The Interaction between Baseball Attendance and Winning Percentage: A VAR Analysis

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ABSTRACT

This study examines the importance of team success for attendance for major league baseball teams. Winning and attendance go together for most baseball teams, but the direction of causation is not obvious. Winning could lead to greater attendance as fans want to see a winner, while an increase in attendance could lead to greater winning as teams' have greater resources to spend on salaries. This study finds that the direction of causation runs from team success to greater attendance, and that a sudden increase in fans does not lead to additional winning in the future. A secondary result suggests that exogenous shocks to attendance have replicating effects on attendance as well.

Key Words: baseball, attendance, vector autoregression

It is only natural that sports fans would want to support a strong performance on the field and attend more games of a more successful team. The quality of play will be higher for a good team, the home team will be more likely to win and the atmosphere will be more enjoyable since other fans will be more excited by a good team. A successful season will also lead to increases in attendance during the following years as the momentum of the previous success draws in more fans through a bandwagon effect. We should therefore expect to see an increase in attendance during and following seasons in which the team played well on the field.

At the same time the argument is often made that a new stadium will lead to the club's putting a better team on the field. For instance, the Pittsburgh Post Gazette claimed in 2001 when PNC Park in Pittsburgh was opening, "No question the Pirates, who have slogged through eight consecutive losing seasons, should be able to jump-start their attitude because of the new park and larger crowds." [1] (Meyer, 2001) The suggestion that a new stadium will lead to a higher winning percentage can be generalized to look at the effect any exogenous increase in attendance has on winning.

In this study we examine the link between winning and attendance in Major League Baseball. Understanding this relationship will help to improve our knowledge about the demand for baseball, as well as the supply, in terms of quality. We study baseball because the long history of the sport allows for a

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longer time series to be analyzed, but the procedure and results likely generalize to other sports.

While studying baseball we hope to better understand the general way in which firms and consumers interact with regard to product quality. We examine whether the firm chooses to increase the quality of the product and then see an increase in sales or whether the firm responds to greater numbers of consumers by increasing product quality or decreasing quality because it is cheaper. Sports teams represent an excellent way of studying this issue because both quantity, in the form of attendance, and quality, in the form of winning percentage, are known.

The idea that causation can run both ways suggests that we need to use a statistical model that can disentangle these two effects. One such model is the vector autoregression (VAR) model, which sets up a series of equations in which the dependent variable of each equation is regressed upon the lags of itself and the other dependent variables. In this paper we use a VAR model to examine the effects of an exogenous shock to winning percentage on attendance and an exogenous shock to attendance on winning percentage.

Previous studies have examined the ways in which team success on the field will be followed by an increase in attendance. Knowles, Sherony and Haupert (1992) estimated that attendance is maximized when the home team's probability of winning is 0.6, specifying how much weight fans put on two

desirable traits of sporting events: their team winning and the uncertainty of outcome. Rascher (1999) estimated that attendance is maximized at .66. Schmidt and Berri (2006) suggested that the importance of winning on attendance has increased in recent years.

However, an exogenous shock to attendance may lead to an increase in winning percentage. The availability of greater revenues could provide the management of the team with more resources to improve the team. One such shock would be the construction of a new stadium. Depken (2006) found that teams on average spend approximately 17 million dollars in increased revenues from a new stadium on player salaries. A secondary result of Depken's study is that shocks to attendance seem to have a persistent effect on attendance in future years, even when the effects of new stadiums are excluded from the model.

I. METHODOLOGY

The statistical analysis used in this paper is a vector autoregression (VAR) model. We use a three variable VAR, including winning percentage, attendance and the average attendance for the other teams in the league. This last variable is included to pick up any factors affecting the overall interest across major league baseball.

The three variable VAR can be written with the following equations:

$$A_t = \sum_{j=1}^{J}(\alpha_{1j}A_{t-j} + \beta_{1j}L_{t-j} + \gamma_{1j}W_{t-j}) + c_1 + \varepsilon_{1t} \tag{1}$$

$$L_t = \sum_{j=1}^{J} (\alpha_{2j} A_{t-j} + \beta_{2j} L_{t-j} + \gamma_{2j} W_{t-j}) + c_2 + \varepsilon_{1t} \tag{2}$$

$$W_t = \sum_{j=1}^{J} (\alpha_{3j} A_{t-j} + \beta_{3j} L_{t-j} + \gamma_{3j} W_{t-j}) + c_3 + \varepsilon_{1t} \tag{3}$$

where A_t is the individual team's attendance at time t, L_t is the league average attendance at time t and W_t is the team's winning percentage at time t. J is the lag length of the VAR, which, using the AIC criterion, is set equal to 4.

