Ticket Pricing Per Team: The Case of Major League Baseball (MLB)

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ABSTRACT

In this paper, we explore the determinants of demand for attendance at Major League Baseball (MLB) games for 23 individual MLB teams during the period 1970 to 2003. Our central focus is to explore team-specific price elasticities of demand for attendance. We use Error Correction Models (ECM) to identify these elasticities. The empirical findings show that factors of demand differ between teams with respect to the factors that determine attendance and to the estimated weights. We find that demand for attendance is mostly inelastic with levels varying between teams.

Keywords: General-to-Specific Model selection, Cointegration, Price Elasticity, MLB Attendance, Long-Run Demand Analysis

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ABSTRACT

In this paper, we explore the determinants of demand for attendance at Major League Baseball (MLB) games for 23 individual MLB teams during the period 1970 to 2003. Our central focus is to explore team-specific elasticities of demand for attendance. We use Error Correction Models (ECM) to identify these elasticities. The empirical findings show that factors of demand differ between teams with respect to the factors that determine attendance and to the estimated weights. We find that demand for attendance is mostly inelastic with levels varying between teams.

I. INTRODUCTION

Sports teams generate revenues from three general sources: ticket sales, concession sales, and the sale of media rights. To generate maximum profits, it is imperative that teams possess knowledge about the relationship between ticket prices and attendance at the team level. A host of factors influences the demand for sports, including the price of tickets, fan income, the population of the drawing area, team quality, and the age of the stadiums in which teams play. While each of these factors generally influence the demand for all teams' games in some manner, the marginal impact that each has on attendance may vary from team to team.

More specifically, the sensitivity of attendance to changes in the price of tickets (the elasticity of demand) and to changes in average incomes (the income elasticity) may vary from team to team. For example, some MLB teams reside in cities without NBA or NHL teams (such as Kansas City) while some reside in metropolitan areas with teams in each league. Some teams reside in cities with one or more other teams from the same league, such as Chicago and New York. A large literature on the demand for sporting events exists and there have been some analyses of team-specific attendance (for example, see Simmons (1996)) and revenue (Burgers and Walters (2003) and Porter (1992)). Yet team-specific attendance in American sports has been largely unexplored.

We attempt to fill this gap by exploring team-specific demand for 23 MLB teams. We examine time-series data that allows us to identify specific factors that affect team-specific attendance and to measure the marginal impact these factors have on attendance at the team level. Using an error correction model (ECM), we are able to estimate the elasticities of demand and income for specific teams. To our knowledge, no other paper applies this approach in analyzing MLB data.

We organize the rest of the paper as follows: Section II presents a review of the literature; section III presents the theoretical framework that explains the equilibrium levels of attendance and ticket prices. We also describe the empirical framework in this section; section IV describes the data; section V presents the empirical results; section VI concludes.

II. Literature Review

Unit Elastic and Elastic Demand Evidence

In American professional sports, researchers generally agree that franchise owners render decisions with an eye towards maximizing profits. In addition, American franchises in the four major sports are granted exclusive territorial rights by their leagues, giving teams a measure of monopoly power in their local markets.

According to economic theory, a single-product firm will generate maximum profits when it produces an amount where the added costs of production (the marginal costs) are just equal to the added revenue from selling the product (the marginal revenue). Moreover, economists have identified a relationship between the marginal revenue and the elasticity of demand. When a firm sells more of a product, its revenue increases, all else equal. However, if the increased sales result from a lowering of the product's price, then the price change gives an offsetting effect on revenue. Do revenues increase, decrease, or remain constant? Knowledge of the elasticity of demand provides the answer to this question.

When the demand for a product is elastic, lowering a product's price causes revenues to increase (marginal revenue is positive). When the demand is unit elastic, revenues neither increase nor decrease (marginal revenue is zero). When demand is inelastic, revenues fall (marginal revenue is negative). Because a firm generates maximum profits by selling where marginal revenues equal marginal costs, a firm facing non-negative marginal costs will set its product price in the elastic or unit-elastic portion of the product demand curve.

If we assume that the marginal cost of allowing a fan into a ballpark is zero (all costs are fixed), then pricing at the unit-elastic point ensures maximum profits. Demmert (1973) examines MLB data covering the period from 1951 to 1969 and found evidence that teams set ticket prices around the unit-elastic portion of the demand curve. Noll (1974) found evidence that MLB teams priced in the inelastic portion of their demand curves on average, but he could not rule out unit-elastic pricing statistically.

Noll noted two important issues in interpreting these results. First, elasticity estimates may be understated because the price of admission is only a portion of the total costs fans pay to attend games.

Second, larger parks have a greater proportion of seats with poor views than smaller parks and estimating demand equations by using simple average ticket prices (adding the various sections' ticket prices and dividing by the number of sections) will not adequately capture the proportion of seats in different sections.

If, however, the elasticity of demand is greater than one in absolute value, demand is elastic, implying that consumers are relatively sensitive to changes in the price of the good. Alexander (2001) analyzes the demand for MLB games and finds that by controlling for the price of other entertainment options, demand is elastic where prices are set.

Simmons (1996) explored the determinants of attendance by team at Premier Soccer League matches in the United Kingdom. After adjusting attendance figures for season ticket buyers and non season ticket buyers, he finds some evidence that some particular teams price in the elastic portion of their demand curves.

