A Test of the Optimal Positive Production Network Externality in Major League Baseball

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Abstract

Unlike most businesses, firms in a sports league need viable competitors. While a certain amount of domination is optimal, from an individual owners perspective, too much will result in league dissolution, and thus a lower utility for every owner. Hence, there is a limited positive production network externality. This paper examines the optimal level of the externality in professional baseball using data from each game of the 1996 MLB season. Both absolute and relative quality are important determinants of the demand for sports contests. In fact, fans prefer a game in which two high quality teams are competing, but the home team has approximately twice as good of a chance as the visiting team of winning.

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Comments appreciated. Send to Dan_Rascher@lecg.com.

Are the Bulls so good they're bad for the NBA?"

-- The Cover of Sports Illustrated
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I. Introduction

Are both absolute and relative quality important in the demand for sports contests? Is the closeness of the contest a significant factor and if so what is the optimal degree of closeness? Alternatively, what is the optimal distribution of talent across the league from the owners' perspective?

Unlike most businesses, firms in a sports league need viable competitors. While a certain amount of domination is optimal, from an individual owners perspective, too much will result in league dissolution, and thus a lower utility for every owner. Hence, there is a limited positive production network externality. Up to a point, many successful competitors are better than none, a major exception to classical economic theory. In fact, what Neale (1964) termed "the peculiar economics of sports" is just the positive production network externality.

Early in the history of professional sports, owners realized that contests with an uncertain outcome were important for attracting large crowds. In fact, the first professional baseball league failed largely because of the dominance of a few teams. Fans began to grow tired of the ``pre-determined" games and eventually stopped showing up (Scully, 1989).

In response, the owners began to insert rules to create more parity throughout the league. Most of these rules (the rookie draft, the waiver rule, salary caps, revenue sharing, luxury taxes, the Rozelle rule, player only trades with no cash involved) are either new or remain intact today. However, the reserve clause has been replaced by limited free agency. The efficacy of these rules in promoting league parity is questionable. Some of them have created a monopsonistic environment keeping player salaries down without necessarily affecting the distribution of player quality across teams.

The sports league model in Rascher (1997) posits a number of hypotheses regarding industrial organization and labor issues. Some of these depend directly on the particular assumption that both relative and absolute quality are determinants of demand. Most empirical analyses test the results of some theory directly. In this case, it is difficult if not impossible to test the effects of changes in revenue sharing or salary caps when neither have changed significantly more than once per league, and those that have changed, have occurred concurrently with other structural changes. Thus, separating the individual effects is not possible. Instead, the analysis performed here tests the assumptions, not the results, to see whether they are reasonable. If the assumptions do not hold true, perhaps it is not worth checking the results, but if the assumptions prove to be acceptable, then we are one step closer to accepting the implications of the model.

The model assumes that the demand for a particular game has the form $Q_h = S_i(AT_i + BT_j + C(T_i - T_j)^2 + other)$, and that $A>B>0>C$. A is the marginal propensity to attend home games with respect to the home team's quality. B is the marginal propensity to attend home games with respect to the visiting team's quality and is assumed to be less important to the home town fans. C is the marginal propensity to attend home games that is attributable to the closeness of contest portion of demand. S_i is a scalar which controls for the potential demand from market size, income, and other factors across cities. Q_h satisfies the consideration that the closeness of the contest as well as high quality play are important aspects of the demand for sports contests. The restrictions on A, B, and C are consistent with the notion that demand is maximized when the probability that the home team wins a particular game is greater than *0.5*, but less than *1*. It is likely that the home team fans care more about changes in the home team's level of quality than changes in the visiting teams quality levels. This demand function prevents two equally-rated low quality teams from enticing the same demand as two equally-rated high quality teams.[2]

To test whether or not this demand function is credible, a game-by-game demand analysis will reveal if: (1) the absolute quality of the two teams is important (A and B are both positive and significant), (2) home town fans respond more to changes in the home team's player quality level than to changes in the visiting team's player quality level ($A > B$), and (3) fans want to see a close game where the winner is determined with uncertainty ($C < 0$ and significant). This last test will reveal whether there truly exists a significant positive production network externality. Additionally, a direct test of the optimal (from the league's perspective) *ex ante* probability that the home team wins a particular game will be performed.[3]

To accomplish this, a large dataset (2267 observations for 58 variables) was created where each observation is a Major League Baseball game played in 1996. This dataset is particularly suited to test demand because in the short run, the supply of contests (and their quality) is fixed, and variation in the quantity sold should result from shifts in the demand function not supply function. A game-by-game or short run demand analysis using attendance as a proxy for demand empirically verifies the above assumptions.

Section two contains a review of related literature. A description of the data comprises section three, followed by the analysis and results section. The last section summarizes the findings.

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[2] The previous literature failed in this respect (see the next section for details). Additionally, imagine two sets of teams. One set contains a high quality and a low quality team. The other set consists of two teams each having equal amounts of player quality, but whose player quality sums to the total player quality of the teams in the first set. Previous models of demand for games within the two sets had the same quantity demanded. The current model allows for the closeness of the game between the teams in the second set to have a positive effect on demand.

[3] It is possible for each team to have a greater than 50% chance of winning its home games because of home field advantage. In fact, it is in the interest of sports leagues (given the findings here) to create a considerable home field advantage for each team in their league.

II. Previous Literature

Most studies of the demand for sports contests have been long-run studies where the unit of observation was a team-season (i.e., each observation was a whole season for a particular team). Beginning with Demmert (1973) and Noll (1974), it has been typical to use attendance as a proxy for revenue. However, Siegfried and Eisenberg (1980) use average revenue in their study of minor league baseball demand, but find no significant differences in their results from the two prior papers.[4]

As expected, these studies have found that team quality (proxied by season winning percentage) has an important effect on demand.[5] However, they haven't tested whether relative, absolute, or both types of team quality are important.

Recently, there have been a number of short run demand studies of professional sports. Hill, Madura, and Zuber (1982) examined baseball data from the 1977 season and found that the quality of the two teams was important (an absolute quality assessment) as well as some of the same results as the current study (higher population centers and weekend games attract more fans).[6] Borland and Lye (1992) show that the uncertainty of the contest is an important factor of demand, but only measure this uncertainty four times during their season of study of an Australian Rules football league. Thus, their results are interesting, but have low power.

