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Daniel, Rascher and Chad, McEvoy and Mark, Nagel and Matt, Brown

University of San Francisco, Illinois State University, University of South Carolina, University of South Carolina

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Daniel A. Rascher

University of San Francisco

Chad D. McEvoy

Illinois State University

Mark S. Nagel

University of South Carolina

Matthew T. Brown

University of South Carolina

Daniel A. Rascher

Sport Management Program

University of San Francisco

Lone Mountain Pacific Wing 116

2130 Fulton St.

San Francisco, CA 94117

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Abstract

Sport teams have historically been reluctant to change ticket prices during the season. Recently, however, numerous sport organizations have implemented variable ticket pricing in an effort to maximize revenues. In Major League Baseball, variable pricing results in ticket price increases or decreases depending on factors such as quality of the opponent, day of the week, month of the year, and for special events such as opening day, Memorial Day and Independence Day (July 4). Using censored regression and elasticity analysis, this paper demonstrates that variable pricing would have yielded approximately $590,000 per year in additional ticket revenue for each Major League team in 1996, *ceteris paribus*. Accounting for capacity constraints, this amounts to only about a 2.8% increase above what occurs when prices are not varied. For the 1996 season, the largest revenue gain would have been the Cleveland Indians, who would have generated an extra $1.4 million in revenue. The largest percentage revenue gain would have been the San Francisco Giants. The Giants would have seen an estimated 6.7% increase in revenue had they used optimal variable pricing.

Variable Ticket Pricing in Major League Baseball

Variable ticket pricing (VTP) has recently been a much-discussed topic in the business of sport, especially as it relates to professional baseball, professional hockey, and college football (King, 2003; Rovell, 2002b). VTP refers to changing the price of a ticket to a sporting event based on the expected demand for that event. For example, Major League Baseball's (MLB) Colorado Rockies had four different price levels for the same seat throughout the season (Cameron, 2002). The different price levels were based primarily on the time of the year (summer vs. spring or fall), day of the week (weekends vs. weekdays), holidays (Memorial Day, Independence Day, etc.), the quality of the Rockies' opponent, or their opponents' star players (e.g., Barry Bonds). The same seat in the outfield pavilion section of Coors Field, the Rockies' home stadium, ranged in price in 2004 from a high of $21 for what the Rockies labeled as "Marquee" games to a low of $11 for what were considered "Value" games. MLB teams who utilized variable ticket pricing in 2004 are detailed in Table 1. Other sport organizations besides MLB franchises utilize VTP as well. Several National Hockey League (NHL) teams utilize VTP strategies, as do a number of intercollegiate athletics programs (Rooney, 2003; Rovell, 2002b).

-- Insert Table 1 about here --

Some MLB teams have concluded that their 81 home games are not 81 units of the same product, but rather, based on the aforementioned characteristics such as the day of the week and quality of the opponent, are 81 unique products. As such, the 81 unique products should each be priced according to their own characteristics that make them more or less attractive to the potential consumer. MLB attendance studies support this notion. For example, in a study including more than 50 independent variables in explaining MLB game attendance, McDonald and Rascher (2000) found variables such as day of the week, home and visiting teams' winning percentages, and weather among many others to be statistically significant predictors of game attendance. Clearly, a variety of factors make some games more appealing and others less appealing to consumers. It seems quite logical to price tickets to these games at different price levels, especially with teams constantly searching for revenue sources to compete with their opponents for players (Howard & Crompton, 2004; Zimbalist, 2003).

Varying quality of games throughout a season often creates a secondary market, as demand for the most popular games may exceed available supply. Independent ticket agents, or *scalpers*, broker tickets obtained from various sources to fans unable or unwilling to purchase tickets from a team's ticket office or licensed ticket agency (Caple 2001; Reese, 2004). Ticket scalpers respond to market demands (often in violation of city ordinances or state laws), but the team initially selling the ticket does not realize any increased revenue during a scalper's transaction ("History of Ticket Scalping," n.d.). For this reason, the Chicago Cubs have recently permitted ticket holders to auction their Wrigley Field tickets on a Cubs affiliated website with a fee being paid to the Cubs for this service (Rovell, 2002a; see also www.buycubstickets.com). It is believed that instituting a comprehensive VTP policy would diminish the influence of scalpers and permit greater revenue to be generated by the team for highly demanded games.

Many industries have previously embraced the variable pricing concept as a method to increase revenue and to provide more efficient service to consumers (Bruel, 2003; Rovell, 2002b). Airline flights are typically more expensive for selected days of the week (Monday, Fridays), times of the day (morning, late afternoon), and days of the year (holidays), when travel demand is higher. The airlines also utilize variable pricing to encourage passengers to book their flights early (typically a purchase at least 10-14 days in advance generates a lower fare) or in some cases at the last minute ("Travel Tips," 2004). Hotel pricing characteristically reflects expected demand, even though the actual physical product does not change, as rooms for weekends or holidays are usually higher priced than weekdays or off-season visits. In fact, sometimes variable pricing even relates to major sporting events like the Super Bowl. Many hotels substantially raise room rates during Super Bowl week (Baade and Matheson, n.d.). Other industries, like transportation, utilize variable pricing, where some toll roads now charge higher toll rates during peak times and lower rates during off-peak times ("Group Commends…," 2001). The arts use variable pricing as well, such as matinee movie pricing (Riley, 2002).

Sports franchises are moving forward with VTP strategies before sufficient research has been done to empirically evaluate its specific merits to the industry. This article provides a straightforward assessment of optimal VTP. First, a review of the literature reveals difficulties in estimating the nature of demand functions in sports. Specifically, optimal pricing is partially determined by price elasticities of demand, yet it is difficult to estimate ticket price elasticities that are consistent over time. Next, a theory of complementary demand is explained that will account for non-ticket products and services and the effect that ticket prices have on the demand for these products and services. Then, using individual game data from the 1996 MLB season, ticket prices and corresponding quantities are estimated that would have maximized ticket revenue. These are compared to actual prices and revenue to determine the yield from initiating a variable ticket pricing policy. The final section contains a discussion of the implications of the results. In summary, this article shows that there are financial benefits from implementing VTP, details how much can be gained from a general VTP policy, and provides strategies for implementing VTP.

Review of Literature

Price Elasticity of Demand in Sports

While the literature specifically investigating VTP in sport is limited, the literature on estimating demand functions and the corresponding elasticities for sporting events is extensive. Typically, these studies estimate the price elasticity of demand to see whether sports teams are setting price to maximize revenue (or profit if it can be shown that variable costs are relatively negligible). In practice, one could adjust season ticket prices and institute a VTP policy that increases revenue based on the results of elasticity studies. One problem is that the results are not consistent across studies. One explanation for this is that it is reasonable for prices to be set in the elastic, inelastic, or unit elastic portion of demand under various circumstances. For instance, profit maximization results in prices that are in the elastic portion of demand if marginal costs are above zero. If marginal costs are not above zero, then optimal prices are such that profit maximization equals revenue maximization – and that occurs at unit elasticity. However, if other revenue streams are accounted for, such as concessions or parking, then optimal pricing can be in the inelastic portion of demand. Thus, each of these three demand elasticity pricing strategies is justifiable. It is generally assumed in sports ticket pricing that the marginal cost of selling an extra seat is so low as to make the elastic part of demand not optimal in terms of pricing. Any price from unit elasticity down into the inelastic portion of demand is a likely finding as shown in the literature.

Noll's (1974) point estimates for elasticity for baseball were -0.49 for the 1970 and 1971 seasons. For the 1984 MLB season, Scully (1989) estimated point elasticities of -0.63 and -0.76. Boyd and Boyd (1996) used Scully's 1984 data, but added a measure of competition (recreational index for each city) and used a recursive feedback loop that incorporated the effects of home field advantage. Namely, not only do more wins increase attendance, but enhanced attendance improves winning as a greater home field advantage is created. In this study, point elasticities ranged from -0.58 to -1.20. Hence, Boyd and Boyd discovered elasticities that were in the expected range, near or above unit elasticity. It is important to note that economists have a habit of referring to price elasticities as being positive even though they are actually negative. A price elasticity of –1.5 is in the expected range for a profit maximizing decision maker. In fact, any price elasticity that is –1.0 or lower (meaning –1.5 or –2.0) is consistent with profit maximization. However, a price elasticity of –2.0 will often be called a *higher* elasticity than –0.8, referring to the absolute value of elasticity and ignoring the sign (which is always negative).

Scully, Noll, and Boyd and Boyd's estimates all had large enough confidence intervals on the ticket price coefficient to not exclude unit elasticity as a possibility. In other words, none of those studies could reject the hypothesis that teams set ticket prices to maximize revenue. However, a study by Whitney (1988), that utilized more observations than those discussed above, did yield an estimate of price elasticity that fell within the inelastic portion of demand. Further, Marburger (1997) found price elasticities in the inelastic part of demand using annual team-level data covering a twenty-year period. The implications of inelastic pricing will be explained in the *Theoretical Foundations* section.

Fort (2004) recently summarized the literature on spectator sports demand analysis and the difficulty in measuring price elasticities. He noted that simply analyzing one revenue stream makes it appear that pricing is not profit maximizing, and that a more complete accounting of all revenue streams (e.g., tickets, concessions, and local television) is consistent with profit maximization pricing. Given this discussion of price elasticities and profit maximization, this study incorporates models attempting to include the relationship between ticket and concession prices.

Ticket Pricing Issues

It has been difficult for researchers to show profit-maximizing ticket pricing by sports teams. There are a number of reasons for this besides the inclusion of other revenue streams. First, most pricing data that is used is a simple average of prices that are available for various seats for each team each season. Currently, Team Marketing Report (TMR) collects pricing data that some researchers have used (e.g., Rishe & Mondello, 2004, and Rascher, 1999). While it is likely an improvement over previously collected pricing data, it has lacked consistency across teams and over time. Numerous discussions by the authors and TMR have revealed that TMR is able to separate out the luxury suite ticket prices. TMR has also separated out club seating prices for some teams, but not all teams. Further, this varies across seasons. TMR relies on the teams to self-report. Because of the prominence of the TMR Fan Cost Index™, some teams potentially manipulate their reported prices to appear relatively inexpensive. Moreover, the number of seats available at each price level does not typically weight these prices. Additionally, the number of seats sold is generally known in aggregate, not separated by seat price. Second, Demmert (1973) noted that there is a correlation between population and ticket price across many seasons (likely based on the connection to income where higher populated areas earn higher incomes, hence increasing demand and therefore prices). This multicollinearity can cloud the interpretation of coefficients on price. Third, as Salant (1992) pointed out, the long-run price of tickets may be optimal (adjusting for risk), but in the short-run a team may be over- or under-pricing in order to maintain consistency. This is a form of insurance where the team bears the risk. Fourth, similar to Fort's (2004) findings, ticket prices may be kept relatively low in order to increase the number of attendees to an event who are likely to spend more money on parking, concessions, and merchandise, and who will drive up sponsorship revenue for the team, thus maximizing overall revenues rather than simply focusing on ticket revenues.