Inelastic Demand Evidence

The evidence that ticket prices are set in the elastic or unit elastic portion of demand is the exception, not the rule. A more consistent finding is that teams on average set ticket prices in the inelastic portion of demand. Below we summarize a set of this research. We direct readers who desire a more in-depth summary of this research to Fort (2004a).

The evidence of inelastic ticket pricing is found across sports and countries. Such pricing is found in the Scottish Football League (Jennett (1984)), in the Spanish Football League (Garcia and Rodriguez (2002)), minor league baseball (Siegfried and Eisenberg (1980)), MLB (Scully (1989) and Zimbalist (1992)), Australian Rules Football (Borland (1987)), and the NFL (Brook (2006)).

One of Noll's (1974) concerns, noted above, was that the price of tickets was only one part of the overall price of attending games. Ignoring costs of traveling to and from games, for instance, would cause overall attendance prices to be understated, thus causing estimates of the elasticity of demand to be biased downwards. Bird (1982) examined Football League attendance in England during the period 1948/49 to 1979/80 and found that after controlling for travel expenses, prices were set in the inelastic portion of demand. Forrest, Simmons, and Feehan (2002) also control for travel costs and find that previous elasticity estimates for English soccer were too low. They however could not rule out inelastic ticket pricing.

Another issue is that watching a game at a stadium is only one way for fans to "consume" the action. When franchise owners allow other avenues through which fans can follow games, they create, to some extent, a substitute for in-person attendance. Thus, whether a particular game is broadcast on television is an important determinant of the demand for tickets. Carmichael, Millington, and Simmons (1999) examine English Rugby League attendance and find evidence of inelastic ticket pricing after controlling for the telecasting of games on the British Sky Broadcasting network.

The finding of inelastic pricing has been a puzzle to economists because it suggests that teams have chosen ticket prices that are "too low" if teams seek maximum profits. If teams indeed price where demand is inelastic, raising ticket prices would generate more ticket revenues. How can such behavior be rationalized? One possibility is that inelastic pricing promotes more people to attend games. For example, Boyd and Boyd (1998) suggest that teams would choose relatively low ticket prices to induce more fans to attend games in order to improve home field advantage. Another possibility, put forth by Fort (2004b), is that teams set lower ticket prices in exchange for public subsidies.

However, Quirk and El Hodiri (1974), Marburger (1997), and Krautmann and Berri (2007) explain that inelastic ticket pricing should be expected in certain situations because of the trade-off between gate revenue and other sources of revenue. In other words, sports teams are not single-product firms but are, instead, multi-product producers. Not only do they sell the action on the field but they also sell concessions, parking, and souvenirs. It is certainly plausible that franchise owners would happily accept lower ticket revenue in exchange for revenues from other sources.

Income elasticity evidence

Income elasticity measures the sensitivity of the quantity demanded of a product with respect to changes in consumer incomes. Estimating income elasticity not only allows for researchers to comment on whether consumers are relatively responsive to changes in income, but they also allow researchers to comment on whether a good is an inferior or normal good. While most of the focus has been on the elasticity of demand, some researchers have commented on income elasticities. Bird (1982) estimates that the demand for English soccer is inferior, suggesting that as average incomes grow, the demand for soccer will fall. However, Simmons (1996) finds that English soccer is a normal good.

The majority of attendance studies provide evidence on inelastic ticket pricing. But as noted earlier, the analyses of American sports have relied on data aggregated by league. Do all teams in a league price in the inelastic portion of their demand curves or do some price in the elastic portion of demand? An analysis of team-specific demand allows us to examine elasticities at team levels. We now move to a brief description of the theoretical framework that explains equilibrium levels of attendance and ticket prices and the empirical model.

III. THEORETICAL AND EMPIRICAL FRAMEWORKS

The Theory

We present a simple theoretical model of attendance in this section that explains the setting of ticket prices in MLB. Our attempt is to construct a model that is consistent with the current findings in the research on sports attendance and to provide a model on which to build the econometric analysis presented below.

We assume MLB franchises have some degree of local monopoly power. We assume teams make decisions to maximize profits in which they choose the level of output (measured by tickets sold) and set prices corresponding to the demand for baseball in their local market. Teams therefore set ticket prices where the marginal revenue of selling the last ticket equals the marginal cost. As noted above, if team costs are fixed during a season, then the marginal cost of selling a ticket is zero and owners will maximize profits by pricing tickets where demand is unit elastic. If marginal costs are positive, then team owners will maximize profits by pricing tickets where demand is elastic.

As noted above, most of the empirical literature on sports attendance has found evidence of inelastic pricing. Therefore, it is necessary that our model be versatile enough to explain inelastic ticket pricing. To this end, we employ a modification of the model, a modification described by Sandy, Sloane, and Rosentraub (2004) in which we treat the multi product team as having negative marginal costs. While this treatment of marginal costs is atypical, it allows us to explain why ticket prices may be set in the inelastic portion of the ticket demand curve where the marginal revenue from ticket sales is negative.

Suppose that each fan who buys a ticket also buys concessions valued at $C > 0$ (assumed, for brevity, to be constant). The rational profit-maximizing team is indifferent between selling a ticket at no marginal costs (who buys no concessions) that also adds nothing to ticket revenue and selling a ticket to a fan whose attendance decreases ticket revenue by *C* but whose concessions purchases generate C in concession revenue. Therefore, we can treat the marginal cost of each ticket sold to be $MC = -C$. The team rationally prices tickets in this case where marginal revenue is negative: in the inelastic portion of the demand curve.

