals at each day out. The confidence intervals used for the tests at each day out were constructed using the pooled mean and standard deviation at each day out. Any mean falling outside the confidence intervals was considered significantly different than the distribution of MAD at each day out.

Then, after differences in data strategies were detected, the sequential analysis continued to examine the extent to which models within the best data strategy differed.

Another planned profile analysis with trend analysis was conducted to test for differences between models at each day out. Graphical examination of MAD at each day out as well as tests for linear, quadratic, and cubic trends provided the initial analysis of models. Finally, post-hoc comparisons of models to the naïve forecasts were done using a confidence interval contrast procedure with a Bonferroni adjustment to account for the 14 comparisons (2 models by 7 days out), resulting in 99.6% confidence intervals for tests of mean differences at each day out. Here, the confidence interval used for each days out test was generated from the pooled mean and standard deviation of the naïve forecast model at each day out. Any mean falling outside the naïve confidence interval was considered significantly different than the distribution of MAD produced by the naïve model at each day out.

Next, the analysis continued to examine potential differences in MAD when changing the sample size from 2-12 in increments of 2. Here again, data strategy was held constant based on prior results and models within the best strategy were examined for MAD differences when sample size was varied over the forecasting horizon. Interactions and main effect of sample size was evaluated graphically and from the results of the second profile analysis.

Finally, the sequential analysis ended with a trend analysis of pooled MAD for all models under the best data collection strategy. Graphical analysis helped in the interpretation of the trend analysis conducted using Minitab 17. Differences in MAD between days out was evaluated through ANOVA and the Tukey grouping method with an adjusted α=.002 to achieve a family error rate of .05. The Tukey method groups significantly different mean values and shows which days out MAD values reliably differed. Assumptions of ANOVA that error terms are independently and identically distributed were assessed through residual plots and were found to be satisfactory using the cube root transformation.

Statistical Procedures: Study Two Profile Analysis

The purpose of the second study's analysis was to develop an understanding of the seat section inventory curves over time and to how these curves differ. As such, profile analysis with a planned trend analysis was utilized to answer the research questions of study two. Profile analysis with trend analysis is the appropriate analytic procedure for this question because the dependent variable (ticket availability/demand) was measured several times prior to game day. Profile analysis is similar to repeated-measures ANOVA and is described as taking a multivariate approach to repeated measures. The main tests in profile analysis include the test of parallelism (RQ5), levels, and flatness (Tabachnick & Fidell, 2001).

RQ5: To what extent do seat section inventory curves differ from parallelism? A test of parallelism is a test of interaction between days out and seat section. This test revealed if the seat section inventory curves differed over time versus follow parallel trajectories. Profile analysis allows for comparison of adjacent days out and essentially answered whether the inventory curves for seat sections reliably differed. After data transformation, multivariate assumptions were met, so initial profile differences were evaluated using Wilks' Lamba for statistical evaluation and strength of association.

RQ6: What is the nature of differences between seat section inventory curves? A trend analysis was planned to determine the extent of differences in seat section slopes and changes in the pattern of slopes across seat sections. A trend analysis with an adjusted alpha error rate of .007 was utilized to account for the seven different tests of trend between the various days out. The test of interaction of trends between seat sections determined if the seat sections had reliably different slopes (linear trend) over the eight days as well as different patterns in slope (quadratic and cubic trends) across days.

To account for the unequal spacing of days out between 20 and 10 days out and 10 and 5 days out, SPSS 22.0 GLM syntax specified the unequal spacing in the POLYNOMIAL command line as (20,10,5,4,3,2,1). Mean and standard deviations for all seat sections were calculated as well as a graphical representation of mean seat section inventory over time. Because seat sections are known to differ in total ticket inventory, it was beneficial for graphical scaling purposes to plot standardized means to aid in interpretation of the shape of inventory curves.

Finally, post-hoc tests of trend were planned at each seat section level to examine the extent to which each section exhibited significant linear, quadratic, and cubic trends. Simple comparisons between seat sections were made by rank ordering the effect sizes for linear trend by seat section and observing which sections produced reliable linear, quadratic, and cubic trend components. Finally, a graphical analysis with plotted slopes in the form of percent changes in inventory between days out highlighted the major differences between seat section inventory curves.

Institutional Review Board Approval

Data collection procedures were submitted to the University of Northern Colorado Institutional Review Board along with a summary of the purpose and methods of this study. The study qualified for exempt status, category 4 because existing, secondary, publicly available administrative data was collected and analyzed for this study. The data collection did not directly involve human participants. Rather, the data collection occurred by navigating to the team's publically available ticketing website and data were collected using the methods outlined in this chapter. Appendix A provides the Institutional Review Board Approval.

CHAPTER IV

AN EXAMINIATION OF FORECASTING STRATEGIES AND MODELS IN SPORT REVENUE MANAGEMENT

It has been suggested that effective revenue management (RM), demand-based pricing strategies will require an understanding of three major disciplines: economics, marketing, and operations (Ng, 2007; Talluri & van Ryzin, 2004). The increased implementation of demand-based pricing strategies in sport has led to recent academic research on the topic. Sport management researchers have turned to other service industry literature to find a conceptual framework for studying dynamic pricing and advance demand (Drayer & Shapiro, 2012; Dwyer et al., 2013).

Service industries such as the airline and hotel industries were at the forefront of developing RM and the more specific form of RM known as dynamic pricing. The literature on these and other service industries has provided an early theoretical base for this emerging sport management literature topic. However, RM researchers have called for a more complete theoretical framework than those currently utilized by sport RM literature (Ng, 2007; Talluri & van Ryzin, 2004). An understanding of consumer behavior, economics, and operations research is needed to have a thorough understanding of the potential applicability and effectiveness of a RM strategy in a sport context.

More sport specific RM research is needed to understand the applicability and sustainability of a RM strategy in sport.

This study offered an examination of sport RM from a ticket operations (forecasting & estimation) angle by testing the accuracy of forecast data strategies and models. To date, no known sport RM literature exists which explores ticket inventory forecasting. This critical component in a comprehensive RM strategy deserves attention and in this study I aimed to provide an initial understanding of forecasting strategies to further researchers' and practitioners' understanding of the complex topic of RM.

Given the significance of ticket pricing to a sport organization's bottom line coupled with the increased use of demand-based pricing strategies, the following research questions were developed to guide this research:

RQ1 To what extent do profiles of data strategy differ in forecast errors?

RQ2 To what extent do profiles of forecast models differ from naïve forecasts?

RQ3 To what extent do forecast errors vary by sample size?

RQ4 To what extent do forecast errors vary by days out?

Empirical work in the RM forecasting literature has suggested pickup data strategies provide more accurate forecasts than non-pickup strategies but this has not been tested in a sport context. General forecasting theory and empirical works (e.g., Bowerman & O'Connell, 1993; Makridaks & Hibon, 2000) have suggested that smoothing models such as exponential smoothing and moving average are the most appropriate models when forecasting in the short term (less than 30 days) but these models have not been tested in a sport context. Further, statistical theory (e.g., central limit theorem) implies that the larger a sample size utilized to generate forecasts, the better the estimate. However, limited empirical work in RM (e.g., Weatherford & Kimes, 2003; Sun, Gauri, & Webster, 2011) have suggested the sample size hypothesis may not hold in a RM context but this too has not been tested in a sport forecasting environment. Finally, forecasting theory suggests that the further out in time a forecast is generated from the event, the worse the forecast becomes. Empirical work in the hotel, airline, and cruise line industries have supported the time horizon theory but no known work in a sport context could be found.

A sequential factorial design using profile analysis with planned trend analyses provide the major analytical strategies to answer the primary research questions (RQ1 and RQ2) followed by ANOVA procedures to answer the secondary research questions (RQ3 and RQ4). This design allows for the sequential testing of the various research questions. Because no known studies examining forecast methods in a sport context could be found, it was believed a sequential design was appropriate to first test data strategies, followed by models within data strategies, then ending with the secondary analysis of sample size and forecasting horizon for each model.

This examination of forecasting strategies built on and contributed to revenue management work primarily with an operations focus. This study empirically tested forecasting and statistical theories and lent support for some while contradicting others. The study added to the limited general RM forecasting literature while beginning the discussion in a sport RM forecasting context.

Practical implications included providing a foundation for ticket operations personnel to monitor and forecast inventory. With three common pickup strategies utilized in RM practice, it will be of value to practitioners to have an understanding of which data strategies produce the most accurate forecasts. Then, if a best data strategy can be identified, the next step is to determine if forecast models offer reliably better forecasts than the simplest naïve (essentially a control group against which to compare relative performance of forecasting methods) forecasts. Obviously, if more complicated models do not perform reliably better than the most simplistic models, there is little justification for the extra cost in time and resources to implement these models. Next, it is of practical importance to have an understanding of how many games should be included to generate forecasts so practitioners know at which point in the season (i.e., number of games played) they can begin to trust forecasts. Finally, practitioners can find value in knowing how forecast errors vary based on how far out in the selling period they are. If forecasts do not reliably differ at various days from game day, then there is little justification for continually updating forecasts. Furthermore, if forecasts can be reasonably trusted at further days out, then marketing strategies (e.g., pricing, promotions) could be employed to influence inventory in one way or the other.

Review of Literature

One wishing to understand revenue management (RM) from an operations research perspective would be inclined to review Belobaba's seminal works (1987a, 1987b, & 1989). Some ten years after Belobaba's works, Botimer and Belobaba (1999) provided a new theoretical framework for pricing and differentiation in the airline industry. Additionally, Bitran and Caldentey (2003) provided an overview of different pricing models for RM including dynamic pricing.

Much of the literature on RM from an operations research perspective focuses on a firm's ability to estimate and forecast demand. Indeed, Littlewood's (1972/2005) classic piece focused on mathematical models to forecast demand and Belobaba's (1987a, 1987b) development and implementation of the expected marginal seat revenue model garnered the attention of academics and practitioners alike with reported increases in airline revenue of 4 to 6 percent. Estimation and forecasting is key to the understanding and proper implementation of a revenue management system (Ng, 2008; Talluri & van Ryzin, 2004; Weatherford & Kimes, 2003).

For example, if one wishes to forecast overall demand for a MLB game, then aggregated attendance data from previous years (or similar games in same year) may be used to develop overall game attendance forecasts for future games. However, because professional sport teams (e.g., MLB, NFL, NBA, etc.) have historically price discriminated based on seat location, one may wish to forecast demand for specific seat sections as price for seat sections can vary considerably in any given venue. In this case, demand and pricing data would need to be collected for each seat section.

Much of statistical methodology focuses on models where error terms are assumed to vary independently. With many statistical methods, dependence between observations is undesirable and randomization is often utilized to validate analysis as if observations were independent (Box, Hunter, & Hunter, 1978). However, there are many instances in business, economics, engineering and natural sciences in which dependent observations are collected repeatedly over time and the nature of the dependence is of interest (Box & Jenkins, 1976). A wide range of forecasting methods are available and range from simple methods (such as using the most recent observations as a forecast) to highly complex econometric systems (Makridakis, Wheelright, & McGee, 1983). Revenue management forecasting is primarily interested in predicting future values of inventory and demand and the success of a RM system lies in a firm's ability to forecast demand (Kimes, 1999; McGill & van Ryzin, 1999; Pak & Piersma, 2002).

Forecasting methods are utilized in a vast number of industries and fields including statistics, computer science, engineering, economics, and weather. Box and Jenkins (1976) provided a seminal text on the subject of time series analysis. The Box and Jenkins text is said to have popularized time series applications and has led to new developments in time series research. In particular, "the importance of diagnostic checking in modeling has become even more critical in this data-rich environment for all statistical analyses" (Mills, Tsay, & Young, 2011, p. 1).

As with any statistical methodology, models can be simple or complex. However, according to Talluri and van Ryzin (2004) most forecasting algorithms in RM practice are not complicated. Rather, the focus of RM forecasting methods is on speed, simplicity, and robustness. The following sections provide an overview of forecasting notation and the mathematics behind certain techniques that can potentially be utilized in a RM forecasting strategy.

Smoothing and Decomposition
Forecasting Methods

Sometimes referred to as structural forecasting methods, smoothing and decomposition forecasting methods are largely heuristic in nature (Makridakis et al., 1983; Talluri & van Ryzin, 2004). These methods have garnered wide appeal from practitioners because their development has been mainly empirically based rather than theoretical (Makrikakis et al., 1983). Despite the lack of strong statistical and theoretical development these methods have been shown to provide accurate forecasts in certain situations (Makridakis et al., 1982; Talluri & van Ryzin, 2004; Weatherford & Kimes, 2003; Wickham, 1995). Some evidence exists which suggests these simple methods provide significantly more accurate forecasts than more complex forecasting methods such as auto-regressive integrated moving average (ARIMA) models (Carbone, Anderson, Corriveau, & Corson, 1983).

Sometimes termed "ad-hoc" forecasting methods, these methods are more commonly known as smoothing and decomposition by time series authors (e.g., Bowerman & O'Connel, 1993; Box & Jenkins, 1978; Makridakis et al., 1983). Authors claim these methods have good theoretical properties despite their largely heuristic origins (Talluri & van Ryzin, 2004). Decomposition methods typically involve breaking up the data and composing the time series data into hypothesized patterns using three types of components: level, trend, and seasonality. According to Talluri and van Ryzin (2004) "Ad-hoc forecasting methods are intuitive, are simple to program, and maintain and perform well in practice. For these reasons, they are prevalent in RM practice" (p.

434). The following sections explain the most common smoothing and decomposition methods.

Moving average. Denoted MA(*T*) for moving average of order *T*, this method assumes that the most recent observations provide the best predictors of future data. As opposed to taking the average of all historical data, this technique simply takes the average of the *T* most recent observations and uses this average to forecast future values. In RM practice, *T* is typically between 3 and 15 (Talluri & van Ryzin, 2004; Weatherford & Kimes, 2003).

Exponential smoothing. Because of their simplicity and robustness, exponential smoothing techniques are commonly utilized in RM practice (Talluri & van Ryzin, 2004; Weatherford & Kimes, 2003). In fact, because of their practical usefulness, exponentially weighted averages were being used prior to theoretical justification (Winters, 1960; Box, Hunter, & Hunter, 1978). Single exponential smoothing is the simplest version of exponential smoothing and includes a smoothing constant, $0 < \alpha < 1$, for the level, A_t. The model for simple exponential smoothing takes the form:

$$\hat{z}_{t+1} = A_t = \alpha z_t + (1 - \alpha)\hat{z}_t$$

This equation provides a simple and convenient way to update forecasts as new data are recorded (Holt, 1957/2004; Box, Hunter, & Hunter, 1978).

Choosing the value for α is a RM design decision with values usually ranging from .05 to .3 in RM applications (Talluri & van Ryzin, 2004). In a study of the accuracy of various airline forecasting techniques, Wickham (1995) used values of .2 and .4 for α. Weatherford and Kimes (2003) tested α levels between .05 and .95 and found the “best” performance (based on mean absolute deviation (MAD)) for various hotel rate categories was found when α was .05, .15, .35, .45, .55, and .65. Sun, Gauri, and Webster (2011) tested α values between .05 and .95 in increments of .05 and found the range of .05 to .3 the best.

Pickup forecasting. More of a strategy for data organization than separate forecasting techniques, pickup forecasting has widely been used in RM applications (Talluri & van Ryzin, 2004). Pickup forecasting methods may utilize any of a number of the forecasting techniques illustrated in previous sections to forecast final and/or incremental demand (e.g., exponential smoothing, moving averages, ARIMA). The design of a pickup data strategy is mostly simple and heuristic. However, despite the relatively simple design, these forecasting strategies have been widely used and reported to perform well in RM applications (Lee, 1990; Talluri & van Ryzin, 2004; Weatherford & Kimes, 2003; Wickham, 1995; Zakhary, Atiya, el-Shishiny, & Gayar, 2011).

Choosing forecasting methods. With so many possible forecasting techniques as well as the combinations of various techniques, how does a forecaster decide what to use? As with many statistical techniques, the answer is often "it depends" and different methods generally produce different forecasts (Makridakis & Winkler, 1983). Newbold and Granger (1974) provided a set of guidelines for selecting forecasting methods but followed their set of guidelines with this cautionary quote:

> Never follow blindly the guidelines (a)-(e)! In many practical situations one knows something of value about the series under consideration. This information should, if possible, be employed in any decision as to how the series should be forecast. (p. 145)

Newbold and Granger (1974) suggested for time series with fewer than 30 observations there is little a forecaster can do but utilize averaging and exponential smoothing techniques. Makridakis, Wheelwright, and McGee (1983) stated that smoothing methods are generally best for immediate or short term forecasting, decomposition and ARIMA methods for short to medium, and regression techniques are best suited for medium to long usage. The “M-competitions” (named after Spyros Makridakis) have become notorious in the forecasting literature for helping answer the questions regarding best forecasting methods.

The M-competitions were largely developed in response to criticism of Makridakis and Hibon’s (1979) conclusion that simpler methods (e.g., averaging, exponential smoothing) provided more accurate forecasts than more sophisticated approaches such as ARIMA (Fildes & Makridakis, 1995; Makridakis & Hibon, 2000). Forecasting competitions are argued to provide important empirical tests of various forecasting methods (Fildes & Makridakis, 1995). There have been three published M-competitions to date: Makridakis et al. (1982); Makridakis et al. (1993); and Makridakis & Hibon (2000).

In the first forecasting competition since the third Makridakis (M3) competition, Athanasopoulos, Hyndman, Song, and Wu (2011) evaluated the performance of various forecasting methods using tourism time series data. According to these authors, this was the first published work in the empirical forecasting literature since 1974 which found that ARIMA models performed as well as, if not better than, other methods. These authors found further evidence of the good performance of Forecast Pro forecasts.

However, like Makridakis and Hibon (2000) they did not provide the models that the Forecast Pro algorithm ultimately selected to generate forecasts. Additionally, in contrast to the wide variety of business and economic time series data sets that the M-competitions utilized, Athanasopoulos et al. (2011) only examined tourism data, limiting the generalizability of their results.

While it would be much easier on researchers and practicing forecasters if the literature had produced a best forecasting method to use, it is clear this is not the case. Selecting a forecasting method is obviously dependent on the situation. Makridaks et al. (1982) summarized the situation by stating “It is important to understand that there is no such thing as the best approach or methods as there is no such thing as the best car or best hi-fi system” (p. 112).