DeSerpa (1994) discussed the rationality of apparently low season ticket prices. Even though many games sell out in the NBA and NFL (focal sports in his study), it is rational for the seller to price below the myopic short-run demand price in order to give a fan a reason to purchase season tickets. In fact, DeSerpa discussed the possibility, but unlikeliness, of charging different prices for each event based on its demand. He surmised that it was administratively expensive and subject to potential negative fan reaction.

DeSerpa (1994) also noted that it is optimal to under-price season tickets if fans will likely want to attend only some of the games and resell the tickets for the remaining contests. The season ticket must be priced low enough for holders to be able to, at the least, recoup their initial investment after assuming the transaction costs of resale (e.g., time, effort, search costs, and actual costs such as postage and advertising). Lower priced season tickets also potentially created a home field advantage for teams. Each argument or concern DeSerpa proffered can be addressed in a variable ticket pricing system.

Marburger (1997) developed a model showing that pricing on the inelastic portion of demand can be explained by accounting for non-ticket purchases, such as concessions. Marburger noted that baseball teams set price on the inelastic portion of demand, but he did not investigate whether it was based on concessions decisions, just that it occurs. Under multiple methods of measuring ticket price, Coates and Harrison (forthcoming) found that ticket demand is also quite price inelastic.

Variable Pricing Literature

Specific to variable pricing, Heilman and Wendling (1976) analyzed ticket price discounting by the Milwaukee Bucks of the National Basketball Association (NBA). The Bucks discounted prices from $5 to $2 and from $3.50 to $2 for 15 games of the 1974-75 season. The fifteen 1973-74 games that corresponded to the 1974-75 discounted games averaged 9,307 fans and had only three sellouts. The discounted 1974-75 games averaged 10,396 fans and had nine sellouts. Certainly, several factors (winter weather, player injuries, or even reversion to the mean) beyond the discounted price could have contributed to the attendance increases. However, other teams did not duplicate the Bucks' attempt to discount tickets. Though the increase in attendance may appear minimal and be due to other factors besides discounting, when ancillary revenue sources (parking, concessions, and merchandise sales) are added to the cost of a ticket, further investigation into VTP was warranted. However, the Bucks remained one of the few teams in American professional sport to implement a form of variable ticket pricing until 1999 (King, 2002a; Rovell, 2002a).

While some research has been conducted regarding VTP, this limited body of knowledge is not yet sufficient to provide evidence concerning the merits of using VTP to set single-game ticket prices for sporting events. Despite this lack of information, some teams have implemented variable pricing, while others have remained skeptical (King, 2002a). This study investigates the financial gains of VTP and provides some direction regarding how it should be implemented in Major League Baseball.

Theoretical Foundations

The demand for baseball games changes from game to game, partially because the quality and the perception of the quality of the home and visiting teams vary as well as non-performance factors such as day of the week or month. For a given price, Table 2 (columns 2 and 3) shows that there is a large variance in attendance across games. The average deviation from the mean is nearly 23%. For 11 of the Atlanta Braves' 81 home games, the deviation from the mean is over 30%, and the Braves are not even in the top half of teams with high attendance variation.

Insert Table 2 about here.

In general, many organizations are trying to minimize the effect of team performance, one of the key factors in the changing demand from game to game, on demand (Brockington, 2003; George, 2003). As shown in the literature, team performance is one of the most significant demand factors that can be affected by an owner. For example, Bruggink and Eaton (1996) and Rascher (1999) analyzed game-by-game attendance and the importance of team performance. Using annual data, Alexander (2001) showed that the variable with the highest statistical significance is the number of games behind the leader, a measure of team performance. Teams are building new stadiums, improving concessions and restaurants, and creating areas where kids and adults can enjoy themselves, but not necessarily watch the game itself (George, 2003). These improvements not only increase demand, but also lessen the importance that team performance uncertainty has on expected revenues.

Concurrently, teams are beginning to use variable pricing to attempt to manage shifting demand from game to game given that they are unable to completely remove the variation. The theory upon which this analysis is based is simply short-run revenue maximization with two goods that are complementary. Tickets and concessions are complementary goods. The demand for tickets is higher if concessions prices are lower because the overall cost of enjoying the game would be higher (Marburger, 1997; Fort, 2004). Similarly, the demand for concessions is higher if ticket prices are lower. The model consists of demand for tickets and a separate aggregate demand for non-ticket products and services (hereafter referred to as concessions) that is affected by ticket price. This is where the complementarity between the two demand functions occurs. The three models below describe increasing degrees of complexity for the relationship between ticket demand and concessions demand. As shown below, VTP policies should account for the extent to which complementarity exists between ticket demand and non-ticket demand.

For Model 1, let

$$Q_1 = \alpha_1 - \beta_1 P_1 \tag{1.1}$$

be the demand for tickets, where Q_1 is quantity demanded, P_1 is ticket price, and α_1 and β_1 are scalars describing the shape of the demand curve. In this model, the demand for concessions, Q_2, will be unaffected by ticket prices. The optimal revenue maximizing ticket price is

$$P_1^* = \frac{\alpha_1}{2\beta_1}. \tag{1.2}$$

The price elasticity of demand (η_{PQ}) at P_1^* and Q_1^*, where $Q_1^* = \frac{1}{2}\alpha_1$, is equal to negative one, a common result from microeconomic theory. Thus, in the model, price is chosen where $\eta_{PQ} = -1$. This model is applicable for teams that do not share in concessions revenues or simply receive a fixed annual payment for concessions rights from a vendor, perhaps having sold them up front to build a new stadium. In general, much of the costs associated with operating a baseball team are fixed costs. The marginal costs of selling an extra ticket are low; hence revenue maximization will be assumed in place of profit maximization. Relaxing this assumption adds a marginal cost term to the analysis, but does not change the fundamental findings. The marginal costs of MLB teams are unknown, and therefore the empirical analysis does not incorporate it.

Model 2 is applicable for teams that receive all or a share of concessions revenue. Let

$$Q_1 = \alpha_1 - \beta_1 P_1 \tag{2.1}$$

be ticket demand as in Model 1. Further, let $Q_2 = Q_1$, meaning that each person who purchases a ticket also buys some concessions. Moreover the price of concessions is exogenously determined by the concessionaire and will be noted by $\overline{P}_2$. Note that concessions do have a non-negligible marginal cost that affects total profitability. A more complete model would include marginal cost in the final optimal ticket price setting equation. However, this would add unnecessary complexity, and more importantly, make it more cumbersome to compare to Model 1 to see how price is affected. The resulting optimal revenue maximizing ticket price is

$$P_1^* = \frac{\alpha_1}{2\beta_1} - \frac{\overline{P}_2}{2}. \tag{2.2}$$

As seen in Equation 2.2, the revenue maximizing, or optimal, ticket price is lower when accounting for the price of concessions (and any other non-ticket products/services such as merchandise and parking) than it would be if it were set in a vacuum where only ticket revenue is accounted for, as in Equation 1.2. This is consistent with findings in the review of literature above. Specifically, $|\eta_{PQ}| = \left[{(\alpha_1 - \overline{P}_2)} \middle/ {(\alpha_1 + \beta_1 \overline{P}_2)} \right] < 1$, meaning that the elasticity for Model 2 is smaller in absolute value terms than for Model 1. The optimal ticket price is set in the inelastic portion of demand. Predictably, for low concessions prices, the impact of concessions revenue on ticket price decision making is minimized. In fact, $\overline{P}_2 \to 0, \eta_{PQ} \to -1$, which is the optimal price elasticity when not accounting for concessions revenues (Model 1).

Model 3 generalizes Models 1 and 2 by adding cross-price effects to ticket demand and concessions demand exhibiting the notion that the total price of attending a game is what matters to customers, not just ticket price. Therefore, let

$$Q_1 = \alpha_1 - \beta_1 P_1 - \gamma_1 \overline{P}_2 \tag{3.1}$$

be ticket demand, where γ_1 is the incremental effect of concessions prices on ticket demand. The demand for concessions will be shown by

$$Q_2 = \alpha_2 - \beta_2 \overline{P}_2 - \gamma_2 P_1 . \tag{3.2}$$

As noted in the equation, ticket price, P_1, affects the demand for concessions in a negative way. If ticket prices are raised, the demand for concessions declines based on γ_2, the marginal propensity to purchase concessions based on ticket price changes. The optimal revenue maximizing ticket price is

$$P_1^* = \frac{\alpha_1}{2\beta_1} - \frac{(\gamma_1 + \gamma_2)\overline{P}_2}{2\beta_1} , \tag{3.3}$$

with P_2 exogenous. Even though the concessionaire often sets concessions prices, removing this assumption does not change the direction of the impact, only the magnitude. Equation 3.3 shows that the ticket prices ought to be lower if fans care about concessions prices. Specifically, higher γ_1 or γ_2 leads to lower optimal ticket prices. The more sensitive customers are to the price of complementary goods and services, the lower ticket prices should be to maximize profits. Thus, it is important to account for cross-price effects when setting prices. Overall, the price elasticity for Model 3 may be higher or lower than for Model 2, depending on the relative magnitudes of β_1, γ_1, and γ_2. However, like Model 2, the absolute value of the price elasticity for Model 3 is lower than for Model 1. In the analysis that follows, variable pricing outcomes will be determined under two scenarios, one without the cross effects (Model 1) and one with the cross effects (Model 3). Again, Model 1 pertains to teams that either do not receive any concessions revenue or receive a fixed payment in exchange for concessions rights. Model 3 applies to teams that receive a share of concessions revenues.

To be clear, these models do not assume profit maximization, win maximization, or something else, only that a team's objectives are consistent throughout the season. For example, if a team is focused primarily on profits, it will set ticket and concessions prices in order to maximize the sum of both revenues. Similarly, if a team is attempting to maximize wins, it will still want to price as a profit-maximizer because its relevant costs are not variable. Such a team would likely spend more on players, in order to improve winning, than a profit-maximizing team. However, it will still want to set prices in order to maximize revenues from tickets and concessions anyway, just as a profit-maximizing team would. An exception to this argument is if a win-maximizing owner chose to price below profit-maximizing levels in order to raise attendance (even though it is lowering revenues) to increase the impact of home-field advantage, which would increase the likelihood of winning more games and, therefore, satisfy his/her objectives.

The models also do not need to assume linear demand functions. Linear demand is chosen for simplicity. As described in the next section, non-linear demand changes the magnitudes of the findings. Using linear demand generates more conservative findings – the gains to be had from variable pricing are lower under linear demand.

The empirical analysis operationalizes this by noting that whatever objective function an owner has (winning or profits or a combination of the two), it is assumed that prices are set to maximize those objectives. For a particular game it may be that prices are too low or too high given demand, but since one price is charged for the entire season, it is objective-maximizing on average.

One hypothesis stemming from these models is that adoption of variable ticket pricing would improve revenues for MLB teams. Another hypothesis is for those teams that are adjusting prices, the amount of adjustment is correct. For instance, the Cardinals had only raised their prices for VTP games by $2 for 2002. In contrast, the Rockies have had prices for particular seats that varied by as much as $6 (Rovell, 2002a). This analysis will provide a benchmark for how much teams should be adjusting their prices.

It is important to note that there are public relations issues that play a role in VTP. For example, the Nashville Predators have been thinking about incorporating VTP but fear a negative fan backlash at a time they are trying to build a loyal fan base (Cameron, 2002). A team therefore may opt to raise its prices only nominally to see if there is a backlash where fans react with an emotional response that actually shifts demand (not slides along demand as price changes are expected to do). This analysis ignores any public relations issues.