In a small dataset, Welki and Zlatoper (1994) examine the National Football League and find that home team quality is important. Jennett (1984) and Peel and Thomas (1988) use soccer attendance data. Jennett shows that an *ex post* measure of uncertainty (the final score) is an important determinant of attendance. Peel and Thomas uncover evidence that the closeness of the contest matters using an *a priori* measure of closeness (pre-game odds data). Their study is similar in flavor to the current study because it directly analyzes the importance of closeness, but not the importance of absolute team quality.

Finally, a paper by Knowles, Sherony, and Haupert (1992) uses 861 games and ten independent variables from the 1988 Major League Baseball season and concludes that the attendance maximizing *ex ante* probability that the home team wins (using gambling odds data) is about *0.6*. The current study has a larger number of observations and more independent variables than any previous study of this nature. It also specifically tests for the effect of absolute and relative quality concurrently as determinants of demand, so that their relative importance can be measured and an *ex ante* optimal probability of the home team winning can be estimated. In addition, it tests other factors such as race and pitcher quality in affecting demand.

[4] See Cairns et. al. 1986, for a brief summary of long run demand studies of professional team sports.

[5] Interestingly, these studies have had problems getting a negative sign on the ticket price variable. Some have concluded that owners are not profit maximizers when setting ticket prices. Likely, it is because of a lack of proper control variables or a simultaneity problem.

[6] Domazlicky and Kerr (1990) find similar results using a limited baseball dataset.

III. The Data

The dataset contains 2,267 observations, one for each game played, for the 1996 Major League Baseball season. Each observation is a particular game and contains the dependent variable, game attendance, which is used as a proxy for game revenue or (without price) quantity sold. The sports league model being tested claims that teams choose player quality to maximize the owners objectives. Owner objectives contain revenue (through a profit function) which is aggregated from individual game revenue. Thus, attendance is a natural outcome variable for testing the effects of owner decision making.

Dependent Variable

Table 1 shows sample statistics for a selection of the variables in the dataset. Attendance ranges from 6,021 fans (an April midweek Oakland A's game against a weak drawing Milwaukee club) to 57,467 fans (the opening day game for the Seattle Mariners) with a mean close to 27,000. Unlike the National Basketball Association where most games sell out, baseball games have a wide range of attendances allowing for the possibility of uncovering determinants of demand (of the 2,267 games, 51 were sellouts). The source was from the internet web site www.sportsline.com.[7]

Time Varying Independent Variables

Included in each observation are variables that change from game to game for a particular team. Some of these relate to team quality while others relate to conditions of the game. The former will be described first, followed by the latter.

Two measures of game excitement are the average number of runs scored in the previous 10 games for the home and visiting team, respectively. It is expected that the sign will be positive because pundits claim that today's fan enjoys a high scoring affair. However, it is possible for the sign to be negative if fans desire a pitching duel. This could be an interesting test of the pundits' claim.

To capture the effect of possible changes in player quality levels (from learning by doing or even trades) during the course of the season, the number of wins in the last 10 games for both the home and visiting teams is used and is expected to exert a positive influence on attendance.

Another measure of team quality is whether a team is in contention for a division title. A proxy, the number of games behind the division leader, is used, but is interacted with the

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[7] The power of the internet was evident in the creation of this dataset. Every variable came directly off of an internet web page for free except the pitcher race variable.

percentage of games left in the season. This distinguishes between being ten games out in May (still in contention) or ten games out in September (out of the race). The current percentage of games played (i.e., 30 of 162 games is 18.5%) is used as a type of trend variable because many of the time-varying regressors (pitcher wins and losses) increase simply because the season wears on.

Unlike most other sports, the quality of a baseball team changes from game to game because a different starting pitcher is used each game (typically a rotation of 4 or 5 pitchers is used throughout the season). To capture this effect, the current wins, losses, and earned run average of both the home and visiting starting pitcher is used. It is expected that more wins, fewer losses, and a lower earned run average for both pitchers will increase attendance, but there should be a larger effect for the home team pitcher.

It is possible that fans relate more to the past career performances of a particular pitcher in making their purchasing decisions, especially at the beginning of a season. Career wins, losses, and earned run average for both the home and visiting starting pitchers is entered as a covariate and expected to have the same sign as the current season version of these variables.

The independent variables above are the team quality factors that vary from game to game. There are a number of interesting game condition variables unrelated to team quality. A weekend dummy variable is expected to have a positive effect on attendance because the opportunity cost of attending a game on the weekend is lower than during the week for people that have a standard work week. Further, each team plays every Friday night, Saturday, and Sunday, but not each day during the week. Thus, the owners must feel that weekend games draw more fans than weekday games or else they wouldn't schedule so many of them. In fact, 48% of games are weekend games. An evening variable is also included for essentially the same reason. Additionally, an opening day variable is used to capture the well-known positive effect that opening day has on attendance.

The temperature and degree of cloudiness at game time are probable factors in the decision to attend a baseball game. Warmer temperatures (although not too warm) and clearer skies are likely to induce higher fan turnouts. The cloudiness index ranges from 0 to 9 with 9 being very cloudy. The average cloudiness of the 1,500 games is about 2. The temperature ranges from 33 to 100 degrees Fahrenheit with a mean and median of about 72.5.

About 52% of the games were televised. Viewing a game on TV is likely to be a substitute for attending a game, thus a negative effect on attendance. However, many pundits claim that these are not competing products because attending a game does not simply involve watching the contest, but experiencing the atmosphere instead. Also, televised games are likely to increase product awareness and thus increase future game attendance figures. This argument has been used to advocate the removal of the blackout rule in professional football.

One measure of the importance or excitement of a game is whether the two teams are rivals. Most rivalries are between two teams in the same division within the league. Additionally, divisions are usually geographically based. Thus, these official rivalries are also likely to be sociological rivalries, e.g., the San Francisco Giants and the Los Angeles Dodgers. A dummy variable was created to denote a game between rivals.