Problem Statement

The importance of forecasting in a revenue management (RM) strategy is clear as Lee (1990) showed that a ten percent improvement in airline demand forecasting could contribute up to a three percent increase in revenue. Despite the fact that accurate forecasts are crucial to effective revenue management, few empirical RM forecasting studies testing the accuracy of methods exist and no sport specific forecasting methodological works could be found. The rapid increase in revenue management strategies such as dynamic ticket pricing (DTP) in sport applications warrants the need for formal studies of forecast strategies and models.

Weatherford and Kimes (2003) provided one of the first methodological RM forecasting works and found exponential smoothing, pickup methods, and moving average models to be the most robust hotel booking forecasting methods. Chen and Kachani (2007) also studied hotel demand forecasting and found exponential smoothing with α=.35 performed well. However, although discussed in their methodology, these authors did not provide results or discussion of the accuracy of more sophisticated methods.

Furthermore, neither Sun et al. (2011), Weatherford and Kimes (2003), nor the Chen and Kachani (2007) works included forecasts for naïve methods. Including naïve forecasts is essential to forming comparisons between other forecast methods' relative performance over the simplistic naïve forecasts (Makridakis et al., 1983). If forecast methods do not significantly outperform naïve forecasts then there is little justification for the extra work and cost of a more sophisticated forecasting method. The current study helps fill this gap in the RM literature by comparing forecast model performance to naïve forecasts.

The majority of empirical forecasting literature has suggested that simpler methods perform as well as, if not better than, more sophisticated approaches such as ARIMA. In the RM forecasting literature, the tendency appears to be toward simple models as well (Sun, Gauri, & Webster, 2011; Talluri & van Ryzin, 2004; Weatherford & Kimes, 2003; Wickham, 1995). Yet, these studies do not indicate whether their best models produced statically reliable results or whether their models reliably differed from naïve forecasts.

The pickup methods illustrated by Lee (1990), Wickham (1995), and Talluri and van Ryzin (2004) all use relatively simple forecasting methods (e.g., simple/weighted average, exponential smoothing, etc.) to forecast the estimated demand to be "picked" up. In general, it appears from prior empirical works that simpler models outperform more statistically sophisticated methods. However, no existing literature testing the performance of simple model forecasting in a sport context could be found.

Selecting an appropriate forecasting strategy and model is a blend of science and art. The research listed in this section provided a foundation for future researchers to begin but as Bowerman and O'Connell (1993) discussed:

> Choosing the forecasting method to be used in a particular situation involves finding a technique that balances the factors just discussed. It is obvious that the "best" forecasting method for a given situation is not always the "most accurate". Instead, *the forecasting method that should be used is one that meets the needs of the situation at the least cost and with the least inconvenience.* (p. 19)

Revenue management research in the sport industry is still in its infancy and no sport specific RM forecasting research can be found. As dynamic pricing strategies become common in sport organizations, a methodological study examining the accuracy of various forecasting methods could provide valuable insight for both the sport and RM literature base.

Methods

Research Design

This study utilized a 3x3x6x7 factorial research design to examine the application and accuracy of various forecasting strategies and methods in a sport RM context. Various forecasting data strategies, models, sample sizes, over a 20 day selling period were examined. Forecasting errors are compared to naïve forecasts which are the equivalent to control groups under each data strategy. Essentially, this study aimed to form an understanding of the third major component of an effective RM strategy: operational research and specifically, estimation and forecasting. As such, much of the theoretical development of forecasting models was discussed in Chapter II under the heading “Operations Revenue Management Research and Theory: Estimation and Forecasting” beginning on page 92.

The study followed a sequential analysis by first identifying the exponential smoothing parameters which minimized absolute forecast error in a training set of data. Then, the exponential parameters which minimized error in the training set were held constant for the remainder of the study. Next, data strategies were tested for reliable differences between strategies. After a superior data strategy was identified, the next phase of the study examined the model, sample size, and time horizon combinations to determine if reliable differences between models existed within the superior data strategy. The following sections describe the various factors examined.

Sampling Strategy

Target population. The target population for this study was all MLB regular season home games. As mentioned previously, the majority of MLB teams are utilizing some form of dynamic ticket pricing (DTP) and as such it is hoped the results of this study can be generalized to some extent to all MLB teams and games. As described in subsequent sections, games can be categorized into profiles based on day of week, time of day, and opponent.

Sampling frame. There are currently 30 MLB teams. MLB teams are divided into two leagues (American and National) each with 15 teams and subdivided into three divisions (East, Central, and West) each with five teams. Starting in April and ending in October, each team plays a total of 162 games (81 home, 81 away). Teams historically have had differing levels of home attendance throughout a season. For the purpose of this study, these attendance numbers are categorized into three tiers (high, mid, and low). These levels were constructed based on 2013 attendance figures collected from espn.com (MLB Attendance, 2013). To be classified as “high” attendance, a team’s attendance had to be in the top quartile of percentage of capacity, “mid” in the interquartile range, and “low” in the first quartile.

Sample. The sample for this study was all 81 home games for the Kansas City Royals. Kansas City was purposefully chosen as the sample team because in 2013 the Royals were in the “mid” attendance category and they contract with tickets.com allowing for ticket price and availability data collection.

A “mid” attendance team is believed to be important for this study because the only other known DTP study of price over time (Shapiro & Drayer, 2012) examined the San Francisco Giants. Not only are the Giants in the “high” attendance category but they have been ranked in the top three in attendance since 2011 (MLB Attendance, 2015). To contribute further to the understanding of DTP strategies, it is important for researchers to examine more teams and with differing levels of attendance. It is reasonable to believe DTP strategies will perform differently for teams with varying levels of attendance.

Furthermore, Kansas City was chosen due to data availability from their official website. The majority of teams in the MLB contract with either tickets.com or ticketmaster.com to offer online ticket purchasing. Teams utilizing tickets.com offer a more convenient way of collecting ticket pricing and availability data and thus provide another reason for the selection of the Royals for this study. The intricacies of this data collection are described in the data collection procedures section.

Description of Variables

Dependent variable. The dependent variable in this study was the forecast error of final game day ticket inventory produced by the various models and conditions. Forecast error was measured by the mean absolute deviation (MAD). Mean absolute deviation provides an intuitive method of comparison in the same units as the original variable.

Independent variables. The independent variables for the current study are the various data strategies, models, sample size, and time horizons prior to game. Data strategies are a categorical variable with the values of non-pickup (NP), classical pickup (CP), and advanced pickup (AP). Models are a categorical variable with three values: naïve (i.e., control), moving average (MA), and exponential smoothing (ES). The time horizon to game is a discrete variable taking on the values 20, 10, and 5 to 1 days prior to a game. The sample size is also a discrete variable taking on the values 2, 4, 6, 8, 10, and 12.

Naïve forecasts. Naïve forecast methods essentially form a control group against which to compare relative performance of forecasting methods. In this study, because three data strategies were utilized, three different naïve forecasts were generated within each data strategy. In most forecasting literature the naïve forecast utilized is simply the last known value within a NP strategy. This study examined a different naive forecast within each revenue management data strategy.

Types of naïve forecasts. Three forms of naïve forecasts were used to form baseline comparisons within each data strategy. In a non-pickup (NP) strategy, the naïve forecast is the traditional naïve forecast found in forecasting literature. The NP naïve forecast simply uses the previous game's final ticket inventory to predict the next games final inventory. Within a classical pickup (CP) strategy, the naïve forecast utilizes the inventory curve of the last known complete game to generate the estimated pickups for future games. The naïve pickup line is then utilized in the standard CP data strategy to produce forecasts. Finally, within an advanced pickup (AP) data strategy, the naïve forecast utilizes the last known final demand to forecast all future games.

Blocking independent variable held constant. MLB game profiles served as blocking variables because it is believed differences in demand/inventory and pricing exist based on the characteristics that define a profile (day of week, time of day, opponent). Eight different MLB game profiles were constructed and the profile with the most games was utilized in the simulated forecast environment. Despite the loss in generalizability to other profiles, it was deemed necessary to only examine one profile due to the low number of games in some profiles which limited the simulated forecasting environment described in subsequent sections.

Holding a particular category of games constant is consistent with other RM studies examining cruise line forecasting (Sun et al., 2011), hotel forecasting (Weatherford & Kimes, 2003), and airline forecasting (Lee, 1990; Wickham, 1995).

Profile characteristics were used to group cruise lines (by cruise line, port, duration), hotel (by day of arrival), and airlines (day of departures). These authors chose to only study one particular day for either hotel arrivals or airline departures and only one cabin class within the cruise line study.

Therefore, selecting and holding constant the profile with the largest sample of games is a consistent approach to prior RM research. If more data can be made available which would permit feasible construction of the simulated forecasting environment, future research should explore blocking on profile to examine potential differences across classification of games.

Creation of Simulated Forecast Environment

Figure 17 displays the simulated forecasting environment used in this study. Cells highlighted in red denote unknown values in the simulated forecasting environment. In this example, a split is created at game 63 (highlighted in grey) showing the last game to be played. As shown by the wedge shape of unknown values, there were seven games at each of the various days out on which to generate forecasts. Notice that the split displayed in Figure 17 meant that game 78 has no known inventory values in this simulation meaning forecasts cannot be generated for this game. This leaves seven completed games and seven future games in the example forecast simulation. Because it was desired to test sample sizes up to 12 games, this meant that the simulated forecast environment required a minimum of 19 games (12 for generating estimates to be forecasted and seven “future” games to forecast). Therefore, any game profiles which did not include this minimum number of games could not be included in this study.

Replications of the forecast simulation are possible by shifting the last known "complete" game down one row and reapplying the forecast methods to the new set of data. In this example, the second replication would split the data at game 64 (the new latest current game). The red wedge shape shifts down and now the latest known value would be the observed ticket inventory for game 78 at 20 days out. The number of replications utilized in this study to achieve desired power are discussed in the following section.

GameNo	Profile	Day20	Day10	Day5	Day4	Day3	Day2	Day1	Day0	Simulated Game Type
53	2	19876	17767	16829	16433	15866	15624	14924	13532	Complete game
54	2	23223	22063	21817	21708	21638	21397	20992	20251	Complete game
55	2	21624	19931	19338	19251	18967	18661	18066	17311	Complete game
59	2	23174	21873	22786	22514	22251	21848	21538	20815	Complete game
60	2	24007	22795	22400	22037	21474	20929	20144	17754	Complete game
61	2	24060	23622	23886	23688	23588	23349	22468	20937	Complete game
63	2	24862	24461	24649	23820	24207	24125	24093	23498	Complete game
64	2	23873	22585	21783	21442	21378	21333	20997	20624	Future game
65	2	24022	23537	22593	22176	22368	22140	21915	21485	Future game
69	2	23688	20637	20374	19939	19379	18749	18088	17240	Future game
70	2	24029	22316	20638	19888	19469	19320	19108	18725	Future game
71	2	24666	24137	23630	23514	23426	23321	23165	22742	Future game
76	2	22325	19541	18630	18308	17813	17447	17271	17085	Future game
77	2	20422	15976	14746	14064	13430	13157	12587	11995	Future game
78	2	20885	18260	16864	16021	15805	15588	14862	13516	Future game

Figure 17: Simulated forecasting environment for MLB games. Data are total ticket inventory recorded at each day out. The grey line at game 63 indicates the data split of completed games and games yet to be played. Cells highlighted in red indicate unknown values in the forecasting simulation. Replications of the forecasting environment are possible by shifting the last known completed game down to the next game. In this case, a second replication would shift the data split down to game 64 and repeat the forecasting process.

Power and Sample Size

Because no known studies have examined forecast method performance in a sport context, estimating power and minimum sample size for this study relied on prior RM forecasting literature to estimate a minimum sample size. Minitab 17's power and sample size procedure for full factorial designs was utilized to determine the minimum number of replications of the forecast environment to achieve a power of 80%.

Lee (1990) stated that a 10% improvement in forecast error can lead to substantial increases in revenue. Therefore, a minimum meaningful significant difference of .1 was used in the power analysis. Additionally, Wickham (1995) suggested the standard deviation of short term forecast errors was 35%. This information was enough to calculate an estimate of the required number of replications to achieve a minimum power of .8. With the full factorial design (3x3x6x7) entered into Minitab's power and sample size tool, as well as values for a maximum difference between main effect means of .1, desired power of .8, and standard deviation of .35, the required number of replications was 7.

Because the maximum number of replications using the data split for this study was 10, it was decided to replicate the forecast 10 times which would produce a power of .96 under the aforementioned assumptions. Because of the higher expected power levels with 10 replications of the forecasting environment, special attention was paid to effect sizes of statistically significant findings. In the post-hoc analyses I discuss effect sizes both in terms of the percent of variance explained by factors through partial η^2 as well percent changes in forecast errors between the levels of the various factors. Any difference of forecast errors of 10% or greater between groups is considered a practically significant effect size for the purposes of this study.

Statistical Procedures

The following data analysis procedures were utilized to answer the research questions related to forecasting methods. A sequential analysis was followed to systemically answer the research questions. Because it was not a primary question in this study, it was decided to limit the number of parameter combinations utilized for the exponential smoothing (ES) model. A small test of games was utilized to test parameters ranging from .05 to .3 in increments of .05. Parameter combinations that minimized mean absolute deviation (MAD) in the test set were then held constant in the main data collection and analysis.

After model parameters were determined and fixed from the test sample, profile analysis was utilized to answer the main research questions of the study. The within-subjects IV treated multivariately was seven days out (time horizon) before game day. The between subjects grouping variable followed the sequential process by first treating the data strategies as the grouping variable to determine how data strategies differed (RQ1). A trend analysis was planned to test for linear, quadratic, and cubic trend differences between data strategies. Post-hoc analyses utilizing a confidence interval contrast procedure was used to determine what model by data strategy combinations produced statically reliable differences at each day out. An adjusted error rate of .0008 was used to adjust for the 63 comparisons in the construction of 99.9% confidence intervals at each day out. The confidence intervals used for the tests at each day out were constructed using the pooled mean and standard deviation at each day out. Any mean falling outside the confidence intervals is considered significantly different than the distribution of forecast errors at each day out.

Then, after differences in data strategies were detected, the sequential analysis continued to examine the extent to which models within the best data strategy differed. Again, profile analysis with trend analysis was conducted to test for differences between models at each day out. Graphical examination of MAD at each day out as well as tests for linear, quadratic, and cubic trends provided the initial analysis of models. Finally, post-hoc comparisons of models to the naïve forecasts were done using a confidence interval contrast procedure with a Bonferroni adjustment to account for the 14 comparisons made (2 models by 7 days out), resulting in 99.6% confidence intervals for tests of mean differences at each day out. Here, the confidence interval used for each day out test was generated from the pooled mean and standard deviation of the naïve forecast model at each day out. Any mean falling outside the naïve confidence interval is considered reliably different than the distribution of forecast errors produced by the naïve model at each day out.

Next, the analysis continued to examine potential differences in MAD when changing the sample size from 2 to 12 games in increments of 2. Here again, data strategy was held constant based on prior results and models within the best strategy were examined for MAD differences when sample size was varied over the forecasting horizon. Interactions and main effect of sample size was evaluated graphically and from the results of the second profile analysis.

Finally, the sequential analysis ended with a trend analysis of pooled MAD for all models under the best data collection strategy. Graphical analysis aids in the interpretation of the trend analysis conducted using Minitab 17. Differences in MAD between days out was evaluated through ANOVA and the Tukey grouping method with an adjusted α=.002 to achieve a family error rate of .05. The Tukey method grouped significantly different mean values and showed which days out forecast error values reliably differed. Assumptions of ANOVA that error terms are independently and identically distributed were assessed through residual plots and were found to be satisfactory using the cube root transformation.

Results

Data Exploration and Screening

Initial data exploration included examining frequencies of ticket inventory by game and days out. Data were collected for all 81 Kansas City Royal home games. Missing data was found for games 1-6. Games 1-6 had missing data for 20 days out and Games 1 and 2 were missing 10 days out data. Because of the real-time nature of the time series data collection for this study, it was not possible to gather the missing data. Data had to be collected from the team's website on the precise reading day (day out) or the data could not be recorded accurately.

Missing data. Time horizon (i.e., days out) of 20 was missing 6 games of data for games 1-6. Of the missing games for Day20, three were from profile 8, two from profile 2, and one from profile 1. Ten days out was missing data for games 1 and 2 which are both classified as profile 8. All other time horizons included data for all 81 Royals home games. Data could only be collected on specific days due to the real-time data collection strategy employed; therefore it was not possible to go back and record the ticket availability for the missing games. Because exponential smoothing cannot be performed with missing data and because the missing data occurred very early in the season when ticket holds (season, group, etc.) are typically at their highest, the decision was made to remove these cases prior to primary analysis.

Descriptive statistics. Descriptive statistics and box plots were examined for each time horizon by game profile. Because the data structure of pickup forecasting utilizes both historical data (e.g., data from previous games) at each of the days out (20, 10, 5, 4, 3, 2, 1, and game day) as well as data collected at each day out for each game (known as the game inventory curve) box plots constructed at each of the days out served as an efficient way to examine both the distribution of game inventory as well as the nature of mean game inventory over time. The box plots showed variability across game profiles as well as within game profiles and between time horizons. The plots also showed the expected downward trend in ticket inventory from Day20 to Day0.

Next, because non-pickup forecasting utilizes only completed games' final game day inventory coded as Day0, box plots and descriptive statistics were used to examine final inventory distributions between game profiles. The plots showed obvious differences in ticket inventory distributions between profiles. In particular, the distribution of final game day ticket inventory for profiles 1, 2, and 7 were higher than other profiles, most obviously profile 4.

The mean game day ticket inventory of profile 4 ($\bar{x}_4$=8962, n=15) was nearly 55% less than the mean of profile 2 ($\bar{x}_2$=19768, n=30), 52% less than profile 1 ($\bar{x}_1$=18860, n=5), and 51% less than profile 7 ($\bar{x}_7$=16290, n=7). This initial analysis of final inventory means suggested differences existed between profiles. Table 7 shows the descriptive statistics of the profiles showing unequal samples sizes, means, and standard deviations between the profiles. Unequal sample sizes of game profiles is expected because profiles are constructed using day of the week and time of day as grouping variables and typical MLB season schedules have more night, weekday games than other types of games.