Methods

The first analysis tested Model 1 where only ticket pricing is accounted for, not concessions quantity and price. The methodology involved analyzing how demand for each game deviated from the average demand for each team. For example, as shown in Figure 1, point 'A' is on the average demand curve for the Atlanta Braves. It represents the actual average ticket price ($13.06) and average attendance (35,793). The slope of the demand curve is based on the assumption that the price elasticity equals -1.0 (This assumption can be relaxed without loss of generality. For instance, it can be assumed that the team prices on the inelastic portion of demand at, say, -0.75). Therefore, slope can be determined from price, quantity, and elasticity.

Insert Figure 1 about here.

Point 'B' is the actual price (still $13.06) and attendance (48,961) for the Braves home opener. This is the demand for that game given the price. Demand is known because looking at actual attendance reveals it. As described in the *Theoretical Foundations* section, ticket prices, on average, were optimal for the Braves. It was assumed that each team was doing its best at determining ticket prices and was setting them to account for the average expected demand for the entire season. Therefore, the price elasticity was set at -1.0 at point 'A'. At point 'B' the elasticity changed to –0.73, thus it is a sub-optimal price. Raising price to $15.46 (point 'C') changed the elasticity back to –1.0 and lowered attendance to 42,371. Revenue was then calculated for this new price and quantity and compared to the actual revenue from that game (measured by multiplying the actual average price charged for that game with the actual quantity of spectators for that game). These measurements were taken for each game of the season for each team in order to be able to see how adjusted ticket prices affect revenue. See the Appendix for a brief description of the calculations.

The example above used linear demand. If a slightly curved demand function is used, the gains from variable pricing would be higher because the loss in number of attendees is compensated by higher pricing due to the curvature of the demand function. As shown in Figure 2, the simplified demand function "Curved Increase" had an optimal price point at "D", while the linear demand function's optimal price point was "C". Table 3 provides the details of each of these demand functions. Each demand function was shifted the same amount (as shown by point "B"). Figure 3 shows the associated revenue at each point. The curved demand resulted in higher revenue ($18.52) from variable pricing (point "D") than for the linear demand ($16.00 at point "C"). Thus, an equal increase in the number of attendees will lead to lower gains using linear demand instead of curved demand. This is also true for a low demand game. Point “G” is the optimal price for the linear demand function and point “F” maximizes revenue for the curved demand. As shown in Table 3, the curved demand function resulted in higher revenues from variable ticket pricing. Intuitively, this was not surprising. For a given price, a curved demand function will result in more attendees (higher quantity) than a linear demand function. A constant elasticity of demand function (CED) has more curvature than the ones shown in Figure 2. Revenue is constant regardless of price for CED. Prices can be set at any level and yield the same revenue. CED is an unrealistic demand function for baseball. An even more extreme demand function, a super-curved demand in which the degree of curvature is greater than that for CED, is such that the revenue function looks U-shaped, not hill-shaped as in Figure 3. In that case, revenue maximizing prices are either very low or very high, and unlikely to be consistent with reality in baseball. An example of this type of demand function is $P = 1/\ln(Q)$. The use of linear demand in the subsequent analysis is conservative in that the gains from variable pricing are a lower bound of what would be the case if demand functions for baseball are curved. This reason, along with simplicity and a lack of research about the shape of baseball demand functions, was justification for using linear demand in the following analysis. Parallel shifts of the demand function were also assumed because of simplicity and a lack of relevant research showing other types of shifts. 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.

Insert Figures 2 and 3 and Table 3 about here

The subsequent analysis accounted for the possibility that the capacity of a stadium prevented the true demand from being revealed. In other words, sellouts typically imply that there was excess demand beyond the capacity of the stadium. The standard result would be to raise prices until the entire stadium is full and there are no persons outside who are interested in attending the game at the new raised ticket price. In order to determine how much to raise prices, the amount of excess demand needed to be estimated. This was done utilizing a censored regression, which can forecast the true demand as if there were not a capacity constraint. It used information from uncensored observations (those without a capacity constraint as shown by not having sold out) to estimate what would have happened without the constraint.

The censored regression used attendance as the dependent variable and various demand factors listed in the second data set described below as the independent variables. The result was an empirical model that can be used to forecast what attendance would have been for the capacity constrained games. The methodology was the same as the first analysis, but used the new forecasted attendance when estimating optimal prices and resulting revenue.

The final analysis included the focus of Model 3, that the prices of complementary goods (tickets and concessions) affect the demand, and hence optimal price, for each other. This analysis created a single demand for the joint product of tickets and concessions, with concessions price exogenously determined. According to *Financial World*, these non-ticket revenues made up 35% of ticket plus non-ticket revenues for MLB teams during 1996 (Badenhausen & Nikolov, 1997). For every dollar spent at a stadium by a patron, thirty-five cents were spent on concessions, merchandise and parking. Therefore, the non-ticket price for each team was set at 54% (54% = 35%/[1-35%]) of the ticket price as team-specific data on non-ticket revenue was unavailable. Given this new joint demand function, optimal prices were set for each game as in the two previous analyses. The censored regression forecasts of attendance were used in this analysis. This analysis accounted for the combined product of tickets and concessions, so as a group the demand elasticity was -1. Given that the concessions price was fixed and positive, the new optimal ticket price would be on the inelastic portion of demand. This was consistent with the findings in the literature.

These three analyses determined the optimal variable ticket price for nearly every game for the 1996 MLB season. The 1996 season was used because during that year no MLB team utilized variable ticket pricing. It should be noted that 1996 was the first full season after the strike of 1994-95. It is possible that the findings here are not typical of a season in Major League Baseball. However, an important factor in this analysis is the shift in demand from game to game. Compared with 2003, attendance for the 1996 season has a standard deviation that is only 5% greater than attendance for 2003. The use of more recent data, which would include teams using VTP, raised validity concerns with the attempt to predict additional revenue generated through the use of VTP. The use of the 1996 data allow the analysis to be consistent across all teams. The analysis showed what ticket price should have been charged with the corresponding results had every team participated in optimal VTP. In order to achieve this, data for 2,193 of the 2,268 scheduled regular season games was used. The few games not used in the analysis either lacked sufficient data, were double-headers, or were rainouts that were never made up.

The data was broken into two sets. One set was used to forecast optimal VTP. It included actual attendance, average ticket price, stadium capacity, and average concessions expenditures. Attendance data came from www.sportsline.com, ticket price data from *Team Marketing Report*, stadium capacity data from www.ballparks.com, and concessions information from *Financial World*'s financial report on baseball for the 1996 season (Badenhausen & Nikolov, 1997). Table 2 (columns 1 & 4) shows average attendance and average ticket price for each team for the 1996 season.

The second set of data was used to make an adjustment to demand for games that are censored by capacity constraints, namely games that are sold out or nearly sold out. This adjusted demand was then used in the VTP analysis. This data set contained actual attendance, the number of wins by the home team and visiting team in the previous season, the population of the local CMSA, indicator variables for opening day, a new stadium, a weekend game, and a game in April. All data for this data set came from www.sportsline.com except population, which was obtained from the U.S. Census Bureau. Table 4 contains summary statistics of the data.

Insert Table 4 about here

Results

Based on the estimates from the test of Model 1, had the Atlanta Braves, for example, raised ticket prices for the opening game, actual attendance would have been 42,371 with actual ticket revenues increasing by $15,817 or 2.5% for that game. An elasticity of –1.0 implies revenue maximization. Yet, the analysis could have begun with any elasticity as long as the resulting elasticity at point 'C' is the same as that at point 'A' (see Figure 1). Therefore, this does not require revenue maximization or profit maximization, only consistency in terms of the objectives of the franchise throughout the season.

Continuing with the Braves example, Table 5 shows the results for every odd home game. The findings show that there are fewer games that have excess demand (although they have a higher average excess demand) than there are games that have lower demand than average (Figure 4). In fact, 30 out of 81 Braves home games had demand exceed the average, and the average optimal price increase is estimated to be 11.0% while the average decreased price is estimated to be -6.5%. Also, as expected, the high demand games generally are for an entire series. Thus, one VTP strategy for the Braves would be to variable price for some high demand series and simply lower prices on the other games in general (as a public relations move and to increase overall revenues).

Insert Table 5 and Figure 4 about here

The bottom row of Table 5 shows the average results for the entire Braves season. The average per game revenue increase for the season is $4,367 or 0.9%. The results for each team are shown in Table 2. Columns 8 and 12 show the result from Table 5 for the Braves. Over the course of the full season, the Braves could have increased their ticket revenues by $353,706 or 0.9%.

Variable pricing would have yielded an average of approximately $504,000 per year in additional revenue for each Major League team, *ceteris paribus*, or over $14 million for the league as a whole. This amounts to only about a 2.6% increase above what occurs when prices are not varied, as shown in Table 2. The amount of variation in ticket prices is just over 11%, on average. That such a large price swing only yields a revenue swing four times smaller is simply based on the large change in attendance that occurs when prices are varied. This occurs with all downward sloping demand curves, and is not unique to baseball. For the 1996 season, the largest revenue gain would have been for the New York Yankees, which would have generated an extra $1.24 million in ticket revenue, or a 3.7% increase. The largest percentage revenue gain would have been for the San Francisco Giants. The Giants would have seen an estimated 6.7% increase in revenue, or $1.01 million, had they used optimal VTP. The smallest amount of impact would have been for the Colorado Rockies, which averaged only plus or minus eighty patrons in absolute deviation from the mean attendance per game throughout the 1996 season. In fact, teams with the lowest average attendance benefit the most from variable pricing. This is not surprising since those teams tend to have the highest variation in attendance allowing them to gain from dynamic pricing.

The reason that the Rockies would apparently gain the least from VTP is that it had many sellouts in 1996. As described in the *Methodology* section, a censored regression is carried out in order to forecast the true demand above the capacity constraint. While there are many more factors that affect game-by-game attendance than those used here, this analysis used only those factors known prior to the time ticket price setting occured. Thus, only factors known prior to the beginning of the season are used to be consistent with what would be known by team management when setting prices. The Wald Chi-squared test of significance showed that the model was significant at the 0.001% level with a Wald statistic of 906.6. A potential problem is that the errors for a series between two teams may not be independent. It is expected that across different groups of games (a three game series for example) there exists independence of the errors, but not necessarily within each group. This type of clustered correlation leads to understating the standard errors. A robust estimator of the variance is used to correct the standard errors. There is no evidence of multicollinearity among the independent variables. As expected, there is evidence of omitted variables missing from the regression. As explained above, performance-specific factors that are only known to price setters once the season has begun, such as the home pitcher's earned run average at that point during the season, were omitted. The variance-inflation factor (VIF) averaged 1.19 across the group of variables tested for multicollinearity, with the largest VIF at 1.58. The Ramsey RESET test shows evidence of omitted variables with an F-statistic of 29.67.

Table 6 shows the results of the censored regression. The signs of the coefficients are as expected. Out of 2,193 games, only 109 were sold out. A sellout for these purposes is defined as any game where actual attendance is 99.0% or higher of stadium capacity. The estimate of attendance for these 109 games is based on the predicted values from the censored regression.

