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When Is the Honeymoon Over?

National Basketball Association Attendance 1971-2000

JOHN C. LEADLEY
Western Oregon University

ZENON X. ZYGMONT
Western Oregon University

This article uses a Tobit analysis to test for the presence of a honeymoon effect for National Basketball Association (NBA) arenas using a pooled cross-section time series sample from 1971 to 2000. No previous NBA attendance-demand or attendance-related study tested for such an effect. The honeymoon effect increases attendance demand 15% to 20% in the first 4 years of the operation of a new arena, an increase that is similar in magnitude to recently constructed Major League Baseball stadiums. The effect is nonlinear and diminishes relatively quickly with the steady state established after Year 10. Because many NBA arenas are subsidized, the effect has public policy implications if revenue projections for a new arena ignore or overestimate the effect.

Keywords: honeymoon effect; basketball; attendance

The honeymoon effect represents the relationship between spectator attendance at a professional sporting event and the age of the sports facility at which the event is held. Opening a new stadium or arena may result in an initial surge in attendance, but in time, the novelty of the new facility fades and attendance begins to decline. Hamilton and Kahn (1997) claimed that for Major League Baseball (MLB) stadiums, "the honeymoon begins to fade after three years and . . . the steady state is
achieved in approximately eight years” (p. 253). Major League Baseball aside, little research has been conducted on the honeymoon effect in professional sports. A plausible explanation for this is capacity constraints; if games are frequently sold out, estimation of the underlying attendance demand function—and the presence and length of the honeymoon—becomes problematic.  

The honeymoon effect has important public policy implications because professional sports facilities continue to receive public subsidies throughout the United States. The demand for subsidies is nothing new (see, e.g., Quirk & Fort, 1997, p. 137), but the quantity of subsidies supplied has increased rapidly since the late 1980s. The growth of new, almost exclusively publicly funded arenas for National Basketball Association (NBA) franchises illustrates this. A recent study by PricewaterhouseCoopers (2001) noted that 22 of 29 NBA teams are playing in arenas built or renovated since 1990, and four other facilities were in the planning stages.  

Proponents of public subsidies argue that these contributions are justified because of the positive impact a team and its facility have on the local economy. These claims are made despite substantial evidence to the contrary—public investment in stadiums and arenas likely does not stimulate the economy and may even retard its growth.  

An important variable in any estimate of the economic impact of a new sports facility is projected attendance. Attendance is one of the primary sources of team revenue; higher projected attendance will increase franchise revenue, which in turn contributes to a larger potential economic impact. If the decline in attendance in time is not taken into account or is stronger than anticipated, the projected economic impact of the sports facility and the justification for subsidization will be biased upward (Baade & Sanderson, 1997a, p. 96).  

This article tests for the presence of a honeymoon effect in the NBA during the period 1971-2000. To the best of our knowledge, none of the extensive literature on the NBA has focused on this issue. Thus, we believe our article makes a useful contribution to the attendance literature for professional sporting events. In addition, our extensive set of panel data incorporates an important period: the building boom in basketball arenas in the 1990s. Our results indicate that the honeymoon effect is an important factor in determining attendance, with an initial increase of approximately 15% that begins to decline in the 4th year. Also, following the work of Burdekin and Idson (1991), we have addressed an important methodological consideration, censored attendance data caused by arena capacity constraints.

Department, Labor Market Information Center). We also thank Jeff Parker (Reed College), Marc Poitras (University of Dayton), Hamid Bahari-Kashani, Dianna Hewett, the staff of Hamersly Library (Western Oregon University), and the following National Basketball Association teams: Boston Celtics, Chicago Bulls, Cleveland Cavaliers, Portland Trailblazers, San Antonio Spurs, Toronto Raptors, and Utah Jazz. The authors appreciate comments made during the presentation of a preliminary version of this article at the Western Economic Association Meetings in Seattle, Washington, July 2002, in particular those by Stephen Shmanske, Stefan Szymanski, and Stephen Walters. The authors also thank two anonymous referees for their helpful comments. Any remaining errors are the sole responsibility of the authors.
LITERATURE SUMMARY

Previous research concerning the honeymoon effect focused almost exclusively on Major League Baseball. For example, articles by Demmert (1973); Noll (1974); Scully (1974); Hill, Madura, and Zuber (1982); Whitney (1988); Baade and Tiefen (1990); Bruggink and Eaton (1996); Coffin (1996); Rascher (1999); and Rivers and DeSchriver (2002) included stadium age as an explanatory variable. Kahane and Shmanske (1997) incorporated a new stadium variable in their study on the impact of MLB team roster turnover on attendance. Burger and Walters' (2003) study concerning market size, team performance and competitive balance also tested for the honeymoon effect.