The initial analysis of the distribution of final game demand between profiles suggested games should be grouped by profile prior to beginning to assess forecasting assumptions and performing the simulated forecasting environment. As described in the section on creating the forecasting environment, profile 2 with 30 games was the only profile that could be examined in this study. While generalizability of findings are limited using this approach, this profile of games represents 37% of all games during the season. Subsequent screening and evaluation of assumptions is limited to profile 2.

Stationarity. For profile 2, time series plots for each day out showed the data were relatively stationary. More formally, the autocorrelation function and partial autocorrelation showed no significant autocorrelations (p<.05 for all lags) signifying the data do not reliably differ from stationarity.

Forecast error outliers within profile 2. Forecast errors were calculated and potential error outliers were examined through box plots in Minitab 17. Minitab denotes an outlier on a box plot when a value falls 1.5 times the interquartile range past either the first or third quartile value. The potential for outliers was assessed at each phase of the study. The estimation phase (phase 1) of the forecasting study utilized a test set to find the model parameter values that minimized the mean absolute deviation for exponential smoothing and moving average under each data collection strategy (non-pickup, classical pickup, advanced pickup). No forecast error outliers were detected in phase 1.

Table 7

Final Game Day (Day0) Inventory.

Profile	n	M	SD
1	5	18860	5838
2	30	19768	3994
4	15	8962	6283
5	6	12873	3660
6	3	14806	1818
7	7	16290	4104
8	15	12687	7198

Note: no games matched the criteria for profile 3.

In phase 2 of the analysis, forecast errors were collected on the entire dataset used to construct the simulated forecast environment. Data grouped by data strategy revealed multiple outliers of absolute error suggesting a possible need to transform the data. Descriptive statistics showed absolute errors were moderately positively skewed suggesting a square root or cube root transformation may reduce skewness and the potential for outliers. A cube root transformation satisfactorily reduced skewness and the presence of outliers so subsequent analysis was performed on the cube root of absolute forecast errors.

Profile analysis assumptions. Because profile analysis was the planned analytical procedure to answer the main research questions of this study, assumptions were evaluated through normal probability and residual plots. Under the cube root transformation, assumptions of profile analysis were adequately met.

Phase One Results

Although not a primary research focus of this study, it was decided to limit the possible parameter combinations for the exponential smoothing model to include only those that offered minimized mean absolute deviation (MAD) values based on a test data set. Future research should more rigorously test for differences in model parameters or researchers should consider an automatic procedure such as optimal ARIMA to determine exponential smoothing parameters.

Table 8 displays the best exponential smoothing parameter combinations within each data collection strategy and their relative improvements over next best (ImpvNB), over the worst (ImpvW), and over the naïve (ImpvNaive). These best model/parameter combinations were utilized in the holdout set of data to determine the best overall forecast model. The biggest change in optimal parameters was found under the advanced pickup (AP) strategy as $\alpha=.05$ offered improvements in MAD ranging from 15%-49%. Under the classical pickup (CP) strategy, little change was found between parameters as $\alpha=.05$ was the best but only by a range of 1-5%. Finally, $\alpha=.3$ was set as the optimal parameter under a non-pickup (NP) strategy with an improvement range of $<1\%$ from the next best to 13% improvement over the worst parameter. Exponential smoothing model parameters were fixed for primary data collection and analysis at $\alpha=.05$ for both the AP and CP data strategies and $\alpha=.3$ for the NP data strategy.

Phase 2 Results

A profile analysis was conducted to answer the main research questions of this 3x3x6x7 full factorial research design. The within-subjects IV treated multivariately was seven days out (time horizon) before from game day. Omnibus tests of all interactions and main effects were evaluated at α=.05. Results from the SPSS GLM procedure showed no significant 4-way or 3-way interactions between data strategy, model, days out, and sample size. None of the interactions involving samples size nor the main effect of sample size was found to be significant. Two, 2-way interactions (further discussed under appropriate research question headings) were found to be statistically reliable suggesting difference in profiles existed between data strategies and models.
Figure 18 displays all two-way interaction plots between data strategy, model, sample size, and days out to aid in interpretation of findings. Findings are organized in subsequent sections labeled by the main research questions of this study.

Table 8

Phase 1: Best Exponential Smoothing Parameter Combinations within Data Strategy

Model	Parameter	DataStrategy	MAPE	MAD	ImpvNB	ImpvW	ImpvNaive
ES	.05	AP	9.32	1530	15%*	49%*	68%*
ES	.05	CP	8.09	1312	1%	5%	72%*
ES	.30	NP	17	2942	0%	13%*	38%*

Note. ES=exponential smoothing; AP=advanced pickup; CP=classical pickup; NP=no pickup; MAPE=mean absolute percentage error; MAD=mean absolute deviation; ImpvNB=improvement over next best model parameter combination; InpvW=improvement over worst model parameter combo within data strategy; ImpvNaive=improvement over naïve forecast.
* Indicates a significant improvement where significant is defined as MAD improvement of 10% or more.

RQ1: To what extent do profiles of data strategy differ in forecast errors? As shown in Figure 18, differences in data strategy forecast errors varied by model, sample size, as well as days out. The differences in data strategy MAD values shown in the top row of Figure 18 are confirmed with a statistically reliable but weak DaysOut by DataStrategy interaction, multivariate $F(12,962)=4.018$, $p<.001$, partial $\eta^2=.048$. This departure in parallelism is further evaluated by an analysis of trends which showed a statistically reliable but weak linear trend for the interaction between DaysOut and DataStrategy, $F(2,486)=21.13$, $p<.001$, partial $\eta^2=.08$. The profile plot in the upper right corner of Figure 18 shows the MAD values produced under the CP data strategy decline rather rapidly from 20 to 10 days out as well as 10 to 5 days out (15% drop in MAD between each day out), followed by a leveling out in MAD improvement between 5 and 2 days out with another sharp decline from 2 and 1 day out (16% drop in MAD).

The significant linear trend interaction implies that the linear trend for CP is greater than for the other two data strategies. The CP data strategy exhibits the theoretically predicted higher to lower MAD values as game day nears. However, while the AP and NP data strategies generally decrease in MAD over the time frame, they both *increase* in MAD 5% and 6%, respectively, between 5 and 4 days out.

Data strategy by model. The first interaction plot in the upper left of Figure 18 shows that the classical pickup (CP) data strategy produced the lowest mean absolute deviation (MAD) values regardless of model while the non-pickup (NP) data strategy produced the highest MAD values. The significant interaction between data strategy and model is most obviously seen by the “V” shape in MAD by model within the advanced

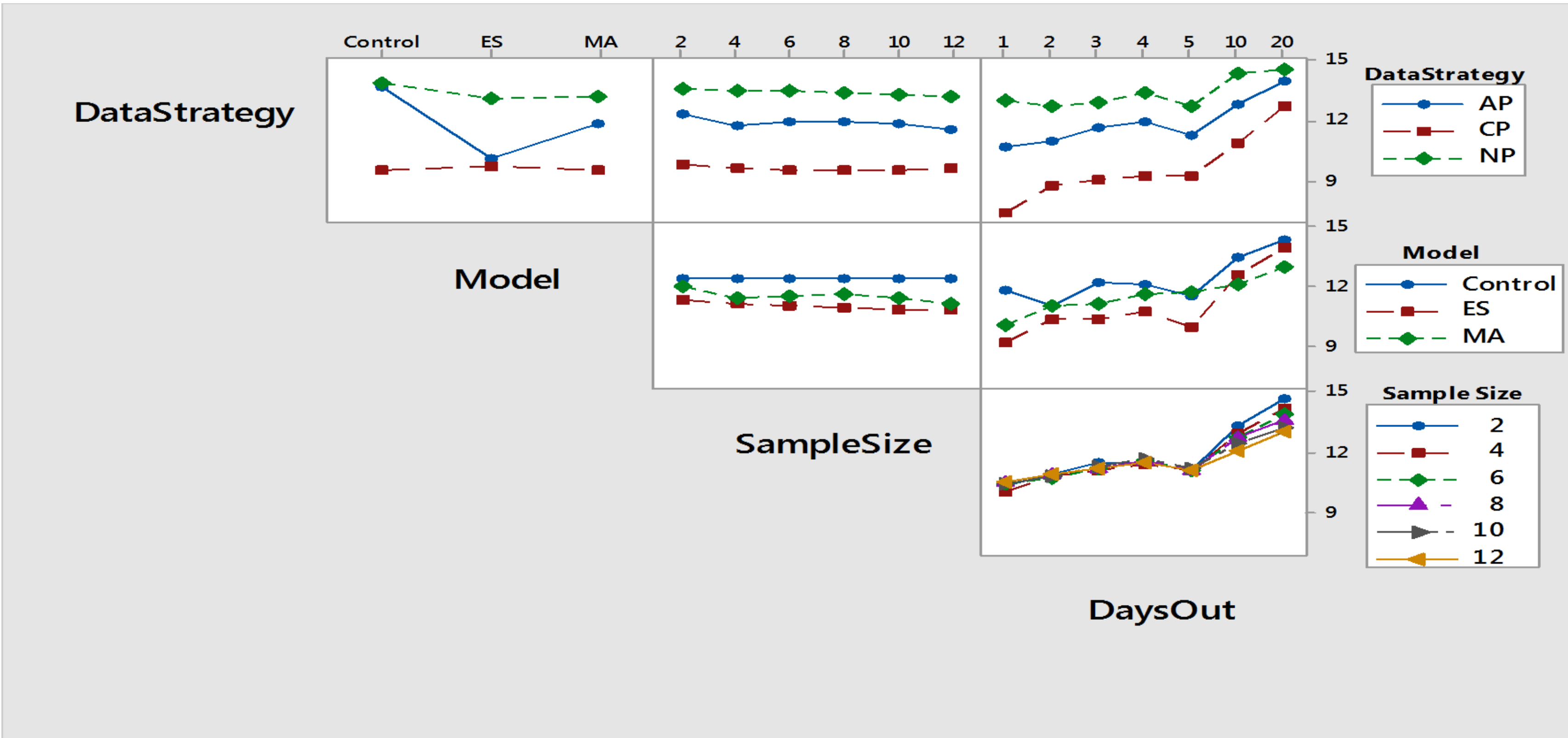

Figure 18: Plots of all 2-way interactions between data strategy, model, sample size, and days out. The three plots on the top row show the CP data strategy produced the lowest MAD values across all models, samples sizes, and days out. The middle row shows the ES model consistently outperformed the other models over all samples sizes but was worse than the MA model at 10 and 20 days out. The middle row of interactions also shows both forecasting models generally outperformed the naïve models across all combinations of sample size and days out with two trivial exceptions at 2 and 5 days out the MA was slightly worse than the naïve. The bottom right plot shows very little difference in the profiles of sample size for 1-5 days but differences between sample sizes in MAD appear to grow at 10 and 20 days out.

pickup (AP) data strategy where the exponential smoothing model produced much lower MAD than other two models.

To test the statistical reliability of differences in MAD evident in the profile plots a post-hoc confidence interval contrast procedure was conducted. Because there were 63 possible comparisons of means to compare (3 levels of data strategy, 3 levels of model, and 7 levels of days out) the decision was to make post-hoc comparisons using a confidence interval approach as outlined by Tabachnick and Fidell (2001a). This contrast procedure utilized a pooled confidence interval by days out to compare means at the various levels of data strategy and model. An adjusted error rate of .0008 was used to adjust for the 63 comparisons in the construction of 99.9% confidence intervals at each day out.

Data strategy by model means were then evaluated to see if they fell outside of the confidence interval at each day out. The calculated 99.9% confidence intervals for these tests are shown in Table 9. Any data strategy by model means falling outside of the days out intervals are considered reliably different.

Non-pickup data strategy. Under the NP data strategy, nearly all models produced MAD values falling higher than the upper limit of the 99.9% confidence intervals. The only exceptions to this result were the ES and MA models which each produced indifferent MAD values at 20 days out.

Advanced pickup data strategy. Under the AP data strategy, the control model produced MAD values that fell outside (all higher than the upper limit) the 99.9% confidence intervals for all days out. The exponential smoothing model produced significantly lower MAD values for days 1-5 and 10 while not falling outside the confidence interval at 20 days out. Finally, the moving average model produced significantly lower MAD values for 1, 2, and 20 days out; higher MAD at 3-5 days out; and insignificant difference in MAD at 10 days out.

Table 9

Summary Statistics by Days Out

					99.9% CI	
DaysOut	n	M	SD	SE	LL	UL
1	540	10.354	4.161	0.179	9.762	10.947
2	540	10.828	3.914	0.168	10.271	11.386
3	540	11.214	3.766	0.162	10.678	11.75
4	540	11.507	3.803	0.164	10.966	12.049
5	540	11.088	3.827	0.165	10.543	11.633
10	540	12.713	3.959	0.17	12.149	13.277
20	540	13.768	4.526	0.195	13.124	14.413

Note. 99.9% confidence interval calculated by pooling data at each day out and applying a Bonferroni adjustment to account for 63 comparisons of models by data strategy of means.

Classical pickup data strategy. Under a CP data strategy, the control and moving average models produced significantly lower MAD values across all days out. The exponential smoothing model produced significantly lower MAD values for days 1-5 and 10 and an indifferent MAD at 20 days out.

Summary of data strategy findings. The profile plots suggested and statistical tests, including a post-hoc confidence interval contrast procedure, provided reliable evidence to suggest that the classical pickup (CP) data strategy is superior to other data strategies analyzed in this study. The first row of the two-interaction plots of Figure 18 clearly showed the CP data strategy produced lower mean absolute deviation (MAD) values across models, sample sizes, and days out. A linear trend analysis showed the profiles of data strategies differed in slope but generally followed the theoretically predicted worse to best pattern of MAD as game day neared.

The significant interactions between data strategy and days out as well as data strategy and model were further analyzed by linear trend and confidence interval contrasts between days out. The CP data strategy exhibited the most consistent linear trend of MAD while the slopes of the other two strategies actually changed from negative to positive between 5 and 4 days out. Finally, a confidence interval contrast procedure was applied to each day out to examine which data strategy and model combinations produced statistically reliable MAD differences.

The results of the confidence interval contrast procedure gave statistically reliable support to the graphical analysis. With the exception of the exponential smoothing model producing an insignificant difference in MAD at 20 days out, all models under a CP data strategy produced reliably lower MAD values across all days out. The only other data strategy and model combination which produced consistently better MAD values across days out was the exponential smoothing model under the advanced pickup (AP) strategy.

While caution must be exercised when interpreting a main effect in the presence of significant interactions, a final interpretation of the differences in data strategy is provided by examination of percent differences between the cube root of forecast errors by data strategy. Table 10 shows a rank ordering of the mean absolute deviation (MAD) of cube root errors where it can be seen that the classical pickup data strategy produced overall MAD values 19% lower than the next best data strategy of advanced pickup (AP).

The advanced pickup strategy produced MAD values which were 11% better than the worst data strategy of non-pickup (NP).

Table 10

Data Strategy Comparisons.

DS	MAD	SD	ImNB
CP	9.61	3.99	19%*
AP	11.91	3.61	11%*
NP	13.40	3.93	

Note: DS=data strategy; CP=classical pickup; AP=advanced pickup; NP=non-pickup; MAD=mean absolute deviation in forecast errors; StDev=standard deviation of absolute forecast errors; ImNB=the percentage improvement of the next best data strategy.
1. Data represented is the cube root of absolute forecast errors.
*Indicates a significant improvement in MAD where significant is defined as 10% or better improvement.

RQ2: To what extent do forecast models differ from a naïve forecast? The next step in the analysis was to determine how formal forecasting models differed from the naïve forecast under an optimal data strategy. Because both graphical and statistical tests suggested the classical pickup data strategy produced consistently lower MAD values than the other two data strategies, this phase of the analysis focused on differences between forecast models within the classical pickup (CP) data strategy only. Figure 19 displays the profiles of the three models tested under a CP data strategy. Differences in slope and patterns of slope appear evident in the graph. Additionally, differences between models appear greater at days 5, 10, and 20 with smaller differences between models occurring as game day approached. In comparison to the naïve (control) model, the exponential smoothing model shows worse mean absolute deviation (MAD) values at 2, 4, 10 and 20 days while the moving average model shows worse MAD at 1,2, 4 and 5 days out. These graphical observations are explored more formally with trend analysis and a confidence interval contrast procedure.

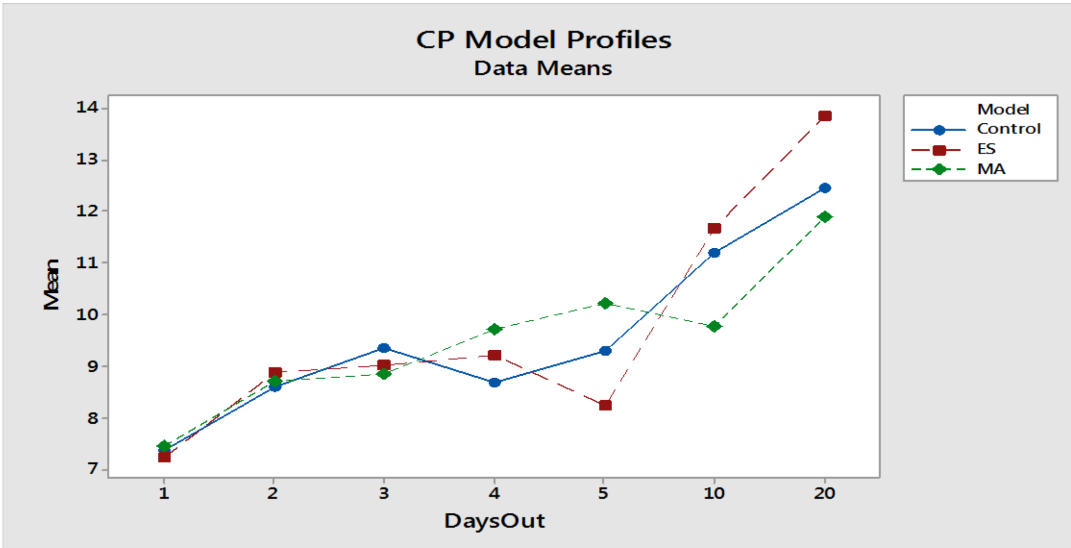

Figure 19. Model profiles under a CP data strategy. The y-axis represents mean absolute deviation (MAD) of the cube root of forecast errors. Differences in MAD between models appear greater at 5, 10 and 20 days out while very little difference in MAD appear to exist at 1-3 days out.