Insert Table 6 about here

As shown in Table 7, ten teams had adjustments to their attendance based on the censored regression. The results are similar to that for Table 2 except column 13 shows the gain for those ten teams, versus Table 2, if they account for the capacity constraint when adjusting their prices for their VTP strategy. Overall, adjusting for demand beyond stadium capacity raises the increased revenue from VTP policies from $14.1 million to $16.5 million for the league as a whole.

Insert Table 7 about here.

The final analysis addressed Model 3 from the *Theoretical Foundations* section by accounting for non-ticket revenues such as concessions, merchandise, and parking. Table 8 shows the results of allowing the team to vary ticket prices while accounting for non-ticket prices in order to maximize its objectives.

Insert Table 8 about here.

Columns 9, 10, and 11 in Table 8 illustrate that the average team would have gained $911,000 in ticket and non-ticket revenue by adopting a variable ticket pricing policy while accounting for non-ticket prices. The league overall would have gained $25.5 million. The Cleveland Indians would have earned the most, over $2.2 million, from such a policy.

Discussion

This analysis has shown that Major League Baseball could have increased ticket revenues by approximately 2.8%, or $16.5 million, and total stadium revenues by about $25.5 million for the 1996 season if teams utilized VTP. Total revenues in MLB are estimated to have grown from $1.78 billion in 1996 to approximately $4.3 billion in 2003, or 250%. Similar changes in the effect of VTP strategies as discovered in this study would yield nearly $40 million in ticket revenue and over $60 million in ticket plus non-ticket revenue for MLB. Therefore, it behooves team owners and the league office to consider and implement VTP strategies, especially since teams and the league are constantly searching for ways to increase revenues.

The San Francisco Giants would have seen an estimated 6.7% increase in ticket revenue, or $1.01 million, had they used optimal VTP in 1996. Interestingly, the Giants had considered utilizing variable ticket pricing since the 1996 season because they had noticed a huge variation in attendance patterns at Candlestick Park, the team's then-home facility (King, 2002a). In addition to weather issues (pleasant for day games, frigid for night contests) in their facility, the Giants of the mid-1990s occasionally fielded teams of lower quality. The results of this study would strongly suggest that teams in similar facility or on-the-field talent situations maximize their revenues through VTP.

The results of this study support the utilization of VTP both to increase as well as decrease prices from average seasonal levels. The data showed fewer games with excess demand than those with diminished demand. However, the selected games with excess demand deviated from the mean at a greater rate than those with decreased demand. Currently, most MLB teams have focused their VTP strategies on the revenue potential of increased prices from highly demanded games (King, 2002a). However, it appears that some teams have begun to realize the potential benefit of attracting fans to less desirable contests by lowering prices (King, 2002b). The New York Yankees sold $5 tickets in certain sections of Yankee Stadium on Mondays, Tuesdays, and Thursdays in 2003 (King, 2003).

Lowering ticket prices for less desirable games would potentially create more positive relationships between teams and local municipalities. Major League Baseball teams have often been chastised for seeking subsidies for new revenue generating facilities that are financially inaccessible to many taxpayers (Pappas, 2002; O'Keefe, 2004). Given the number of games in a typical season that have demand below the yearly average (Figure 4), lowering prices creates an opportunity for teams to potentially attract new or disenfranchised fans and presents local governments with a more favorable reaction to their public policy decisions supporting the local franchise. Marketing less desirable games with lower ticket prices as "value" games, as the Chicago Cubs, Colorado Rockies, New York Mets, Tampa Bay Devil Rays, and Toronto Blue Jays did in 2004, allows teams to reach market segments perhaps otherwise unreachable due to pricing/income issues, in addition to the aforementioned public relations benefits.

Currently, teams might not want to implement multiple price points for each game as shown in Figure 4. As discussed in Levy, Dutta, Bergen and Venable (1997), *menu costs* affect the frequency and desire to change prices to reflect changes in demand or supply. *Menu costs* are costs associated with physically changing prices on products, having to look up prices to tell a customer the price for a particular game, or more generally any costs associated with having more than one price for a product or service. Additionally, asymmetric information, search costs, and simple confusion for customers regarding the price for different games may cause franchises to have fewer prices for a particular seat throughout the season than variable pricing predicts. For this reason, many teams have only utilized a minimal number of ticket-pricing tiers, usually two-to-four, in their variable ticket pricing system (Rovell, 2002a)

Confusion and the additional costs associated with changing ticket prices may already be in the process of being eliminated. Kevin Fenton, Colorado Rockies senior director of ticket operations, noted that once the initial confusion regarding multiple price points for games is overcome, patrons realize that tickets can be priced like other industries (Rovell, 2002a). In the near future, the negative fan reaction to changing ticket price will likely be alleviated if not eliminated (Adams, 2003). Ticket offices are also now better equipped to handle menu costs issues. Although ticket offices were not prepared to handle extensive variable ticket pricing in the 1990s, recent technological advances have allowed most American professional sport teams to implement new ticket policies such as bar coded and print-at-home tickets and to prepare for extensive variable ticket pricing in the future (Zoltak, 2002).

An initial VTP recommendation is that for every 10% increase in attendance (or specifically, expected attendance) above the average, teams should raise ticket prices by 5% and receive a gain of 1.2% in ticket revenue. The practical use of variable pricing, however, would entail creating at most five different prices for each seat in a stadium throughout the season, not a different price for each game. High demand games or series should be priced accordingly, but teams should not forget the potential benefits of lowering price for less desired games. The present findings reinforce previous research identifying factors such as day of the week or rivalry game as affecting demand for MLB tickets.

Using the Atlanta Braves again as an example, the average attendance was 35,793. Based upon the variable pricing ticket prices from Table 5, the recommended pricing schedule for 1996 would have been $12.00, $13.06, and $15.50. A descriptive analysis of Braves attendance revealed three tiers of games that corresponded with the three price points: games with attendance below 28,831 (greater than -1 SD from the mean), games with an attendance of 28,832 to 42,755 (between 1 and -1 SD from the mean), and games with an attendance over 42,756 (greater than 1 SD from the mean). A factor analysis of games falling within each tier was then performed to finalize the recommended pricing schedule.

For the Braves, a Tier One game (average price of $12.00) would have included games from the second game of the season to May 14, played Sunday to Thursday. Fifteen games would have therefore been classified as Tier One. A Tier Three game (average price of $15.50) would have included all games played on Saturday, opening day, the July 4 game, the final home stand of the season, and games played after May 14 against the Los Angeles Dodgers, a former division rival. Twenty-two games would have fallen into this tier. The remaining 44 games would have been classified Tier Two with an average ticket price of $13.06, which was the average ticket price for the 1996 season.

The hypothesis that the few teams that are administering variable ticket pricing are doing so properly is consistent with the findings. In fact, the present analysis shows that optimal variable ticket pricing is managed by small changes in ticket prices. The Giants expected to gain an additional $1 million from variable ticket pricing in 2002 (Isidore, 2002; Rovell, 2002a). The Giants VTP strategy in 2002 affected only 39 of their 81 home games (all weekend dates). The present analysis shows a gain of about $1 million for the 1996 season if optimal pricing were used by the Giants.

In 2002, the Atlanta Braves instituted a VTP strategy for 21 home games – Fridays from May through August and Saturdays throughout the whole season. During these games ticket prices were increased by $3, or about 14%. Testing the same policy for the 1996 data, the Atlanta Braves would have 22 home games with VTP utilizing a

9% increase in price. Interestingly, the Braves actual policy is more aggressive than the data show for 1996. The St. Louis Cardinals raised prices in 2002 for summer games by $2, or 8%. The 1996 data show that an optimal VTP strategy would raise prices by about 9%.

Directions for Future Research

There are many areas of inquiry for the future. An analysis of more recent data that include teams utilizing VTP is warranted. The practical application of VTP requires one to be able to accurately forecast the relative attendance of future games. In other words, in order to know which games to have higher prices for and which games to have lower prices for, team management needs to know whether there is consistency from one season to the next in terms of relative attendance. An interesting behavioral issue is whether the implementation of VTP in earlier games affects the demand for subsequent games.

One factor unaccounted for in this study is the marketing strategies utilized by organizations in conjunction with VTP price levels. The projected revenue increases identified in this study could potentially be increased substantially by incorporating VTP pricing into teams' marketing plans. Although many MLB teams assign each game/product into VTP levels based on game/product characteristics, little research has investigated how those games of varying characteristics are marketed to different demographic segments of consumers.

In addition, research investigating education and public relations activities related to variable ticket pricing should be conducted. Although fans may initially perceive variable pricing as a gauging mechanism, for some fans variable ticket pricing may allow some “expensive” games to now become more affordable. Methods to assuage consumer fears and to attract potentially new consumers should be researched. Additionally, implementation costs of VTP programs, such as menu costs and staff training, should be examined and accounted for in future economic examinations of VTP.

Finally, future research should investigate the practical application and public reaction to future variable pricing systems utilizing technology to change prices by the day, hour, or even minute. Few teams have implemented VTP at this point, believing that widespread use of ticket pricing based completely on supply and demand would not be met with agreement by some consumers (Cameron, 2002). In particular, research should be conducted to identify methods to protect or enhance value to season ticket purchasers when a minute-by-minute VTP policy is implemented.

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Appendix

In order to calculate the new price and quantity where revenue is maximized ($\eta = -1$) when the demand curve shifts, refer to Figure 1 at Point A and let

$Q_A = 35{,}793$, $P_A = \$13.06$, and set $\eta_A = (P_A / Q_A) * (\Delta Q_A / \Delta P_A) = -1$.

At Point C, let

$Q_C = (Q_A + Q_B)/2 = (35{,}793 + 48{,}961)/2 = 42{,}377$,
$P_C = \eta_A * Q_C * (-P_A / Q_A) = -1 * 42{,}377 * (-\$13.06/35{,}793) = \$15.46$

The results for the new price and quantity rely on two attributes of linear demand functions. First, the optimal quantity (Q_C) is simply the average of the old quantity (Q_A) and the new actual quantity (Q_B). Second, the new optimal price utilizes the elasticity formula, $\eta_C = (P_C / Q_C) * (\Delta Q_A / \Delta P_A) = -1$, and solves for P_A. A key substitute is to note that $(\Delta Q_A / \Delta P_A) = -P_A / Q_A$, because the inverse of the slope is constant for the old demand and new demand. Also, P_A and Q_A are given, and η_A is set equal to -1. This can be seen in the elasticity formula from above, $\eta_A = (P_A / Q_A) * (\Delta Q_A / \Delta P_A) = -1$.

Table 1

2004 MLB Variable Ticket Pricing Programs[a]

Team	Levels	Levels (price for typical outfield bleacher seats)
Arizona Diamondbacks	3	Premier ($18), Weekend ($15), Weekday ($13)
Atlanta Braves	2	Premium ($21), Regular ($18)
Chicago Cubs	3	Prime ($35), Regular ($26), Value ($15)
Chicago White Sox	2	Weekend ($26), Weekday ($22)
Colorado Rockies	4	Marquee ($21), Classic ($19), Premium ($17), Value ($11)
New York Mets	4	Gold ($16), Silver ($14), Bronze ($12), Value ($5)
San Francisco Giants	2	Friday-Sunday ($21), Monday-Thursday ($16)
Tampa Bay Devil Rays	3	Prime ($20), Regular ($17), Value ($10)
Toronto Blue Jays	3	Premium ($26), Regular ($23), Value ($15)

Note. Different seating configurations of each stadium make comparing like seats difficult; however, this attempt was made to provide the reader with an idea of the range of price levels used by each team for similar seats.

