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 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, Sports Management, Price Elasticity, MLB Attendance

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Abstract

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Introduction

In North America, various professional sporting leagues, such as the Xtreme Football League (XFL), the Women's National Basketball Association (WNBA), and the National Rookie League (NRL), were began play during the 1990s, not always to great success (the XFL folded after one season). Yet the four major sport leagues in the U.S., Major League Baseball (MLB), the National Basketball Association (NBA), the National Hockey League (NHL), and the National Football League (NFL), have been relatively successful for decades. For instance, during the seasons for which league champions were determined in 2004, MLB produced \$132.4 million, NBA teams collectively generated \$277.2 million, the NHL lost a collective \$96 million, and the NFL generated \$850.3 million according to estimates produced by Forbes and gathered at Rodney Fort's website (http://www.rodneyfort.com/SportsData/BizFrame.htm).

In sports leagues, each team obtains revenues from three general sources: public resources including that from hard taxes (general property and general sales tax), soft taxes (tourist development, hotel-motel, car rental, sin, and player tax), grants, subsidies, and tax abatements; private sector resources include investment capital, corporate sponsorship, and donations; and sports enterprise sources including ticket and concession revenue, PSLs, naming rights, luxury seating, licensed merchandise revenue, advertising and membership fees, and media fees (Lee & Chun, 2002; Howard & Crompton, 2005).

Understanding the intricate relationship between ticket pricing and attendance levels at the team level is an important factor that franchise owners, current and potential, must have in order to obtain maximum returns for their investment. Several researchers, the work of who are described below, have examined the demand for baseball at the league level. Generally speaking, the quantity of tickets that fans demand is determined by the price of tickets as well as a host of other factors including fan income, team performance, and the age and the location of the team's stadium location. While these factors are important in general, the impact that each has on team attendance is likely to vary from team to team. Moreover, the sensitivity of fans to changes in the price of tickets - the elasticity of demand - is likely to vary from team to team. How the demand factors and the elasticity of demand vary between teams has been largely unexplored using MLB data.

Our purpose in this study is to fill this gap by exploring the main determinants of the team-specific demand for attendance to MLB games for the 23 teams for which sufficient data are available. To this end, we briefly describe a theoretical framework from which equilibrium levels of attendance and equilibrium ticket prices are determined. Empirically, we use Error Correction Models (ECM's) to identify the elasticities of demand price elasticities on attendances while controlling for other team-specific factors. The rest of the paper is organized into the following sections: Section II presents the literature review. Section III presents the theoretical framework and the empirical framework. Section IV describes the data used in the analysis. Section V presents the empirical results. Section VI concludes.

LITERATURE REVIEW

In American professional sports, researchers generally agree that franchise owners render decisions with an eye towards maximizing profits. Fort (2004, p.87) writes "a current finding in estimates of the gate demand for sports events is pricing in the inelastic portion of demand." This finding has puzzled analysts who study the demand for sporting events because it suggests that owners could raise ticket revenue by raising ticket prices. While there is much evidence for this proposition, some researchers find otherwise. We review some of the literature on the demand for attendance to sporting events below.

Unit Elastic and Elastic Demand Evidence

Demmert (1973) examining MLB data covering the period from 1951 to 1969, found evidence that franchise owners set ticket prices around the unit-elastic portion of the demand curve. Siegfried and Eisenberg (1980) presented similar findings for minor league professional baseball. These findings are interesting because they provide some evidence on the objectives of franchise owners when setting ticket prices. When an owner sets ticket prices at the unit-elastic point on a demand curve, revenue from ticket sales are maximized. 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.

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. Garcia (2002) estimated the demand for attendance to 1992/3 season Spanish Football League games and concluded that ticket prices are set in the elastic portion of the demand curve. Bird (1982) and Simmons (1996) explored the determinants of attendance at Premium Soccer League matches in the United Kingdom. Simmons (1996) also examined the Premium Soccer League. Simmons' approach allowed him to differentiate between season ticket holders and other attendees. He argues that not differentiating in this manner would likely lead to a downward bias in elasticity estimates. He also presented evidence suggesting that non-season ticket holders are more price sensitive than season ticket holders.