In order to compute impulse response functions from the VAR, we need to impose some structure on the model. We use the Cholesky ordering, but this methodology requires an ordering of the variables so that some variables contemporaneously affect others. We allow the winning percentage to influence both the league average attendance and the individual team's attendance. As the team succeeds during the year, it will draw in more fans. Whether to allow winning percentage to affect league average attendance or vice versa is debatable. A reasonable null hypothesis would be that the two variables have very little effect on each other and therefore the ordering does not matter. We use the current ordering to allow for the unlikely possibility that a certain team's having success will give baseball a more national following and could lead to an increase in league attendance. For instance, teams like the Boston Red Sox, New York Yankees and Chicago Cubs are covered more in both the sports and general media, pushing baseball into the national consciousness and possibly causing fans

to attend games in other cities. We want to allow the league average attendance to influence individual team attendance in the current year because league attendance is our proxy for league-wide influences on attendance such as wars and strikes.

The impulse responses are based on exogenous shocks to the three variables in the system. Exogenous shocks to winning percentage can take place when the team has an unexpectedly good year due to finding an unexpected superstar or if the team experiences some lucky breaks. Schmidt and Berri (2001) discuss some exogenous shocks that have taken place with regard to the league attendance series, specifically citing the ends of World Wars I and II and labor disputes in 1972, 1981 and 1994.

There are also exogenous shocks to team-specific attendance. Depken (2006) found that the construction of a new stadium for a team increases attendance by 13,308 fans per game. The entry or departure of a rival team in the same city can also have an effect on attendance. Lastly, major changes in population or wealth of the city could cause exogenous shocks to attendance. For instance, regardless of the performance of the team, we would expect there to be a fall in attendance in 2006 for the AAA New Orleans Zephyrs baseball team following the decrease in population due to Hurricane Katrina. Other factors that might affect attendance could include weather conditions during the summer or

the availability of other activities during the summer (e.g., the Olympics in the city).

Multiple shocks to the different variables can take place at the same time. Matheson (2006) analyzes the effect on attendance in the 1990s and finds that the creation of new stadiums mitigated the attendance fall-off from the 1994-1995 strike.

II. DATA

Major League Baseball currently includes 30 teams, each of which provides a series of data, which can be used to analyze the relationship between attendance and winning percentage. However, since the VAR must estimate a large number of coefficients and the attendance data is available on an annual basis, we must restrict our observations to only a handful of the teams. We limit our analysis to the ten major league baseball teams that have played in the same city for over 100 years. This list includes five National League teams: the Chicago Cubs, Cincinnati Reds, Philadelphia Phillies, Pittsburgh Pirates and St. Louis Cardinals; and five American League teams: the Boston Red Sox, Chicago White Sox, Cleveland Indians, Detroit Tigers and New York Yankees.[2]

Despite restricting the sample to only those teams we still feel it is representative of most of the teams in baseball. It includes teams that play in markets with multiple teams like the two Chicago teams or teams that have had the market to themselves the entire time like the Detroit Tigers. There are teams

that have had success throughout most of the sample (the Yankees), as well as teams that have performed poorly throughout most of the century (the Phillies). However, one way in which these teams are not representative is that they were the teams that were able to survive in their markets for a long time. The teams that chose to relocate or were expansion teams might exhibit a different set of behaviors.

For the attendance data, we use per-game attendance. Usually each team will play 77 home games (before 1961 or 1962) or 81 home games (after 1961 or 1962), but occasionally because of weather or discrepancies in the schedule a team will play a few more or less than usual. So that missing a home game or two during a season does not distort our results, we use per game attendance.

League average attendance is an average of the per-game attendance for the league as a whole excluding the team under consideration. We compare NL teams to other NL teams and AL teams to other AL teams only because in the earlier years of the twentieth century the two leagues were quite separate.

The winning percentages come from http://www.rodneyfort.com/ and the attendance data comes from http://www.baseball-reference.com/.