Models of attendance demand for the NBA typically focus on questions about racial discrimination, not the honeymoon effect (Berri, 2003, and Kahn, 1991, provide excellent surveys of the extensive NBA literature). Of the empirical studies that examined the determinants of attendance more broadly—Hansen and Gauthier (1989), and Zhang, Pease, Hui, and Michaud (1995)—neither included a new arena or an arena-age variable.

THE MODEL

Prior attendance studies for professional sports have typically used ticket price, arena capacity, team performance, and city characteristics as regressors. Although this approach results in a high R², it lacks a theoretical basis and may not estimate the demand function as intended. The role of arena capacity, a supply variable, in determining demand is questionable, and price and attendance are at least partially determined simultaneously. Ticket prices are set prior to the beginning of the season, so that the error in the attendance equation will be independent of the price variable, but the team will still choose those prices based on the expected market conditions that will also affect the level of attendance.

Our model is a variation of one used by Jones and Ferguson (1988) to estimate attendance per game in the National Hockey League. The model relies on several simple assumptions. First, attendance demand is a linear function of ticket price, or \( Q = a - bP \), which results in price elasticity of demand equal to \( (a - Q)/Q \). Second, marginal costs are 0, so that expected ticket revenue and profit are maximized at the point where elasticity of demand is equal to 1. Setting \( (a - Q)/Q \) equal to 1 yields \( Q^* = a/2 \) and \( P^* = a/2b \) as the optimal quantity and price.

Taking the natural log of both \( Q^* \) and \( P^* \) results in

\[
\ln Q^* = \ln 1/2 + \ln a \tag{1}
\]

\[
\ln P^* = \ln 1/2 + \ln a - \ln b. \tag{2}
\]
The third assumption is that the natural logs of the intercept and slope of the demand curve are linear functions of a vector of the natural log of team and city characteristics \((x)\), so that

\[
\ln a = \alpha_0 + \alpha_1 \ln x \tag{3}
\]

\[
\ln b = \beta_0 + \beta_1 \ln x \tag{4}
\]

Combining these assumptions gives

\[
\ln P^* = \ln 1/2 + \alpha_0 + \alpha_1 \ln x - \beta_0 - \beta_1 \ln x
\]

\[
= \ln 1/2 + (\alpha_0 - \beta_0) + (\alpha_1 - \beta_1) \ln x \tag{5}
\]

\[
\ln Q^* = \ln 1/2 - 0 + -1 \ln x. \tag{6}
\]

There is considerable empirical evidence that teams actually maximize profits by pricing in the inelastic region of the demand curve for tickets (see Fort, 2004), although the estimated values range from close to 1 to as low as 0.25. A common explanation for this pricing decision is that reducing ticket prices increases the revenue for concessions and parking from additional fans by more than the decrease in ticket revenue. The effect of such behavior on our model is relatively benign. If teams select ticket prices for which elasticity equals \(\varepsilon\), then \(Q^* = a/1 + \varepsilon\) and \(P^* = \varepsilon a/(1 + \varepsilon)b\). This will change only the constant terms in Equations 5 and 6. This is because a shift in demand, represented by a change in the intercept \(a\), will still change actual attendance by a fraction of that shift, whether it is by one half if elasticity equals one or by two thirds if elasticity is 0.5. Although the coefficients for the independent variables in Equation 6 will measure the effect on actual attendance irrespective of the value of \(\varepsilon\), the implied shift in demand will vary with \(\varepsilon\). If teams price where elasticity is equal to 1, then the shift in demand is twice as large as the change in \(Q^*\). If elasticity is set equal to 0.5, then the shift in demand is 1.5 times larger than change in \(Q^*\). Lacking any consistent alternative value in the literature, we will continue the exposition assuming that price elasticity is equal to 1 but also recognize that shifts in demand implied by changes in \(Q^*\) will probably be smaller than those implied by our estimated coefficients.