The Empirical Framework

This theoretical framework suggests that team-specific attendance will be a function of the factors that influence the team-specific demand for games and the marginal cost of producing them. Following this and the literature described above that examines the determinants of attendance in sports, we postulate a long-run relationship between attendance and two generally important demand factors for each MLB team, the real price of tickets prices and real per-capita income, as follows:

$$A_{it} = \beta_0 + \beta_1 P_{it} + \beta_2 I_{it} \tag{1}$$

where A is the logarithm of attendance, P is the logarithm of the real price of tickets, and I is the logarithm of real per capita income in the home city. i and t denote team and year identifiers respectively.

The test for a long-run relationship described by equation (1) requires a test for the stationarity of the series. A series is said to be "stationary" if the mean, variance, and autocorrelation of the series are unchanged over time. If two (or more) series are each non-stationary but a linear combination of the series is non-stationary, then the series is said to be "cointegrated." Fortunately, equation (1) can be easily cointegrated.

It is well-accepted that habit persistence and long memory usually formulates demand functions: the current consumption of a good depends, in part, on consumers' past consumption of the good. By including lagged demand terms for attendance (Deaton & Muellbauer (1980), Borland (1987), and Simmons (1996)), the demand equation (1) can be written as an autoregressive-distributed lag model

$$\begin{aligned} \Delta A_{it} = \beta_0 + \beta_1 \Delta P_{it} + \beta_2 \Delta P_{it-1} + \beta_3 \Delta I_{it} + \beta_4 \Delta I_{it-1} + \beta_5 A_{it-1} + \\ \beta_6 P_{it-1} + \beta_7 I_{it-1} + \varepsilon \end{aligned} \tag{2}$$

where Δ denotes the difference operator. We can estimate equation (2) by using an error correction model (ECM). In other words, equation (2) is the same with the following ECM parameterization:

$$\begin{aligned} \Delta A_{it} = \beta_0 + \beta_1 \Delta P_{it} + \beta_2 \Delta P_{it-1} + \beta_3 \Delta I_{it} + \beta_4 \Delta I_{it-1} + \\ \beta_5 [A_{it-1} + (\beta_6 / \beta_5) P_{it-1} + (\beta_7 / \beta_5) I_{it-1}] + \varepsilon \end{aligned} \tag{2'}$$

Equation (2') is a typical ECM and the parameterization from (2) to (2') is similar to that employed by Simmons. For the interpretation of short-run dynamics, we assume a stationary process in the variables given the cointegrated variables in the long-run. Thus, the differenced values in P and I are the same as long as the time lags are the same, and the equation (2') can be rewritten as follows:

$$\Delta A_{it} = \beta_0 + (\beta_1 + \beta_2)\Delta P_{it} + (\beta_3 + \beta_4)\Delta I_{it} + \\ \beta_5[A_{it-1} + (\beta_6/\beta_5)P_{it-1} + (\beta_7/\beta_5)I_{it-1}] + \varepsilon \qquad (2'')$$

Even if the parameters β_1, β_2, β_3 and β_4 are not separately identified in equation (2''), the cointegrating properties of the equation are not affected and the equation can be used for interpreting the short-run dynamics. Hence, we can interpret $\beta_1+\beta_2$ as the short-run price elasticity, $\beta_3+\beta_4$ as the short-run income elasticity, β_6/β_5 as the long-run price elasticity and β_7/β_5 as the long-run income elasticity. In addition, the coefficient β_5 can be interpreted as the speed-of-adjustment factor for the residual terms in the stationary long-run cointegration process between the dependent variable and the explanatory variables depicted in equation (1).

We can incorporate our basic ECM into a more general ECM specification with team-specific factors that affect attendance, such as team quality. Thus, we write the general model as:

$$\Delta A_{it} = \beta_0 + \beta_1\Delta P_{it} + \beta_2\Delta P_{it-1} + \beta_3\Delta I_{it} + \beta_4\Delta I_{it-1} + \beta_5 A_{it-1} + \\ \beta_6 P_{it-1} + \beta_7 I_{it-1} + \theta X_{it} + \varepsilon \qquad (3)$$

where θ is a vector of parameters to be estimated and X_{it} is a matrix of team-specific variables. We describe these variables in the next section.

Since the estimation of equations (2) and (3) are rationalized only by establishing the existence of the long-run relationship given by equation (1), establishing cointegration between the non-stationary processes is a necessary condition for the estimation of an error correction model such as equation (3) (Engle & Granger (1991)). Without cointegration, the statistical properties in equation (3) may be spurious. Hence, we test for cointegration by using the procedure proposed by Engle and Granger (1987) and Kremers, Ericsson, and Dolado (1992) and developed by Kanioura & Turner (2003). These authors show that a cointegration test based upon a conventional F-test for the joint significance of the levels terms is advantageous because its distribution does not depend on the specific parameters of the problem being considered. We present our test results with our empirical results below.