III. RESULTS

Figure 1 shows the impulse responses for the Cincinnati Reds, which are pretty typical for the teams analyzed. The only unusual aspect for Cincinnati was the significant negative effect of Cincinnati's winning percentage on the average

attendance for the rest of the league, which may be due to Cincinnati being one of the smaller cities in the sample and less important for the national media. However, it is probably not very important as it is not a large effect and is not found in the other smaller cities. The VAR panels of greatest interest are the lower left and upper right panels of the figure. Here we see that there is a significant 3-year impact on attendance of a shock to winning percentage. However, a shock to attendance has little effect on winning percentage. The Reds over this period did not seem to respond to an increase to their attendance by improving the team on the field.

Figure 2 shows the responses of team attendance to shocks in winning percentage for the other 4 NL teams. The pattern for each of them is similar, but there is some variation in the persistence to the shocks. Chicago and Philadelphia show more persistence in the shock, whereas St. Louis shows a very rapid drop-off. Figure 3 shows the same responses for the five AL teams. The overall pattern is similar to the National League teams. However, the Yankees seem to have a weaker response to winning than the other American League teams. Perhaps the Yankees' historically superior performance on the field has bored their fans. The Yankees mean winning percentage is 56.8%, and no other team in the sample is above 52%. The uncertainty of outcome effect may also have been kicking in more often with the Yankees because of the higher mean value.

Figures 4 and 5 show the responses of winning to shocks in attendance for the NL and AL teams respectively. About half the teams show an up-tick to winning following an increase in attendance and the other half show it decreasing. However, with the exception of the Indians, none of them show a significant response of winning to attendance. For the Indians, the increase in attendance is substantial enough for it to be significant in year 3. This result may be due to differences in fan behavior or ownership in Cleveland.

Figures 6 and 7 show the response of attendance to a shock in attendance for the NL and AL teams respectively (and in the lower right panel of Figure 1 for the Cincinnati Reds). The teams exhibit a very high degree of persistence in the response of attendance to shocks in attendance.

IV. TECHNICAL DISCUSSION OF RESULTS

4.1 Lag Length

The lag length for the VAR is 4 years, determined by using the AIC statistic, comparing lag lengths up to 8 years. Each team has a set of AIC statistics for each of the different lag lengths. The suggested lag length is the one with the lowest AIC statistic, and for all of the teams the lowest AIC is for some length between one and four years. Four years is uniformly imposed so that comparisons could be made across teams.

4.2 Stationarity and Cointegration

Another potential problem when examining attendance data is nonstationarity. A stationary series is one in which the probability distribution is not dependent on time. Many inferences are not valid for regressions on nonstationary processes, so there has been much attention focused on whether attendance series are stationary.

In analyzing the AL and NL attendance data, Schmidt and Berri (2001) found that both of those series are nonstationary. Fort and Lee (2006) suggested that the attendance data are stationary with break points in the data. We examine the presence of a unit root in the data (a form of nonstationarity) and return to the issue of structural breaks in the next section. Using slightly different series for league-wide attendance than Schmidt and Berri, but using the same tests (Augmented Dickey-Fuller and Phillips-Perron), we find that attendance does exhibit a unit root if we do not include a trend term in the unit root test (see Table 1). We find that each individual team's attendance series exhibits a unit root, with none of the series being able to be rejected at a 5% level for either the ADF or the Phillips-Perron statistics. However, the picture is more mixed if we include a trend term in the unit root test (Table 2), with many of the series appearing to be stationary.

The standard solution for a unit root in the data is to first-difference the data (i.e. use the change since the preceding period). There are three reasons for

not using this approach with our current data. First, the evidence on whether the series exhibit a unit root is not universal, in particular, when a trend term is considered. Second, we are interested in looking at the level of attendance and not the change, so by first differencing the data we lose a little focus. The last and more important issue is that we have two series in each regression (the attendance and the league average attendance) which are potentially nonstationary. Therefore, these two series may be cointegrated. Hamilton (1994) suggested that one proper approach is to include the series in the VAR in levels and that the statistical tests will be asymptotically consistent.

4.3 Stability Tests and Structural Breaks

Fort and Lee (2006) examined the ways in which structural breaks can take place and lead researchers to find nonstationarity where it otherwise does not exist. For each team we estimated the individual equations (1)-(3), and then performed two tests for a structural break for each of those equations. The first test is the CUSUM test of Brown, Durbin and Evans (1975) which tests for a structural break throughout the entire sample. However, the test often can have poor power against certain alternatives. The second test is the Chow (1960) breakpoint test. Under this test we must specify a date when the break occurred. Since many changes took place to MLB in the 1970s, in particular the beginning of free agency, we test for a break in 1975. This date is also the date when

Schmidt and Berri (2006) find evidence of variation across teams in terms of attendance.