[a]Source: www.mlb.com.

Table 2

Summary of Effects of Variable Ticket Pricing (no capacity or non-ticket revenue adjustment)

	Avg. Attendance (1)	Avg. Absolute Change (2)	Avg. Deviation from Mean (3)	Avg. Ticket Price (4)	Avg. Absolute Change in Price (5)	Avg. Actual Ticket Revenue (6)	Avg. Var. Pricing Ticket Revenue (7)	Avg. Change in Ticket Revenue (8)	Total Actual Ticket Revenue (9)	Total Var. Pricing Ticket Revenue (10)	Total Change in Ticket Revenue (11)	% Change in Revenue (12)
Atlanta	35,793	5,832	16.3%	$13.06	8.1%	$467,458	$471,825	$4,367	$37,864,102	$38,217,807	$353,706	0.9%
Baltimore	45,475	1,930	4.2%	$13.14	2.1%	$597,539	$597,909	$371	$48,400,634	$48,430,660	$30,026	0.1%
Boston	28,687	3,847	13.4%	$15.43	6.7%	$442,643	$445,436	$2,794	$35,854,064	$36,080,352	$226,288	0.6%
California	22,476	4,899	21.8%	$8.44	10.9%	$189,697	$193,539	$3,842	$15,365,441	$15,676,653	$311,212	2.0%
Chicago (AL)	21,115	4,530	21.5%	$14.11	10.7%	$297,927	$303,781	$5,854	$24,132,054	$24,606,230	$474,176	2.0%
Chicago (NL)	28,606	6,854	24.0%	$13.12	12.0%	$375,309	$382,932	$7,622	$30,400,069	$31,017,468	$617,399	2.0%
Cincinnati	24,097	4,492	18.6%	$7.95	9.3%	$191,568	$194,618	$3,049	$15,517,036	$15,764,032	$246,996	1.6%
Cleveland	41,983	512	1.2%	$14.52	0.6%	$609,592	$609,629	$37	$49,376,968	$49,379,960	$2,992	0.0%
Colorado	48,037	80	0.2%	$10.61	0.1%	$509,675	$509,679	$4	$41,283,673	$41,284,030	$357	0.0%
Detroit	14,464	5,018	34.7%	$10.60	17.3%	$153,322	$162,531	$9,209	$12,419,066	$13,165,021	$745,954	6.0%
Florida	21,839	4,541	20.8%	$10.37	10.4%	$226,469	$230,737	$4,268	$18,343,988	$18,689,707	$345,720	1.9%
Houston	24,394	7,362	30.2%	$10.65	15.1%	$259,793	$268,433	$8,640	$21,043,206	$21,743,062	$699,856	3.3%
Kansas City	17,949	4,013	22.4%	$9.74	11.2%	$174,828	$178,510	$3,682	$14,161,039	$14,459,292	$298,253	2.1%
Los Angeles	39,364	7,038	17.9%	$9.94	8.9%	$391,274	$395,669	$4,394	$31,693,231	$32,049,165	$355,934	1.1%
Milwaukee	16,847	5,594	33.2%	$9.37	16.6%	$157,853	$165,387	$7,535	$12,786,054	$13,396,356	$610,302	4.8%
Minnesota	17,930	4,899	27.3%	$10.16	13.7%	$182,170	$188,905	$6,735	$14,755,746	$15,301,288	$545,542	3.7%
Montreal	19,982	7,149	35.8%	$9.07	17.9%	$181,240	$190,229	$8,989	$14,680,457	$15,408,584	$728,127	5.0%
New York (AL)	28,371	8,999	31.7%	$14.58	15.9%	$413,655	$428,965	$15,310	$33,506,040	$34,746,176	$1,240,136	3.7%
New York (NL)	20,260	4,610	22.8%	$11.83	11.4%	$239,676	$245,833	$6,157	$19,413,778	$19,912,512	$498,734	2.6%
Oakland	14,339	5,183	36.1%	$11.34	18.1%	$162,607	$171,942	$9,335	$13,171,166	$13,927,263	$756,097	5.7%
Philadelphia	23,077	4,679	20.3%	$11.01	10.1%	$254,072	$258,556	$4,483	$20,579,872	$20,943,035	$363,163	1.8%
Pittsburgh	17,039	5,914	34.7%	$10.09	17.4%	$171,919	$179,698	$7,779	$13,925,450	$14,555,555	$630,106	4.5%
San Diego	27,258	10,474	38.4%	$9.88	19.2%	$269,311	$284,010	$14,698	$21,814,230	$23,004,773	$1,190,543	5.5%
San Francisco	17,548	6,898	39.3%	$10.61	19.7%	$186,182	$198,697	$12,515	$15,080,772	$16,094,448	$1,013,676	6.7%
Seattle	33,593	9,398	28.0%	$11.59	14.0%	$389,349	$400,760	$11,411	$31,537,236	$32,461,526	$924,289	2.9%
St. Louis	32,912	6,038	18.3%	$9.91	9.2%	$326,153	$330,616	$4,463	$26,418,415	$26,779,886	$361,472	1.4%
Texas	36,111	6,664	18.5%	$11.96	9.2%	$431,888	$437,077	$5,189	$34,982,929	$35,403,253	$420,324	1.2%
Toronto	31,600	2,718	8.6%	$13.93	4.3%	$440,190	$441,845	$1,655	$35,655,410	$35,789,472	$134,063	0.4%
Average	26,827	5,363	22.9%	$11.32	11.4%	$310,477	$316,705	$6,228	$25,148,647	$25,653,127	$504,480	2.62%

Note: The total change in ticket revenue accounting for VTP across MLB is $14.1 million.

Table 3

Difference in revenue gain from non-linear demand versus linear demand

Model	Demand Function	Price	Quantity	Revenue	Corresponding Point on Graph	Gain in Revenue from New Price vs. Using Old Price
Linear	P=8-4Q	$ 4.00	1.00	$ 4.00	A	N/A
Curved	$P=(Q-3)^2$	$ 4.00	1.00	$ 4.00	A	N/A
Linear Increase	P=16-4Q	$ 8.00	2.00	$ 16.00	C	33.33%
	P=16-4Q at old price	$ 4.00	3.00	$ 12.00	B	N/A
Curved Increase	$P=(Q-5)^2$	$ 11.11	1.67	$ 18.52	D	54.32%
	$P=(Q-5)^2$ at old price	$ 4.00	3.00	$ 12.00	B	N/A
Linear Decrease	P=6-4Q	$ 3.00	0.75	$ 2.25	G	12.50%
	P=6-4Q at old price	$ 4.00	0.50	$ 2.00	E	N/A
Curved Decrease	$P=(Q-2.5)^2$	$ 2.78	0.83	$ 2.31	F	15.74%
	$P=(Q-2.5)^2$ at old price	$ 4.00	0.50	$ 2.00	E	N/A

Table 4

Summary Statistics of the Censored Regression Data

	Mean	Std. Dev	Min	Max
Game Attendance	26,868	11,852	6,021	57,467
Home Team Previous Season's Wins	81.92	10.02	56	100
Visiting Team Previous Season's Wins	81.99	10.11	56	100
Opening Day	0.008	0.090	0	1
Weekend Game	0.477	0.499	0	1
New Stadium	0.215	0.411	0	1
Population of CMSA	5,997,132	4,774,503	1,640,831	18,107,235
Game is Played During April	0.162	0.368	0	1

Table 5

Summary of Atlanta Braves Game-by-Game Variable Pricing Outcomes (odd-numbered games are shown to save space)

Game Number	Attendance	Difference from Avg.	Percentage Change from Avg.	Variable Pricing Attendance	Avg. Ticket Price for Season	Variable Pricing Ticket Price	Percentage Price Change	Actual Revenue	Variable Pricing Revenue	Revenue Increase	% Revenue Increase
1	48,961	13,168	36.8%	42,377	$13.06	$15.46	18.4%	$639,431	$655,247	$15,817	2.5%
3	30,271	-5,522	-15.4%	33,032	$13.06	$12.05	-7.7%	$395,339	$398,121	$2,782	0.7%
5	34,649	-1,144	-3.2%	35,221	$13.06	$12.85	-1.6%	$452,516	$452,635	$119	0.0%
7	26,635	-9,158	-25.6%	31,214	$13.06	$11.39	-12.8%	$347,853	$355,504	$7,651	2.2%
9	25,300	-10,493	-29.3%	30,547	$13.06	$11.15	-14.7%	$330,418	$340,462	$10,044	3.0%
11	31,893	-3,900	-10.9%	33,843	$13.06	$12.35	-5.4%	$416,523	$417,910	$1,388	0.3%
13	33,080	-2,713	-7.6%	34,437	$13.06	$12.57	-3.8%	$432,025	$432,696	$671	0.2%
15	37,697	1,904	5.3%	36,745	$13.06	$13.41	2.7%	$492,323	$492,653	$331	0.1%
17	35,471	-322	-0.9%	35,632	$13.06	$13.00	-0.4%	$463,251	$463,261	$9	0.0%
19	29,976	-5,817	-16.3%	32,885	$13.06	$12.00	-8.1%	$391,487	$394,573	$3,087	0.8%
21	28,583	-7,210	-20.1%	32,188	$13.06	$11.74	-10.1%	$373,294	$378,036	$4,742	1.3%
23	30,917	-4,876	-13.6%	33,355	$13.06	$12.17	-6.8%	$403,776	$405,945	$2,169	0.5%
25	49,553	13,760	38.4%	42,673	$13.06	$15.57	19.2%	$647,162	$664,433	$17,271	2.7%
27	29,984	-5,809	-16.2%	32,889	$13.06	$12.00	-8.1%	$391,591	$394,669	$3,078	0.8%
29	33,186	-2,607	-7.3%	34,490	$13.06	$12.58	-3.6%	$433,409	$434,029	$620	0.1%
31	32,199	-3,594	-10.0%	33,996	$13.06	$12.40	-5.0%	$420,519	$421,697	$1,178	0.3%
33	39,463	3,670	10.3%	37,628	$13.06	$13.73	5.1%	$515,387	$516,615	$1,229	0.2%
35	49,726	13,933	38.9%	42,760	$13.06	$15.60	19.5%	$649,422	$667,129	$17,708	2.7%
37	32,934	-2,859	-8.0%	34,364	$13.06	$12.54	-4.0%	$430,118	$430,864	$746	0.2%
39	34,823	-970	-2.7%	35,308	$13.06	$12.88	-1.4%	$454,788	$454,874	$86	0.0%
41	49,365	13,572	37.9%	42,579	$13.06	$15.54	19.0%	$644,707	$661,509	$16,802	2.6%
43	31,971	-3,822	-10.7%	33,882	$13.06	$12.36	-5.3%	$417,541	$418,874	$1,333	0.3%
45	33,186	-2,607	-7.3%	34,490	$13.06	$12.58	-3.6%	$433,409	$434,029	$620	0.1%
47	49,060	13,267	37.1%	42,427	$13.06	$15.48	18.5%	$640,724	$656,779	$16,055	2.5%
49	41,619	5,826	16.3%	38,706	$13.06	$14.12	8.1%	$543,544	$546,640	$3,096	0.6%
51	33,208	-2,585	-7.2%	34,501	$13.06	$12.59	-3.6%	$433,696	$434,306	$610	0.1%
53	36,953	1,160	3.2%	36,373	$13.06	$13.27	1.6%	$482,606	$482,729	$123	0.0%
55	32,708	-3,085	-8.6%	34,251	$13.06	$12.50	-4.3%	$427,166	$428,035	$868	0.2%
57	32,036	-3,757	-10.5%	33,915	$13.06	$12.37	-5.2%	$418,390	$419,678	$1,288	0.3%
59	32,401	-3,392	-9.5%	34,097	$13.06	$12.44	-4.7%	$423,157	$424,207	$1,050	0.2%
61	46,064	10,271	28.7%	40,929	$13.06	$14.93	14.3%	$601,596	$611,219	$9,623	1.6%
63	39,210	3,417	9.5%	37,502	$13.06	$13.68	4.8%	$512,083	$513,148	$1,065	0.2%
65	31,587	-4,206	-11.8%	33,690	$13.06	$12.29	-5.9%	$412,526	$414,140	$1,614	0.4%
67	29,213	-6,580	-18.4%	32,503	$13.06	$11.86	-9.2%	$381,522	$385,471	$3,950	1.0%
69	38,210	2,417	6.8%	37,002	$13.06	$13.50	3.4%	$499,023	$499,555	$533	0.1%
71	35,176	-617	-1.7%	35,485	$13.06	$12.95	-0.9%	$459,399	$459,433	$35	0.0%
73	47,130	11,337	31.7%	41,462	$13.06	$15.13	15.8%	$615,518	$627,242	$11,724	1.9%
75	32,109	-3,684	-10.3%	33,951	$13.06	$12.39	-5.1%	$419,344	$420,582	$1,238	0.3%
77	37,193	1,400	3.9%	36,493	$13.06	$13.32	2.0%	$485,741	$485,919	$179	0.0%
79	49,265	13,472	37.6%	42,529	$13.06	$15.52	18.8%	$643,401	$659,956	$16,555	2.6%
81	49,083	13,290	37.1%	42,438	$13.06	$15.48	18.6%	$641,024	$657,135	$16,111	2.5%
Avg. [1]	35,793	5,832	16.3%	35,793	$13.06	$13.06	8.1%	$467,458	$471,825	$4,367	0.9%