Scully (1974), using baseball data from 1967, shows that Black pitchers were discriminated against at the gate with fewer fans showing up to watch them pitch. Indicator variables for Latino, Black, and Asian starting pitchers for both the home and away team are created to assess whether customer discrimination against certain races is a factor of demand. About 6% of the starting pitchers are Black, about 15% are Latino, and only two pitchers (Hideo Nomo and Chan Ho Park, both of the Los Angeles Dodgers) are Asian.

There are two groups of variables that are of major interest for the empirical test of the sports league model. The first group contains the home team's measure of player quality (current home team's winning percentage or T_i), the visiting team's measure of player quality (current visiting team's winning percentage or T_j), and the difference of these two squared ($(T_i - T_j)^2$).[8] It is expected that the coefficients of these variables will be positive, smaller, but positive, and negative, respectively. This corresponds to the test of the assumption that $A > B > 0 > C$. Because of the high variability of these variables at the beginning of the season, this test will be performed on the data corresponding to the last half of the season. Table 1 shows that both home team and visiting team winning percentages range from 28% to 64% with a predictable mean of 50%.

The second group of variables is simply the probability that the home team will win a particular game created by converting the pre-game odds data. On odds betting of this type, there is no vigorish or commission for the bookie.[9] Instead, the odds for betting on the favorite are not symmetrical to the odds for betting on the underdog. For example, if the home team's line is 175 and the visiting team's line is 165 with the home team favored, then a \$175 bet placed on the home team will pay \$100 if the home team wins, and a \$100 bet placed on the visiting team will pay \$165, if the visiting team wins, not \$175. The bookie makes a profit because the odds are not symmetric and bettors place bets on both the underdog and the favorite.

To get a probability that the home team will win from the odds data, assume that the odds presented are for a fair bet. Then, if the probability that the home team will win is P_h, $100P_h - 175(1-P_h) = 0$ implying that $P_h = 0.636$. For a bet placed on the visiting team the fair bet equation, $165P_h - 100(1-P_h)$, yields $P_h = 0.623$. These probabilities are not the same because the difference allows the bookie to make a profit. The average of the two

[8] Because winning percentage is not linear in wins, it is necessary to correct for the high volatility of winning percentage at the beginning of the season by interacting it with the percentage of games played in the season. This essentially creates a variable that is linear in wins.

[9] Betting on spreads, say in basketball, usually follows an 11 for 10 rule meaning that a bet of \$11 gets a chance to win \$10 because the bookie keeps the vigorish of \$1. In spread betting, the bettor can bet on either side of the spread with the same payoff structure.

will be used here for the home team's probability of winning. In this case, $P_h = 0.63$, or the home team has a 63% chance of winning the game. The resulting probabilities for the home team winning have an average of 54% with a minimum of 25% and a maximum of 82%.

Time Constant Independent Variables

There are a number of potentially important independent variables that are constant throughout the season for a given team, but vary across teams. A straight average ticket price for each team is used as a proxy for the actual ticket prices paid by consumers. Obviously this may be an influential determinant of demand. However, as discussed in the review section, many previous studies have found ticket price to have the opposite sign or be insignificant.[10] Average ticket prices range from $7.95 to $15.43 with a mean of $11.43.

Perhaps a better measure of the real cost of attending a game is the Fan Cost Index from the Team Marketing Report. This index assumes a family of four purchases a fixed number of products (four hot dogs, four sodas, two peanuts, two caps, four mid-level tickets, and parking). The average Fan Cost Index is $103 with a minimum of $81 and a maximum of $122.

Median income, the local unemployment rate, and the local population are all candidates for inclusion in a demand model. The expected effects are positive, negative, and positive, respectively. The racial composition of the local geographic area, if baseball appeals to certain cultures more than others, may affect attendance levels. Rascher (forthcoming) shows that National Basketball Association annual attendance figures are partially predicted by the percentage of the local population that is Black. Here, the percentage Black and the percentage Latino is used to capture cultural differences across baseball cities. It will be interesting to see if and how the sports differ in this respect.

Owners believe that characteristics of the baseball park affect attendance since these are part of the product space. The data set contains two variables related to stadium age. One is an indicator variable which takes on one if a stadium is new (built since 1987, which is the new generation of stadia) and zero if it is old. Also, because of the allure of the two classic ballparks, Wrigley field in Chicago and Fenway Park in Boston, a dummy variable is created for them.

A measure of alternative recreation is included as a factor in determining annual attendance figures in order to capture the notion of substitute products for professional baseball. Pundits consistently claim that west coast fans are more fickle either because many more of them are transplants than fans in eastern cities, or because of the extra recreation available in west coast cities.

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[10] Although, a recent article seems to have solved this dilemma using a winning percentage feedback loop and a good measure of alternative entertainment sources (Boyd, 1997).

Finally, the number of home team and visiting team wins from the previous season is used as a measure of expected quality. This may be more important at the beginning of the season, but is probably also a factor in season ticket sales, which in turn affect game by game attendance figures throughout the season. Table 2 shows simple statistics for the interpretable independent variables.

IV. Analysis and Results

Analysis

The primary analysis consists of three tests that are performed by running three multivariate regressions and interpreting the results. The first test examines whether $A > B > 0 > C$ from the demand function in the model. This determines if both absolute and relative quality are important factors of demand and their respective weights.

Using pre-game odds data, the second test solves for the *ex ante* optimal probability that the home team wins based on attendance. The regression uses a simple quadratic to allow for a maximum. Thus, the signs of the probability and the probability squared should be positive and negative, respectively.

The current home and visiting team winning percentages can be converted into a probability that the home team wins and can be examined in exactly the same way as the second test. This third test can be compared to the second test to see whether fans use all of the data available to them in making their decision (pre-game odds data) or use winning percentages as a proxy for the quality of the contest. In predicting attendance, it is not obvious which piece of information is more likely to be used by the fans.