Ticket prices are announced before the start of the season, so management must forecast demand for the upcoming season based on expected team performance and economic conditions. Some demand-side variables are known, such as the age of the arena and the length of time the team has played in that city. The known variables are denoted by \(z\), and the forecasted variables by \(w\). We will assume that for the latter, teams use the naïve forecast that next season will be like this one, so the price equation should be estimated using the values from the previous season.
(w−1). Fans also forecast team performance for the upcoming year when deciding whether to purchase season tickets.

\[
\ln P^* = \ln \frac{1}{2} + (\alpha_0 - \beta_0) + (\alpha_1 - \beta_1) \ln z + (\alpha_2 - \beta_2) \ln w_{-1}. \tag{7}
\]

The impact of uncertain demand and the inability to adjust price are more complicated for the attendance equation. Demand may be higher or lower than expected based on the actual values of the \(w\) variables, but ticket prices are fixed in advance and cannot be adjusted to move attendance to the new revenue maximizing point. If the intercept increases from \(a\) to \(a'\), attendance does not increase from \(a'/2\) but rather to \(a/2 + (a' - a)\). We assume that the intercept of the demand curve changes by a multiplicative factor based on the ratio of the actual value of \(w\) to the expected value \((w_{-1})\).

\[
\ln a = \alpha_0 + \alpha_1 \ln z + \alpha_2 \ln w_{-1} + \gamma_1 \ln w/w_{-1}. \tag{8}
\]

The resulting attendance equation is

\[
\ln Q = \ln 1/2 + \alpha_0 + \alpha_1 \ln z + \alpha_2 \ln w_{-1} + \gamma_1 \ln w/w_{-1}
= \ln 1/2 + \alpha_0 + \alpha_1 \ln z + \alpha_2 \ln w_{-1} + \gamma_1 (\ln w - \ln w_{-1}). \tag{9}
\]

In the NBA, arena capacity is likely to be a significant constraint so that teams may not be able to reach the point on the demand curve at which revenue and profits are maximized. For our sample, nearly 15% of the observations were sellouts for the entire season. If this censoring is not accounted for, the estimated coefficients will be biased downward. The attendance equation (Equation 9) can be estimated by using a maximum-likelihood Tobit procedure with arena capacity as the right censoring value (this approach was also used by Burdekin & Idson, 1991, for NBA attendance). Ticket prices will also be affected, with the left censoring value equal to the price from the demand curve at arena capacity. The censoring value of the dependent variable is not known, so the condition that attendance is equal to arena capacity is used as an indicator of censoring in the Tobit procedure for Equation 7.

An additional 12% of observations are for teams with average attendance equal to 95% of arena capacity, with the likely result that attendance for a significant number of games during those seasons was constrained. A dummy variable equal to 1 if attendance was greater than or equal to 95% of capacity was used as an alternative indicator of censoring with very similar results. The only notable difference is a slightly higher set of estimated coefficients for the new arena variables, which is to be expected given that these teams were unable to increase attendance for many games during those seasons by the full desired amount.
THE VARIABLES

The dependent variables are average attendance per home game and the general admission ticket price (in 1984 dollars). Attendance per game is used instead of the more common season total because of the 1998 labor dispute and lockout, which resulted in a decrease in the number of games played. A dummy variable for that year could be used to account for the decrease in season attendance, but the interpretation of its coefficient would be ambiguous. Total attendance could have been affected by the decrease in the number of games or a change in attendance per game played. Average attendance for games played avoids this problem.

Previous attendance studies have measured ticket prices using a constructed price index (the weighted average price for all seats offered for sale), a realized price (the weighted average price for tickets sold), the median or unweighted average price, or a representative price (for example, a courtside or general admission ticket). The strengths and weaknesses of each method are discussed at length in the literature.7

Our choice to use general admission prices is due in part to data availability issues. The number of tickets offered at each price level was not published for most NBA teams and for most years, so a constructed price index could not be calculated. Data on team revenue were also not consistently available, so realized price could not be determined. The price of a general admission ticket was available for most years.

The general admission price is for the lowest price, nondiscounted, adult ticket available on or before the day of the game. This excludes promotional prices and discounts for senior citizens, children, and standing room only. It also does not include ticket-processing charges. Ticket prices were collected from a number of sources, including media guides, pocket schedules, and team archives. Prices were not available for a total of 22 observations.