[1]The averages in the last row are averages of the absolute value of each number.

Table 6

Censored Regression Results to Create Forecasts for Capacity Constrained Attendance

Dependent Variable	Game-by-Game Attendance
Number of observations	2193
Number of uncensored observations	2084
Wald Chi^2	906.60
Prob > Chi^2	0.000
Log Likelihood	-21,989.20

					95% Confidence Interval	
	Coefficient	Std.Error	z	P>|z|	Lower Bound	Upper Bound
Constant Term	-28,220.88	5,587.69	-5.05	0.00	-40,513.80	-15,927.96
Home Team Last Season's Wins	512.18	32.97	15.53	0.00	439.65	584.72
Visiting Team Last Season's Wins	138.59	33.14	4.18	0.00	65.68	211.50
Opening Day	14,522.00	3,024.93	4.80	0.00	7,867.16	21,176.84
Weekend Game	6,182.30	357.90	17.27	0.00	5,394.92	6,969.68
New Stadium	13,208.40	1,197.69	11.03	0.00	10,573.48	15,843.32
Population of CMSA	0.000053	0.0000090	5.84	0.00	0.000033	0.000073
Game is Played During April	-3,045.52	745.38	-4.09	0.00	-4,685.36	-1,405.68

Table 7

Summary of Effects of Variable Ticket Pricing (with capacity adjustment, no non-ticket revenue adjustment)

	Avg. Attendance (1)	Avg. Absolute Change (2)	Avg. Deviation from Mean (3)	Avg. Ticket Price (4)	Avg. Absolute Change in Price (5)	Avg. Actual Ticket Revenue (6)	Avg. Var. Pricing Ticket Revenue (7)	Avg. Change in Ticket Revenue (8)	Total Actual Ticket Revenue (9)	Total Var. Pricing Ticket Revenue (10)	Total Change in Ticket Revenue (11)	% Change in Revenue (12)	Change in Revenue vs. VTP w/o capacity adj. (13)
Atlanta	35,793	5,878	16.4%	$13.06	8.2%	$467,458	$472,549	$5,091	$37,864,102	$38,276,489	$412,387	1.1%	$58,682
Baltimore	45,475	2,098	4.6%	$13.14	2.3%	$597,539	$600,204	$2,665	$48,400,634	$48,616,492	$215,859	0.4%	$185,832
Boston	28,687	3,952	13.8%	$15.43	6.9%	$442,643	$447,216	$4,574	$35,854,064	$36,224,534	$370,470	1.0%	$144,182
California	22,476	4,899	21.8%	$8.44	10.9%	$189,697	$193,539	$3,842	$15,365,441	$15,676,653	$311,212	2.0%	$0
Chicago (AL)	21,115	4,530	21.5%	$14.11	10.7%	$297,927	$303,781	$5,854	$24,132,054	$24,606,230	$474,176	2.0%	$0
Chicago (NL)	28,606	7,044	24.6%	$13.12	12.3%	$375,309	$385,912	$10,603	$30,400,069	$31,258,882	$858,813	2.8%	$241,414
Cincinnati	24,097	4,549	18.9%	$7.95	9.4%	$191,568	$195,364	$3,796	$15,517,036	$15,824,475	$307,439	2.0%	$60,442
Cleveland	41,983	1,716	4.1%	$14.52	2.0%	$609,592	$627,443	$17,851	$49,376,968	$50,822,889	$1,445,921	2.9%	$1,442,929
Colorado	48,037	144	0.3%	$10.61	0.1%	$509,675	$510,365	$690	$41,283,673	$41,339,542	$55,869	0.1%	$55,512
Detroit	14,464	5,018	34.7%	$10.60	17.3%	$153,322	$162,531	$9,209	$12,419,066	$13,165,021	$745,954	6.0%	$0
Florida	21,839	4,541	20.8%	$10.37	10.4%	$226,469	$230,737	$4,268	$18,343,988	$18,689,707	$345,720	1.9%	$0
Houston	24,394	7,362	30.2%	$10.65	15.1%	$259,793	$268,433	$8,640	$21,043,206	$21,743,062	$699,856	3.3%	$0
Kansas City	17,949	4,013	22.4%	$9.74	11.2%	$174,828	$178,510	$3,682	$14,161,039	$14,459,292	$298,253	2.1%	$0
Los Angeles	39,364	7,038	17.9%	$9.94	8.9%	$391,274	$395,669	$4,394	$31,693,231	$32,049,165	$355,934	1.1%	$0
Milwaukee	16,847	5,594	33.2%	$9.37	16.6%	$157,853	$165,387	$7,535	$12,786,054	$13,396,356	$610,302	4.8%	$0
Minnesota	17,930	4,899	27.3%	$10.16	13.7%	$182,170	$188,905	$6,735	$14,755,746	$15,301,288	$545,542	3.7%	$0
Montreal	19,982	7,155	35.8%	$9.07	17.9%	$181,240	$190,326	$9,086	$14,680,457	$15,416,441	$735,984	5.0%	$7,857
New York (AL)	28,371	8,999	31.7%	$14.58	15.9%	$413,655	$428,965	$15,310	$33,506,040	$34,746,176	$1,240,136	3.7%	$0
New York (NL)	20,260	4,610	22.8%	$11.83	11.4%	$239,676	$245,833	$6,157	$19,413,778	$19,912,512	$498,734	2.6%	$0
Oakland	14,339	5,183	36.1%	$11.34	18.1%	$162,607	$171,942	$9,335	$13,171,166	$13,927,263	$756,097	5.7%	$0
Philadelphia	23,077	4,679	20.3%	$11.01	10.1%	$254,072	$258,556	$4,483	$20,579,872	$20,943,035	$363,163	1.8%	$0
Pittsburgh	17,039	5,914	34.7%	$10.09	17.4%	$171,919	$179,698	$7,779	$13,925,450	$14,555,555	$630,106	4.5%	$0
San Diego	27,258	10,532	38.6%	$9.88	19.3%	$269,311	$284,842	$15,531	$21,814,230	$23,072,216	$1,257,986	5.8%	$67,444
San Francisco	17,548	6,898	39.3%	$10.61	19.7%	$186,182	$198,697	$12,515	$15,080,772	$16,094,448	$1,013,676	6.7%	$0
Seattle	33,593	9,398	28.0%	$11.59	14.0%	$389,349	$400,760	$11,411	$31,537,236	$32,461,526	$924,289	2.9%	$0
St. Louis	32,912	6,110	18.6%	$9.91	9.3%	$326,153	$331,541	$5,388	$26,418,415	$26,854,854	$436,439	1.7%	$74,968
Texas	36,111	6,664	18.5%	$11.96	9.2%	$431,888	$437,077	$5,189	$34,982,929	$35,403,253	$420,324	1.2%	$0
Toronto	31,600	2,718	8.6%	$13.93	4.3%	$440,190	$441,845	$1,655	$35,655,410	$35,789,472	$134,063	0.4%	$0
Average	26,827	5,433	23.0%	$11.32	11.5%	$310,477	$317,737	$7,260	$25,148,647	$25,736,672	$588,025	2.83%	$83,545

Note: The total change in ticket revenue accounting for VTP and capacity issues across MLB is $16.5 million.