We estimate equation (3) for each team, a process preferable to using dynamic pooled estimation. Pesaran and Smith (1995) show that if there is coefficient heterogeneity between teams, pooling the data may generate a serial correlation problem. Estimation of an autoregressive distributed lag (ADL) model with lagged dependent variables, in the presence of this serial correlation, yields inconsistent estimates. In addition, Simmons (1996) shows that fixed effects may not be sufficient to deal with these team-level idiosyncrasies. He also argues that it is unclear how to define the correct form of a pooled equation because of those idiosyncracies. Hence, estimations for separate teams allow us to capture specific team-level effects more precisely, especially those relating to team quality where the effects may vary considerably across teams. In particular, since we base our model specification upon a stationary process of error terms given long-run cointegration, we need not consider autoregressive integrated moving average (ARIMA) terms. In addition, since all the variables on the right-hand side of the equation are exogenously determined, we use simple ordinary least squares to estimate the model.

In general, stadium capacity constraints are not a problem with our data. In the 34 years of our analysis, only one of 782 total records, the San Francisco Giants in 2000, had attendance of 100% of annual capacity. A total of 10 records had attendance values at 95% of capacity or above and a total of 26 had attendance values at 90% of capacity or above. Since capacity constraints are not a problem, we do not use censored regression analysis.

We obtain the final form of model specification for each team using a 'general-to-specific' specification search, a process particularly popularized by Hendry and Mizon (Hendry, 1995; Mizon, 1995; Hendry, 1993; Hendry & Mizon, 1990). Hendry and Krolzig (2001) recommend the use of multiple search paths in the process of moving from a generalized unrestricted model (GUM) to a parsimonious specification. There are two reasons for using this process. First, it allows us to avoid deleting an important variable that we should ideally retain in the final specification along any single search path. Second, it allows us to minimize the risk that the final model is overparameterised. Therefore, we determine the final form of the general ECM equation (3) estimated for each team by parsimony, satisfactory performance against diagnostic tests incorporated with the Schwarz criterion, evidence of cointegration, and the implied long-run relation of equation (1).

IV. DATA AND DESCRIPTION OF VARIABLES

The data comprise the 23 U.S. MLB teams that competed each year during the period from 1970 to 2003 (excluding 1989 and 1990 when no ticket price data was available). Because of the lack of sufficient data points, we exclude teams that began play after 1970 (Seattle, Florida, Colorado, Arizona, and Tampa Bay) from the analysis. We also exclude Toronto and Montreal from the analysis because of the lack of metropolitan-specific data for their respective metropolitan areas.

Table 1 summarizes the variables used in the analysis. We calculated ticket prices using weighted average ticket prices obtained from the late Doug Pappas (www.roadsidephotos.com) and from past personal correspondence with Roger Noll. Pappas and Noll each made their calculations using ticket prices by section for each team and each used the number of seats in each section as weights. In years where the Pappas and Noll data each had values for each team (1975-2005), we took the average of the values reported in each rather than choose between them. Ticket price data was only available from Pappas for 1970-1974 and 1990-2003. The Noll data only had values for 1986-1988. As noted above, neither source had ticket price data for 1989 and 1990. Therefore, we dropped records for those years from the analysis.

We obtained population and per-capita income for the U.S. metropolitan areas served by MLB clubs from the Bureau of Economic Analysis' Regional Economic Information System (REIS).

We obtained team productivity data, measured by team winning percentage, from the Lahman database (www.baseball1.com). We include each team's current and previous years' winning percentage in the regression models. The latter helps control for fan expectations about the upcoming season.

In any given year, a team in the hunt for the playoffs may attract larger attendance levels over and above that driven by a high winning percentage. To control for this effect, we include a dummy equal to one for each team that made the playoffs. Between 1969 and 1994, teams made the playoffs by winning their division in a two-division format. In 1995, MLB installed a three-division format and teams could make the playoffs by winning their division or by winning the wild card (being the team with the best record that did not win its division). Consequently, the playoff dummy was set equal to one if a team won its division prior to 1995, to one if a team won its division or the wild card in 1995 and thereafter, and to zero otherwise. Note that the 1994 players' strike resulted in the cancelling of the playoffs that year, so no team literally won a division. However, we treated teams that led their division at the time the strike began as having won its division.

We also include dummies equal to one for each of the strike years (1981, 1994, and 1995), strikes which shortened the length of the MLB season. Schmidt and Berri (2004) show that there are no long-lasting effects of labor strikes/lockouts in U.S. professional sports: the effects of strikes are felt only during the period when the strike occurred. Consequently, we only include dummies for the strike years.

We include the age of the team's stadium in the model. This is included as a control because new stadiums present a unique draw for residents in a metropolitan area, and some will attend games to experience this new aspect of the team. Age is included quadratically in the analysis because as a stadium ages, it loses some of its newness and attendance will likely fall as a result (all else equal). However, it is plausible that an older stadium may become a historical attraction in its own right, leading to an increase in attendance once it hits a certain age. An alternative specification would be to use a dummy variable to control for new stadiums. We did not use such a variable because we wanted to estimate the gradual effect that an aging stadium has on attendance growth. In addition, stadium age will act like a time trend for teams that did not begin play in a new stadium during the sample period (such as the Boston Red Sox, the New York Yankees, and the Chicago Cubs). Care must be taken in interpreting estimated coefficients for the age variables for these teams.

Lastly, all dollar values are expressed in constant 2003 dollars using the seasonally-adjusted consumer price index for all urban consumers obtained from the Bureau of Labor Statistics data website (stats.bls.gov).