Model trend analysis. The differences in profiles of the model by days out MAD values shown in Figure 19 are supported with a statistically reliable but weak omnibus test of DaysOut by Model interaction, multivariate $F(12,314)=2.61$, $p=.002$, partial $\eta^2=.089$. However, a trend analysis using an adjusted error rate of .008 to account for the 6 test of trends did not show a significant model by days out interaction for linear ($F[2,162]=1.28$, $p=.282$, partial $\eta^2=.005$), quadratic ($F[2,162]=2.27$, $p=.17$, partial $\eta^2=.022$) or cubic ($F[2,162]=3.07$, $p=.049$, partial $\eta^2=.036$) trends. Observed power for these insignificant tests was low with .098, .154, and .319 for linear, quadratic, and cubic trends, respectively, which likely explains the insignificant trends even though the graphical analysis shows apparent differences in slope and changes in slope between models.

To further analyze the apparent differences in MAD at various days out, a confidence interval approach to compare the means at each day out is used to assess statistically reliable differences at each day out. Because 14 comparisons were made (2 models by 7 days out), 99.6% confidence intervals were constructed. Table 11 shows the results which indicated the only significantly different MAD between models and the naïve forecasts was produced by the moving average model at 10 days out ($\bar{x}_{MA} = 9.78$, 13% improvement in MAD). The observed power for tests conducted at each day out were all low with power ranging from .07 to .18.

Exponential smoothing versus classical pickup naïve. Although no statistically reliable differences were detected by the confidence interval contrast procedure between the exponential smoothing and naïve MADs, examining percent differences in mean absolute deviation shows the exponential smoothing model performed 11% better than the naïve model at 5 days out which would be considered a practically significant finding. However, the exponential smoothing model produced a practically significant *worse* (by 11%) forecast than the naïve model at 20 days out.

Moving average versus classical pickup naïve. The moving average model produced the only statistically reliably different mean (13% improvement) over the naïve model at 10 days out. However, although not statistically reliable based on the confidence interval contrast procedure, the moving average model produced practically significant worse mean absolute deviation values at 5 days (10% worse) and 4 days (12% worse).

Table 11

Model Comparisons to Naïve Forecasts

	Naive Summary							
			99.6% CI		Model Means			
DaysOut	M	SD	LL	UL	ES	MA	ESDiff	MADiff
1	7.38	3.98	5.84	8.92	7.24	7.46	-2%	1%
2	8.61	3.00	7.45	9.77	8.90	8.72	3%	1%
3	9.37	3.61	7.97	10.77	9.02	8.85	-4%	-5%
4	8.70	3.63	7.30	10.11	9.22	9.71	6%	12%[p]
5	9.32	3.08	8.13	10.51	8.25	10.23	-11%[p]	10%[p]
10	11.20	2.81	10.11	12.29	11.68	9.78*	4%	-13%[p]
20	12.47	4.46	10.75	14.20	13.86	11.91	11%[p]	-4%

Note. 99.6% confidence intervals constructed by pooling the forecast errors for the control group over at each day out. Because of the 14 comparisons, a Bonferroni adjustment was applied to achieve family error rate of 5%.
ES=exponential smoothing with smoothing parameter α=.05; MA=moving average;
*Indicates statistically different at α=.004
[p] Indicates a practically significant differences in MAD of 10% or more.

Summary of models versus naïve. Under the classical pickup (CP) data strategy, differences in mean absolute deviation (MAD) between forecast models and days out depend on the day out as indicated by the statistically reliable but weak multivariate interaction. Only the moving average model at 10 days out produced a significantly better forecast than the naïve model. Practical significance was evaluated by a 10% difference in MAD from which the exponential smoothing model produced better forecasts than the naïve model at 5 days out. However, reliable evidence did not exist to show forecasting models consistently outperform the CP naïve model across all days out. In fact, at 20 days out the exponential smoothing model was 11% worse than the naïve model. Furthermore, the moving average model was 10% and 12% worse than the naïve model at 5 and 4 days respectively. Finally, little difference exists between the forecast models and the CP naïve model from 3, 2, and 1 days out.

RQ3: To what extent do forecast errors vary by sample size? Profile plots in Figure 18 suggested little differences exist in mean absolute deviation (MAD) between samples sizes tested. Profiles of sample size MADs are all relatively flat and parallel suggesting little differences between samples sizes and no interaction between data strategies or models. More formally, the test of days out by sample size was insignificant, multivariate $F(30,1926)=.415$, $p=.998$, partial $\eta^2=.005$. The observed power for this test was .122 suggesting little chance of detecting a significant difference.

Table 12 displays the mean absolute deviation values for each forecasting model under the CP data strategy. Small improvements in MAD occurred as sample size increased under the exponential smoothing model. However, the improvement from 2 to 12 games was only 7%. The moving average model did not exhibit the expected improvement in MAD as sample size increased. Rather, the lowest MAD was found when T=6 but this offered a trivial 4.8% improvement over T=2.

Table 12

CP MAD by Sample Size

n	ES	MA
2	10.20	9.70
4	9.88	9.43
6	9.71	9.23
8	9.66	9.46
10	9.50	9.60
12	9.47	9.71
MaxDiff	-7%	-5%

Note. ES=exponential smoothing with smoothing parameter α=.05; MA=moving average; Sample size refers to the value of K games used to start the exponential process and the value of T games used in the moving average process. MaxDiff=the percent difference between the lowest MAD value and the highest.

RQ4: To what extent do forecast errors vary by days out? Figure 20 displays a fitted line plot for mean absolute deviation values produced under the classical pickup (CP) data strategy. In this final phase of the study, results are pooled over all models for the CP data strategy to assess how forecast accuracy varies with days out. The model utilizing linear, quadratic, and cubic trend components to fit the model shows the theoretically predicted best to worst values of MAD as days out increases. It is clear from the graph that forecasts are worst 10 and 20 days out. Additionally, forecasts appear to dramatically improve from 2 to 1 day out as shown by the steeper slope of the curve between these two days. Finally, it appears from Figure 20 that the MAD values from 5 to 3 days out do not deviate significantly.

To formally test for differences in MAD values between days out an ANOVA was performed on the cube root of error with seven levels of days out. The Tukey method was used to group statistically indifferent days out means with an adjusted α=.002 to achieve a family error rate of .05. The results of the Tukey grouping method displayed in Table 13 show the obvious differences between 20, 10, and 5 days out as well as the significantly better forecasts at 1 day out compared to the rest of the days. However, forecasts at days 5 through 2 do not reliably differ.

Results Summary

The multi-phase analysis to find the best forecasting data strategy and models began by identifying the model parameters which minimized mean absolute deviation (MAD) when applied to a test set of ticket inventory data. As summarized in Table 8, optimal parameters varied depending on what data strategy was used. For the study to move forward, the parameters which minimized MAD in this first phase remained fixed for the remainder of the study. Then, the models were applied to a holdout set to produce forecasts and subsequent errors in a simulated forecasting environment utilizing three different data strategies: non-pickup (NP), classical pickup (CP), advanced pickup (AP).

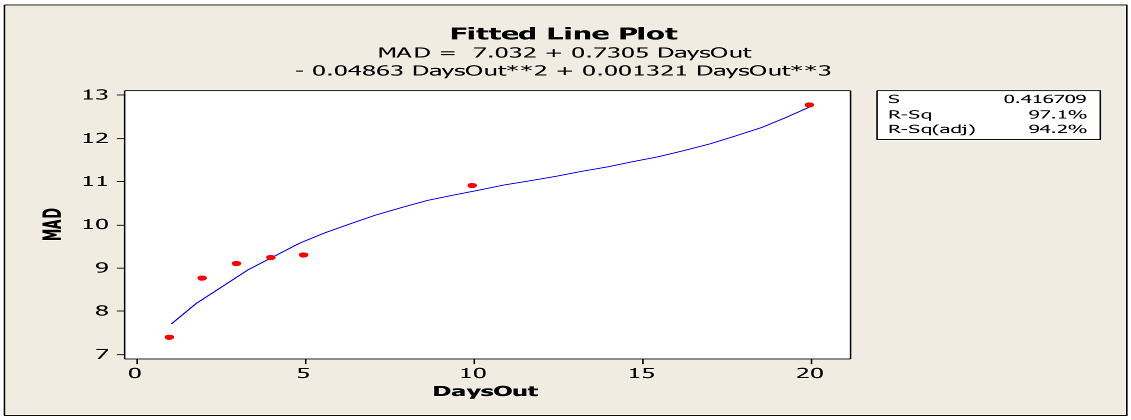

Figure 20: Model describing the relationship of MAD and days out for the CP data strategy. The significant linear, quadratic, and cubic trends show the theoretically predicted best to worst pattern in MAD as days out increases.

Table 13

Tukey Grouping of MAD by Days Out

DaysOut	M	Grouping			
20	12.747	A			
10	10.885		B		
5	9.265			C	
4	9.211			C	
3	9.081			C	
2	8.742			C	
1	7.359				D

Note. Tukey comparisons are shown with an adjusted error rate of α =.002 to achieve a family error rate of .05. Means which do not share a letter are significantly different. Grouping information shows the obvious graphical differences are statically reliable with 20 days out producing significantly worse forecasts than 10 days out which in turn was significantly worse than 5 days out. However, no reliable differences were detected from 5 and 2 days out. Finally, 1 day out provided the expected lowest MAD**.**

The CP data strategy was found to produce reliably better forecasts of final game day inventory. Profile plots showed obvious differences in data strategies existed while trend analysis and confidence interval contrasts provided statistically reliable evidence to support the graphical displays. While significant interactions confound the interpretation of the main effect of data strategy, the CP data strategy produced a 19% improvement over the next best data strategy.

Under the CP data strategy, models did not provide consistently better forecasts than the CP naïve forecast generated using a moving average of order 1 approach. In fact, on some days out the formal forecasting models produced *worse* forecasts than the CP naïve model. Sample size used in the forecasting models did show reliable differences across all days out. This observation coincides with models not performing reliably different than the naive model which uses only the last complete game (n=1) to generate the pickup line used to make forecasts.

Finally, differences in MAD by days out follows the theoretically expected best to worst pattern as days out increases with the worst forecasts occurring 20 days out. However, no reliable MAD differences were found between 2 and 5 days out suggesting forecasts at 5 days out are statistically just as good as 2 days out. The implications of this finding and others are discussed in the following section.

Discussion

Consistent with forecasting literature, this study utilized a multiphase, sequential approach in the search for the best model parameter combination between two common short term forecasting models: exponential smoothing and moving average. This study only begins to scratch the surface of potential forecasting models and procedures that sport organizations could utilize in a revenue management (RM) strategic plan. As mentioned in the literature review, finding optimal forecasting models, parameters, and data strategies is an iterative process.

This study first identified the optimal model parameters based on a sample test dataset, followed by a second phase to identify the data strategy that produced the lowest mean absolute deviation (MAD) values, then a third phase to examine potential differences between models and samples size within the best data strategy. Consistent with prior RM forecasting literature (e.g., Sun et al., 2011; Weatherford & Kimes, 2003, etc), models applied in either of the pickup strategies performed better than models applied in a non-pickup (NP) strategy.

The results indicated the classical pickup (CP) data strategy offered reliably better forecasts than the other two data strategies. However, models within this strategy did not offer reliably better forecasts than using the CP naïve model. Of course, models could have been compared to the traditional naïve forecasts which are only applied under a non-pickup (NP) data strategy. If the naïve NP model was used as the comparison (a common approach taken in forecasting literature), all models under the CP would be superior as it was shown the models under the classical pickup strategy provided reliably better forecasts than either of the other two data strategies. However, as a practitioner wishing to use the results of this study to guide decisions regarding forecasting models, I wanted to develop naïve forecasting models under *each* data strategy to better understand what models could be applied if a clearly superior data strategy was identified.

Based on the results presented, a practitioner could expect to get as good as (or nearly as good as) forecasts of final game day inventory by simply creating pickup estimates from the last known completed game. The distinction that must be clear is that this result only holds if the practitioner is utilizing the CP data strategy. The traditionally used naïve forecast under the NP strategy is clearly an inferior forecast model to those under a CP strategy.

Directions for Future Research

The results of this study are limited to the type of games that fit the profile examined (weekday night games against a non-marketable opponent). Although these types of games represent over a third of the total games in a season, more research is needed to generalize to an entire MLB season. Despite this limitation, this study offered a first attempt to find the best forecasting model to apply in a sport revenue management context. Much more research is needed to find forecasting models that consistently produce accurate forecasts of ticket inventory, pricing, and demand. Future research should examine forecasting models with different teams, sports, and at different levels of data aggregation (e.g., total game inventory versus seat section inventory).

Levels of aggregation. After deciding on the type of estimation approach, another critical decision is how to aggregate data and subsequently make forecasts. In this study, ticket inventory was aggregated to the game level. It is likely forecasts could be improved by aggregating at the seat section level for each game. The choice of level of aggregation largely depends on data availability and purpose of forecast. Research has shown that disaggregated forecasts outperform aggregated forecasts in hotel forecasting

(Weatherford, Kimes, & Scott, 2001) but errors have been high for disaggregated forecasts in airlines application (Weathford & Kimes, 2003). More research is needed to understand what level of data produces the best forecasts in a sport setting. However, in order to test forecasting models at various levels of data aggregation, better access to data is needed.

Partnerships with sport organizations. For research in sport revenue management to progress, it is essential that researchers and practitioners find ways to form mutually beneficial partnerships. One form of revenue management, dynamic ticket pricing (DTP), is clearly a hot topic in the world of sport with more teams implementing the strategy every season. Are practitioners effectively applying DTP to maximize revenue? How can rigorous academic research exploring optimal forecasting models of demand help maximize the use of DTP? The answer to the first question requires an analysis of detailed sales and inventory data provided from sport organizations. The answer to the second can help academics justify access to the detailed sales data.

This study is believed to help with the second question. The search for an optimal forecast strategy led to the conclusion that the classical pickup data strategy could offer a superior strategy to advanced pickup and non-pickup. By being able to more accurately predict inventory levels at various days out, organizations can not only plan pricing strategies but can also plan other marketing activities in efforts to influence demand for an event. For example, if it is predicted that available ticket inventories will be too high (i.e., demand is too low) for a particular game to generate the desired ticket revenue for that game, pricing can be adjusted up or down and/or additional promotional activities can be included in an attempt to sell more tickets and meet the budgeted revenue. Forecasts generated along the selling period can offer signals to marketing and promotion teams to ramp up marking activities. If researchers can find ways to show practitioners the value their research can have on an organization's bottom line, then perhaps more academic-practitioner relationships can be formed.

Without this relationship, researchers must resort to manual data collection of ticket inventory and pricing from team websites which can make achieving minimum sample size to achieve desired power an arduous endeavor. While forecasting inventory and pricing is an important aspect to an effective revenue management system, having detailed sales data will add a level of analysis which has largely eluded sport management researchers. An analysis of actual sales data by seat section could provide valuable insight to both practitioners as well as researchers.

There are many possibilities for future research to advance the understanding of forecasting within a sport revenue management context. This study utilized a multi-phase approach to begin this understanding but much more work needs to be done to provide validity and generalizability to the results found. In addition to the obvious need to test forecast models for different teams and sports, different types of games need to be explored. This study focused on weekday night games in order to minimize the possibility of forecast outliers but more rigorous work needs to be done to 1) verify the need to classify games, and 2) determine if various classification of games have reliably different demand/inventory profiles which would justify the need for calibrating forecast models to each type of game. Then, more work would need to be done on how best to calibrate forecast models.

Identifying optimal model parameters. This study was also limited by the formal testing of parameters for the exponential smoothing model. A simple approach to identifying the optimal parameter was taken in order to minimize the possible factors explored in subsequent phases. While this approach was consistent with prior RM forecasting literature, more rigorous testing of optimal parameters is needed. Future research could more rigorously test for optimal parameter estimates and/or test whether this step is even necessary considering statistical software packages such as Minitab, SAS, and SPSS offer automatic calibration of optimal parameters using an ARIMA optimization process. Thus, it may not be worth the extra effort to formally experiment with testing of parameters especially since optimal parameters are likely to change as the forecast environment changes.

More statistically sophisticated models. While forecasting literature has suggested the best models in a short term forecasting environment are simple smoothing models such as moving average and exponential smoothing, future research should explore whether more statistically sophisticated models such as the auto regression integrated moving average (ARIMA) or regression could provide significantly better forecasts. The classical pickup forecasting data strategy seems to lend itself particularly well to testing regression models. In fact, the pickup strategy resembles the workings of a regression approach because the pickup strategy utilizes information from past values to create the pickup line. The pickup line then provides estimates of inventory to be picked up based on various days out. Depending on what day out from game day a forecaster wishes to forecast, the appropriate estimate of pickup from the pickup line is subtracted from current inventory to generate the forecast of game day inventory. This is similar to a regression approach without the statistical calculations to estimate the parameters of a regression model. Therefore, it seems natural to test whether regression models can provide reliably better forecasts then traditional pickup models.

CHAPTER V

AN EXAMINATION OF SEAT SECTION INVENTORY PROFILES

The recent surge in the practice and research of revenue management (RM) can largely be attributable to advances in technology allowing for improved data collection and storage capabilities. Improvements to computing power and data storage have made the once daunting and expensive task of data collection and analysis practical for many firms. Without these improvements and subsequent reductions in the costs of data collection and storage, forecasting and other forms of analysis were simply not an option for all but the largest firms (Kimes, 2010; Ng, 2008).

Sport demand studies to date have only been able to estimate demand based on aggregate game attendance data (Borland & MacDonald, 2003; Rascher et. al, 2007; Soebbing & Watanabe, 2014). This is attributed to the difficulty (if not impossibility) of obtaining section level data directly from sport franchises (Soebbing & Watanabe, 2014). This limitation in data collection makes forecasting ticket inventory and/or demand difficult. Estimates of elasticity of demand in sport have been forced to use aggregate demand and revenue to calculate average ticket price. This poses problems in the calculation of elasticity of demand because most of the average price data do not weight based on the number of seats sold in particular sections (Noll, 1974; Rascher et al., 2007;

Salant, 1991). To further the understanding of demand and pricing in sport, disaggregated section level data is needed.