Table 8

Summary of Effects of Variable Ticket Pricing (with capacity adjustment and non-ticket revenue adjustment)

	Avg. Attendance (1)	Avg. Absolute Change (2)	Avg. Deviation from Mean (3)	Avg. Ticket Price (4)	Non-Ticket Price (5)	Avg. Actual Ticket Revenue (6)	Avg. Var. Pricing Ticket Revenue (7)	Avg. Var. Pricing Ticket + Non-Ticket Revenue (8)	Total Actual Ticket + Non-Ticket Revenue (9)	Total Var. Pricing Ticket + Non-Ticket Revenue (10)	Total Change in Ticket + Non-Ticket Revenue (11)	% Change in Total Revenue (12)	Total Actual Ticket Revenue (13)	Total Variable Pricing Ticket Revenue (14)	% Change in Total Ticket Revenue (15)
Atlanta	35,793	5,878	16.4%	$13.07	$7.18	$467,458	$475,184	$732,451	$58,689,358	$59,328,558	$639,200	1.1%	$37,864,102	$38,489,896	1.7%
Baltimore	45,475	2,098	4.6%	$13.16	$7.23	$597,539	$601,064	$930,316	$75,020,982	$75,355,563	$334,581	0.4%	$48,400,634	$48,686,180	0.6%
Boston	28,687	3,952	13.8%	$15.46	$8.49	$442,643	$449,290	$693,186	$55,573,799	$56,148,028	$574,229	1.0%	$35,854,064	$36,392,476	1.5%
California	22,476	4,899	21.8%	$8.44	$4.64	$189,697	$195,652	$299,985	$23,816,434	$24,298,812	$482,378	2.0%	$15,365,441	$15,847,819	3.1%
Chicago (AL)	21,115	4,530	21.5%	$14.11	$7.76	$297,927	$307,000	$470,860	$37,404,684	$38,139,656	$734,972	2.0%	$24,132,054	$24,867,027	3.0%
Chicago (NL)	28,606	7,044	24.6%	$13.16	$7.22	$375,309	$391,059	$598,164	$47,120,107	$48,451,267	$1,331,160	2.8%	$30,400,069	$31,675,750	4.2%
Cincinnati	24,097	4,549	18.9%	$7.96	$4.37	$191,568	$197,327	$302,814	$24,051,406	$24,527,936	$476,530	2.0%	$15,517,036	$15,983,459	3.0%
Cleveland	41,983	1,716	4.1%	$14.73	$7.99	$609,592	$632,454	$972,537	$76,534,300	$78,775,478	$2,241,177	2.9%	$49,376,968	$51,228,769	3.8%
Colorado	48,037	144	0.3%	$10.62	$5.84	$509,675	$510,557	$791,065	$63,989,693	$64,076,289	$86,597	0.1%	$41,283,673	$41,355,136	0.2%
Detroit	14,464	5,018	34.7%	$10.60	$5.83	$153,322	$167,596	$251,923	$19,249,553	$20,405,782	$1,156,229	6.0%	$12,419,066	$13,575,296	9.3%
Florida	21,839	4,541	20.8%	$10.37	$5.70	$226,469	$233,085	$357,643	$28,433,181	$28,969,046	$535,865	1.9%	$18,343,988	$18,879,853	2.9%
Houston	24,394	7,362	30.2%	$10.65	$5.86	$259,793	$273,185	$416,071	$32,616,970	$33,701,747	$1,084,777	3.3%	$21,043,206	$22,127,983	5.2%
Kansas City	17,949	4,013	22.4%	$9.74	$5.36	$174,828	$180,535	$276,690	$21,949,610	$22,411,903	$462,293	2.1%	$14,161,039	$14,623,331	3.3%
Los Angeles	39,364	7,038	17.9%	$9.94	$5.47	$391,274	$398,086	$613,286	$49,124,509	$49,676,206	$551,697	1.1%	$31,693,231	$32,244,929	1.7%
Milwaukee	16,847	5,594	33.2%	$9.37	$5.15	$157,853	$169,531	$256,350	$19,818,383	$20,764,351	$945,968	4.8%	$12,786,054	$13,732,021	7.4%
Minnesota	17,930	4,899	27.3%	$10.16	$5.59	$182,170	$192,609	$292,802	$22,871,407	$23,716,997	$845,590	3.7%	$14,755,746	$15,601,336	5.7%
Montreal	19,982	7,155	35.8%	$9.07	$4.99	$181,240	$195,308	$295,006	$22,754,708	$23,895,483	$1,140,776	5.0%	$14,680,457	$15,819,930	7.8%
New York (AL)	28,371	8,999	31.7%	$14.58	$8.02	$413,655	$437,386	$664,896	$51,934,362	$53,856,573	$1,922,211	3.7%	$33,506,040	$35,428,250	5.7%
New York (NL)	20,260	4,610	22.8%	$11.83	$6.51	$239,676	$249,220	$381,042	$30,091,356	$30,864,393	$773,037	2.6%	$19,413,778	$20,186,815	4.0%
Oakland	14,339	5,183	36.1%	$11.34	$6.24	$162,607	$177,076	$266,509	$20,415,308	$21,587,258	$1,171,950	5.7%	$13,171,166	$14,343,116	8.9%
Philadelphia	23,077	4,679	20.3%	$11.01	$6.06	$254,072	$261,022	$400,762	$31,898,801	$32,461,705	$562,903	1.8%	$20,579,872	$21,142,775	2.7%
Pittsburgh	17,039	5,914	34.7%	$10.09	$5.55	$171,919	$183,977	$278,532	$21,584,447	$22,561,111	$976,664	4.5%	$13,925,450	$14,902,112	7.0%
San Diego	27,258	10,532	38.6%	$9.89	$5.43	$269,311	$293,227	$441,505	$33,812,057	$35,761,936	$1,949,879	5.8%	$21,814,230	$23,751,402	8.9%
San Francisco	17,548	6,898	39.3%	$10.61	$5.84	$186,182	$205,580	$307,980	$23,375,197	$24,946,394	$1,571,197	6.7%	$15,080,772	$16,651,969	10.4%
Seattle	33,593	9,398	28.0%	$11.59	$6.37	$389,349	$407,036	$621,177	$48,882,717	$50,315,365	$1,432,648	2.9%	$31,537,236	$32,969,885	4.5%
St. Louis	32,912	6,110	18.6%	$9.92	$5.45	$326,153	$334,308	$513,889	$40,948,543	$41,625,024	$676,481	1.7%	$26,418,415	$27,078,914	2.5%
Texas	36,111	6,664	18.5%	$11.96	$6.58	$431,888	$439,931	$677,470	$54,223,540	$54,875,042	$651,502	1.2%	$34,982,929	$35,634,431	1.9%
Toronto	31,600	2,718	8.6%	$13.93	$7.66	$440,190	$442,756	$684,860	$55,265,885	$55,473,682	$207,797	0.4%	$35,655,410	$35,863,207	0.6%
Average	26,827	5,433	23.0%	$11.33	$6.23	$310,477	$321,466	$492,491.88	$38,980,403	$39,891,842	$911,439	2.83%	$25,148,647	$26,038,717	4.34%

Note: The total change in ticket + non-ticket revenue accounting for VTP, capacity issues, and non-ticket revenue across MLB is $25.5 million.

Figure Caption

Figure 1. Optimal variable pricing adjustment. (Atlanta: solid line is average demand; dashed line is demand for one game)

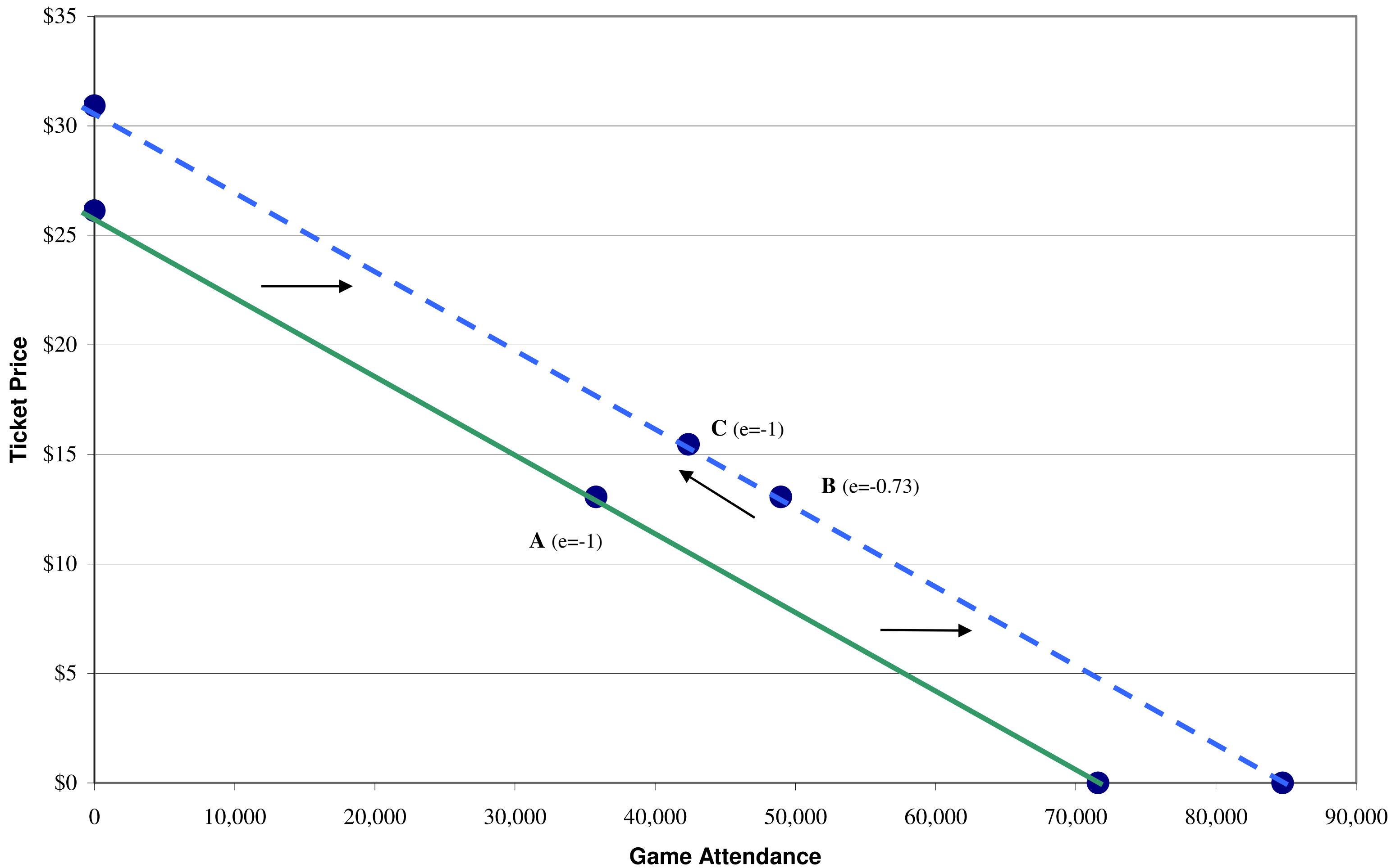
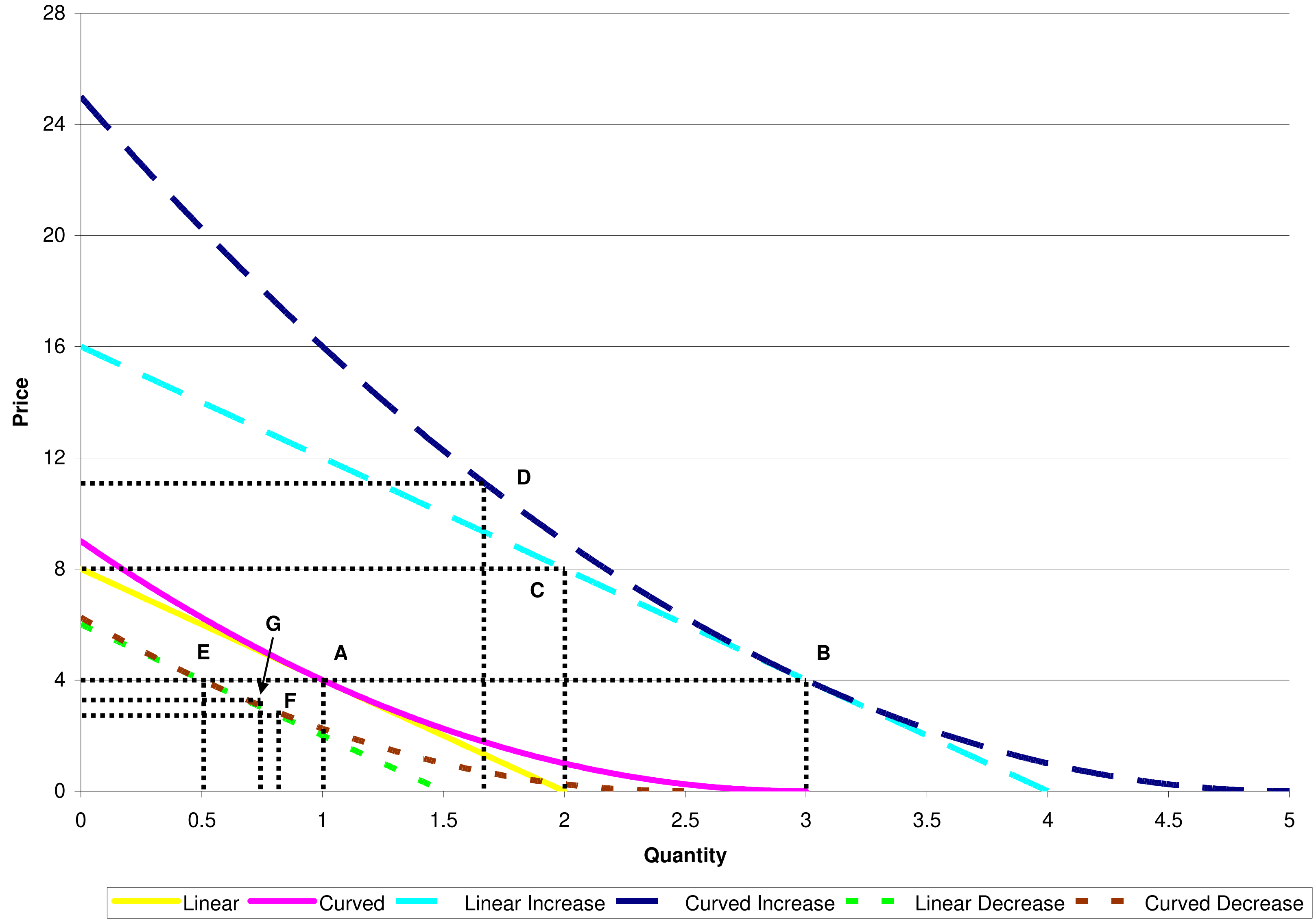