To predict which team will win a particular game, the odds data is expected to perform better than the modified winning percentage data. A test of which variable is a better forecaster of game outcomes will be undertaken.[11]

Results

Because of the possibility of truncation of the dependent variable due to sellouts, a censored regression was run. It is similar to a tobit analysis except that it allows the dependent variable to have more than one truncation point, i.e., a different one for each stadium capacity. The results are virtually identical to those from an OLS analysis. This is not surprising since there were only 51 sellouts out of a possible 2,267 games.

[11] The data for the second half of the season will be used in analyses using winning percentage because of the excessive volatility present in this variable at the beginning of the season.

Another potential data problem is that the errors for an *n-game* series between two teams may not be independent. It is expected that across different groups of games (a three games series for example) there exists independence of the errors, but not necessarily within groups. This type of clustered correlation leads to understating the standard errors. A robust estimator of the variance is used to correct the standard errors.

It is possible that the time-constant independent variables will be correlated with the error term (a causality issue). For example, larger population centers may exhibit higher variances in attendance that may or may not error or one side of the fitted equation. If so, the estimates will be biased. To correct for this, a team fixed effects model without any time-constant independent variables is used as an alternative to the full model. As with most fixed effects models, the fit is higher because there are specific intercepts for each team which capture the omitted team-specific variables, like advertising and ballpark atmosphere.

Table 2 shows the results of the three regressions using team specific variables.[12] The first column is the analysis of the demand specification directly. Home team current winning percentage has a positive coefficient ($A > 0$). Visiting team current winning percentage also has a positive, but smaller, effect on attendance ($A > B > 0$). Finally, the square of the difference between the two measures of team player quality has a negative coefficient ($0 > C$).[13] Thus, fans are more sensitive to changes in their own team's player quality level than to changes in the visiting team's player quality level. They also desire close contests. During the middle of the season, an average win increases an average team's winning percentage by 0.0125 leading to an increase in attendance by 690 fans for each game.

Table 3 contains the results for the team fixed effects regressions. The adjusted R-squared increased from about 0.62 to 0.73. Almost three fourths of the variation in game-by-game attendance is explained by the current set of variables. The findings for the main variables of interest are similar, but smaller, than those found in Table 2.

As in previous studies of annual attendance, the American League attracts 5,000 fewer fans, all else equal. Increases in the Fan Cost Index decrease the number of fans attending games, although the result isn't significant.[14] Similar to Scully (1974), Black pitchers face customer discrimination at the gate of about 2,000 fans for the home team pitcher, while Latino and Asian pitchers increase demand above and beyond their skills, as compared to white pitchers. As expected this effect is less important for the visiting pitcher than for the home pitcher.[15]

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[12] Some of the control variables were left out of the analysis because of collinearity problems (the cloudiness index with temperature, the ticket price data with Fan Cost Index). Others were removed because of low explanatory power in the spirit of stepwise regression.
[13] The levels of significance for A, B, and C are 1\%, 10\%, and 6\%, respectively.
[14] Even if it were statistically significant, the implied elasticity would be near -0.20, and thus not be very important anyway.
[15] The Asian pitcher variables are somewhat misleading because both Asian pitchers in the league pitch for the Los Angeles Dodgers. Statistically, this variable is related to a team fixed effect variable for the

The home team pitchers career wins and losses have unexpected signs, even though the percentage of games played is included as a control for the normal increase in these variables that occurs over the course of the season. Greater career losses increases demand and greater career wins decreases it. However, there is a correlation between career and season wins and losses. Subsequent analysis shows that net career winning percentage works as expected. The visiting pitchers career wins and losses follow the expected pattern, but are generally not significant.

The home and visiting pitcher's season wins and losses follow the expected pattern of having positive and negative effects on attendance, respectively. An extra win for the home team pitcher increases attendance by about 250 spectators. Again, the home pitcher's numbers are more important to the home town fans with respect to demand than the visiting pitcher's.

The effect of night games is unexpectedly negative, but only marginally significant. Perhaps work or school nights accounts for some of this result. A weekend game draws an extra 5,000 fans to the park. Thus, the owners are correct to fill all weekend days with games, and allow the breaks in the season to occur during the week. Opening day attracts almost 12,000 additional fans to the stadium. Warmer temperatures increase fan attendance by about 900 fans per one degree Fahrenheit increase, but the effect is decreasing as temperatures rise (the negative coefficient on temperature squared).[16]

Cities with relatively large Black and Latino populations have lower attendances, all else equal. Brent Staples (1987) claims that about 93% of ticket buying fans are White. This may explain the city racial composition effect. It also may explain the discrimination effect against Blacks, although not the attendance premium afforded Latino players. The population effect is extremely consistent. An increase in the local population by one million is associated with an increase in attendance by about 850 fans per game.

As expected, larger stadiums allow for more fans to attend games. On average, 5 more seats is associated with an increase in attendance of 1 more fan per game.[17] This result is smaller than the result from Rascher (1998) using NBA data. Because NBA games are 95% filled to capacity, an additional seat at an NBA game has a higher marginal effect than one at a baseball park. Thus, the finding here is not surprising.

Dodgers. Thus, it is hard to separate out the L.A. effect from the Asian pitcher effect. In fact, in the fixed effect regressions in Table~3, Los Angeles and one other variable (St. Louis) had to be removed to avoid singularity. Of course, one fixed effect variable has to be removed because of singularity and is used as the comparison variable for the other fixed effect variables.

[16] This appears to be quite a large effect. Perhaps a control for month of the season interacted with temperature might explain the result.

[17] The causality of this result is uncertain given that many new stadiums have been built recently, perhaps reacting to the excess demand that already existed.

The most significant factor of demand is the new stadium effect. A new stadium attracts an extra 16,000 fans to the park per game.[18] Apparently, there is more to attending a baseball game than the quality of the teams on the field.

The two classic stadiums increase attendance by about 8,000 fans. To capture both of these effects at the same time, the last few new stadiums built have been designed to look like the classic ballparks of the past.

Each team's number of wins from the previous season has a lasting effect on the current season. For each extra win the home team had in 1995, about 300 additional fans per game showed up to watch a baseball game during the 1996 season. The effect is predictably smaller for the visiting team. Also, the second half of the season, as expected, is less affected by this phenomenon.