We now present the results of the empirical analysis.

V. Empirical Results

We report the estimates obtained from a general-to-specific specification search based upon all the diagnostic tests in Table 2. Each equation does not fail the tests for first-order serial correlation, functional form misspecification, and non-normality and heteroskedasticity of residuals. We evaluated each test statistic at the 5% significance level. We tested all variables in the final equations for whether the attendance, real price and real per capita income processes are integrated of order 0 (*I(0)*) or of order 1 (*I(1)*). We verified the stationarity of all variables using the following tests: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Kwiatkowshi, Phillips, Schmidt and Shin (KPSS), and Ng-Perron (NP). Table 2 shows the ADF test statistics for the unit root process of attendance (*A*). Each test shows that prices and incomes are *I(1)*. The attendance processes for most teams are *I(1)*, but there is uncertainty regarding the order of integrations of the following teams' attendance values: the Chicago White Sox (CHW), the Detroit Tigers (DET), the Kansas City Royals (KCR), the Los Angeles Dodgers (LAD), the Milwaukee Brewers (MIL), the New York Mets (NYM), the Philadelphia Phillies (PHI) and the Pittsburgh Pirates (PIT)). Given the sample size (32 observations), the low power of the test, and the test statistics being close to the critical values (allowing rejection of the unit root null), we can avoid the strict interpretation of the ADF test with our stationarity test of the residuals in the cointegrated estimation equation.

The test statistics from the residuals of the cointegration results are crucial to verifying the final specification for each team. The findings show that the null hypothesis of non-cointegration can be rejected for most teams at the 5% or 10% level of significance except for MIL and the Boston Red Sox (BOS). These results suggest that there is strong evidence for the existence of a long-run cointegration relationship for each team. In particular, the long-run cointegrating relationship includes the real ticket price or real per capita income except for CHW. In particular, the DW statistics are also higher than the R^2, which suggests the existence of a cointegration relationship (Sargan & Bhargava, 1983).[1]

Tables 3a and Table 3b present the results of the estimated models. The tables show that the real ticket price, real per-capita income, each team's current winning percentage, and the year dummy D1981 are the primary determinants of attendance changes common across most teams. Most of the estimated coefficients on the price variable are negative, except for the Baltimore Orioles (BAL), BOS, and NYY. The estimates show no relationship between attendance and ticket prices for the Cincinnati Reds (CIN), the Cleveland Indians (CLE), LAD, and NYM.

The coefficients on current team winning percentage are positive and significant for all teams except the Milwaukee Brewers (MIL) and NYY. Our analysis suggests that the growth rate of attendance is not altered by changes in winning percent for MIL and NYY. The significant results suggest that, for example, a 1% increase in the Anaheim Angels' winning percentage would increase the growth rate of attendance by 1.98%. Winning has the largest impact on the San Francisco Giants (SFG), where a 1% increase in team win percent drives the growth rate of attendance higher by 3.46%. For the Minnesota Twins (MIN), a 1% increase in team win percent drives the growth rate of attendance higher by 3.10%. Both Atlanta (ATL) and the Chicago White Sox have estimated coefficients above 3.0, suggesting that a 1% increase in team win percent drives the growth rate of attendance by better than 3%. Winning has the smallest impact on the growth rate of attendance for BOS, where a 1% increase drives the growth rate of attendance higher by less than 1% (0.9%) on average. A potential reason for this is that the Red Sox play in one of the smallest parks in MLB. In 8 of the 34 years in our sample period, the Red Sox had attendance levels at 90% to 98% of annual capacity. They, therefore, do not have a lot of room to grow.

The coefficients on lagged winning percentage are positive and significant for 9 of the 23 teams. The results suggest that lagged winning percentage has the largest influence on the attendance growth rates of ANA, CHC, KCR, MIL, and MIN. For example, if the lagged win percent of MIN increases by 1%, its attendance growth rate the following year rises by 2.57%. If the lagged win percent of KCR increases by 1%, its attendance growth rate rises by 2.45%. Of the teams with significant coefficients, lagged win percent has the smallest effect on attendance growth rates for Baltimore (BAL), the Red Sox, the Reds (CIN), and Texas (TEX). If lagged win percent grows by 1%, each of these sees the growth rate of attendance increase by less than 1% on average.

The coefficients on the playoff dummies were significant for only a handful of teams (the Atlanta Braves (ATL), NYY, and the TEX. The results suggest that making the playoffs caused attendance growth to rise by 0.31% the following year in ATL and by 0.15% for NYY. The sign on the estimated coefficient on the playoff dummy for TEX is unexpected since it suggests that attendance changes were smaller when the Rangers made it to the playoffs after controlling for other factors.

The age of the stadium is important in determining the change in attendance in just over half of the models. Since we entered stadium age[2] quadratically, not only do the models tell us about the effect of the age of the stadium on attendance changes but also on the rate of change of the impact of stadium age. A negative linear term along with a positive quadratic term suggests that as a stadium ages, attendance changes fall but the rate of decrease diminishes as the stadium ages. This finding is consistent with the honeymoon effect documented by Leadley and Zygmont (2005) and Clapp and Hakes (2005). Indeed, for HOU, KCR, PIT, and TEX, the teams for which a honeymoon effect is present, attendance growth rates peak when their stadiums were 17.5, 15, 25, and 20 years of age respectively. Also note that each of these teams had new stadiums built during the sample period, so the age of the stadium does not correspond with a time trend.