Borland (1987) studying the demand for Australian Rugby Football from 1950 to 1986, noted three important points about estimating demand equations for sporting leagues. First, an increase in real ticket prices has significant negative effect on attendance (demand curves slope downward). Second, lagged attendance is an important determinant in explaining attendance variation. Third, the uncertainty of short run (within a season) and long run (between seasons) outcomes are also an important determinant in explaining changes in attendance.

Inelastic Demand Evidence and Other Evidence

When the elasticity of demand for a good is less than one in absolute value, demand is said to be inelastic. When demand is inelastic, consumers are relatively unresponsive to changes in the price of a good and increases in the price of the good drive larger consumer expenditures on the good. In the extreme, consumers are completely unresponsive to changes in the price of a good (the case of perfectly inelastic demand). There is evidence for perfectly inelastic demand in sports (Jannet (1984) who examines the Scottish Football League), but this evidence, however, is isolated. There is much more evidence for inelastic pricing. Below we summarize a set of this research. Readers who desire a more in-depth summary of this research are directed to Fort (forth coming)

Noll (1974) and Scully (1989) each found evidence that MLB ticket prices are set in the inelastic range of demand. Noll noted three 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. Third, significance tests on the elasticity estimates could not rule out unit elasticity.

Cairns, Jannet, and Sloane (1985) summarized the results of various attendance demand estimations and gave two interpretations of their summary. First, there is substantial evidence that ticket prices are set where demand is highly inelastic. Second, various data problems have led to the true relationship being unidentified.

Watching a game at a stadium is only one way for fans to "consume" games. When franchise owners allow other avenues through which fans can follow games, they create, to some extent, a substitute for in-person attendance. Baimbridge, Cameron, and Dawson (1995) examine the effect of the emergence of satellite and cable broadcasting on attendance at English rugby league games. Their evidence suggests that the demand for rugby is upward sloping (positive relationship between the average price of tickets and attendance).

The finding that ticket prices are set in the inelastic portion of demand that is highly inelastic could be indicative that teams have chosen different levels of ticket prices that are "too low" if franchise owners seek maximum profits. One possibility for such pricing is that it is made to promote people to attend games. However, Quirk and El Hodiri (1974) 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 and souvenirs. It is certainly plausible that franchise owners would happily accept lower ticket revenue in exchange for higher concession revenue. After all, revenue from beer sales spends just as well as revenue from tickets.

Below, we add to the literature on the demand for sporting events by examining time-series data by team for a set of MLB clubs. Doing so allows us to identify team-specific factors that affect attendance. There is little reason to believe that Boston Red Sox fans make decisions in exactly the same way that Minnesota Twins fans do. Moreover, our procedure allows us to estimate team-specific demand and income elasticities. To our knowledge, no other paper applies this approach in analyzing MLB data. We now move to a brief description of a theoretical framework and the empirical model.

THEORETICAL AND EMPIRICAL FRAMEWORK

MLB franchises are assumed to have some degree of local monopoly power. Franchise owners are assumed to make decisions to maximize profits and are assumed to theoretically choose the level of output (measured by attendance) and set ticket prices corresponding to the demand for baseball in their local market. In other words, franchise owners set their ticket prices where the marginal revenue of allowing the last fan through the gate equals marginal cost. As noted above, if team costs are fixed during a season, then the marginal cost of allowing each fan through the door 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 were demand is elastic. Sandy, Sloane, and Rosentraub (2004) model the multi product team as having negative marginal costs. Suppose that each fan who attends a game buys concessions valued at $C > 0$ (assumed, for brevity, to be constant). The rational profit-maximizing team is indifferent between serving a fan at no marginal costs (who buys no concessions) whose attendance adds nothing to ticket revenue and letting a different fan in 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 fan to be $MC = -C$. In such a case, the franchise owner will rationally price tickets where marginal revenue is negative: in the inelastic portion of the demand curve.

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

$$A_{it} = \beta_0 + \beta_1 P_{it} + \beta_2 I_{it} \qquad (1)$$

where *A* is log attendance, *P* is logarithm of real ticket price and *I* is logarithm 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. If the series is integrated of the same order, a cointegrating vector might be then found such that a linear combination of the on-stationary variable obtained with that vector is, itself, stationary.