Using either pre-game odds data or converting winning percentages into probabilities gave similar results regarding the *ex ante* optimal probability that the home team wins a particular game. The attendance maximizing probability is between 60% and 70%.[19] Home town fans want their team to have about twice the chance to win the game as the visiting team.

Surprisingly, the wins and runs scored in the last 10 games by both the home and visiting teams appear to be ineffective predictors of attendance. Overall team winning percentage and pitcher quality may overshadow these effects.[20]

The interaction between the percentage of games played and the team's winning percentage is predictably positive. Wins are more important as the season progresses with respect to attendance.

Similarly, the interaction of games behind the leader and the percentage of games left in the season for a particular team is positive. If there are a lot of games left in the season, the further behind the leader a team is, the less effect it has on attendance. However, these coefficients are barely marginally significant in only a few of the regressions.

As expected, the odds data provided a superior forecast of game outcome than the probability using winning percentage. The χ^2 for the former was 13.14, and for the latter, 7.55 for a probit analysis of outcomes on probabilities.

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[18] A back of the envelope analysis shows that this leads to an extra 1.3 million fans for the season for a particular team. If each fan spent $15 at the game, that leads to almost $20 million in extra revenues. Most stadiums cost $100 - $200 million. Thus, their costs could be recovered in five to ten years (excluding the real interest rate).

[19] Assuming a quadratic relationship between probability and attendance leads to an equation of the form $Y = aP + bP^2$. Taking the derivative with respect to P further leads to $a + bP = 0$. Next, solving for P gives $P = -(a/2b)$.

[20] The correlation table shows that there is an association between some of these variables.

V. Conclusion

This paper contains an empirical investigation of one aspect of the sports league model in Rascher (1997). It shows that fans are more sensitive to changes in their home team's player quality level and that they prefer close contests, but still want to see the home team win. Thus, there exists empirical support for the notion of a positive production network externality in professional sports.

An original dataset is collected that contains many potential factors of demand for baseball games. Questions of customer discrimination, marketing ability, marginal productivity, public financing of stadiums can be addressed using this dataset.

The assumptions of the demand specification are empirically verified in both a fundamentals model and a team fixed effects model. The *ex ante* optimal probability that the home team wins is about 66%. Thus it is between 0.5 and 1.0 as assumed by the model. The answer to the quote "Are the Bulls so good they're bad for the NBA?" is a cautious yes. If the optimal probability that the home team wins is similar in basketball to baseball, and if the Chicago Bulls were to continue dominating, then fans across the NBA would likely stop coming to games. As Danny Ainge, coach of the NBA's Phoenix Suns, puts it "it'll be better when the Bulls break up. More teams will feel they have a chance to win it all." Further, the fans will realize this as well and begin showing up at the gate again.

This analysis also reconfirmed Scully's findings of customer discrimination against Black pitchers, and found owners are correct in their use of weekend games and new stadiums to attract additional fans. The probability of the home team winning using odds data outperforms a similar variable using winning percentage as both predictors of attendance and of winning.

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Table 1. Sample Statistics of the Game By Game Baseball Data

	Minimum	Mean	Maximum
Dependent Variable:			
Game Attendance	6021	26,868	57,467
Time Varying Variables:			
Prob. the Home Team Wins (Odds)	0.25	0.54	0.82
Prob. the Home Team Wins (Wpct)	0.26	0.50	0.74
Current Home Team's Win Percent	0.28	0.50	0.64
Current Visiting Team's Win Percent	0.28	0.50	0.64
Home Team's # of Runs in Last 10 Games	0	5.02	12.5
Home Team's # of Wins in Last 10 Games	0	4.8	10
Home Team's Current # of Losses	0	40.03	108
Home Team's Current # of Wins	0	39.9	97
Home Pitcher's Career ERA	0	4.00	16.2
Home Pitcher's Career Losses	0	37.6	176
Home Pitcher's Career Wins	0	43.8	231
Home Pitcher's Season ERA	0	4.60	81.0
Home Pitcher's Season Losses	0	4.26	17.0
Home Pitcher's Season Wins	0	4.77	22
Visitors Current # of Losses	0	39.90	103
Visitors Current # of Wins	0	39.99	99
Visiting Pitcher's Career ERA	0	3.98	14.14
Visiting Pitcher's Career Losses	0	37.60	176
Visiting Pitcher's Career Wins	0	43.55	231
Visiting Pitcher's Current ERA	0	4.57	81
Visiting Pitcher's Current Losses	0	4.24	17
Visiting Pitcher's Current Wins	0	4.73	23
Visitor's Runs in Last 10 Games	0	5.02	15
Visitor's Wins in Last 10 Games	0	4.85	9
Night Game	0	0.66	1
Game is a Weekend Game	0	0.48	1
Cloudiness Index	0	2.06	9
Temperature at Game Time	33	72.5	100
Time Constant Variables:			
Home Team's Previous Season's Wins	56	71.92	100
Visitor's Previous Season's Wins	56	71.99	100
Average Ticket Price	$7.95	$11.30	$15.43
Fan Cost Index	$81.31	$103.03	$121.76
Median Income of Local CMSA	$26,501	$35,046	$41,459
Percentage Black of Local CMSA	0.006	0.127	0.260
Percentage Latino of Local CMSA	0.005	0.099	0.331
Population of Local CMSA	1,640,831	5,997,132	18,107,235

Recreation Index of Local CMSA	81.32	93.72	99.02
Unemployment Rate of Local CMSA	0.034	0.061	0.113
Stadium Seating Capacity	33,871	50,655	64,593
Stadium Age	0	28.5	84