Positive linear terms along with negative quadratic terms tell us that as a stadium ages, attendance changes rise but at a decreasing rate. This latter nature is exhibited for some teams that play in classic stadiums: BOS, LAD, and NYY. It is possible that in terms of increasing the growth rate of attendance, these classic stadiums have some historical value to fans. However, the coefficients suggest that attendance growth rates peaked at 67.5, 20 and 75 years of age respectively for these three teams. Since each of these teams played in the same stadium throughout the sample period, the age of the stadium corresponds with a time trend, so these results must be used with care.

Indeed, this interpretation of historical value is consistent with models that show negative linear terms with positive quadratic terms. Together these estimates tell us that as new stadiums grow older, attendance changes fall but that the fall subsides up until some point where historical interest begins to take over. Of course if all stadiums were classic, then it is quite possible that the historical value might be subject to diminishing marginal utility. We can say something similar about newer stadiums.

The parameter estimates for the strike-year dummy variables for 1981 and 1994 have the expected signs and are both statistically significant for most teams. In particular, the 1981 strike shows significant effects on 19 teams' attendance growth, all except for ANA, ATL, MIN and OAK. Additionally, the magnitude exceeds 0.5 in absolute value for 14 out of those 19 teams. In other words, attendance growth rates were lower by over 0.5% for these teams. In particular, the Padres (SDP) were most affected in 1981 as their growth rate in attendance fell by nearly 1%. In 1994, the Yankees (NYY), the Padres, the Mets (NYM), the Rangers (TEX), and the Dodgers (LAD) all saw their attendance growth rates shrink by at least 0.5%. This is expected because both years were shortened because of the strikes. Only a handful of teams (CHC, CIN, KCR, NYY, and the San Diego Padres (SDP)) had lower attendance changes in 1995 as a result of the 1994 strike. The dummy for 1995 is significant for only 5 of the 23 teams studied. Since both 1994 and 1995 were shortened because of the players' strike, the change in attendance between those years is explained by the other factors for most teams.

Table 4 presents the long-run price elasticities calculated from the results. Consistent with others' findings (summarized by Fort (2004)), more teams exhibit inelastic rather than elastic demand. The results suggest that the size of the long-run price elasticities varies considerably across teams. Some teams such as KCR, MIL, OAK and SDP have long-run elastic demand indicating that lowering ticket prices would lead to increased ticket revenue. However, most teams' long-run price elasticities are significantly less than 1 in absolute value, suggesting that those teams price in the inelastic portion of their demand curves. In particular, two teams, TEX and PHI, have long-run price elasticities lower than 0.5. Recall that Quirk and El Hodiri (1974), Marburger (1997), and Krautmann and Berri (2007) argued that inelastic pricing should not be surprising when teams receive revenues from sources other than ticket sales. While our data do not allow us to examine ancillary revenue sources by team, it is possible that KCR, MIL, OAK, and SDP rely more-heavily on the sales of tickets to generate revenue compared to teams such as PHI and TEX that have estimated price elasticities well below 1.

The estimated signs of the long-run price elasticities are negative in every case except for BAL, BOS and NYY. BOS and NYY are classic rivals with a large legion of loyal fans. Moreover, both teams played in classic ballparks during the entire sample period. It is possible that our specifications do not adequately control for these effects. Baltimore, on the other hand, was the first franchise to move into a new "retro" stadium. Although we control for the newness of stadiums in our models, we may not adequately control for the uniqueness of Baltimore's stadium in particular.

The long-run income elasticity is also presented for 15 teams in Table 4. In all but one case, the estimate is positive and greater than one indicating that baseball attendance is income elastic and a normal good for fans in those particular teams' cities. Some teams, including BOS, DET, and NYM are shown to have demand that is income inelastic, meaning that attendance is relatively insensitive to changes in per-capita income. The estimated average long-run income elasticity is 1.88 across all teams for which we give values, indicating that for every 1% increase in per capita income the attendance has gone up by 1.88 percent. Baseball in Oakland, according to the results, is an inferior good.

[Tables 3a and 3b here]

[Table 4 here]

VI. CONCLUSION

Our purpose in this paper is to investigate the team-specific demand for attendance for the 23 MLB clubs that competed each year between 1970 and 2003 and to estimate the long-run elasticity of demand for each team. We developed a theoretical model to explain the setting of prices and argued that if teams receive revenues from sources other than ticket sales, inelastic pricing can be expected. Empirically we found that factors such as the price of tickets, the level of per-capita income in a team's host city, the team's current winning percentage, and dummy variables that control for strike periods were significant factors in explaining changes in attendance. Other factors that affect the demand for some team's games are the age of the stadium, the previous performance of the team, and whether the team made the playoffs. We also find that the weights given to these factors vary from team to team. We also find evidence for both elastic and inelastic pricing of tickets at the team level although most teams price in the inelastic portion of their demand curves. This finding is consistent with the notion that sports teams in general are not single-product firms with market power but are, instead, producers of multiple products.

The policy implications of our work are as follows: if a team prices tickets in the inelastic portion of its demand curve, then to increase its overall revenue, it can either increase ticket prices or it can generate offsetting revenue from the sales of concessions, souvenirs, parking, or other ancillary products. If a team prices its tickets in the elastic portion of its demand curve, then as long as the costs of serving fans at the margin is close to zero, profits can be raised by decreasing ticket prices.