Service industries such as the airline and hotel industries were at the forefront of developing RM and the more specific form of RM known as dynamic pricing. The literature on these and other service industries has provided an early theoretical base for this emerging sport management literature topic. However, RM researchers have called for a more complete theoretical framework than those currently utilized by sport RM literature (Ng, 2007; Talluri & van Ryzin, 2004). An understanding of consumer behavior, economics, and operations research is needed to have a thorough understanding of the potential applicability and effectiveness of a RM strategy in a sport context. More sport specific RM research is needed to understand the applicability and sustainability of a RM strategy in sport.

This study built on and contributed to sport revenue managment literature. Specifically, the study was guided by the theoretical framework provided by Ng (2007) which melds the three major disciplines subsumed within RM (consumer behavior, economics, and operations) into a comprehensive theory of advance demand. At least two different frameworks borrowed from the service industry have already been utilized in the limited sport RM research. Yet, neither framework fully integrated the three major RM disciplines nor adds the additional complexities inherent in the sport product. Thus, another contribution of this study was to examine what is believed to be a more complete RM theoretical framework.

By examining seat section inventory curves over time, this study added an initial sport contextual empirical investigation of the theory of advanced demand. Guided by Ng's (2007) theoretical framework of advanced selling and demand, the study examined forecasting abilities over an advanced selling period of a mid-attendance Major League Baseball (MLB) team. Ng's theory suggested two main types of consumers that are inclined to purchase at different times in the advance selling period.

The results provided an empirical examination of the possibility of the two types of consumers suggested by Ng's theory of advanced demand. As inventory sharply declined at 20 and 10 days out, followed by a leveling from 5 to 2 days out, finally followed by a steeper decline from 2 to 0 days out provided empirical evidence that there could exist a segment of consumers buying further in the selling period (with higher acquisition risks) and consumers buying closer to game day (with higher valuation risks). Furthermore, the results support a theory that consumers are further segmented by seat sections suggesting demand and pricing models be constructed at the seat section level.

As some sections exhibited steeper slops than others, it is important to base pricing and inventory decisions at the seat section level as opposed to applying global price changes (e.g., 20% increase in price across all seat sections). Furthermore, some sections exhibited positive inventory slopes suggesting too much inventory was being held early in the selling period. Improvement in quantity based (i.e. ticket inventory) RM is needed in conjunction with pricing strategies to offer a comprehensive and effective RM strategy.

Review of Literature

Revenue management (RM) has now been in practice by the airlines for about 36 years. While some academic research can be found dating back earlier (e.g., Rothstein, 1971, 1974; Littlewood, 1972/2005), RM research is believed to have been fueled by the work of Peter Belobaba in 1987 and 1989 and Sheryl Kimes in 1989. Kimes' seminal piece *Yield Management: A Tool for Capacity-Constrained Service Firms* has been cited in over 400 articles and is believed to have broadened the scope and applicability of RM to virtually any service industry meeting certain criteria. Talluri and van Ryzin's (2004) comprehensive text provided a comprehensive resource for both practical and theoretical RM considerations.

Before Kimes' (1989a, 1989b) works, RM research focused almost entirely on airlines and was dominated by operations research which was heavily mathematical and related to forecasting demand (Ng, 2007). This makes sense considering the airline industry was most widely using the practice. Much of Kimes' work has been developed around the application of RM to the hotel industry but her 1989a, 2003, and 2010 pieces provided a framework to apply RM to other industries.

Kimes (1989b) credits Belobaba (1987a, 1987b, & 1989) for providing a framework for application of RM. Belobaba's (1989) seminal work has been cited by over 500 articles and propelled RM research in operations research (Ng, 2007). Belobaba's expected marginal seat revenue model got the attention of researchers and practitioners by helping Western airlines increase revenue by 6.2 percent (Kimes, 1989b).

The early research on RM provided by Belobaba and Kimes helped form a foundation and propel future research and practice of RM. Kimes (2003) classified the research on revenue management into three broad categories: descriptive (application of RM); pricing control (development and improvement); and inventory control (management of demand patterns). Following the seminal works of Belobaba and Kimes, RM practice and research began to surface in the restaurant (Kelly, Kiefer, & Burdett, 1994), rental car (Carol & Grimes, 1995; Geraghty & Johnson, 1997), cruise lines (e.g., Maddah, Moussawi-Haidar, El-Taha, & Rida, 2010; Sun et al., 2011) and other service industries. Recently, sport management research applying the principles of RM has begun to surface (e.g., Drayer, Shapiro, & Lee, 2012; Shapiro & Drayer, 2012).

While RM research in sport management is limited, recent work applied Kimes' (1989b) RM framework to help explain sport pricing. Sport management RM literature has begun to take shape with the work of Drayer et al. (2012) and Shapiro and Drayer (2012). While there is an abundance of sport demand studies in the sport economics literature, Shapiro and Drayer's (2012) study is believed to be the first work in the sport management literature that specifically applies Kimes' (1989b) and Kimes et al.'s (1998) RM framework in a sport ticket price setting.

Early sport management RM authors provided a critical examination of the applicability to sport for each of the seven major criteria for RM: segmentable markets, perishable inventory, advance sales, low marginal costs, high marginal production costs, fluctuating demand, and predictable demand. Drayer et al. (2012) concluded that RM is a good fit for sport ticket pricing based on Kimes' criteria and added that the existence of a vibrant secondary marketplace helps confirm the need for sport organizations to develop a more efficient pricing strategy.

However, a thorough understanding of revenue management requires more than applying a set of criteria to a particular context. While Kimes' (1989a;1989b) works provided a framework in which RM could be applied to many service industries, much of the research on revenue management has been single discipline focused (Ng, 2007). Ng (2007) provided a critical analysis of RM research and provided a theoretical framework to help understand why revenue management practices work. To do this, Ng provided an analysis that required an in-depth understanding of three major disciplines subsumed in effective RM: consumer behavior, economics, and operations research in service firms.

An examination of the theoretical foundations of each of these three major disciplines and how each ties into effective RM is essential to advancing this topic in the sport literature (Ng, 2007; Talluri & van Ryzin, 2004). Revenue management has been mentioned as a driving force integrating pricing and operations and it is imperative that one wishing to fully understand RM has an understanding of these three major disciplines (Fleischmann, Hall, & Pyke, 2004; Ng, 2007; Talluri & van Ryzin, 2004). While overlap of the disciplines is certain to occur within revenue management articles, the following provides an overview of literature with an emphasis in one or the other.

Revenue Management

Despite its recent research interest, dynamic pricing is not a new idea. Varying prices to manage inventory and demand can be traced back to the beginnings of commerce (Talluri & van Ryzin, 2004). Businesses and individuals have generally always wanted to get the best price for selling their product and have had to make price adjustments based on consumer demand. What has changed in recent times is that technological advances have allowed for more sophisticated scientific methods for optimally applying a dynamic pricing strategy. Online retailers, such as Amazon.com, have emerged as prominent examples of dynamic pricing in practice.

Examining dynamic ticket pricing in a sport setting is believed to require an understanding of revenue management (RM) and the theory of advance demand (Drayer et al., 2012; Ng, 2007). Sport studies examining RM or advance inventory and demand are limited but the topics have recently gained attention from researchers (e.g., Dwyer et al., 2013; Shapiro & Drayer, 2014; Shapiro & Drayer, 2012). Early sport management researchers have followed the conceptual frameworks of revenue management provided by Kimes (1989a, 1989b) and justified the applicability of revenue management to sport (Drayer et al., 2012). Ng's (2007) theory of advance demand deserves consideration when attempting to understand demand-based pricing strategies.

Talluri and van Ryzin (2004) discussed common elements of any RM system and Ng (2007) provided a conceptual framework that attempted to combine the three major disciplines RM subsumes: consumer behavior, economics, and operations (largely focusing on forecasting and estimation). The following sections offer an introduction to the literature on revenue management followed by a review of RM literature which focuses on each of the three major disciplines of revenue management.

Virtually any revenue seeking industry would like to find ways in which to maximize revenue. What one may naturally like to do is charge the highest price possible for all the units available for sale. However, any experience in a sales environment would quickly lead to the realization that not all customers are willing to pay the highest price possible and inventory subsequently goes unsold. Therefore, a strategy should be developed in order to sell the right number of units to the right customers at the right prices. The need to do this efficiently led to the development of yield (now commonly known as revenue) management.

The airline industry is credited for the advent of this revenue strategy (Belobaba, 1987a; Kimes, 1989a). Increased competition following deregulation in the 1970s forced airlines to find ways to gain a competitive advantage. Before deregulation, airlines would charge only one price for a ticket between cities. After deregulation in 1978, many startup airlines emerged that began selling discounted seats between cities. This ended up forcing the large airlines such as United, Delta, and American to respond with advance computerized systems that allowed for variable pricing to undercut the discount airlines. Eventually, start-up discount airlines such as People's Express went out of business largely because they did not have the capability to implement a RM strategy (Belobaba, 1987a; Kimes & Chase, 1998). This need for more efficient operation and increased revenues led to the innovative strategy of yield management which is now commonly known as revenue management (Kimes, 1989a).

Definition of revenue management. What is revenue management (RM)? Revenue management has been defined as "the process of allocating the right type of capacity to the right kind of customer at the right price so as to maximize revenue or yield" (Kimes, 1989a, p. 15). Basically, RM requires effective pricing and inventory control (Belobaba, 1987a). Revenue management addresses three basic categories of demand-management decisions: structural decisions, pricing decisions, and quantity decisions (Talluri & van Ryzin, 2004). Structural decisions include which selling format to use (e.g., posted prices or auction prices), which segmentation and differentiation mechanisms, and bundling decisions. Price decisions include setting posted prices, pricing over time, and how to price different product categories. Quantity decisions include how much inventory to release or holdback for sale, how to allocate inventory to different market segments, and whether to accept or reject a purchase offer.

In the case of airlines, RM helps allocate a fixed inventory of seats at various prices, at different times, to various customers (e.g., frequent business traveler versus casual traveler). One might expect an airline sales manager would prefer to sell all seats at the highest price possible. However, a tradeoff obviously exists between high prices and the risk of not selling out all the seats on the airline. RM seeks to help balance the tradeoff between high prices and high sell out percentages to increase overall revenue (Kimes, 1989b).

Kimes, Chase, Choi, Lee, and Ngonzi (1998) built upon Kimes' (1989a) definition by defining RM as managing what they called the four Cs in order to manage a fifth C, customer demand. The four Cs offered by Kimes et al. (1998) are:

- Calendar (how far in advance the reservations are made)
- Clock (the time of day service is offered)
- Capacity (the inventory of service resources)
- Cost (the price of the service)

While various researchers have attempted to define RM, others have contended there is not a satisfactory definition of RM (e.g., Jones, 1999; Weatherford & Bodily, 1992). The lack of a universally accepted definition of RM is likely because RM has evolved over its 37 year history and has been applied to an increasing body of industries which modify various aspects of previous definitions of RM to fit a particular industry mold (Ng, 2008).What is implicit in all definitions of RM is the time-perishable nature under which many service industries operate and the necessity to understand advance demand and pricing. As Ng (2007) noted "perishability and inseparability of services results in the advance pricing of services, i.e., revenue management is the management of advance revenues" (p. 533).

Contrary to a typical retail business selling tangible goods, service industries are challenged by the fact that once the service event (e.g., flight, hotel stay, ball game) takes place there is no recouping or storage of lost inventory to be sold at a later date. Therefore, advance sales strategies must be put into place in order to sell as much inventory as possible at the right prices to maximize revenue. Talluri and van Ryzin (2004) refined the definition and knowledge base of revenue management by classifying RM as either "Quantity-based RM" or "Price-based RM."

Quantity-based revenue management. Quantity-based RM refers to the demand-management practices of product rationing and availability control (Talluri & van Ryzin, 2004). While pricing decisions also play a role in quantity-based RM, the primary focus of a quantity-based RM system is how much inventory to sell to which customers and when to accept or reject requests for product. Common examples of quantity-based RM can be found within the airline, hotel, and rental car industries. While inventory rationing decisions are of primary concern in a quantity-based RM system, price-based RM utilizes price as the primary factor in demand decisions.

Belobaba (1989) provided a seminal piece in the quantity-based RM literature. In his operations-focused work, Belobaba introduced the Expected Marginal Seat Revenue (EMSR) model which would serve as a foundation for quantity-based RM research. The EMSR analysis was designed to help solve inventory allocation problems in the airline industry but it has also been applied to other service industries such as hotels and car rentals (Netessine & Shumsky, 2002). The EMSR model was designed to help decision makers determine the number of seats to allocate to different fare classes.

Major components of a quantity-based RM strategy include setting booking and protection levels. Booking limits refer to controls that limit the number of units that can be sold to a particular segment (class) at a particular time. Protection levels refer to the number of units to reserve or protect for a particular class (Talluri & van Ryzin, 2004). In a sport context, booking limits can be found in the number of tickets that are sold for each section while protection levels occur when organizations hold tickets for various groups (e.g., season ticket holders, groups, VIPs).

Booking limits can be expressed as a function of protection levels. That is, the booking limit, b_j for a particular class, j, can be expressed as total capacity, C, minus the j-1 protection level, y_{j-1}:

$$b_j = C - y_{j-1,}\ j = 2,3, \dots, n$$

Where n is the number of classes.

Booking limits can either be partitioned or nested. In a partitioned system, booking limits divide the available units into blocks for each class of consumer. For example, if capacity is 30 units, a partition booking limit could set booking limits for three different classes at 12, 10, and 8 for classes 1, 2, 3, respectively. Each class is essentially a segment of the population willing to pay a certain price for the product (e.g., $100, $75, or $50). The initial units allocated (i.e., the partitioned booking limits) for each class could be the result of forecasted demand based on historical data or some other form of estimation. In a sport context, booking limits have been constructed largely based on the seat sections' proximity to the field and optimal viewing conditions.

With partitioned booking limits, once the booking limit for a particular class has been met, that class would be closed regardless of how much inventory remained in the other classes. This is in contrast to a nested booking limit in which the higher-ranked (i.e., higher paying) classes would have access to all the lower class allocations. Using the same example as above, the nested booking limit for class 1 would be the entire capacity of 30 units. Nested booking limits are optimal when demand is uncertain which is often the case for many firms. Sport franchises have historically applied a partitioned booking limit scheme as seat sections have clearly designated lines. If sport franchises were to apply a nested booking scheme, this would mean the seat section lines would not be fixed based on location but would rather be allowed to fluctuate based on the demand for tickets at particular prices.

Figure 21 gives a visualization of nested booking limits and protection levels adopted from Talluri and van Ryzin, 2004, p. 29:

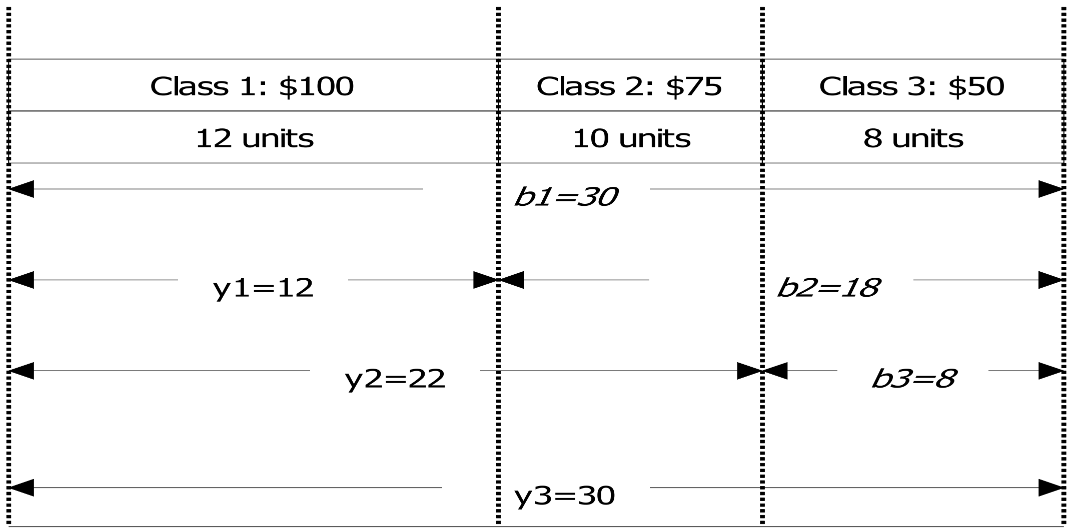

Figure 21: Example of nested booking limits and protection levels. The b_i's represent booking limits while the y_i's represent protection levels.

In Figure 21, b_1, b_2, and b_3 represent the nested booking limits for the three classes and y_1, y_2, and y_3 the protection levels. In the figure it can be seen that the nested booking limits are 30, 18, and 8 for classes 1, 2, and 3, respectively. The major benefit of nested booking limits is that they allow the firm to continue to sell higher level classes until capacity is met. Contrast this with a partitioned structure where the firm would only sell at most 12 units to class 1 even if demand were higher. Furthermore, in the nested design the firm would sell at most 18 units to classes 2 and 3 combined, and at most 8 units to class 3 alone. The model can be expanded to more classes in which the notation b_j and p_j represent the booking and protection levels for the j^{th} class.

While booking limits indicate the amount a firm is willing to sell to a particular class, protection levels indicate the quantity the firm wishes to reserve or protect for a particular class j and all other higher ranking classes. Referring again to the example in

Figure 21, the protection level for class 1, y_1, is 12 units. Of course, in a nested structure, if demand from class 1 exceeded its protection level the firm would continue to sell to class 1. The protection level simply keeps lower ranking classes from consuming certain portions of capacity from higher ranking classes. In general, given a firm has a *C* units of capacity available for sale, the firm accepts offers for booking as long as (1) there is capacity remaining and (2) the requested amount of capacity for a class *j* is below the booking limit for that class, b_j .

Price-based revenue management overview. A price-based revenue management (RM) system attempts to optimize how to price to various consumers and how to optimally change pricing over time. Dynamic pricing and auctions are the most commonly utilized mechanisms in price based RM (Talluri & van Ryzin, 2004). Industries providing common examples of price-based RM include manufacturing and retail. Recently, the sport industry has also appeared to have adopted a price-based RM system as teams have begun to implement dynamic ticket pricing strategies (Drayer & Shapiro, 2012; Rische, 2012).