Table 2. Correlations of Selected Variables

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	Probability the Home Team Wins	1.00																
2	Attendance	0.29	1.00															
3	Average Ticket Price	0.25	0.29	1.00														
4	Cloudiness Index	-0.03	-0.02	0.13	1.00													
5	Fan Cost Index	0.13	0.16	0.75	0.14	1.00												
6	Home Team's Previous Season's Wins	0.41	0.41	0.32	0.05	0.31	1.00											
7	Home Team's # of Runs in Last 10 Games	0.13	0.08	0.17	0.02	0.12	0.08	1.00										
8	Home Team's # of Wins in Last 10 Games	0.26	0.17	0.11	0.01	.0.1	0.16	0.50	1.00									
9	Home Team's Current # of Losses	-0.19	-0.05	-0.07	0.01	-0.02	-0.14	-0.04	0.05	1.00								
10	Home Team's Current # of Wins	0.08	0.17	0.05	-0.04	0.02	0.09	0.04	0.24	0.87	1.00							
11	Home Pitcher's Career ERA	-0.02	-0.03	-0.04	-0.04	-0.05	-0.06	0.06	0.02	-0.06	-0.03	1.00						
12	Home Pitcher's Career Losses	0.25	0.14	0.11	0.04	0.01	0.25	-0.03	0.05	-0.15	-0.04	-0.09	1.00					
13	Home Pitcher's Career Wins	0.32	0.17	0.21	0.04	0.09	0.33	-0.01	0.08	-0.17	-0.04	-0.13	0.94	1.00				
14	Home Pitcher's Season ERA	-0.19	-0.06	0.03	0.01	0.06	-0.07	0.11	0.00	0.09	0.04	0.03	-0.11	-0.12	1.00			
15	Home Pitcher's Season Losses	-0.01	0.01	-0.02	0.01	-0.01	-0.05	-0.01	0.08	0.65	0.62	-0.03	0.10	0.11	0.03	1.00		
16	Home Pitcher's Season Wins	0.28	0.21	0.11	-0.04	0.03	0.13	0.04	0.19	0.53	0.70	0.03	0.15	0.16	-0.14	0.64	1.00	
17	Median Income of Local CMSA	-0.05	-0.08	0.31	-0.05	0.40	-0.02	0.10	-0.04	0.23	-0.03	-0.10	-0.13	-0.08	0.11	0.04	-0.02	1.00

Table 2. Correlations of Selected Variables (cont.)

		18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
1	Probability the Home Team Wins	0.04	0.14	0.09	0.08	0.06	0.07	-0.18	0.05	-0.26	-0.33	0.14	-0.06	-0.32	-0.11	-0.28	-0.42	0.01
2	Attendance	-0.07	0.09	-0.01	0.20	-0.01	0.06	0.07	-0.06	-0.01	0.01	-0.04	0.03	0.04	-0.01	-0.02	0.07	0.24
3	Average Ticket Price	-0.07	0.28	-0.21	-0.08	-0.02	0.01	-0.02	0.01	0.00	0.01	0.02	-0.01	-0.02	0.09	0.02	-0.02	0.00
4	Cloudiness Index	0.01	0.26	-0.11	-0.18	-0.13	-0.01	-0.02	-0.02	0.00	0.00	0.00	0.02	-0.01	-0.03	-0.01	-0.01	-0.03
5	Fan Cost Index	-0.10	0.41	-0.16	-0.11	-0.21	0.01	-0.01	0.00	0.00	0.00	-0.01	-0.01	-0.01	0.06	0.01	-0.02	0.00
6	Home Team's Previous Season's Wins	0.04	0.21	0.11	0.04	-0.07	0.00	-0.03	-0.01	-0.03	-0.03	-0.01	-0.02	-0.03	-0.01	-0.07	-0.08	-0.01
7	Home Team's # of Runs in Last 10 Games	0.03	-0.05	-0.12	0.03	-0.15	0.01	-0.01	-0.02	-0.02	-0.02	0.07	0.01	0.00	0.14	-0.05	0.00	0.01
8	Home Team's # of Wins in Last 10 Games	0.07	-0.03	0.00	0.17	0.02	0.17	0.13	-0.02	-0.01	-0.02	0.09	0.15	0.10	-0.08	0.01	-0.04	0.02
9	Home Team's Current # of Losses	0.05	-0.02	-0.01	0.30	-0.01	0.93	0.94	-0.06	-0.08	-0.06	0.06	0.63	0.62	-0.03	0.17	0.03	0.02
10	Home Team's Current # of Wins	0.07	0.00	0.02	0.34	0.03	0.94	0.93	-0.06	-0.10	-0.09	0.05	0.64	0.61	-0.06	0.15	0.00	0.03
11	Home Pitcher's Career ERA	0.00	-0.05	-0.02	0.02	-0.10	-0.05	-0.05	0.01	0.00	-0.01	0.00	-0.02	-0.05	0.04	0.02	0.02	0.00
12	Home Pitcher's Career Losses	0.07	0.14	0.06	0.05	0.01	-0.09	-0.11	0.04	-0.04	-0.05	0.01	-0.07	-0.07	0.01	-0.03	-0.02	-0.01
13	Home Pitcher's Career Wins	0.06	0.17	0.04	0.05	0.04	-0.10	-0.11	0.03	-0.04	-0.04	-0.01	-0.08	-0.07	-0.01	-0.04	-0.03	-0.01
14	Home Pitcher's Season ERA	-0.03	-0.06	-0.06	-0.02	-0.08	0.07	0.06	0.01	0.01	0.02	0.09	0.05	0.06	0.06	0.08	-0.02	0.03
15	Home Pitcher's Season Losses	0.03	0.01	0.04	0.25	0.00	0.64	0.64	-0.01	-0.07	-0.05	0.04	0.43	0.41	-0.04	0.11	0.00	0.01
16	Home Pitcher's Season Wins	0.07	0.07	0.05	0.28	0.03	0.62	0.61	-0.04	-0.08	-0.06	0.05	0.40	0.37	-0.01	0.12	0.00	0.01
17	Median Income of Local CMSA	-0.13	-0.06	0.09	-0.19	-0.12	0.00	0.00	0.03	0.04	0.05	0.09	-0.01	0.01	0.15	0.03	0.01	0.01

Table 2. Correlations of Selected Variables (cont.)