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Table 1 Variable Descriptions

Variable Name	Description
C	Concession Value
A	*Log(Attendance)*
Δ	*Difference operator, eg.* $\Delta A_t = A_t - A_{t-1}$, $\Delta P_t = P_t - P_{t-1}$
P	Log(real ticket price)
I	Log(real per capita income)=log(real income/population)
W	Winning percentage
Age	Stadium age
Pf	Playoff dummy, 1=make the playoffs in the previous season
D81	Strike dummy, 1= union strike in year 1981
D94	Strike dummy, 1= union strike in year 1994
D95	Strike dummy, 1= union strike in year 1995
X	Matrix notation [W, Age, Pf, D81, D94]'
β	Regression estimators
ε	Regression residuals (error terms)

Table2 ADF Unit root tests

Team Name	Attendance (A)
ANA	-1.75
ATL	-1.67
BAL	-1.43
BOS	-2.52
CHC	-1.76
CHW	-3.41
CIN	-2.44
CLE	-1.52
DET	-3.20
HOU	-1.89
KCR	-3.16
LAD	-3.97
MIL	-3.05
MIN	-2.06
NYM	-3.60
NYY	-1.75
OAK	-1.61
PHI	-5.20
PIT	-3.25
SDP	-2.55
SFG	0.36
STL	-2.05
TEX	-1.59

Test critical values are as follows: -3.646342 (1% level), -2.954021(5% level) and -2.615817(10% level) -

Table 3a Restricted Estimates of ECM (Dependent Variable: ΔA_t, sample: 1970-2003)

	ANA	ATL	BAL	BOS	CHC	CHW	CIN	CLE	DET	HOU	KCR	LAD
A_{t-1}	-.84	-.81	-.81	-.74	-.87	-.57	-.56	-.62	-.65	-.39	-.94	-.54
	(5.79)	(7.63)	(7.39)	(4.26)	(9.29)	(5.23)	(6.43)	(6.05)	(6.01)	(2.87)	(9.41)	(4.24)
P_{t-1}	-.74	-.46	.58	.42	-.49					-.90	-1.37	
	(3.66)	(4.15)	(5.91)	(2.05)	(3.12)					(2.75)	(4.62)	
I_{t-1}	1.72	.88	1.47	.70			1.09	1.70	.51		2.55	
	(3.64)	(2.65)	(3.91)	(2.21)			(5.13)	(3.73)	(2.48)		(4.35)	
ΔP_t					-.63	.92			.29		-.47	
					(2.29)	(1.94)			(1.84)		(1.77)	
ΔP_{t-1}	.98				.39						.80	
	(2.76)				(1.94)						(3.14)	
ΔI_t		3.52										
		(3.19)										
ΔI_{t-1}				-1.23								-1.40
				(1.26)								(2.13)
W_t	1.98	3.17	2.04	.90	1.84	3.01	1.39	2.85	1.96	2.32	2.22	1.48
	(4.09)	(5.24)	(8.36)	(.42)	(5.25)	(5.39)	(4.78)	(5.95)	(5.44)	(3.04)	(4.03)	(4.60)
W_{t-1}	1.66		.76	.72	1.55		.82				2.45	
	(3.35)		(2.24)	(2.22)	(2.50)		(2.96)				(5.58)	
Age				.27	.04					-.07	-0.03	.04
				(3.32)	(8.45)					(2.70)	(1.82)	(3.31)
Age^2				-.002			-.000			.002	0.001	-.001
				(3.34)			(3.10)			(2.68)	(1.34)	(3.11)
Pf		.31										
		(2.69)										
D81			-.44	-.63	-.72	-.40	-.71	-.54	-.52	-.57	-.46	-.34
			(25.0)	(20.3)	(7.51)	(2.61)	(7.57)	(3.09)	(4.24)	(3.06)	(4.68)	(3.97)
D94			-.42	-.23	-.21	-.37	-.21		-.44	-.45	-.36	-.65
			(18.56)	(6.99)	(2.40)	(2.16)	(2.11)		(3.61)	(2.60)	(3.35)	(4.29)
D95					-.21		-.25				-.46	
					(2.40)		(2.53)				(4.13)	
R^2	0.76	.89	.93	.91	.94	.71	.83	.68	.80	.62	.94	.82
DW	1.80	1.89	2.23	1.48	2.42	2.07	2.36	2.17	2.07	1.89	2.08	1.73
REST	2.17	1.64	4.52	6.23	0.09	2.53	0.05	1.66	1.35	1.12	3.39	.003
NRM	1.28	0.29	0.44	0.47	0.48	4.94	0.09	4.43	1.05	0.65	0.27	4.19
LM	1.21	.68	4.13	2.72	0.50	0.05	0.91	1.14	0.67	0.87	0.79	0.39
W	0.74	1.22	0.72	4.78	0.68	1.20	0.69	0.61	0.39	0.87	0.44	0.92
ECM	-5.38	-4.38	-6.36	-3.75	-5.96	-4.34	-6.92	-6.12	-5.49	-4.65	-4.32	-4.82

t-statistics in bracket. Δ indicates first difference. REST is Regression Specification Error Test proposed by Ramsey (1969). NRM is the Jarque-Bera statistic for testing normality. LM is a Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals (Engle 1982). W is a test for heteroskedasticity in the residuals from a least squares regression (White, 1980). ECM is the test statistics for Engle-Granger cointegration test. The critical values are -5.75 at 1%, -4.53 at 5% and -.3.99 at 10%.