It is well-accepted that habit persistence and long memory usually formulates the demand function. 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

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

to be estimated by using an error correction model (ECM) where Δ denotes the difference operator. That means, the equation (2) is exactly the same with the following ECM parameterization.

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

The Equation (2') is a typical format of ECM. Hence, we can interpret β_1+β_2 as the short-run price elasticity, β_3 +β_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 which is depicted in equation (1). We can incorporate our basic ECM into a more general form of ECM specification with team-specific factors. Thus, we write the most general model as:

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

where θ is a vector of parameters to be estimated and X_{it} is a matrix of team-specific variables, and the team-specific variables include team winning percentage (*W*), stadium age (*Age*), a playoff dummy equal to one for all teams that made the playoffs in the previous season (*Pf*), and the three strike year dummies (*D81, D94* and *D95*) equal to one for the years in which the players' union struck during our sample period. Increases in winning percentage (*W)* and the comparable figure for the visiting team are hypothesized to lead to increased attractiveness and hence greater attendance (Carmichael, Millington, & Simmons, 1999). They point out that games between teams at the top of their division tend to be especially intense and may attract larger attendance levels than other games. Schmidt and Berri (2004) show that the effects of strikes in US professional sports only affect the immediate period during which the strike occurred and that there are no long-lasting effects. In other words, fans come back to watch games soon after strikes end.

The age of the stadium is included as a regressor because new stadiums present a unique opportunity for residents in a metropolitan area to experience a new aspect of the team. Moreover, each time a new stadium is built, an old stadium is necessarily replaced meaning there are fewer old stadiums. It is plausible that these older stadiums may become attractions in their own right. Therefore, it is important to control for the age of the stadium when estimating demand equations in sports.

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 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 developed by Kanioura & Turner (2003) and proposed by Engle and Granger (1987) and Kremers, Ericsson, and Dolado (1992). These authors show that the cointegration testing 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 use OLS to estimate equation (3) for each club, a process that makes them preferable to using dynamic pooled estimates. For instance, Pesaran and Smith (1995) show for the pooled estimators that coefficient heterogeneity may generate a serial correlation problem that gives inconsistent estimates with lagged dependent variables in ADL regressions. In addition, Simmons (1996) shows that fixed effects may not be sufficient to deal with 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.

The final forms of model specifications for each team are obtained from 'general-to-specific' specification search which has been popularized particularly by Hendry (Hendry, 1995; Mizon, 1995; Hendry, 1993; Hendry & Mizon, 1990). Hendry and Krolzig (2001) have recommended the use of multiple search paths in the process of moving from a Generalised Unrestricted Model (GUM) to a parsimonious specification. The reason for this recommendation is to avoid the risk of deleting an important variable which should ideally be retained in the final specification along any single search path and to minimize the risk of retaining as proxies for the missing variable with the result that the final model is overparameterised. Therefore, our final form of each team in the general EC model equation (3) is determined by parsimony, satisfactory performance against diagnostic tests incorporated with Schwarz criterion, evidence of cointegration and the implied long-run relation of equation (1).

DATA AND DESCRIPTION OF VARIABLES

The full data set comprise the 23 US Major League Baseball teams that competed each year during the period from 1970 to 2003 (except for 1989 and 1990 when no ticket price data was available). Toronto and Montreal are excluded from the analysis because of the lack of metropolitan-specific data for their respective metropolitan areas. Teams that began play after 1970 (Seattle, Florida, Colorado, Arizona, and Tampa Bay) are excluded from the analysis because of a sufficient lack of data points. All team productivity data was obtained from the Lahman database (www.baseball1.com). Team performance is measured by team winning percentage and in each regression, a team's current year's winning percentage and previous year's winning percentage are included in the models.

Team ticket price data was calculated using weighted average ticket price data obtained from the late Doug Pappas (www.roadsidephots.com) and from past personal correspondence with Roger Noll. Both Pappas and Noll made their calculations using ticket price data by section for each team. The weights used in their calculations are the number of seats in each section. 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 dataset rather than choose between them. Ticket price data was only available from the Pappas dataset for the years 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, records for those years were dropped.