The rationale for using a general admission ticket is that it is roughly comparable among teams and in time. Unfortunately, the nature of a general admission seat has changed recently as teams have introduced more sophisticated price discrimination. In the past, most teams offered a small number of ticket categories. In recent years, the number of categories has increased and some of the previous general admission seats have been offered at higher prices. In addition, the nature of a general admission ticket may be different in large and small arenas. The number of seats close to the court is approximately equal, whereas the larger arena has more seats farther from the court. Combined with the increased price discrimination, general admission seats in newer larger arenas may be less desirable than in the past.

The standard analysis of panel data can account for differences in the intercept or slope coefficients among individuals using fixed or random effects. With a large number of independent variables and no a priori reason that a given coefficient will vary among teams, we chose to model the team differences in terms of the intercept

7
only. We used a fixed-effects approach because our sample includes all NBA teams. The random-effects approach would be appropriate when using a limited sample to draw inferences for a larger population.

It is also common with panel data to allow the intercept to vary in time, with the effect the same for all cross-section observations. This will account for a change in attendance that affects all teams equally. Indeed, it is readily apparent that the NBA experienced a sharp increase in popularity in the mid-1980s following a period of more modest growth in the 1970s. The alternative to using dummies for each year is to impose a functional form to the time trend. The advantage of this approach is that the number of estimated coefficients is reduced (for our sample, from 30 to 1). We believe, however, that the loss in degrees of freedom is offset by the lack of restrictions. Why should the trend in the 1970s, 1980s, and 1990s be assumed to be the same?

Prior attendance studies have included a selection of city-level variables assumed to influence demand such as unemployment, per capita income, and population. We excluded the latter two variables after noting a high degree of collinearity with the team dummies. The host cities that had a high per capita income at the beginning of the sample period also had a high income at the end. The same was generally true for population. The unemployment rate in each city exhibited much more variation in time than income and thus avoided the collinearity problem. Unemployment is expected to have a negative effect on attendance. If, however, unemployed fans use their free time to attend games, a positive effect is possible.

A new arena can affect demand by its novelty or by improving the fan experience. For baseball attendance, Noll (1974), Baade and Tiehen (1990), and Coffin (1996) assumed a linear decline after the 1st year. Coffin determined that the best fit occurred with a 4-year decline, whereas the other authors assumed a decrease in 10 years. Other studies included a dummy for newer facilities, usually equal to 1 if the stadium age is 5 years or less. Rather than impose a structure to the decline in time, we chose to include separate dummy variables for each of the first 15 years after a new arena was built. If the honeymoon does not extend beyond the 10 years assumed by most authors, we expect to find zero coefficients for those latter years. A total of 35 arenas were built or significantly renovated during the sample period. In addition, seven arenas were built within 15 years of the start of the sample period.

Fans may be more likely to attend games for a team that has recently located in their city. To capture this effect, we defined dummy variables for each of the first 15 years of a team’s operation in a city. If the decline is nonlinear, this approach is preferred to the ad hoc assumption used in previous studies that the decline is linear in time. If the decline is linear, then the use of separate dummies reduces efficiency. For the period 1971 to 2000, there were 12 new teams, including 4 teams from the former American Basketball Association, and 4 teams relocated to a new city at least once. In addition, in the 1960s, 5 teams were formed and 1 team relocated. If most of the new teams had been formed late in our sample period, so that the new
teams’ dummies were equal to 1 for all of those observations, those variables would be highly collinear with the teams’ fixed-effect dummies. Fortunately, most teams were new for only a fraction of their included years.

Team performance has been found to be a significant determinant of attendance in a vast majority of studies. A team’s performance can be measured absolutely or relative to other teams in its division. Our measure of absolute performance is the team’s winning percentage for that season, whereas relative performance is measured by the number of games behind the first-place team in its division at the end of the season.

The price equation includes lagged team performance, whereas the attendance equation includes both lagged and current performance. Lagged performance is not available for the 1st year of expansion teams. To avoid losing these observations, we calculated the mean of games behind and the winning percentage for all expansion teams in their 1st year, and entered these values for lagged performance. For a new team, it is reasonable for management and fans to expect their team to be similar to other expansion teams in their 1st year. For teams that were in the American Basketball Association prior to their entry into the NBA, we used performance in their last year in the ABA.