The CUSUM test does not indicate a structural break for many of the 30 equations, which might only be due to its restrictive nature. Table 3 presents a summary of the stability tests performed for the three equations for each of the eight teams using the Chow test. At a 5% level of significance, the Chow test indicates a structural break in eight of the 30 equations in 1975. However, there seems to be little pattern to the breaks. They occur with all three types of equations and five of the ten teams. Further study of this issue is needed but is beyond the scope of this paper.

4.4 The Attendance Shocks.

We can separate the attendance shocks into two types. The first would be a shock that would be expected to only necessarily affect a single year. Weather conditions would be an example of a transitory effect. If a city had a particularly rainy summer, attendance would probably be depressed. There would be no reason to expect the shock itself to continue until the next year. However, there might be an effect on attendance if the drop in attendance leads to further drops in attendance, because the games are less enjoyable in empty stadiums or because fans found other activities. The VAR would even allow for the fall in attendance because of a lower winning percentage (through lower payroll) and then lower attendance in response to the inferior team.

Most of the shocks we would associate with attendance would be of this transitory nature. However, one major shock that would likely have direct permanent effects would be the construction of a new stadium. Changes in attendance due to changes in capacity, new amenities and different locations would be expected to continue into future seasons. The new stadium would also likely have a transitory component to it as well from the stadium being new.

These two different types of shocks might have different impacts on the other variables. To attempt to control for this, we examine a slightly different sub-sample of teams and years. We examine five combinations of teams and stadiums that were used together for a long time and re-estimate the VARs. The five combinations are the Boston Red Sox with Fenway Park (1912-2005), the Chicago Cubs with Wrigley Field (1916-2005), the Chicago White Sox with Comiskey Park (1911-1990), the Detroit Tigers with Tiger Stadium (1912-1999) and the Pittsburgh Pirates with Forbes Field (1910-1969). These are the examples of teams that stayed in a single stadium long enough to estimate a VAR. All of the other teams only resided in any one stadium for a relatively short period of time.[3]

Figures 8 and 9 show the responses of winning percentage and attendance to shocks in attendance for the new samples. A comparison of the results with those in Figures 2, 3, 6 and 7 shows very little difference in the impulse responses. This finding suggests one of three possibilities: that there is very little

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difference between the permanent and transitory shocks, that the transitory shocks predominate or that there are unaccountable permanent shocks that drive the results. The first two of these explanations suggest a remarkable amount of habit formation in attendance and suggest that transitory shocks to attendance have long lasting effects on attendance.

V. CONCLUSION

The three-variable VAR presented here suggests that winning has a substantial and long-lasting effect on attendance, as all ten teams showed a significant increase in attendance. However, there is little support for the idea that shocks to attendance lead to future success on the field for the team, as only one team (Cleveland Indians) showed a significant increase in winning following a shock to attendance. There is also some indication that attendees at sporting events exhibit habit formation in their behavior, as shocks in attendance last for years after the shock.

The above results are useful for researchers examining sports attendance. They suggest that the direction of causation runs from winning percentage to attendance and researchers can proceed under that assumption.

Further work should extend these results. One extension would be an examination of game by game attendance to ensure that the assumption of no contemporaneous effect of attendance on winning exists. Also more advanced econometric techniques should be employed to examine those other teams that do

not have enough data to estimate a VAR model, including expansion teams and

relocated franchises. Lastly, further examination of the unit roots and structural

breaks of the attendance series is needed.

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[1] The Pirates may have jump-started their attitude that year, but they still were not very successful as the team went 62-100, their worst year since 1985.

[2] For each combination we have 105 observations (1901-2005), except for the New York Yankees who moved from Baltimore in 1902. For the Yankees we have 103 observations (1903-2005).

[3] The Yankees have been in Yankee Stadium for over 70 years. However, the stadium went through a major renovation in the 1970s that required the team to play in Shea Stadium, keeping the sample from being consistent throughout. While a couple of the stadiums that are included in the list above also went through renovations, they occurred during the off-season and did not require a move elsewhere for a season.