$35
$30
$25
$20
$15
$10
$5
$0
Ticket Price
C (e=-1)
B (e=-0.73)
A (e=-1)
0
10,000
20,000
30,000
40,000
50,000
60,000
70,000
80,000
90,000
Game Attendance

Figure Caption

Figure 2. Curved demand functions versus linear demand functions.



28
24
20
16
12
8
4
0
Price
D
C
G
E
A
B
F
0
0.5
1
1.5
2
2.5
3
3.5
4
4.5
5
Quantity
Linear
Curved
Linear Increase
Curved Increase
Linear Decrease
Curved Decrease

Figure Caption

Figure 3. Revenue functions of curved demand versus linear demand.

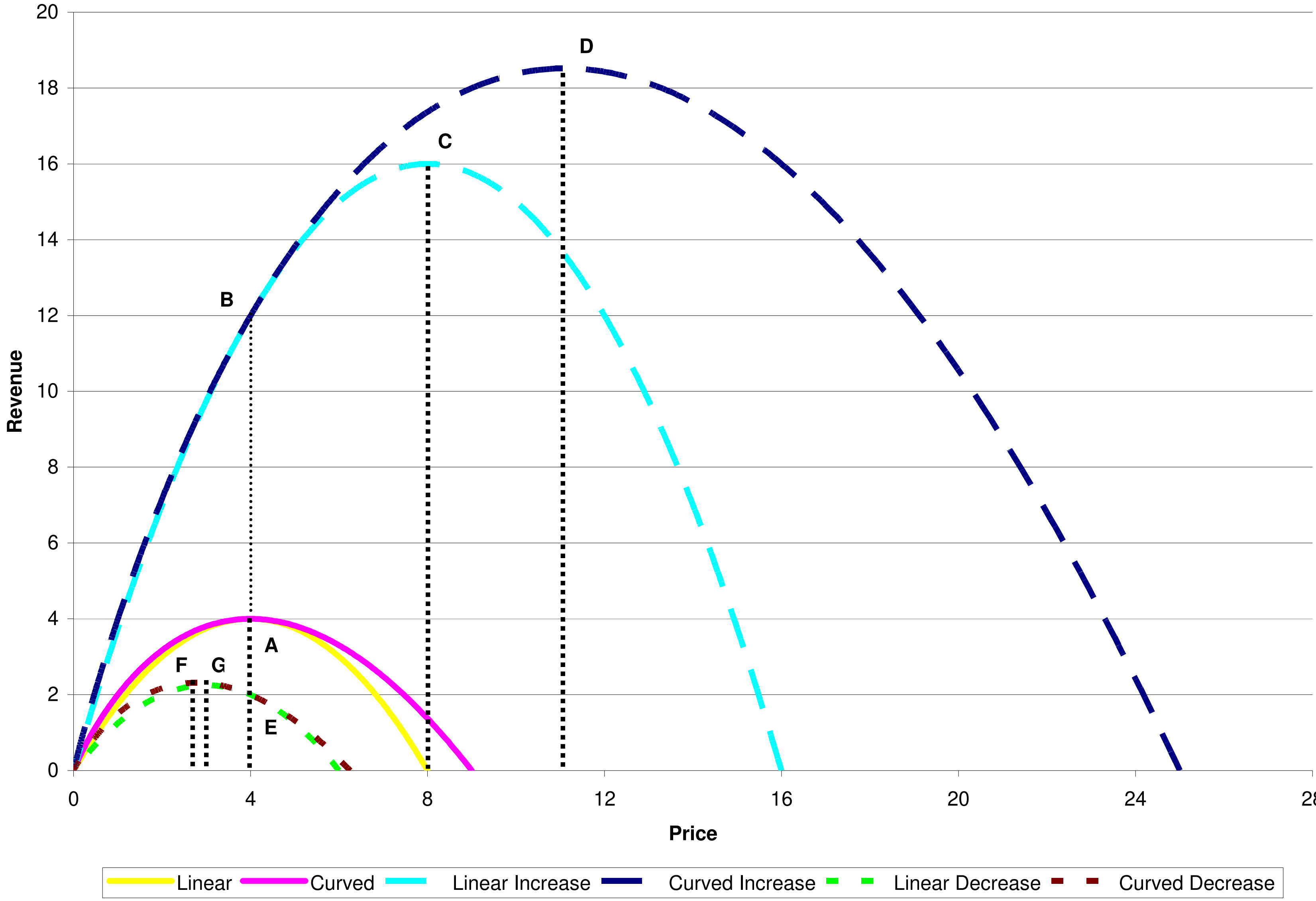
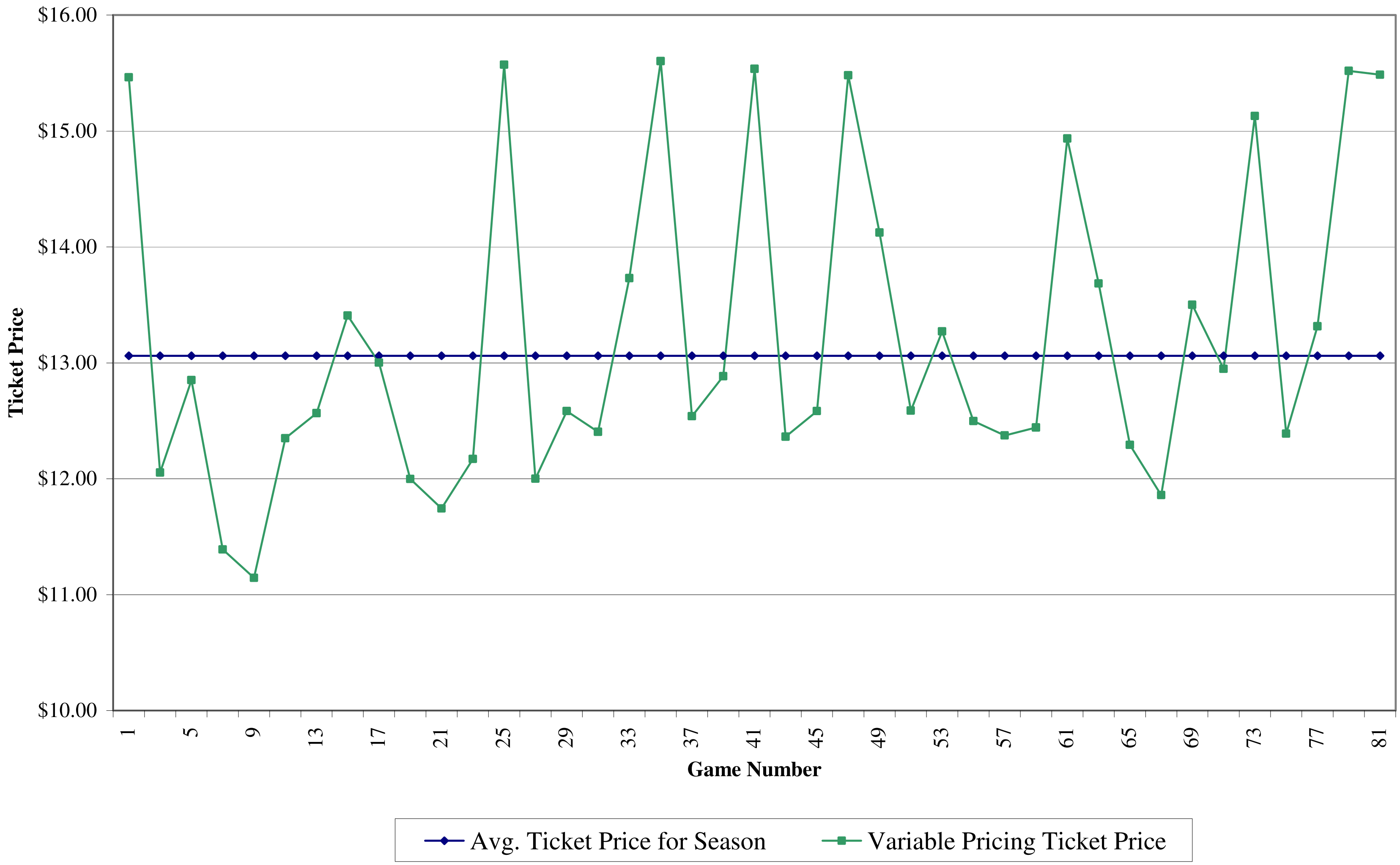

Revenue
Price
A
B
C
D
E
F
G
0
2
4
6
8
10
12
14
16
18
20
0
4
8
12
16
20
24
28
Linear
Curved
Linear Increase
Curved Increase
Linear Decrease
Curved Decrease

Figure Caption

Figure 4. Atlanta Braves Variable Pricing.


$16.00
$15.00
$14.00
$13.00
$12.00
$11.00
$10.00
Ticket Price
1
5
9
13
17
21
25
29
33
37
41
45
49
53
57
61
65
69
73
77
81
Game Number
Avg. Ticket Price for Season
Variable Pricing Ticket Price