Arena capacity is used in the Tobit procedure to indicate censored observations. Several teams played for a short period in large multipurpose arenas, such as the Kingdome in Seattle, Washington, and the Superdome in New Orleans, Louisiana. These domed stadiums were used until an arena could be constructed. The official capacity of those facilities, more than 75,000 in the case of the Superdome, far exceeds the number of seats available when configured for basketball. By contacting the teams directly, we were able to get more accurate data for seating in the basketball configuration except for 5 years in the Kingdome and 1 year in the Metrodome in Minneapolis, Minnesota. Rather than simply replace the capacities for these 6 years with more “reasonable” values, we chose to exclude them from the analysis.

Table 1 summarizes these variables and the data sources. The descriptive statistics are reported in Table 2. The sample consists of NBA teams from 1971 to 2000. The number of observations for which a complete set of data was available is 680.

RESULTS

The adjusted R² for the estimated attendance reduced-form equation is .748, with a log likelihood of 142.71. Because a dummy was used to indicate censoring of the price variable, rather than a value of the dependent variable itself, the EViews program did not report an R² statistic. The log likelihood for this regression is 82.83. The estimated coefficients and robust (Huber/White) z statistics are given in Table 3.

As noted by McDonald and Moffitt (1980), the estimated coefficients from a Tobit regression must be interpreted with care. Although this method estimates the
coefficients in Equations 7 and 9, those coefficients measure the effect of changes in the independent variables on desired attendance, not on actual attendance. If a team’s winning percentage increases, more fans will wish to attend and the demand for tickets will increase, but the probability of selling out the arena also increases. The change in expected actual attendance can be measured by multiplying the estimated coefficient from the Tobit regression by 0.85, which is the percentage of observations that were not censored.11

Caution must also be exercised when interpreting the estimated coefficients for winning percentage, games behind, and local unemployment. The lagged values of

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**TABLE 1: Data Sources**

<table>
<thead>
<tr>
<th>Variable: Attendance per home game</th>
<th>Sources: Various team media guides, Association for Professional Basketball Research (APBR; <a href="http://www.apbr.org">http://www.apbr.org</a>)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variable: Arena age (dummies for the first 15 years after construction or major renovation)</td>
<td>Sources: Munsey and Suppes (2001; <a href="http://www.ballparks.com">http://www.ballparks.com</a>)</td>
</tr>
<tr>
<td>Variable: Team age (dummies for the first 15 years for an expansion or relocated team)</td>
<td>Sources: Munsey and Suppes (2001; <a href="http://www.ballparks.com">http://www.ballparks.com</a>)</td>
</tr>
<tr>
<td>Variable: Team winning percentage at end of season</td>
<td>Sources: APBR (<a href="http://www.apbr.org">http://www.apbr.org</a>)</td>
</tr>
<tr>
<td>Variable: Games behind at end of season</td>
<td>Sources: APBR (<a href="http://www.apbr.org">http://www.apbr.org</a>)</td>
</tr>
</tbody>
</table>
these variables are included in both equations because we assume that teams use them to forecast demand for the upcoming season. Because ticket prices are set prior to the start of the season, they will not be affected by the actual conditions in the following season. Attendance will, however, depend on whether those expectations were fulfilled. Thus, the variables for the current season appear in the attendance equation but not the price equation.

The interpretation of the coefficients for the lagged variables in the price equation is relatively straightforward. The winning percentage in the previous season will affect the expected intercept and slope for the demand curve. The coefficient in the reduced-form price equation equals the difference between the effects on the intercept and the slope ($\alpha - \beta$). Note that it is possible for an increase in winning percentage to have no effect on ticket price if the expected increase in demand is offset by a decrease in elasticity of demand (flatter demand curve).

To interpret the coefficients for the attendance equation, one must distinguish between an expected change in demand and the actual change. If team performance improves, we assume that management will expect the same for the following year and forecast high demand for tickets. If that expectation is fulfilled, so that $w/w_{-1} = 1$, then attendance will change with a coefficient of $\alpha$ from Equation 9. If performance in the following season does not improve as expected, then the effect on attendance of the change in $w_{-1}$ is reduced to $\alpha - \lambda$. Given the specification of the model, there is a different impact on attendance for an expected change in performance that does not occur and a change in performance that is not expected. The effect of an unexpected change in current season performance ($w$), that is, holding prior performance ($w_{-1}$) constant, is measured by $\lambda$.