		181	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
18	Night Game	1.00																
19	Percent Black in local CMSA	-0.02	1.00															
20	Percent Latino in local CMSA	0.07	-0.01	1.00														
21	Temperature at Game Time	0.10	0.15	0.09	1.00													
22	Unemployment Rate of local CMSA	0.06	-0.19	0.35	0.03	1.00												
23	Visitors Current # of Losses	0.06	0.00	0.00	0.32	0.00	1.00											
24	Visitors Current # of Wins	0.06	-0.02	0.00	0.32	0.01	0.88	1.00										
25	Visiting Pitcher's Career ERA	-0.02	-0.01	0.00	-0.01	0.01	-0.06	-0.06	1.00									
26	Visiting Pitcher's Career Losses	-0.01	-0.03	-0.04	-0.05	0.01	-0.14	-0.03	-0.07	1.00								
27	Visiting Pitcher's Careeer Wins	0.01	-0.04	-0.04	-0.06	-0.01	-0.14	-0.01	-0.12	0.95	1.00							
28	Visiting Pitcher's Current ERA	-0.02	-0.03	-0.00	0.02	-0.03	0.08	0.03	0.00	-0.10	-0.11	1.00						
29	Visiting Pitcher's Current Losses	0.05	-0.01	-0.01	0.22	0.00	0.65	0.62	-0.01	0.13	0.15	0.05	1.00					
30	Visiting Pitcher's Current Wins	0.05	-0.02	-0.01	0.23	0.01	0.54	0.69	0.03	0.17	0.20	-0.12	0.64	1.00				
31	Visitor's RUns in Last 10 Games	0.02	-0.07	0.00	0.00	-0.04	-0.11	0.01	0.04	0.01	0.02	0.13	-0.09	0.01	1.00			
32	Visitor's WIns in Last 10 Games	0.03	-0.04	-0.03	0.10	0.06	0.07	0.25	0.01	0.07	0.08	0.05	0.05	0.20	0.47	1.00		
33	Visitor's Previous Season's Wins	0.00	-0.03	-0.01	-0.02	0.01	-0.10	0.12	-0.09	0.26	0.35	-0.05	-0.03	0.14	0.15	0.22	1.00	
34	Game is a Weekend Game	-0.28	0.00	0.00	0.03	0.00	0.03	0.02	-0.02	-0.01	-0.02	0.05	0.02	0.00	0.03	0.03	-0.01	1.00

Table 3[a]. Regression Results of the Demand Specification Analysis

Dependent Variable: Game Attendance	A > B > 0 > C [b]	Optimal Prob. with Odds Data	Optimal Prob. with Winning Percentage Data [b]
Adjusted R-squared	0.631	.603	0.64
F value	37.82	55.23	40.86
Number of Observations	1102	2193	1102
Home Team Current Win Percent	55560 (7.202)	-	-
Visiting Team Current Win Percent	12804.6 (1.578)	-	-
Square of the Difference in Win Percents	-33429 (-1.827)	-	-
Prob(Home Team Wins): Odds Data	-	42201 (1.821)	-
Prob(Home Team Wins): Squared	-	-31452 (-1.748)	-
Prob(Home Team Wins): Win Percents	-	-	48266 (2.256)
Prob(Home Team Wins): Squared	-	-	-34219 (-1.885)
Optimal Probability Home Team Wins	-	0.671	0.70
Percent of Games Played by Home Team	69924 (2.446)	63613 (3.026)	8824 (0.286)
Percent of Games Played by Visiting Team	-71549 (-2.486)	-99846 (-4.447)	-62322 (-1.937)
Percent of Games Played * Win Percent (H)	54957 (3.450)	59583 (5.767)	62017 (4.385)
Percent of Games Played * Win Percent (V)	20913 (1.548)	22504 (1.770)	-15998 (-0.523)
Games Behind Leader * Pct Games Left (H)	17238 (1.594)	15359 (1.695)	-6938 (-0.245)
Games Behind Leader * Pct Games Left (V)	1812 (0.916)	1924.4 (0.188)	12920 (0.348)
Intercept	-41335 (-2.079)	-36269 (-2.178)	-18234 (-0.678)
Home Team Wins in Last 10 Games	227.8 (0.913)	-43 (-0.259)	119 (0.484)
Visiting Team Wins in Last 10 Games	-226.8 (-1.016)	-254 (-1.620)	-293 (-1.345)
Home Team Runs in Last 10 Games	187 (0.595)	-43 (-0.208)	113 (0.354)
Visiting Team Runs in Last 10 Games	303 (1.042)	205 (0.953)	368 (1.311)
American League Dummy	-4683 (-5.079)	-4914 (-6.415)	-4701 (-5.16)
Fan Cost Index	-42 (-0.886)	-46.8 (-1.22)	-42 (-0.903)
Home Team Pitcher is Asian	14585 (6.972))	16190 (9.683)	14593 (6.941)
Home Team Pitcher is Black	-2061 (-2.323)	-1283 (-1.998)	-2221 (-2.664)
Home Team Pitcher is Latino	2844 (3.378)	1635 (2.637)	2667 (3.184)

Visiting Team Pitcher is Asian	6933	3959	6477
	(2.704)	(2.439)	(2.696)
Visiting Team Pitcher is Black	-1960	-1115	-1731
	(-2.153)	(-1.622)	(-1.869)
Visiting Team Pitcher is Latino	500	1247	518
	(0.674)	(2.204)	(0.712)
Home Pitcher's Career Losses	60	40.8	56
	(2.570)	(2.409)	(2.429)
Visiting Pitcher's Career Losses	-9.5	-19.8	-12.4
	(-0.501)	(-1.327)	(-0.653)
Home Pitcher's Career Wins	-37	-26.8	-34
	(-1.928)	(-1.886)	(-1.826)
Visiting Pitcher's Career Wins	16	24.4	18.5
	(1.140)	(2.028)	(1.328)
Home Pitcher's Season Wins	302	141	241
	(4.194)	(2.131)	(3.355)
Visiting Pitcher's Season Wins	-26	70	-33
	(-0.427)	(1.165)	(-0.544)
Home Pitcher's Season Losses	-461	-327	-443
	(-5.663)	(-4.682)	(-5.551)
Visiting Pitcher's Season Losses	-101	-141	-93
	(-1.274)	(-2.174)	(-1.185)
The Game is Played at Night	-489	-588	-551
	(-1.104)	(-1.706)	(-1.248)
The Game is Played on the Weekend	5055	5735	5036
	(9.89)	(15.93)	(9.309)
Percentage Black in the Local CMSA	-8528	-17738	-7517
	(-1.152)	(-3.205)	(-1.043)
Percentage Latino in the Local CMSA	-30927	-37419	-31358
	(-5.818)	(-8.94)	(-5.981)
Population of the Local CMSA	0.000800	0.000854	0.000802
	(4.257)	(5.764)	(4.32)
Unemployment Rate of the Local CMSA	-1441	-1352	-1393
	(-4.475)	(-5.615)	(-4.349)
Recreation Index of the Local CMSA	-18	-29	-21
	(0.17)	(-0.366)	(-0.201)
Temperature at Game Time	1394	327	1090
	(3.454)	(1.608)	(2.665)
Temperature at Game Time Squared	-8.9	-1.40	-6.9
	(-3.344)	(-0.969)	(-2.587)
Stadium Capacity	0.33	0.21	.35
	(4.247)	(3.725)	(4.451)
Stadium Built Within Last Decade	16913	16547	16855
	(15.044)	(18.86)	(15.293)
Classic Stadium	10544	5966	10794
	(6.077)	(4.628)	(6.470)
Opening Day	-	11962	-
		(3.465)	
Home Team's Previous Season's Wins	161	292	149
	(3.146)	(7.637)	(3.017)
Visiting Team's Previous Season's Wins	59	103	54
	(1.579)	(3.511)	(1.474)