Dynamic pricing. Common examples of dynamic pricing include retail markdown pricing and discount airline pricing. Each of these types of dynamic pricing could be useful in a sport setting. These pricing strategies are briefly described in the following sub-sections.

Retail markdown pricing. Many consumers know about or have experienced some form of retail markdown pricing. The most common retailing examples of this price-based RM strategy can be found in sporting goods, apparel, and perishable-foods (Talluri

& van Ryzin, 2004). Retailers typically utilize markdown pricing to clear seasonal inventory because the inventory is either perishable or has little salvage value. Therefore, it is usually in a retailer's best interest to clear inventory at lower prices rather than try to collect negligible salvage value. Important demand information can be learned from markdown pricing.

By utilizing markdown pricing retailers can learn which products are popular with customers. It is difficult for a retailer to know which, out of hundreds if not thousands of, products will be popular with customers. Therefore, as Lazear (1986) proposed, markdown pricing can serve as a demand learning mechanism by starting prices high and marking down over time. According to Lazear, the rate at which prices fall will be a function of the number of customers, the proportion of customers who are actually buyers (as opposed to those simply shopping without purchasing), and as more is learned about the value of the good.

Another way markdown pricing informs demand knowledge is by assuming that those customers who purchase early in the selling period have higher reservations prices for the good. On the contrary, those who wait have lower reservations prices. Reasons some consumers may have higher reservation prices than others include the utility these consumers give to the good and the potential prestige for being one of the first to own a particular good (Talluri & van Ryzin, 2004). For example, it is common for lines to form outside retailers when the computer manufacturer Apple releases a new version of its popular iPhone. The prices of new releases are typically much higher immediately following the release versus a few months later. Some customers place a high utility and/or prestige to being one of the first to own the new iPhone and are willing to pay a premium while others wait sometimes as long as a year or more after release before purchasing at a much lower price. What is learned in this type of markdown pricing is that there are clearly different segments of consumers for the same product.

Discount airline pricing. Another common example of dynamic pricing includes discount airline pricing. While some airlines typically follow a quantity-based RM strategy to manage demand, discount airlines such as Jetblue primarily utilize price-based RM (Talluri & van Ryzin, 2004). A major difference in the pricing strategy used in airlines from retail markdown pricing is that prices typically go *up* over time as opposed to down. It is well known that the airline industry was at the forefront of implementing and improving RM strategies so it is no surprise that the industry was at the forefront of dynamic pricing strategies.

It has been suggested that the value consumers place on plane tickets increases over time (Netessine & Shumsky, 2002; Ng, 2008; Talluri & van Ryzin, 2004). Under the discount airline pricing scheme, why do prices go up as opposed to down as in retail markdown pricing? One reason given for increasing prices is that there are different segments of customers which attach different utilities or risk preferences to the value of an airline ticket (Ng, 2007; Shugan & Xie, 2000). Consumers are believed to multiply the probability of using the ticket by the price (i.e., value) of the ticket (Shugan & Xie, 2000).

Those booking far in advance typically attach a lower probability of using the ticket because of various factors that may prevent the consumer from using the ticket. As such, consumers typically expect a lower price to compensate for lower probability of consumption. While some customers prefer to get the lowest price and book early, some customers prefer to wait hours or minutes before the flight to book and subsequently subject themselves to higher prices. These consumers have a much higher probability of using the ticket and therefore are willing to accept the higher price.

A commonly cited example of why flight prices typically increase over time is the leisure traveler who tends to book earlier while the business traveler tends to book later in the selling timeframe. A leisure customer planning a vacation will likely book months in advance but could then encounter many obstacles (e.g., illness or death in family, weather, changes in employment, etc.) that could prevent the consumer from actually utilizing the ticket. Therefore, the leisure customer typically commands a lower advance price to account for the possibility of not being able to use the ticket. However, a business traveler who must attend an urgent meeting in another city will place a high value on securing a seat close to the departure date and will therefore be willing to accept a higher price for essentially the same product as the leisure traveler.

Limited research in the sport industry has suggested sport franchises utilizing dynamic pricing are following the airline model and increasing prices as game time nears (Shapiro & Drayer, 2012). More research is needed to determine if sport franchises appear to be utilizing this type of dymaic pricing strategy and understand the potential effectiveness for sport pricing. In addition to dynamic pricing strategies, some sport organizations have recently begun experimenting with the other major form of price-based RM, auction pricing.

Auction pricing overview. Traditionally, auctions have been utilized in industries such as real estate, vehicle sales, financial markets, and livestock. The Internet, and in particular eBay, has allowed auctions to be utilized for nearly anything. Talluri and van Ryzin (2004) contended that auctions are important to the study of pricing both practically and theoretically.

On the practical side, auctions are encountered in many different situations for many different industries. Auctions allow firms to achieve near-perfect first-degree price discrimination and extract nearly optimal prices without needing to estimate demand functions and consumers' willingness to pay (Talluri & van Ryzin, 2004). In contrast to other price discrimination strategies, auctions allow a firm to achieve more optimal prices without the need for as much consumer information. Theoretically, the study of auctions provides interesting opportunities to study pricing models in which consumers act strategically as opposed to the more unrealistic assumption of myopic consumers assumed in many dynamic pricing problems. Two common auction types include the open ascending (English) auction and the open descending (Dutch) auction.

In an open ascending (English) auction the firm starts with an opening price and consumers indicate their willingness to buy (typically by raising a hand or number). If the firm receives a bid, it will raise the price to determine if there are bids at the higher price. This process continues until there are no bidders at a given price and the firm awards the bidder at the last accepted price (bid) for the product.

In an open descending (Dutch) auction, a firm starts at a high price and drops the price until it receives a bid. If a firm has multiple units of an item (e.g., tickets to an event), the process of dropping prices will continue until all units have been sold. Typically, the price paid by consumers will be the lowest price at which all units have been sold. So consumers bidding at a higher price than the price that clears the inventory will end up paying less than their willingness to buy.

Auction-based pricing can be found in many industries and has even begun to surface in the sport industry. For example, Northwestern and Stanford universities have applied Dutch auction pricing to some of their more popular football games (Steinbach, 2013). The payoffs of using this pricing strategy have so far been dramatic as Northwestern reported sideline tickets selling at $195 for a home game against Ohio State. This represented a 178% increase in the highest priced ticket the year before of $70. Although the current trend in ticket pricing in the sport industry appears to be following the dynamic pricing approach, auction-based ticket pricing appears to be a fascinating avenue for research and practice.

Summary of revenue management. A clear dichotomy between price-based and quantity-based revenue management will rarely exist within industries or even firms within industries. For example, while many airlines would fall under the quantity-based RM strategy, discount airline companies (e.g., Southwest, Frontier) typically utilize more of a price-based RM strategy. Additionally, while retailers typically apply price-based RM they will also find creative ways to hold back inventory (quantity-based RM) in centralized warehouses and later release the inventory across their stores as opposed to allocating all inventory at one time.

Despite this blending of revenue management approaches, Talluri and van Ryzin (2004) suggested research classify RM into one of these categories based on whether a firm primarily utilizes capacity-allocation decisions (quantity-based RM) or price-based decisions (price-based RM) as the primary tactical tool to influence demand. These authors contended that classifying RM using this dichotomy is necessary because both the theory and practice of RM differs depending on what tactic is used to manage demand.

Recent trends in sport ticket pricing would indicate that sport franchises have begun utilizing a price-based RM strategy. Dynamic pricing strategies are being applied by most teams in Major League Baseball (MLB) and efforts by MLB franchises are being made to explain their dynamic pricing policies (Dynamic Pricing FAQ, 2015). Also, auction-based pricing has also been applied to NCAA division I football programs (Steinbach, 2013). Additionally, the concept of ticket holds and releases would fall under quantity-based revenue management although no research could be found that examines ticket inventory. Based on the limited research and practice of RM in a sport setting, this study offered an important contribution to the growing sport RM literature base.

Statement of Problem

The purpose of this study was to investigate quantity-based RM in sport through the examination of advance seat section inventory. Data collection strategies and the analytic focus at the seat section level offered a unique contribution to the literature. Early sport dynamic ticket pricing and advance pricing research has examined pricing for one MLB team and one NHL team (Drayer & Shapiro, 2012; Dwyer et al., 2013). In this study I provided an analyses of a different MLB team with a lower historical attendance than previous research.

Game ticket inventory was collected in a real time, advance selling scenario, at a more disaggregated level (seat section) than prior research and offered a first glimpse into the differences in seat section inventory curves. Given the significance of ticket inventory and pricing to a sport organization's bottom line coupled with the increased use of demand-based pricing strategies, the following research questions were developed to guide this research:

RQ5 To what extent do seat section inventory curves differ from parallelism?

RQ6 What is the nature of differences between seat section inventory curves?

These questions were answered by collecting and analyzing seat section ticket inventory data for from the entire 2014 home season for the Kansas City Royals. Profile and trend analyses provided the answers to research questions.

Methods

The goal of this study was to form an understanding the nature of seat section ticket inventory over time. As Ng (2007) pointed out the pricing of services is concerned with advance demand and pricing. To form an understanding of potential sport RM strategies utilizing dynamic ticket pricing and ticket inventory holds, one must gain an understanding of the nature of the seat section inventory/demand curves over time.

Armed with this information, researchers and practitioners can begin to understand the potential benefits of a RM strategy such as dynamic ticket pricing and how this interacts with inventory decisions. For example, if one has an understanding of the nature of the ticket inventory curve over time, a question a business decision maker may ask is: to what extent could we expect inventory to change if we implemented a 20% price increase/decrease at various times leading up to game time? Unfortunately, there is no known published research which examines seat section inventory patterns over time despite the fact that most teams are now implementing dynamic ticket pricing strategies.

This study used a nonexperimental, longitudinal research design to answer the research questions related to demand for MLB games over time. Profile analysis procedures were utilized to examine potential differences in ticket inventory based on time before game and seat section. Observations are recorded as ticket availability at eight different time points prior to an MLB game.

Description of Variables

Dependent variable. The dependent variable for this study was the ticket availability as recorded from the Kansas City Royals' official websites. Ticket availability is a continuous variable and will be collected for 11 seat sections at eight different times before the game. An estimate of ticket demand can be calculated by differencing the ticket availability at adjacent data recording days. For example, to calculate ticket demand between four days prior to a game and three days prior, one would simply take the difference of ticket availability on day four and day three.

Independent variables. The independent variables examined in this study were the 11 seat sections located in the Royals stadium. The primary goal of this study was to gain an understanding of seat section inventory curves over time. As such, seat sections served as the grouping independent variable (IV) with 11 levels. The 11 seat sections represent seat sections at every price level the Royal's offer. The Royals classify seat sections as Premium, Field/Plaza Level, Fountain, Loge Level, and Hy-Vee Level. The range of single game prices for each of the 11 seat sections examined in this study are displayed in Table 14. As can be seen, the sections vary considerably in the range of prices. Therefore, it was important to collect inventory at each section level.

Table 14

Seat Descriptions and Price Ranges

Team	SectionName	SectionCategory	MinP	MaxP
Royals	KiaDiamondClubSeats	Premium	83	126
Royals	Loge	Loge Level	23	71
Royals	HyVeeInfield	Hy-Vee Level	5	27
Royals	HyVeeOutfield	Hy-Vee Level	8	26
Royals	HyVeeBox	Hy-Vee Level	18	33
Royals	FoutainSeats	Fountain	17	69
Royals	FieldPlaza	Field/Plaza Level	10	69
Royals	OutfieldBox	Field/Plaza Level	23	53
Royals	FieldBox	Field/Plaza Level	36	82
Royals	DugoutPlaza	Field/Plaza Level	39	109
Royals	DugoutBox	Field/Plaza Level	52	140

Note. Sections are classified by name and a broader category based on seat location and pricing. MinP=minimum single game price observed over the season; MaxP=maximum price observed over the season.

Sampling Strategy

Target population. The target population for this study is all seat sections contained within an MLB ballpark. Data were collected for all seat sections and all games of the 2014 season. As mentioned previously, the majority of MLB teams are utilizing some form of dynamic ticket pricing and as such it is hoped the results of this study can be generalized to some extent to a wide variety of seat sections and MLB games.

Sampling frame. There are currently 30 MLB teams. MLB teams are divided into two leagues (American and National) each with 15 teams and subdivided into three divisions (East, Central, and West) each with five teams. Starting in April and ending in October, each team plays a total of 162 games (81 home, 81 away). Teams historically have had differing levels of home attendance throughout a season. For the purpose of this study, these attendance numbers are categorized into three tiers (high, mid, and low). These levels were constructed based on 2013 attendance figures collected from espn.com (MLB Attendance, 2013). To be classified as “high” attendance, a team’s attendance had to be in the top quartile of percentage of capacity, “mid” in the interquartile range, and “low” in the first quartile.

Sample. The sample for this proposed study are the seat section ticket availability data collected for 81 home games for the Kansas City Royals. Kansas City was purposefully chosen as the sample team because in 2013 the Royals were in the “mid” attendance category and they contract with tickets.com allowing for ticket price and availability data collection.

A “mid” attendance team is believed to be important for this study because the only other known dynamic ticket pricing study of price over time (Shapiro & Drayer, 2012) examined the San Francisco Giants. Not only are the Giants in the “high” attendance category but they have been in the top three in attendance since 2011 (MLB Attendance, 2015). To contribute further to the understanding of revenue management (RM) strategies, it is important for researchers to examine more teams and with differing levels of attendance. It is reasonable to believe RM strategies will perform differently for teams with varying levels of attendance.

Furthermore, Kansas City was chosen due to data availability from their official website. The majority of teams in the MLB contract with either tickets.com or ticketmaster.com to offer online ticket purchasing. Teams utilizing tickets.com offer a more convenient way of collecting ticket pricing and availability data and thus provide another reason for the selection of the Royals for this study. The intricacies of this data collection are described in the data collection procedures section.

Data Collection Procedures

Previous research on demand and pricing in sport has largely relied on secondary data collection techniques. Recent research has utilized average season attendance data provided from the *Red Book* and *Green Book* to study price dispersion in the MLB (Soebbing & Watanabe, 2014). Additionally, Dwyer et al. (2013), guided by Schwartz's (2000) advance-booking model, utilized survey data collection methods to assess time's influence on consumers' estimation of ticket availability and price. However, no data collection on ticket availability and pricing could be found at the seat section level. This level of detail is typically only available to researchers with a relationship with an organization (Shapiro & Drayer, 2014). The data collection strategy described below provides a unique contribution to the existing literature that does not require the elusive relationship with a partner organization.

Seat Section Data Collection Procedures

Due to the proprietary nature of pricing and demand information it is difficult to obtain seat section pricing and demand data directly from professional baseball teams. As such, the data collection strategy for this study was to manually collect data from the team's ticketing websites. As shown in Figure 22, ticket price and available inventory can be viewed by scrolling over each section number. In the example shown it can be seen that a seat section number (139) in section name "Dugout Box" has a ticket price of $82.00 and there are 11 seats available for purchase.

A Microsoft Access database was created to collect and store seat section pricing (11 section names), ticket availability (157 section numbers), date of game, time of game, opponent, section name, and number. The data were recorded for all 81, 2014 Kansas City Royal home games at eight different lead times before game day (20 days, 10 days, 5-0 days). This resulted in 7,128 (11 sections by 81 games by 8 lead times) records for seat section pricing and 101,736 (157 section numbers by 81 games by 8 lead times) records for seat section ticket availability.

Statistical Procedures

The purpose of this study was to develop an understanding of the seat section inventory curves over time and to how these curves differ. As such, profile analysis with a planned trend analysis was utilized to answer the two research questions. Profile analysis with trend analysis is an appropriate analytic procedure for this question because the dependent variable (ticket availability/demand) is measured several times prior to game day. Profile analysis is similar to repeated-measures ANOVA and is described as taking a multivariate approach to repeated measures. The main tests in profile analysis include the test of parallelism (RQ5), levels, and flatness (Tabachnick & Fidell, 2001).

Figure 22: Ticket price and availability data collection example. The data collected was the price and ticket availability as shown. A MS Access Database was utilized to collect and store ticket price and availability data across 11 different seat sections indicated by the colors scheme seen in the stadium map.

RQ5: To what extent do seat section inventory curves differ from parallelism? A test of parallelism is a test of interaction between days out and seat section. This test revealed if the seat section inventory curves differed over time versus follow parallel trajectories. Profile analysis allowed for comparison of adjacent days out and essentially answered whether the inventory curves for seat sections reliably differed.

After multivariate assumptions were met through data transformations, initial profile differences were evaluated at a significance level of .05 using Wilks' Lamba for statistical evaluation and strength of association.

RQ6: What is the nature of differences between seat section inventory curves? A trend analysis was used to determine the extent of differences in seat section slopes and changes in the pattern of slopes across seat sections. A trend analysis with an adjusted alpha error rate of .007 was utilized to account for the seven different tests of trend between the various days out. The test of interaction of trends between seat sections determined if the seat sections had reliably different slopes (linear trend) over the eight days as well as different patterns in slope (quadratic and cubic trends) across days.

To account for the unequal spacing of days out between 20 and 10 days out and 10 and 5 days out, SPSS 22.0 GLM syntax specified the unequal spacing in the POLYNOMIAL command line as (20,10,5,4,3,2,1). Mean and standard deviations for all seat sections were calculated as well as a graphical representation of mean seat section inventory over time. Because seat sections are known to differ in total ticket inventory, it is beneficial for graphical scaling purposes to plot standardized means to aid in the final interpretation of the shape of inventory curves.

Finally, post-hoc tests of trend were planned at each seat section level to examine the extent to which each section exhibited significant linear, quadratic, and cubic trends. These tests aimed at further understanding the differences in inventory curves between sections. Simple comparisons between seat sections were made by rank ordering the effect sizes for linear trend by seat section and observing which sections produced reliable linear, quadratic, and cubic trend components. Finally, a graphical analysis with plotted slopes in the form of percent changes in inventory between days out highlighted the major differences between seat section inventory curves.