For the attendance equation, a team’s winning percentage for the previous season has a positive and significant effect. This suggests that an increase in winning percentage in one season that occurs again the next season, as expected by manage-

### Table 2: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attendance</td>
<td>13,328</td>
<td>4,377</td>
<td>3,518</td>
<td>26,638</td>
</tr>
<tr>
<td>Real ticket price</td>
<td>$6.38</td>
<td>$1.95</td>
<td>$1.55</td>
<td>$15.58</td>
</tr>
<tr>
<td>Unemployment</td>
<td>6.1</td>
<td>2.1</td>
<td>2.0</td>
<td>16.2</td>
</tr>
<tr>
<td>Winning percentage</td>
<td>0.504</td>
<td>0.152</td>
<td>0.110</td>
<td>0.878</td>
</tr>
<tr>
<td>Games behind</td>
<td>15.13</td>
<td>12.48</td>
<td>0</td>
<td>59</td>
</tr>
<tr>
<td>Capacity</td>
<td>17,311</td>
<td>2,990</td>
<td>7,853</td>
<td>27,894</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>New arenas</td>
<td>35</td>
</tr>
<tr>
<td>New teams</td>
<td>22</td>
</tr>
</tbody>
</table>

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ment and fans, will increase attendance by a significant amount. The coefficient on the ratio of current to lagged winning percentage, which measures the effect of an unexpected increase in winning percentage, is also positive and significant. Note that the estimated coefficient of 0.21 for the latter is smaller than the 0.27 for an expected change in winning percentage. The difference between these coefficients,

<table>
<thead>
<tr>
<th>TABLE 3: Regression Results</th>
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<tbody>
<tr>
<td></td>
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<tr>
<td>Lagged unemployment</td>
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<tr>
<td>Lagged winning %</td>
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<tr>
<td>Lagged games behind</td>
</tr>
<tr>
<td>Current—lagged unemployment</td>
</tr>
<tr>
<td>Current—lagged winning %</td>
</tr>
<tr>
<td>Current—lagged games behind</td>
</tr>
<tr>
<td>New arena year 1</td>
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<tr>
<td>New arena year 2</td>
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<tr>
<td>New arena year 3</td>
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<tr>
<td>New team year 14</td>
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<tr>
<td>New team year 15</td>
</tr>
</tbody>
</table>

Statistical significance using a two-tailed test indicated by * for the 0.10 level, ** for the 0.05 level, and *** for the 0.01 level. T statistics are in parentheses.
or 0.06, which measures the effect of a change in expected winning percentage that does not actually occur, is positive but not statistically significant. Apparently, the increase in season ticket and early-season sales in anticipation of another good season is not large enough to increase attendance for a poor-performing season.

In the price equation, the effect of lagged winning percentage is positive, as expected, and significant.

The coefficient on the number of games behind from the previous season on attendance is negative and significant. An increase in games behind in a season, if it also happened the previous season and thus was expected to occur, will reduce attendance. If that drop in performance was not expected, the decline is still negative and significant at the 10% level, but not at 5%. The effect is also smaller in magnitude than for an expected change, which is not surprising given that games behind is largely a factor later in the season. An expected increase in games behind that does not actually occur also has a negative and significant effect on attendance. If fans purchase fewer season tickets because they also expect a poor performance, even if the team finishes better than expected, the effect on season attendance will be negative. The effect of lagged games behind in the price equation is also negative, but it is not significant.

The coefficients for the unemployment rate, both lagged and the ratio of current to lagged, are not statistically significant in the attendance equation. Lagged unemployment is also not significant in the price equation.