Table 3b Restricted Estimates of ECM (Dependent Variable: ΔA_t, sample: 1970-2003)

	MIL	MIN	NYM	NYY	OAK	PHI	PIT	SDP	SFG	STL	TEX
A_{t-1}	-.97 (8.52)	-.96 (11.71)	-.55 (6.31)	-.59 (5.18)	-.46 (4.81)	-.76 (11.02)	-.80 (8.00)	-.84 (6.66)	-.65 (5.91)	-.68 (6.21)	-.91 (8.53)
P_{t-1}	-1.11 (4.13)	-.44 (1.81)		.43 (1.78)	-1.01 (-4.16)	-.32 (3.10)	-.51 (1.75)	-1.11 (2.80)	-.40 (2.75)	-.40 (3.21)	-.19 (1.97)
I_{t-1}	2.43 (7.38)	1.25 (5.27)	.47 (2.75)		-1.74 (1.72)		1.36 (3.87)		1.28 (3.76)	1.35 (5.32)	1.75 (7.49)
ΔP_t											
ΔP_{t-1}											
ΔI_t					-2.83 (2.19)	-1.87 (1.93)					
ΔI_{t-1}											
W_t		3.10 (5.65)	1.95 (4.61)		2.68 (5.48)	1.80 (6.32)	1.93 (3.40)	1.66 (3.07)	3.46 (6.15)	2.40 (5.29)	2.43 (7.44)
W_{t-1}	2.57 (4.65)	1.68 (3.38)									.63 (1.84)
Age				.15 (3.75)	0.05 (2.45)		-.05 (2.73)				-.08 (6.04)
Age^2	-.001 (5.36)	-.001 (7.34)		-.001 (3.61)			.001 (2.58)	.001 (3.75)			.002 (5.67)
Pf				.15 (2.47)							-.24 (3.01)
D81	-.62 (4.08)		-.52 (3.23)	-.51 (15.0)		-.46 (4.71)	-.75 (6.96)	-.97 (8.82)	-.63 (3.60)	-.70 (5.49)	-.53 (5.88)
D94			-.54 (3.46)	-.55 (13.4)				-.55 (7.53)		-.29 (2.34)	-.51 (4.38)
D95				-.38 (5.85)				-.56 (6.24)			
R^2	.84	.82	.71	.73	.70	.87	.78	.87	.81	.81	.88
DW	2.45	1.88	2.28	2.29	2.78	2.15	1.90	1.71	1.64	1.71	2.47
REST	4.25	1.72	3.65	0.15	0.30	1.43	0.41	3.70	2.28	1.26	0.04
NRM	0.24	0.17	0.01	1.57	0.27	0.21	0.19	0.05	6.56	1.11	1.44
LM	1.59	0.62	1.06	3.18	2.27	0.75	0.35	1.03	0.60	1.02	2.44
W	1.22	0.40	3.90	0.53	2.68	1.27	0.83	0.51	0.53	1.16	1.34
ECM	-3.64	-4.77	-6.41	-5.75	-7.53	-4.59	-5.75	-4.62	-4.47	-4.65	-6.78

t-statistics in bracket. Δ indicates first difference. REST is Regression Specification Error Test proposed by Ramsey (1969). NRM is the Jarque-Bera statistic for testing normality. LM is a Lagrange multiplier (LM) test for autoregressive conditional heteroskedasticity (ARCH) in the residuals (Engle 1982). W is a test for heteroskedasticity in the residuals from a least squares regression (White, 1980). ECM is the test statistic for Engle-Granger cointegration test. The critical values are -5.75 at 1%, -4.53 at 5% and -.3.99 at 10%.

Table 4 Long-run Elasticities of Attendance

Team	Price	Income
ANA	-0.88	2.05
ATL	-0.57	1.09
BAL	0.72	1.81
BOS	0.57	0.95
CHC	-0.56	
CHW		
CIN		1.95
CLE		2.74
DET		0.78
HOU	-2.31	
KCR	-1.46	2.71
LAD		
MIL	-1.14	2.51
MIN	-0.46	1.30
NYM		0.85
NYY	0.73	
OAK	-2.20	-3.78
PHI	-0.42	
PIT	-0.64	1.70
SDP	-1.32	
SFG	-0.62	1.97
STL	-0.59	1.99
TEX	-0.21	1.92
Average	-0.67	1.41

For calculating the long-run elasticities, refer to the equation (2')

[1] As Sargan and Bhargava (1983) point out, DW will approach zero as the sample size increase if the residuals are non-stationary. That means that the DW statistics from the cointergrating regression can be used as an alternative cointegrating regression test.

[2] If a team played in the same stadium during the entire sample period, then the age variable coincides with a time trend. Teams that played in the same stadium from 1970-2003 are Anaheim (ANA), Boston (BOS), the Chicago Cubs (CHC), the Los Angeles Dodgers (LAD), the New York Mets and Yankees (NYM and NYY respectively), Oakland (OAK), Philadelphia (PHI), San Diego (SDP), St. Louis (STL). Care must be taken in interpreting the results of the age variable for these teams.