Note: T-stats are in parentheses.

a These regressions have robust corrected standard errors for the cluster correlation problem.

b This analysis is performed using only data from the second half of the season to allow for the winning percentages to become stable.

Table 4[a]. Fixed Effects Regression Results of the Demand Specification Analysis

Dependent Variable: Game Attendance	A > B > 0 > C [b]	Optimal Prob. with Odds Data	Optimal Prob. with Winning Percentage Data [b]
Adjusted R-squared	0.74	.72	0.75
F value	80.14	168.49	83.11
Number of Observations	1102	2193	1102
Home Team Current Win Percent	35187 (2.622)	-	-
Visiting Team Current Win Percent	10849 (1.819)	-	-
Square of the Difference in Win Percents	-18429 (-1.524)	-	-
Prob(Home Team Wins): Odds Data	-	26332 (1.949)	-
Prob(Home Team Wins): Squared	-	-22435 (-1.875)	-
Prob(Home Team Wins): Win Percents	-	-	28751 (2.100)
Prob(Home Team Wins): Squared	-	-	-20841 (-1.911)
Optimal Probability Home Team Wins	-	0.59	0.69
Percent of Games Played by Home Team	6673 (0.266)	13149 (0.724)	7123 (0.313)
Percent of Games Played by Visiting Team	-11500 (-0.455)	-40246 (-2.174)	-19374 (-1.128)
Percent of Games Played * Win Percent (H)	32151 (3.010)	35031 (3.246)	43589 (2.315)
Percent of Games Played * Win Percent (V)	21917 (1.421)	25494 (3.593)	-43010 (-2.357)
Games Behind Leader * Pct Games Left (H)	3211 (0.594)	4236 (0.614)	-31482 (-0.1.217)
Games Behind Leader * Pct Games Left (V)	1243 (0.805)	-2371 (-0.320)	54979 (2.096)
Intercept	-41335 (-2.079)	-10332 (-0.836)	-3820 (-0.182)
Home Team Wins in Last 10 Games	146 (0.701)	-227 (-1.799)	155 (0.799)
Visiting Team Wins in Last 10 Games	-96 (-0.589)	-186 (-1.604)	-130 (-0.815)
Home Team Runs in Last 10 Games	127 (0.556)	-236 (-1.559)	38 (0.171)
Visiting Team Runs in Last 10 Games	-130 (-0.534)	-302 (-1.88)	-34 (-0.144)
Home Team Pitcher is Asian	6105 (1.954)	5718 (3.480)	5990 (1.959)
Home Team Pitcher is Black	-1047 (-1.696)	-1055 (-2.230)	-1267 (-2.103)
Home Team Pitcher is Latino	351 (0.579)	-126 (-0.264)	218 (0.354)
Visiting Team Pitcher is Asian	3681 (3.668)	3231 (2.765)	3817 (3.653)

Visiting Team Pitcher is Black	-1583	-1250	-1434
	(-2.129)	(-2.294)	(-1.908)
Visiting Team Pitcher is Latino	729	1223	764
	(1.291)	(2.883)	(1.371)
Home Pitcher's Career Losses	25	6	20
	(1.323)	(0.418)	(1.092)
Visiting Pitcher's Career Losses	3.5	-14	1.5
	(0.214)	(-1.183)	(0.088)
Home Pitcher's Career Wins	-20	-2	-16
	(-1.287)	(-0.161)	(-1.028)
Visiting Pitcher's Career Wins	3	15	6
	(0.243)	(1.492)	(0.471)
Home Pitcher's Season Wins	168	127	131
	(2.697)	(2.294)	(2.093)
Visiting Pitcher's Season Wins	-6	3.7	2
	(-0.113)	(0.071)	(0.038)
Home Pitcher's Season Losses	-235	-186	-245
	(-3.565)	(-3.259)	(-3.747)
Visiting Pitcher's Season Losses	-101	-88	-128
	(-1.622)	(-1.657)	(-1.977)
The Game is Played at Night	-616	-772	-654
	(-1.587)	(-2.651)	(-1.684)
The Game is Played on the Weekend	5364	5608	5353
	(11.89)	(16.30)	(12.041)
Temperature at Game Time	934	106	694
	(2.875)	(0.535)	(2.076)
Temperature at Game Time Squared	-6.3	-0.07	-4.7
	(-2.901)	(-0.051)	(-2.110)
Home Team's Previous Season's Wins	388	340	388
	(2.568)	(3.237)	(2.543)
Visiting Team's Previous Season's Wins	65	96	66
	(2.340)	(5.127)	(2.355)

Note: T-stats are in parentheses.

a These regressions have robust corrected standard errors for the cluster correlation problem. The team specific fixed effects variables are left out of the table.

b This analysis is performed using only data from the second half of the season to allow for the winning percentages to become stable.