The coefficients for the new arena dummies are presented in Figure 1. They are positive and significant in the attendance equation for each of the first 8 years. After increasing slightly during the first 4 years, the new arena effect begins a steady decline and disappears after Year 10. Figure 1 indicates that a honeymoon effect does exist at NBA arenas, a result that heretofore has not been demonstrated in the literature. The effect is relatively short-lived, however: After Year 4, the novelty of the arena and its amenities fades quickly. From the perspective of the owners of an NBA team who demand public subsidies, this is relatively good news because it makes it likely that their promises to city officials and voters of significant increases in attendance, and attendance-related spending will be realized in the short run. The bad news for owners and local taxpayers is that these promises may not hold true in the long run. Financial projections and revenue flows estimated prior to the construction of an arena may turn out to be lower than expected if the effect is ignored or weaker than anticipated. For the price equation, the coefficients are not statistically significant, indicating that while demand shifts outward it also becomes more elastic, resulting in an unchanged price.

The estimated coefficients for the dummy variables for a new team are not significant in any year for either equation, although the coefficients in the attendance equation do exhibit a pattern of decline after an estimated increase of nearly 10% in the 1st year. The lack of significance is surprising but not entirely unexpected. There may be good reasons why those cities did not already have NBA franchises that counteract the newness effect. With time, the city may evolve to the point that
attendance will equal that in cities with more established teams. Given that the estimated coefficients are 0 in later years, when the newness factor should have disappeared, this appears to have occurred.

The estimated coefficients for the year effects for the two equations are shown in Figure 2 and Figure 3. The effects are compared to the year 1971, which is assumed to have a value of 0. Although not restricted to any particular functional relationship, there is a very clear upward trend in the attendance equation. The most rapid increase occurred during the 1980s, with little growth during the 1990s. The lingering effect of the 1998 labor disputes can also be seen, although it is small in magnitude. The coefficients in the price equation show a substantial decline beginning in 1974, with a recovery starting in 1982. The sharp decline for 1999 and 2000 is due to a mandate by the NBA that every franchise make some seats available at a maximum price of $10 (Walker, 2002). Presumably, this was in response to the rapid rise in average ticket prices in the 1990s, slower growth in attendance, and the 1998 labor dispute and lockout. Eliminating these years from the sample did not result in any substantive change in the results.
The centered leverage values indicate whether there are any observations that have undue influence on the estimated coefficients. The values for two teams were higher than 0.5, which indicates that omission of one observation will have a significant effect. The Sacramento Kings spent 2 years of our sample period in Cincinnati, Ohio, and the Utah Jazz franchise was located in New Orleans, Louisiana, for 5 years. The small number of observations for estimating those cities’ dummies is not a serious problem, however, as we do not attempt to interpret the city dummy coefficients.

To test for possible multicollinearity, we examined the variance inflation factor (VIF) for each independent variable. The highest value was 3.6 for the unemployment variable, and this is less than the commonly used critical value of 10. The condition indices indicate that unemployment is somewhat collinear with some of the year dummies, which is not surprising. The unemployment rate will be high in most cities during recessions and low during periods of prosperity.

For both equations, the Durbin-Watson statistic indicates the probable existence of serial correlation of the error terms. Unfortunately, the EViews software program does not permit an autoregressive specification for the error term in censored regression models. To determine how this might affect our results, we estimated uncensored OLS models with and without correction for serial correlation. Simple OLS gave similar results for the team performance variables but a shorter honey-
moon, just 6 years instead of 8 in the Tobit model. The shortened effect is not surprising given that OLS estimates are biased downward when censoring occurs. The addition of a first-order autoregressive error term had estimated coefficients closer to those from Tobit, with the new arena effect of similar length, magnitude, and statistical significance.

CONCLUSION/SUMMARY

Our analysis makes several contributions to the existing literature on attendance demand for professional sports. Our article is the first to use a large cross-section, time-series data set to confirm the presence of a honeymoon effect in the NBA. Second, we find the initial increase in attendance demand for a new basketball arena is approximately 15% to 20%. This is comparable to the estimated effect for major league baseball stadiums, particularly baseball-only parks (e.g., Rascher, 1999). The effect on actual attendance will be somewhat smaller than the increase in the demand for tickets due to the capacity constraint, which is more of an issue for the NBA than for MLB. Multiplying the change in demand by the percentage of observations that are at capacity approximates the effect on actual attendance. For the 1st year of a new basketball arena, the expected percentage increase in actual attendance is approximately half as large as for a new baseball stadium. Third, the effect
begins to diminish in Year 5, falling to near zero after the 10th year; unlike similar studies for MLB, we do not assume a particular functional form for that decline. This downward, albeit nonlinear, trend in demand suggests that Hamilton and Kahn’s (1997, p. 253) claim that the honeymoon effect for a typical MLB stadium lasts about 8 years is roughly equivalent for the NBA. Fourth, we believe we have made a methodological contribution by using a theoretical model of profit maximization and incorporating arena size as a capacity constraint in the regression analysis. Finally, our findings have public policy implications. Given the routine demands for public subsidies by city officials and allied interest groups, claims that a new arena will generate a large initial and prolonged increase in attendance, and attendance-related spending, may be far too optimistic.