Population and per-capita income of the US metropolitan areas served by MLB clubs were obtained from the Bureau of Economic Analysis' Regional Economic Information System (REIS).

Other variables included in the analysis are the age of each team's stadium and a dummy equal to one if a team had been in the playoffs the previous season. Between 1969 and 1994, teams made the playoffs by winning their division in a two-division format. In 1995, MLB went to a three-division format and teams could make the playoffs by winning their division or by winning the wild card – the team with the best record that did not win its division. Consequently, the lagged 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.

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), each of which shortened the length of the MLB season.

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).

Empirical Results

The estimates obtained from a general-to-specific specification search based upon all the diagnostic tests are reported in table 1. Each equation passes the test for first-order serial correlation, functional form misspecification, and non-normality and heteroskedasticity of residuals. Each test statistic was evaluated at the 5% significance level. All the variables in the final equations are tested whether the processes of attendance, real price and real per capita income are *I(0) or I(1)*. The stationarity of all the variables are verified by using the following tests: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Kwiatkowshi, Phillips, Schmidt and Shin (KPSS) and Ng-Perron (NP). All the test results show that prices and incomes are *I(1)*. The attendance values are *I(1)* even though there is uncertainty regarding the order of integrations of some particular teams' attendance values (including those for the Chicago White Sox (CHW), Detroit Tigers (DET), Kansas City Royals (KCR), Los Angeles Dodgers (LAD), Milwaukee Brewers (MIL), New York Mets (NYM), Philadelphia Phillies (PHI) and Pittsburgh Pirates (PIT)). The highly-strict interpretation of the ADF test can be avoided with our stationarity test of the residuals in the cointegrated estimation equation given the sample size of (32), the low power of the test, and the test statistics close to the critical values which allow rejection of the unit root null.

The test statistics from the residuals of the cointegration results are crucial to verifying the final specification model for each team. The findings show that the null hypothesis of non-cointegration can be rejected for most teams at 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]

The estimated coefficients across teams shows 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 common across most teams. Most of the estimated coefficients on the price dummy are negative, except for the Baltimore Orioles (BAL), BOS, and the New York Yankees (NYY). The models show no relationship between attendance and ticket price for the Cincinnati Reds (CIN), the Cleveland Indians (CLE), LAD, and NYM. The current team winning percentage is positive and significant for all teams but the Milwaukee Brewers and the New York Yankees. Lagged winning percentage is positive and significant for 9 of the 23 modeled teams. The playoff dummy was significant for only a handful of teams (the Atlanta Braves (ATL), the New York Yankees, and the Texas Rangers (TEX). The estimated coefficient on the playoff dummy for TEX is odd 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 attendance in just over half of the models. Since stadium age was entered quadratically, not only do the models tell us about the effect of the age of the stadium on attendance patterns 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 diminished as the stadium ages. Positive linear terms along with negative quadratic terms tell us that as a stadium ages, attendance changes accelerate but at a decreasing rate. This latter nature is exhibited for some of the teams that play in classic stadiums: BOS, the Chicago Cubs (CGC) and NYY. It is possible that these classic stadiums have some historical value to fans. Indeed, this interpretation is consistent with the models that show negative linear terms with positive quadratic terms. Together these estimates tells 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

[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.

value might be subject to diminishing marginal returns. A similar thing can be said of the newer retro stadiums.

The attendance effect of the strikes of 1981 and 1994 have the expected signs and are both statistically significant for most of teams. In particular, the 1981 strike shows the most significant effects on 19 team's attendance values except for ANA, ATL, MIN and OAK, and the magnitude exceed 0.5 14 teams out of those 19 teams. 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.

Table 2 presents the long-run price elasticities calculated from the model results. More teams exhibit inelastic demand at the observed prices than exhibit elastic demand. The size of the implied 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 of 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. As noted above, this behavior is consistent with a profit maximization objective if these teams obtain appreciable offsetting revenue from the sales of concessions and souvenirs.

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 the stadium, we may not adequately control for the uniqueness of it.

The long-run income elasticity is presented for 15 teams in Table 2. 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 which is income inelastic meaning that attendance is relatively insensitive to changes in per-capita income. The estimated average income elasticity is 1.88 across all teams for which values are given, indicating that for every one percent 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.