Results

A profile analysis was performed on seat section inventory using SPSS GLM. Ticket inventory represents the total available tickets per seat section as collected via tickets.com. Ticket inventory was measured for each game and by seat section over eight different times (days out). Eleven seat sections formed the between-subjects independent variable. The within-subjects independent variable treated multivariately were the eight different days out: 20, 10, 5, 4, 3, 2, 1, 0. A trend analysis was conducted the main effect of days out and the seat section by days out interaction. Post-hoc comparisons for linear, quadratic, and cubic trends via trend analysis provided a simple effects analysis to shed light on the nature of differences between seat section inventory curves.

Data Screening

Minitab descriptive statistics and boxplots were used to examine the extent and pattern of missing data, general shape and distribution of variables, and univariate outliers. The first six games were missing Day20 data leaving 75 games with complete data for all days out. The decision was made to remove the first six games which left 75 games and 825 observations. Unequal sample size per cell was not an issue because each seat section by day out combinations had 75 games per cell which is 9.375 as many cases as dependent variables. The distributions of seat section inventory at the various days out showed moderate negative skewness suggesting a reflected square root transformation may provide improved distribution of means and conformance to statistical assumptions of profile analysis.

Further confirmation of the need for transformation is found through the examination of mean and standard deviations which show the dramatic differences in seat section inventory and variance. For example, the mean ticket inventory at 20 days out for the HyVeeInfield section was 9,494 with a standard deviation of 942. By contrast, the KiaDiamondClubSeats had a mean of 16.44 and standard deviation of 7.05 at 20 days out. This example clearly shows the need to transform the data prior to formal statistical analysis because the F_{max} =173 is clearly a violation of the homogeneity of variance assumption. Therefore, the decision was made to transform the data using a reflected square root transformation prior to further examination of outliers and other statistical assumptions.

Data transformation. As the initial descriptive analysis suggested, a need for transformation was obvious prior to performing further analysis of outliers and assumptions of profile analysis. Because seat sections exhibited a moderate negative skewness for the various days out, the following steps were taken to transform the data:

1. The data were sorted by seat section and then days out within each seat section.
2. One was then added to the maximum value within each group and days out combination.
3. A new value for each original value was then found by subtracting the original value from the value in (2).
4. Finally, a square root transformation was applied to the values in (3).

The effect of this transformation on the original values is a reflection followed by a square root. Note that the lowest value in each group by days out combination is 1 under this transformation. Under the transformation, average seat section inventory skewness was reduced from -.52 to -.25 and F_{max} values were also reduced. However, F_{max} as high as 16.37 was still found between the HyVeeInfield and KiaDiamondClubseats. The next highest ratio of variances was found between the HyVeeInfield and HyVeeBox sections with a value of $F_{max} = 6$. With equal sample sizes between groups an $F_{max} < 10$ can be tolerated (Tabachnick & Fidell, 2001a). Because of the high F_{max} values both with and without transformation when including the KiaDiamondClubSeats section, the decision was made to remove the KiaDiamondClub-Seats group from the profile analysis with a discussion of this section in post-hoc analysis.

Outliers. Univariate outliers were identified as ticket inventory (the dependent variable) values that fell more than 1.5 times the interquartile range for each section and days out combination. Minitab boxplots provided a quick and simple identification of univariate outliers within groups. Games 79, 80, and 81 were identified as low outliers with unusually low ticket inventories for multiple days out. These games were removed from the main analysis but will be described in further detail in the discussion section. After the removal of these three games, univariate outliers were still present. On a second round of univariate detection the following games were identified as univariate outliers: 11, 12, 17, 18, 26, 46, 46, 51, 57, 68, 71, 72, 75. Of these games, 12, 18, 36, 68, and 72 produced observations identified as outliers for more than one dependent variable.

To help in the decision to retain or remove univariate outliers, multivariate outliers were identified using SPSS REGRESSION where multivariate outliers were defined by Mahalanobis distance with $p<.001$ and $\chi2(8)=26.125$. Multiple games were identified through various seat sections as multivariate outliers. It was decided to remove any game which was identified as a multivariate outlier in more than half of the seat sections. Therefore games 7, 68, 72, 8, and 12 were removed in the first round of deletion leaving 67 games and 670 total observations in the data set. After removal of these five games, preliminary analyses were conducted both with and without outliers.
Results of the profile analyses did not change when including the outliers in the dataset. Therefore, the decision was made to retain the multivariate outliers to maintain a final sample size of 72 games and 720 observations.

Evaluation of conformance to the assumptions of profile analysis. Statistical assumptions of profile analysis of grouped data include normality of sample means, homogeneity of variance between groups, linearity between dependent variables, and multicolinearity and singularity. Because the sample size for each cell was 72 games, the central limit theorem should assure acceptably normal sampling distributions of means for use in the profile analysis (Tabachnich & Fidell, 2001a). Next, linearity was expected and confirmed through bivariate scatterplots as inventory over days out exhibited a negative linear relationship.

Homogeneity of variance. After transformation and removal of the KiaDiamondClubSeats the highest value of F_{max} was 5.99 between the HyVeeOutfield and HyVeeBox sections on the three days out transformed variable. Because of equal sample sizes between cells, conformance to homogeneity of variance is acceptable with this value of F_{max}.

Multicollinearity and singularity. Correlation between days out is expected to be high. It is not expected the correlation between the dependent variables would be so high as to threaten statistical multicollinearity. Most statistical programs will not perform statistical tests if a serious violation of this assumption is made so violation of this assumption did not appear evident.

Strategies to alleviate violations of assumptions. The decision was made to eliminate the KiaDiamondClubSeats from the main profile analysis due to its unusually low possible range of inventory values causing severe violations of the homogeneity of variance assumption. It is important to note that because trend analysis is the planned contrast procedure, assumptions of multivariate analysis do not apply to this procedure because the test of trends uses a single degree of freedom (Tabachnick & Fidell, 2001a, p. 423). Simple effects trend analysis for linear, quadratic, and cubic trends were analyzed using an adjusted α=.007 to achieve a family error rate of α=.05.

RQ5: To what extent do seat section inventory curves differ from parallelism?

The test of parallelism (interaction) tests whether the inventory curves of section were statistically different. For ease of interpretation, cell means and standard deviations for the untransformed dependent variables over all combinations of seat sections and days out are in Table 15. On the transformed data, Wilks' Lamda was used to test the omnibus test of seat section by days out interaction. This test of deviation from parallelism was statistically reliable and large, multivariate $F(63, 3971)=32.17$, $p<.001$, partial $\eta^2=.282$. This result indicated seat sections do not have identical profiles over the eight days out examined. Although seat section and days out main effects were also statistically reliable, they are not interpreted in the presence of the reliable interaction.

RQ6: What is the nature of differences between seat section inventory curves?

A trend analysis was performed to assess the shape of the inventory curves for seat sections over the eight days out. Statistical tests were performed to assess the statistical reliability and strength of linear, quadratic, and cubic trends while graphical and simple effects analysis aids in the interpretation of significant findings. An adjusted $\alpha=.007$ was used as the significance level to compensate for inflated type I error in testing for linear, quadratic, and cubic trends. The linear trend for the interaction between seat section and days out was statistically reliable and quite large for the days out by seat section interaction, $F(9,710)=41.8$, $p<.001$, partial $\eta^2=.346$; the quadratic trend was reliable and moderate, $F(9,710)=14.4$, $p<.001$, partial $\eta^2=.154$; and the cubic trend was reliable and moderate with, $F(9,710)=21.3$, $p<.001$, partial $\eta^2=.213$. It should be noted that SPSS 22.0 GLM output indicated the observed power for these tests to be 100% so finding statistical significance was assured. The focus of the post-hoc analyses, therefore, was on the trend component effect sizes and interpreting the general differences between seat section profiles which could have practical significance.

Table 15

Ticket Inventory Over Eight Days for Eleven Seat Sections

	Days Out							
Seat Section	20	10	5	4	3	2	1	0
DugoutBox								
M	534	512	520	509	498	482	462	432
SD	191	214	230	229	228	227	224	219
DugoutPlaza								
M	1093	1023	1029	1012	992	958	919	870
SD	347	383	429	432	443	444	449	450
FieldBox								
M	2278	2156	2119	2083	2036	1985	1926	1810
SD	454	571	624	640	662	680	689	712
FieldPlaza								
M	2018	1781	1638	1589	1522	1448	1357	1235
SD	656	720	766	776	813	825	850	856
FoutainSeats								
M	201	174	162	156	147	139	130	114
SD	157	151	144	141	139	137	134	130
HyVeeBox								
M	261	251	252	248	247	238	230	222
SD	47	57	60	64	74	71	77	82
HyVeeInfield								
M	9553	9121	8945	8817	8752	8643	8509	8215
SD	915	1206	1427	1444	1504	1564	1634	1780
HyVeeOutfield								
M	3466	3323	3255	3215	3177	3106	3035	2896
SD	713	876	958	967	962	1015	1050	1119
KiaDiamond								
M	17	17	21	20	19	17	17	16
SD	7	12	16	16	15	15	14	13
Loge								
M	833	804	801	788	772	758	734	701
SD	262	286	308	309	311	314	317	320
OutfieldBox								
M	639	586	567	551	541	521	498	456
SD	220	234	245	248	245	247	262	255

Interpretation of Trends

The significant interaction was first interpreted by plotting standardized means of the untransformed data. Recall that a reflected square root transformation was applied to satisfy assumptions of profile analysis. The difficulty in applying this transformation in in enhanced difficulty of interpretation because the original data were essentially reversed before applying the square root transformation. Therefore, in the post-hoc analyses, it was decided to plot standardized means of the original data. Standardization of the mean ticket inventory was done because seat sections naturally have varying ranges of inventory. Thus, to examine the seat section profiles over the eight days out, it was beneficial for graphical scaling purposes to plot standardized means rather than original means.

The significant interaction of linear trend indicated the seat sections have different slopes over the eight days. The significant quadratic trend of interaction suggested the seat sections have different patterns (changes in slope) over the days out. Finally, the significant cubic interaction trend is interpreted as sections starting out with steeper slopes, followed by a middle time frame of “flattening” out (shallower slopes), with the flattening out followed by steeper slopes for the latter part of the time frame. This interpretation of the cubic trend is based on the general shape of the cubic function.

Figure 23 displays the standardized means of profiles of the 11 seat sections over the eight time periods. While the KiaDiamondClubSeat section was excluded from the statistical tests, it is shown in Figure 23 to illustrate its unique parabolic shape compared to other sections. The plot of standard means shows the shape of section profiles that the statistical tests support. With the exception of KiaDiamondClubSeat, the general downward linear trend from 20 to 5 days out can be seen, followed by varying levels of “flattening out” between 5 and 3 days out, before the profiles resume a steeper trend downward again from 2 days out until game day.

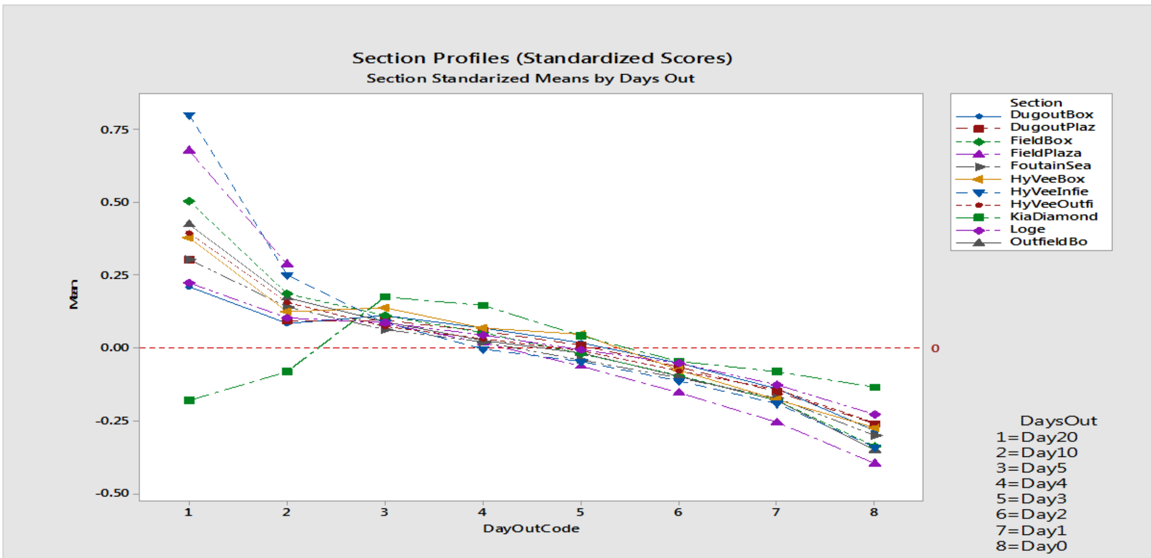

Figure 23: Section profiles over time. Standardized means used for graphical scaling purposes. Significant linear, quadratic, and cubic trend components for the days out by seat section interaction can be seen in the graph as described below:
1. Significant linear trend interaction is shown by the varying slopes (degrees of steepness) of the lines and most obvious when lines actually intersect each other.
2. Significant quadratic trend interaction is shown by the different patterns (changes in slopes from steep to shallow and in some cases from negative to positive) between the sections.
3. Significant cubic trend is interpreted as the steep (20 to 5 days out) to shallower (5 to 3 days out) to steep (3 days out to game day) slopes.
4. The unique KiaDiamondClub profile resembles a parabola with increases in inventory from 20 to 5 days out before beginning a downward trend at day 5 until game day.

The varying slopes of seat sections is most obviously seen as some seat sections actually change *direction* of slope and cross the profiles of others. For example, in addition to the obvious change in direction displayed by the KiaDiamondClubSeats, the

DugOutBox, DugoutPlaza, and HyVeeBox sections decrease from 20 until 10 days out but *increase* inventory from 10 and 5 days out.

Simple Effects Trend Analysis

A simple effects trend analysis at each level of seat section was performed to test the statistical reliability and strength of linear, quadratic, and cubic trends for seat sections individually over the eight days out. While statistical significance was virtually assured with observed power over 85% (many were at 100%) for most of the tests of the three trends, examination of effect sizes helps shed light on the differences between seat section profiles.

Table 16 sorts the sections by highest linear trend effect size, and displays the *p*-values and effect sizes for linear, quadratic, and cubic trends for each seat section. With the exception of the KiaDiamondClubSeats, all other seat sections show a significant linear trend component with varying effect sizes from partial η^2=.746 to .130. The insignificant linear trend for the KiaDiamondClubSeats is most likely attributed to its parabolic shape of rising inventory from 20 days to 5 days out before exhibiting a downward trend until game day.

Three sections (HyVeeOutfield, DugOutBox, and KiaDiamondClubSeats) did not exhibit statistically reliable quadratic trends. Finally, only the DugOutPlaza and KiaDiamondClubSeats did not exhibit significant cubic trends (*p*=.518 and .05, respectively). To facilitate the discussion of differing inventory curves between sections, the focus of this analysis turned to the two sections with statistically reliable but with the lowest and highest effect sizes for linear trend. Specifically, the DugOutPlaza was the section with the lowest significant linear trend effect size with 13% of the variance in ticket inventory over time attributable to linear trend compared to 74.6% of the variability explained by linear trend in the FieldPlaza section. Figure 24 displays the differences of standardized inventory curves of these two sections with slopes between days out represented as percent change in inventory.

Table 16

Trend Analysis for Simple Effects of Days Out by Seat Section.

	Linear		Quadratic		Cubic	
Section	p-value	η^2	p-value	η2	p-value	η^2
FieldPlaza	<.001*	.746	<.001*	.476	<.001*	.556
HyVeeInfield	<.001*	.711	<.001*	.494	<.001*	.540
FieldBox	<.001*	.676	<.001*	.337	<.001*	.668
Loge	<.001*	.602	<.001*	.389	<.001*	.711
OutfieldBox	<.001*	.595	.001*	.156	0.003*	.118
HyVeeBox	<.001*	.498	<.001*	.860	<.001*	.372
HyVeeOutfield	<.001*	.495	.123	.033	<.001*	.487
DugOutbox	<.001*	.319	.079	.043	<.001*	.553
FountainSeasts	<.001*	.316	<.001*	.297	<.001*	.131
DugOutPlaza	0.002*	.130	.001*	.141	0.518	.006
KiaDiamondClub	.415	.011	.033	.074	.050	.063

Notes: η^2 = partial η^2; data sorted from highest to lowest η^2 for linear trend.
*Denotes significant at Bonferroni-adjusted α=.007

The varying slopes between seat sections are clearly highlighted in the comparison of these two sections. The FieldPlaza section decreased in inventory by 11.7% from 20 to 10 days out while the Dugoutbox only decreased 6.4%. From 10 to 5 days out the FieldPlaza decreased again at a rate of 8% but the Dugoutbox actually *increased* inventory a slight .6%.