NOTES

1. Noll (1974) indicated that “a newer facility may attract fans because of its greater comfort or because it affords a better view of the game” (p. 118); and Seredyński, Jones, and Ferguson (1994) suggested that a new facility will “attract crowds irrespective of team quality” (p. 667, n. 13). For other discussions of the honeymoon effect, see Austrian and Rosentraub (1997, p. 380), Baade and Sanderson (1997a, p. 96; 1997b, p. 461), and Noll and Zimbalist (1997, pp. 16-17).

2. Quirk and Fort (1997) noted that because “sellouts are the rule rather than the exception” in other leagues, “capacity is an effective constraint” (p. 140). An NBA team plays about one-half as many home games as an MLB club (41 versus 81) in a facility with roughly one-half the seating capacity of a modern MLB stadium (20,000 versus 40,000). This suggests that a typical MLB team has approximately 3,240,000 seats available per season, whereas a typical NBA franchise has 820,000. This latter number is closer in magnitude to that of the National Football League (NFL), where it is likely that no honeymoon effect is discernible because of the capacity constraints mentioned by Quirk and Fort (playoffs aside, each NFL team has eight home games per season; an NFL team with a seating capacity of 80,000 has 640,000 seats available each season). This example suggests that if a professional sports franchise has a relatively small number of tickets available during the course of the season, sellouts are more likely and the presence and length of a honeymoon effect may be difficult to uncover. For the 2000-2001 season, one-third of all games in the NBA were sellouts. In 2002, the Washington Wizards sold out every home game and 35 of 39 road games during Michael Jordan’s final season.

3. The newly built and renovated arenas received approximately $1 billion in subsidies (Rosentraub & Swindell, 2002, p. 19).

4. See, for example, Noll and Zimbalist (1997), Coates and Humphreys (1999), and Hudson (2001).

5. Noll (1974) considered the impact of new facilities in the other major professional sports leagues and concluded that there is no honeymoon effect in professional basketball, football, or hockey. Unfortunately, he did not provide support for this conclusion.

6. Examples of the discrimination studies include Schollaert and Smith (1987); Kahn and Sherer (1985); Brown, Spiro, and Keenen (1991); Burdekin and Idson (1991); Jenkins (1996); Hoang and Rascher (1999); and McCormick and Tollison (2000).

7. See Cairns, Jennett, and Sloane (1986) for a survey of past studies, and Coffin (1996) for a more recent discussion.

8. Demmert uses the number of years the team has been located in that city, up to a maximum of 5. Coffin (1996) uses 4 minus the number of years, with zero after the 4th year.

9. Expansion teams were formed in Buffalo, New York, Charlotte, North Carolina, Cleveland, Ohio, Dallas, Texas, Miami, Florida, Minnesota, Orlando, Florida, and Portland, Oregon, Denver, Colorado,
Indiana, New Jersey, and San Antonio, Texas, moved from the ABA. The Rockets, Clippers, Kings, and Jazz relocated.


11. For dependent variables that are left censored at zero, the Tobit coefficients are multiplied by the normal distribution function at the value of the estimated equation, evaluated at the sample means of the dependent variables, and divided by the estimated standard deviation of the error term. This simple method cannot be used in our model because the censoring value (arena capacity) varies from team to team and in time. An approximation used by McDonald and Moffit (1980) is the fraction of the observations that are not censored.

REFERENCES


John Leadley is Associate Professor of Economics at Western Oregon University in Monmouth, Oregon. He earned his Ph.D. in 1985 from the University of Wisconsin–Madison.

Zenon X. Zygmont is Assistant Professor of Economics at Western Oregon University. He earned his Ph.D. from George Mason University in 1994 and has taught at Reed College and George Mason University.