[Table 1 here]

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 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 controlled 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 or not 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 are not single-product firms with market power but are, instead, the producer of multiple products.

The policy implications of are 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, 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.

REFERENCES

Baimbridge, M., Cameron, S., & Dawson, P. (1995). Satellite broadcasting and match attendance, the case of rugby league. *Applied Economics Letters,* **2**, 343-346.

Bird, P. (1982). *The demand for league football. Applied Economics,* **14**, 637-649.

Borland, J. (1987). The demand for Australian rules football. *Applied Economics,* **24**, 220-230.

Cairns, J., Jannet, N., & Slone, P. (1985). The economic of professional team sport, a survey of theory and evidence. *Journal of Economic Studies,* **13**, 3-80.

Carmichael, F., Millington, J., & Simmons, R. (1999). Elasticity of demand for rugby league attendance and the impact of BskyB. *Applied Economic Letters*, **6**, 797-800.

Deaton, A., & Muellbauer, J. (1980). *Economics and consumer behavior*. Cambridge University Press, Cambridge.

Demmert, H. (1973). *The economic of professional team sports*. Lexington, MA: Lexington Books.

Engle, R. (1982) Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation. *Econometrica*, **50**, 987-1008.

Engle, R., & Granger, C. (1987). Cointegration and error correction: Representation, Estimation, and Testing, *Econometrica*, **55**, 251-276.

Engle, R., & Granger, C. (1991). *Long-run economic relationships: Readings in cointegration*, Oxford University Press, Oxford.

Fort, R. (2004). Inelastic sports pricing. *Managerial and Decision Economics*. **25**, 87-94.

Fort, R. (2006 forthcoming). "Inelastic Pricing at the gate? A survey." In Andreff, W., Borland, J., & Szymanski, S. (eds.) *The Handbook on the economics of sport*. Northampton, MA: Edward Elgar Publishing, Inc.

Garcia, J. (2002). The determinants of football match attendance revisited empirical evidence from the Spanish football league. *Journal of Sports Economics,* **3**(1), 18-38.

Hendry, D. (1993). *Econometrics: Alchemy or science?* Oxford: Black Well Publishers.

Hendry, D. (1995). *Dynamic econometrics*. Oxford University Press.

Hendry, D., & Krolzig, H. (2001). *Automatic econometric model selection using PcGets*. London: Timberlake Consultants Ltd.

Hendry, D., & Mizon, G. (1990). Procrustean econometrics: Or stretching and squeezing data, In: C. Granger (ed.), *Modeling Economic Series: Readings in Econometrics Methodology*, Oxford University Press, 121, 36.

Howard, D., & Crompton, J. (2005). *Financing sport (2nd ed).* Mogantown, WV: Fitness International Technology.

Jannet, N. (1984). Attendance, uncertainty of outcome and policy in Scottish league football. *Scottish Journal of Political Economy,* **31**, 176-198.

Kanioura, A., & Turner, P. (2003). *The error correction model as a test for cointegration*. University of Sheffield Working Paper.

Kremers, J., Ericsson, N., & Dolado, J. (1992). The power of cointegration test. *Oxford Bulletin of Economics and Statistics*, **54**, 325-348.

Lee, S., & Chun, H. (2002). Economic values of professional sports franchises in the United States. *The Sport Journal,* **5**(3), Retrieved March 10, 2006 from http://www.thesportjournal.org/2002Journal/Vol5-No3/econimic-values.asp

Mizon, G. (1995). Progressive modeling of macroeconomic time series: The LSE methodology. *EUI Working Paper*, ECO No 95/10, European University Institute.

Noll, R. (1974). Attendance and price setting. In R. Noll (Ed) *government and the sports business.* Washington, D.C.: Brooklings Institution.

Pesaran, H., & Smith, R. (1995). Estimating long-run relationships from dynamic heterogeneous Panels. *Journal of Econometric,* **68**, 79-130.

Quirk, J., & El Hodiri, M. (1974). The economic theory of a professional sports league. In R. Noll. (Ed.) *Government and the sports business*. Washington, D.C.: Brooklings Institution.

Ramsey, J. (1969). Tests for specification errors in classical linear least squares regression analysis. *Journal of the Royal Statistical Society*, Series B, **31**, 350-371.