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Table 1: Unit Root Tests (Intercept Only)

	Team Attendance		League Attendance	
	ADF	Phillips-Perron	ADF	Phillips-Perron
Cubs	-0.700	0.019	0.020	0.552
Reds	-1.594	-1.594	-0.355	0.628
Phillies	-1.275	-0.847	-0.344	0.626
Pirates	-2.467	-2.467	0.135	0.741
Cardinals	-0.376	0.644	-0.011	0.498
Red Sox	-0.691	-0.505	-0.350	-0.211
White Sox	-2.096	-1.613	-0.326	-0.183
Indians	-1.851	-1.978	-0.199	0.043
Tigers	-2.597	-2.184	-0.232	-0.132
Yankees	-0.500	-0.374	-0.244	-0.082

t-tests of test of null hypothesis that given series has a unit-root. * significant at 5% level.

Table 2: Unit Root Tests (Intercept and Trend)

	Team Attendance		League Attendance	
	ADF	Phillips-Perron	ADF	Phillips-Perron
Cubs	-2.396	-2.281	-4.038*	-3.462*
Reds	-3.437	-3.518*	-3.541*	-3.331
Phillies	-3.426	-3.472*	-3.452	-3.192
Pirates	-4.915**	-5.054**	-3.551*	-3.225
Cardinals	-3.492*	-3.492*	-4.035*	-3.320
Red Sox	-3.173	-3.323	-2.259	-2.263
White Sox	-4.189**	-4.034*	-2.282	-2.393
Indians	-2.578	-2.578	-2.298	-2.329
Tigers	-5.063**	-4.892**	-2.138	-2.126
Yankees	-2.306	-2.306	-2.313	-2.262

t-tests of test of null hypothesis that given series has a unit-root. * significant at 5% level.

Table 3: Chow Test p-values for Structural Breaks in 1975

|	(1)	(2)	(3)
Cubs	.006	.031	.079
Reds	.017	.040	.388
Phillies	.006	.041	.859
Pirates	.145	.034	.200
Cardinals	.136	.109	.134
Red Sox	.402	.310	.964
White Sox	.081	.196	.549
Indians	.063	.055	.254
Tigers	.801	.130	.042
Yankees	.605	.102	.379

The p-values from the F-statistic for the Chow test of rejecting the null hypothesis of no break in 1975. Column (1) is for the attendance equation, Column (2) is for the league attendance equation and Column (3) is for the winning percentage equation.