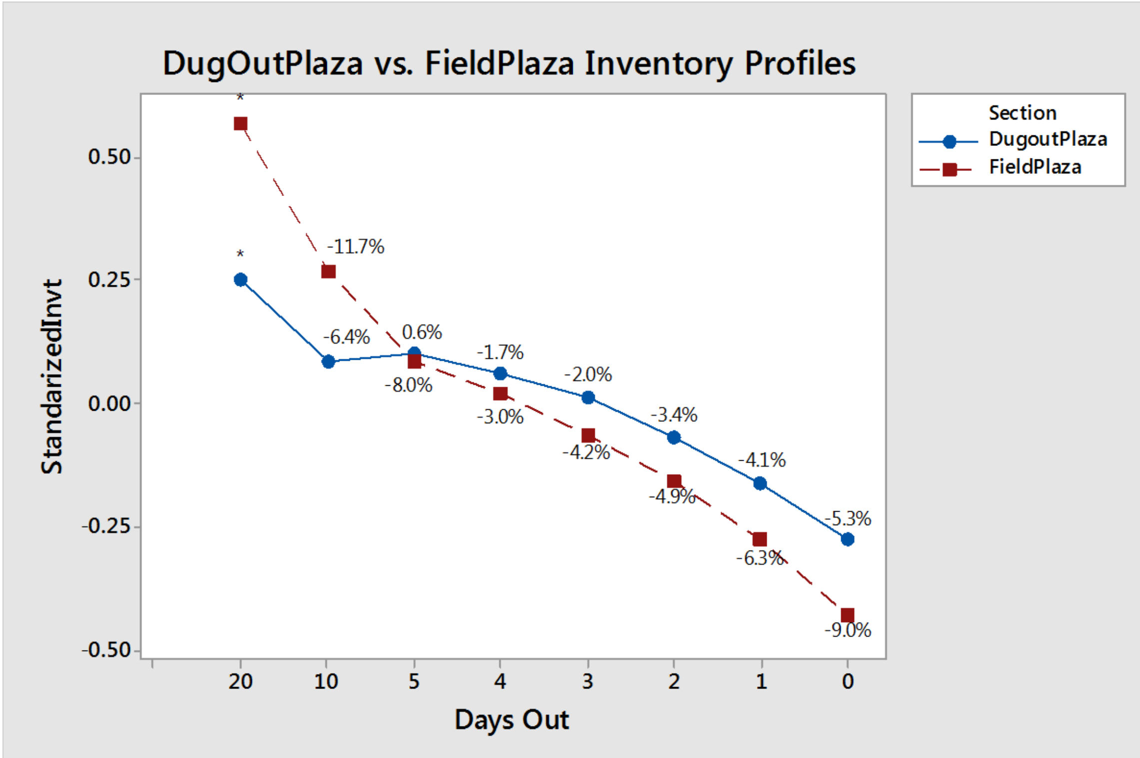

Figure 24: Comparison of seat sections which exhibited the most statistically reliable variance explained by linear trend (FieldPlaza) to the least variance explained by linear trend (DugoutPlaza). Slopes are presented in the graph as percent change of original inventory values between adjacent days out. While these seat sections each exhibited significant linear and quadratic trends, only the FieldPlaza exhibited a significant cubic trend. The differing slopes (linear trend) and changing pattern in slopes (quadratic trend) are clearly displayed with the following notes:

1. The FieldPlaza has nearly twice as steep of slopes for all days out than the DugoutPlaza.
2. The FieldPlaza has a continuous decrease in inventory while the DugoutPlaza actually *increases* from 10 and 5 days out.
3. From 5 days out until game day, slopes for both sections gradually increase as game day nears. The slope of the FieldPlaza tripled from -3% to -9% while the DugoutPlaza over doubled from -2.0% to -5.3%.

Both seat sections exhibited a steady increase in slope steepness from 5 days out until game day with the FieldPlaza maintaining a steeper decent (from -3% to -9%) than the DugoutPlaza (from -1.7% to -5.3%). While other comparisons of sections are certainly possible, the comparisons of these two sections highlights the differences in inventory curves shown by the significant interaction of days out and seat section.

Discussion and Implications

This study aimed to provide what is believed to be the first examination of differences in seat section inventory profiles in the sport management literature. Rascher et al. (2007) examined demand curves for aggregate attendance but stated data collection at the seat section level was difficult (if not impossible) and did not examine demand over time. A few recent studies have studied pricing over time (e.g., Drayer & Shapiro, 2014; Dwyer et al, 2013) as well as the consumer choice process over time (Moe, Fader, & Kahn, 2011) but no studies could be found that examined the inventory or demand curves over time *or* at the seat section level. Existing literature has professed the difficulty in obtaining sales and inventory data from sport organizations so analysis at the seat section level and over time has been difficult, if not impossible, to date.

The data collection procedures of this study offered a method for future researchers to gather seat section level pricing and inventory data without the need for a special relationship with sport organizations. As such, the study provided a first glimpse into the nature of seat section inventory curves through profile and trend analysis. While sales data at the seat section level would have provided estimates of seat section demand curves, examining inventory curves is an important consideration to an effective revenue management system as protection and booking levels are based on current and expected inventory and demand (Talluri & van Ryzin, 2004).

Indeed, sport organizations are constantly examining ticket inventory levels when making decisions regarding how many tickets to hold (i.e., protection levels) for such groups as season ticket holders, group discounts, VIPs, departmental and organization complimentary tickets, etc. Additionally, sport organizations also look to manipulate seat section booking levels by adding or moving seat sections to different price levels (M. Biggers, personal communication, January, 2016). For example, if it is found a particular section(s) are not selling at a high enough rate in their current price level, sport organizations may move these sections to a lower price level in hopes of increasing demand. These examples of protection and booking levels illustrate the use of quantity-based revenue management in sport which can also coincide with the more commonly known price-based revenue management strategies such as dynamic ticket pricing.

The constant balancing of when to hold and when to release ticket inventory was evident in the examination of the section profiles in this study as it was shown some sections *increased* inventory at various days out. Without the concept of ticket holds and subsequent release of holds, inventory curves would naturally fall from 20 days until game day and demand curves could accurately be constructed from adjacent days out by subtracting the inventory from the next day from the inventory of the prior day (e.g., day0 inventory subtracted from day1 inventory would give an estimate of demand from 1 day out until game day). It is the quantity-based revenue management function of booking and protection levels and changing of these levels as game day nears that produces the positive inventory slopes as seen in this study. In addition to inventory considerations, price obviously plays a critical role in development of an effective revenue management plan.

Early sport management research (e.g., Drayer et al., 2012; Rascher et al, 2007) has focused on price-based revenue management (RM) strategies such as variable ticket pricing and dynamic ticket pricing. However, until this study, no sport management research could be found that examined the other critical component in revenue management: inventory. This study adds the quantity-based component of sport revenue management to the literature by offering a first examination of seat section inventory curves. The significant interaction of days out and seat section suggested a RM strategy in sport should consider seat section inventory curves individually in preparation for other RM functions such as forecasting and setting prices. An understanding of pricing and inventory strategies form the foundation for developing a comprehensive and effective revenue management plan.

Practical Implications

Although receiving recent attention in the academic literature, whether it was called revenue management or not, sport organizations have been practicing a form RM for quite some time. This is based on the fact that sport organizations have price differentiated by location of seats for years. In Major League Baseball (MLB), seat sections follow a higher to lower price based on proximity to field level and home plate. Starting from home plate and moving outwards in either direction toward first or third base, seat sections are traditionally marked by somewhat arbitrary lines based on the distance from home plate. In essence then, teams create booking limits by restricting the number of seats they sell at a particular price based on proximity. While recent attention has been paid to the RM practice of dynamic ticket pricing, sport organizations have been applying a form of quantity-based RM for quite some time.

In addition to limiting the number of seats sold at a particular price based on seat location, sport organizations also place inventory restrictions (protection levels) within each seat section based on various ticket holds. Particularly, prior to the season as well as the early part of seasons, season ticket holds are common practice amongst sport organizations (M. Biggers, personal communication, October 15, 2015). Because season ticket holders represent a large portion of a sport organization's overall ticket revenue, it is critical to hold back seats for 1) season ticket holder renewals, and 2) prospective new season ticket holders. This likely explains why many of the first games in the dataset for this study exhibited changing slopes from negative to positive as game day neared because the Royals were holding more tickets early in the selling period prior to releasing them upon confidence they would not sell to season ticket holders. Later games did not exhibit the same negative to positive inventory slopes as early games.

The results of this study can begin to help practitioners in the development of a comprehensive revenue management plan. Results showed inventory curves vary in slope and changes in slope from 20 days out until game day. As such, the development of a sport revenue management plan should begin at the seat section level. Management should decide the optimal mix of holds, available inventory, and pricing within each seat section as opposed to one global strategy across all sections. Discussions with Ticket Operations Manager A. Williams and Strategic Sales Director L. Lew (personal communication, January, 2016) suggested hold levels have been set based on somewhat arbitrary levels. The positive slopes of some sections found in this study suggested too much inventory was being held at various times prior to game day so improvements can be made to optimize inventory and hold levels.

Each team will need to examine previous inventory and sales data so that ticket quantities to hold in each seat section can more formally and accurately be forecasted. Quantities to forecast include season ticket renewal rates, new season ticket holder sell rates, group sell rates, and single game sell rates. These forecasted values should be provided over time so decision makers can prepare at what point in time to release held tickets. For example, if it is forecasted that very few season ticket renewals and/or new season ticket sales occur within five days of a particular game, the decision to release season ticket holds should obviously occur at five days or perhaps earlier. In addition, it could be found that group sell rates increase as game day nears suggesting the need to hold these seats longer into the selling period. Clearly, many ticket inventory dynamics are at play in developing a sport revenue management plan.

Finally, teams wishing to implement dynamic ticket pricing could use the results of this study to help maximize this pricing strategy. Because it was found that seat section inventory slopes increased (to varying degrees) as game day neared this indicated that inventory was selling faster as game day approached. This indication of higher demand as game day nears could signal an appropriate time to implement dynamic pricing. As opposed to a global strategy of increasing, for example, all prices 20% at 3 days out, the sections with the steepest slopes could be the optimal candidates for price increase. This strategy would align with Shapiro and Drayer's (2012) findings that showed the San Francisco Giants increased prices leading up to game day. However, although dynamic ticket pricing is often associated with price increases, sections with shallower slopes (i.e., less demand) could be candidates for *decreasing* price in hopes of inducing more demand.

Summary of Findings

In summary, this study offered a first look at seat section ticket inventory curves over time. While revenue management (RM) has become a recent topic in the sport management literature, examination of quantity (i.e., ticket inventory) over time has eluded researchers. In order to offer this examination of inventory curves, this study provided a data collection technique that can be utilized if researchers cannot obtain inventory and sales data directly from a sport organization.

Both quantity and pricing decisions must be considered in an effective revenue management plan so this study offers another piece of the puzzle that has yet to be explored. Seat sections examined in this study exhibited both differing slopes and differing rates in changes of slopes across a 20 day selling period. The findings suggested the need for planning inventory and pricing decisions at the seat section level. Sections with the steepest slopes (i.e., highest demand) are likely the best candidates for increasing prices as game day nears while sections with the shallowest slopes (i.e., lower demand) could be candidates for decreasing price.

Limitations and Directions for Further Research

While this study was grounded in sound revenue management (RM) theory, the findings only begin to scratch the surface of this complex topic within sport. Other service industries provided the foundation on which to build a sport RM theoretical framework, but much more work needs to be done to understand how the unique properties of sport fit into and which need adaption to the larger framework of RM. For instance, Ng's (2007) theory of advance demand suggested there are two main types of consumers of services: 1) those that have more acquisition risk; 2) those that have more valuation risk. In the case of airlines and hotels, the literature has largely identified these two groups as either leisure or business travelers. Leisure travelers typically have more acquisition risk and buy early in the selling process and business travelers who have more valuation risk buy closer to consumption day. More research is needed to understand if sport consumers can be classified into a similar segments.

This study's generalizability to other MLB teams and other sports is limited due to only examining one team. However, the 72 game sample nearly represents an entire MLB home schedule with a wide variety of games against varying opponents, times of day, and days of week. This variety of game characteristics should be tested for other teams and sports in order to compare and contrast inventory and/or demand curves. Additionally, due to the time required to manually collect ticket inventory, only eight different days out were examined with 20 days out the furthest point in time. Future research should explore further days out. Obviously, forming a partnership with a sport organization which can provide sales and inventory data would go a long way in achieving this endeavor. Finally, the power achieved by statistical results suggested statistical significance of trends was virtually assured. Therefore, interpretation of significant findings focused on the varying effect sizes of linear, quadratic, and cubic trend components as well as graphical analysis in an attempt to establish practical significance as well as statistical significance.

While the results of this study suggested sharper decreases in inventory as game day nears, no formal attempts to identify potential segments of fans was taken. Do the significant linear, quadratic and cubic trends begin to show that differing demand curves exist which support at least two main types of consumer segments? Could the increases in slope as game day nears be attributed to a segment of consumers with higher valuation risk waiting to purchase until they know more about the quality of the game and other outlays (e.g., teams' and opponents' win/loss records, weather, work/family needs, etc)? Research is needed which tracks consumers over the sport selling period in attempts to evaluate consumers level and type of risk.

Outlier discussion. In addition to the first six games which had missing data, three games (79, 80, and 81) were identified as outliers at the end of the season and were subsequently removed from the main analysis. Closer examination of these games sheds light as to why these games were outliers. These three games represented the last three Royal home games of the season against division rival Detroit Tigers. The Tigers and Royals were number 1 and 2 in their division at time of these three games. As such, these games had playoff implications. Furthermore, these games were part of a weekend series starting on Friday night and ending on Sunday afternoon. It is no surprise that these games had much lower ticket inventory (i.e., higher demand) because of these reasons. In fact, these games left many zero values for ticket inventory leaving no inventory curve to examine. Therefore, the decision was made to remove these three games from the primary analysis leaving 72 games. Games that sell out could be an interesting extension of this study to determine if there is an early point in the selling period at which sellouts can be predicted. Subsequent price changes and/or inventory holds could then be implemented if desired. Additional research ideas are discussed in the following sections.

Future Research

Obviously, examined in isolation, price and inventory cannot shed light onto the potential revenue gains a sport organization can realize under a new pricing strategy such as DTP. As detailed by Talluri and van Ryzin (2004), revenue management strategies can focus on either a price-based or quantity-based strategy but these components must obviously be examined together to form revenue maximization strategies. Future research is needed to understand the optimal pricing and inventory allocation mix for revenue maximization. Finally, formulating a comprehensive RM plan will involve integrated aspects of consumer behavior, economics, and operations.

Ng's (2007) theory of advanced demand suggested two main types of consumers that could play a significant role in how future revenue management plans are developed. Additionally, consumer choice models such as those presented by Moe et al. (2011) offer an interesting start to further understanding the complex sport consumer decision making process over time. These theories should be further tested in a sport revenue management context where those with higher valuation risks are inclined to buy closer to game day and those with higher acquisition risks are inclined to buy further in advance of game day. What factors contribute to differences in the levels of valuation and acquisition risk? To what extent do these groups differ in the price they are willing to pay for tickets? Are those consumers who choose to buy on game day (i.e., they have higher valuation risk) willing to pay more for tickets? What strategies can sport teams employ to reduce valuation risk and encourage more purchases in advance of game day? Is it possible that teams could employ scarcity tactics, whereby increasing acquisition risk, by holding back more inventory? What are the ethical considerations to increasing acquisition risk through scarcity tactics? These questions and more are left to be answered in future sport revenue management studies.

From an economic standpoint, further research is needed to assess whether games can be classified into groups to assess inventory/demand curves for games that are thought to be of higher demand (e.g., games against nationally popular teams such as the New York Yankees) versus games that are considered more “normal” games. To what extent do weekend night games produce inventory curves that are different than weekday night games? To what extent does time of game (night or day) change the inventory profiles? If researchers can form mutually beneficial partnerships with sport organizations, demand curves by seat section can be examined for the days out included in this study as well as further days out in attempts to identify whether different demand curves exists further out in time as opposed to closer to game day. If varying demand curves can be found at different points in time, this could support the theory of advance demand and suggest there are at least two segments (based on time before game) of sport consumers. These are but a few of the questions that need to be answered from an economic viewpoint.

Finally, from an operations angle, the significant linear, quadratic, and cubic trends found in the simple effects analysis of most seat sections suggest regression forecasting models be built and tested with these trend components. These more complex models should be compared to other common revenue management forecasting strategies such as exponential smoothing and moving average. To what extent does a more complicated regression model with second and third order terms differ in forecast errors compared to simpler methods and pickup strategies? Do seat sections need separate forecasting models or is it possible certain sections can be grouped and the same model applied to the grouped sections? For example, do lower level seat sections exhibit similar inventory and/or demand curves such that one forecasting model can accurately forecast across all lower level sections? To what extent do the slopes of higher demand game curves differ from lower demand game curves? At what level of aggregation should forecast models be applied? It is clear much more work is needed to understand how forecasting can improve sport revenue management.

Obviously, each of the main topics (consumer behavior, economics, and operations) comprising a comprehensive revenue management plan needs to be further examined. Sport management research is needed to develop this complex topic theoretically as well as offer practical recommendations to improve sport organizations' bottom line. A wealth of empirical research opportunities are available from either of the main disciplines outlined above. This study offered a data collection strategy that can be applied to more teams and sports so long as online ticket inventory and pricing information is available.

Finally, theoretical work is needed to examine how the uniqueness of sport further complicates the already complex topic of revenue management. How do theories of consumer choice such as the one offered by Moe et al. (2011) interact with revenue management theory? Do avid versus casual fans react differently to sport firms' use of dynamic ticket pricing? It is hoped this study has offered a springboard to many future research opportunities in the fascinating topic of sport revenue management.

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APPENDIX A

IRB APPROVAL

UNIVERSITY of NORTHERN COLORADO

Institutional Review Board

DATE:	July 17, 2014
TO:	Micah McGee, M.S.
FROM:	University of Northern Colorado (UNCO) IRB
PROJECT TITLE:	[621283-1] Dynamic Ticket Pricing in Major League Baseball
SUBMISSION TYPE:	New Project
ACTION:	APPROVAL/VERIFICATION OF EXEMPT STATUS
DECISION DATE:	July 15, 2014

Thank you for your submission of New Project materials for this project. The University of Northern Colorado (UNCO) IRB approves this project and verifies its status as EXEMPT according to federal IRB regulations.

Hello Micah,

I am pleased to approve your IRB Application. Thank you for the opportunity to review this fascinating proposal and good luck with your study.

Please give my greetings to your Research Advisor, Dr. Grey.

Sincerely,

Nancy White, PhD, IRB Co-Chair

We will retain a copy of this correspondence within our records for a duration of 4 years.

If you have any questions, please contact Sherry May at 970-351-1910 or Sherry.May@unco.edu. Please include your project title and reference number in all correspondence with this committee.

This letter has been electronically signed in accordance with all applicable regulations, and a copy is retained within University of Northern Colorado (UNCO) IRB's records.

APPENDIX B

LIST OF ACRONYMS

The following table lists various acronyms and their meaning used throughout the dissertation. The page on which the acronym is first used is also given.

Acronym	Meaning	Page
RM	Revenue management	3
FCI	Fan Cost Index	7
ARIMA	Autoregressive integrated moving average	14
VTP	Variable ticket pricing	22
DTP	Dynamic ticket pricing	24
ACF	Autocorrelation function	101
PACF	Partial autocorrelation function	101
MA	Moving average	103
AP	Advanced pickup	112
CP	Classical pickup	112
PU	Pickup	112
MSE	Mean squared error	121
MAD	Mean absolute deviation	127
MAPE	Mean absolute percentage error	127
NP	Non-pickup	138
ES	Exponential smoothing	140
IV	Independent variable	145
DV	Dependent variable	163