Sandy, R., Sloane, P., & Rosentraub, M. (2004). *The economic of sport – An international perspective*. Palgrave, Houndmills, Basingstoke, Hampshire.

Sargan, J., & Bhargava, A. (1983). Testing residuals form least squares estimators for being generated by the Gaussian Random Walk. *Econometrica*, **51**(1), 153-174.

Schmidt, M., & Berri, D. (2004). "The impact of labor strikes on consumer demand: An application to professional sports." *American Economic Review*, **94**(1), 344-357.

Scully, G. (1989). *The business of major league baseball*. Chicago, IL: University of Chicago Press.

Siegfried, J., & Eisenberg, J. (1980). The demand for minor league baseball. *Atlantic Economic Journal,* **8**, 59-69.

Simmons, R. (1996). The demand for English league football, a club-level analysis. *Applied Economics,* **28**, 139-155.

White, H. (1980). A heteroskedasticity-consistent covariance matrix and a direct test for heteroskedasticity. *Econometrica*, **48**, 817-838.

Table 1a Restricted Estimates of ECM (Dependant Variable: ΔA_t, sample: 1970-2003)

	ANA	ATL	BAL	BOS	CHC	CHW	CIN	CLE	DET	HOU	KCR	LAD
A_{t-1}	-.84 (5.79)	-.81 (7.63)	-.81 (7.39)	-.74 (4.26)	-.87 (9.29)	-.57 (5.23)	-.56 (6.43)	-.62 (6.05)	-.65 (6.01)	-.39 (2.87)	-.94 (9.41)	-.54 (4.24)
P_{t-1}	-.74 (3.66)	-.46 (4.15)	.58 (5.91)	.42 (2.05)	-.49 (3.12)					-.90 (2.75)	-1.37 (4.62)	
I_{t-1}	1.72 (3.64)	.88 (2.65)	1.47 (3.91)	.70 (2.21)			1.09 (5.13)	1.70 (3.73)	.51 (2.48)		2.55 (4.35)	
ΔP_t					-.63 (2.29)	.92 (1.94)			.29 (1.84)		-.47 (1.77)	
ΔP_{t-1}	.98 (2.76)				.39 (1.94)						.80 (3.14)	
ΔI_t		3.52 (3.19)										
ΔI_{t-1}				-1.23 (1.26)								-1.40 (2.13)
W_t	1.98 (4.09)	3.17 (5.24)	2.04 (8.36)	.90 (.42)	1.84 (5.25)	3.01 (5.39)	1.39 (4.78)	2.85 (5.95)	1.96 (5.44)	2.32 (3.04)	2.22 (4.03)	1.48 (4.60)
W_{t-1}	1.66 (3.35)		.76 (2.24)	.72 (2.22)	1.55 (2.50)		.82 (2.96)				2.45 (5.58)	
Age				.27 (3.32)	.04 (8.45)					-.07 (2.70)	-0.03 (1.82)	.04 (3.31)
Age^2				-.002 (3.34)			-.0003 (3.10)			.002 (2.68)	0.001 (1.34)	-.001 (3.11)
Pf		.31 (2.69)										
D81			-.44 (25.0)	-.63 (20.3)	-.72 (7.51)	-.40 (2.61)	-.71 (7.57)	-.54 (3.09)	-.52 (4.24)	-.57 (3.06)	-.46 (4.68)	-.34 (3.97)
D94			-.42 (18.56)	-.23 (6.99)	-.21 (2.40)	-.37 (2.16)	-.21 (2.11)		-.44 (3.61)	-.45 (2.60)	-.36 (3.35)	-.65 (4.29)
D95					-.21 (2.40)		-.25 (2.53)				-.46 (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 Engel-Granger cointegration test. The critical values are -5.75 at 1%, -4.53 at 5% and -.3.99 at 10%.

Table 1b Restricted Estimates of ECM (Dependant 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 statistics for Engel-Granger cointegration test. The critical values are -5.75 at 1%, -4.53 at 5% and -.3.99 at 10%.

Table 2 Long-run Elasticities of Attendance

Elasticity	Real Ticket Price	Real Per Capita 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