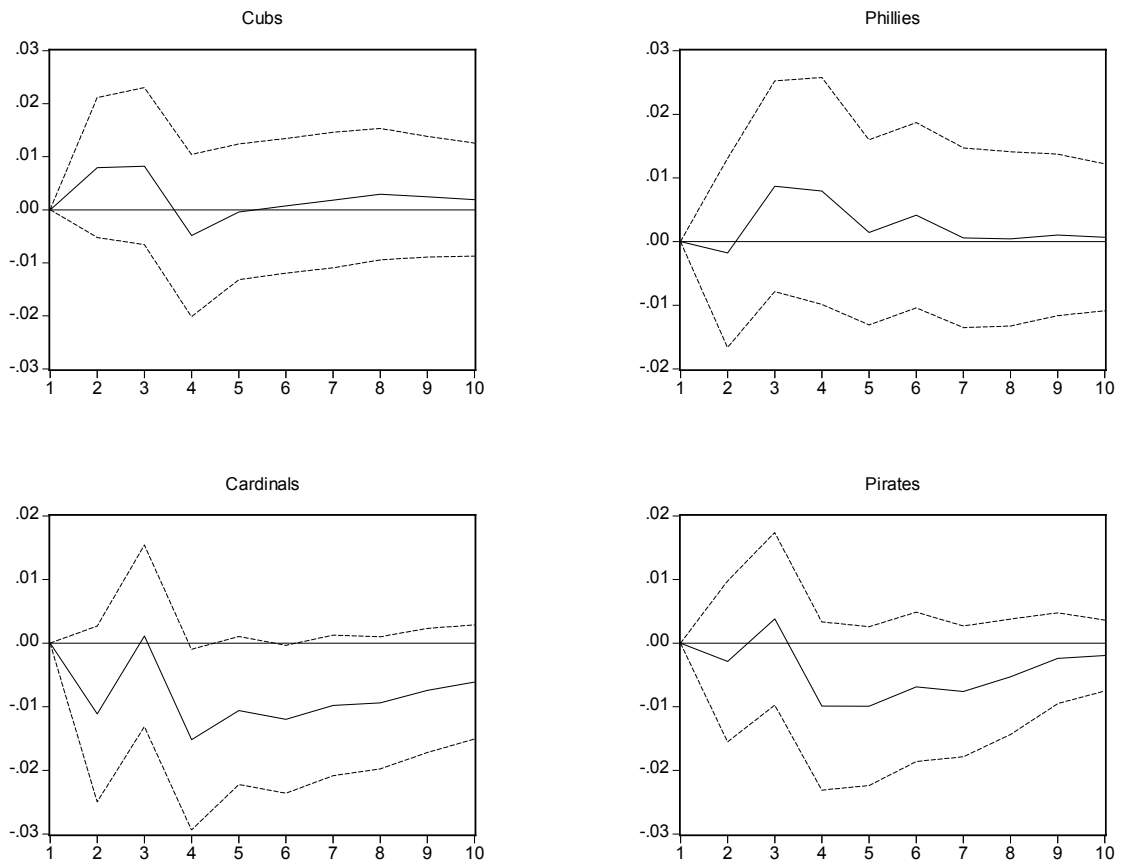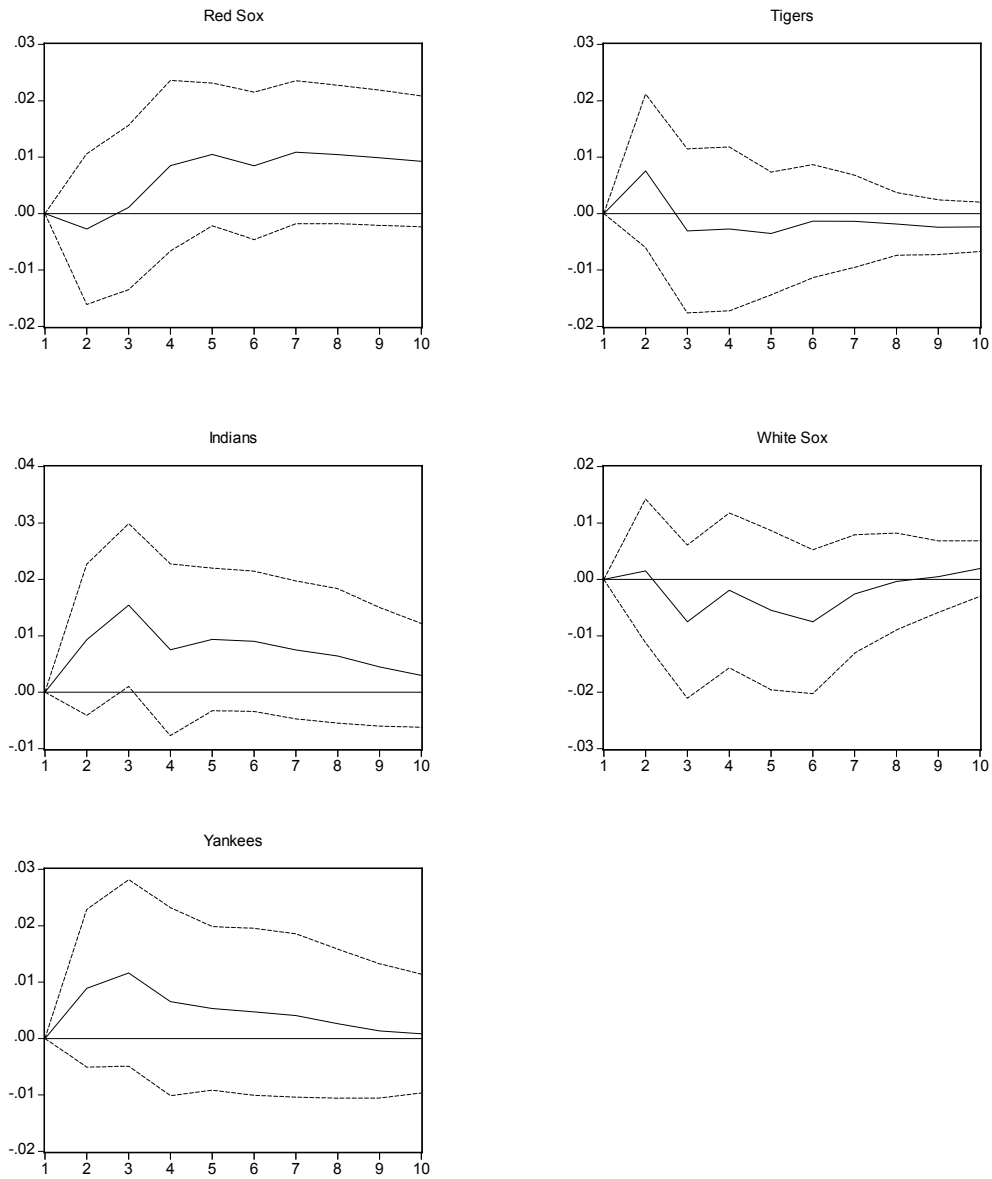Figure 1: Impulse Response Functions for Cincinnati Reds
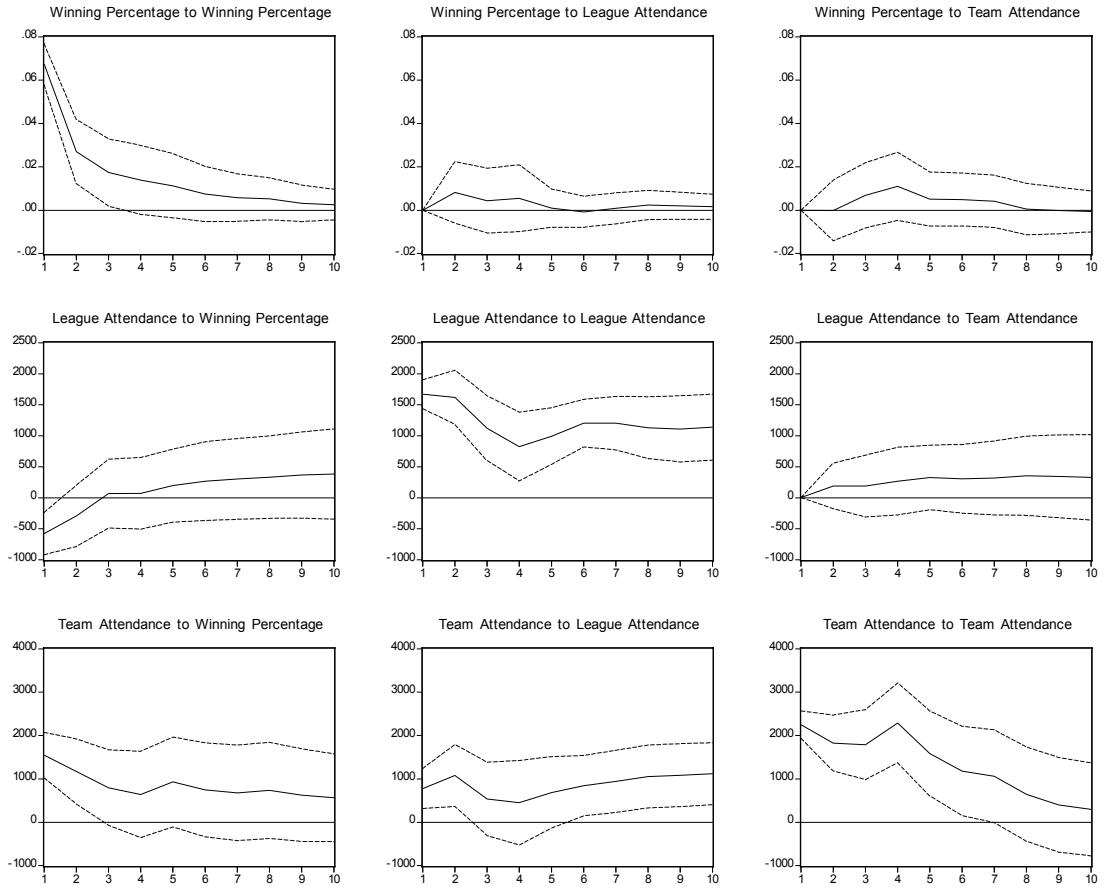
Solid line represents impulse responses. Dashed line represents two standard error bounds. Figures show responses to a one standard deviation shock. Y-axis represents years.

Figure 2: Impulse Responses of Attendance to Shock
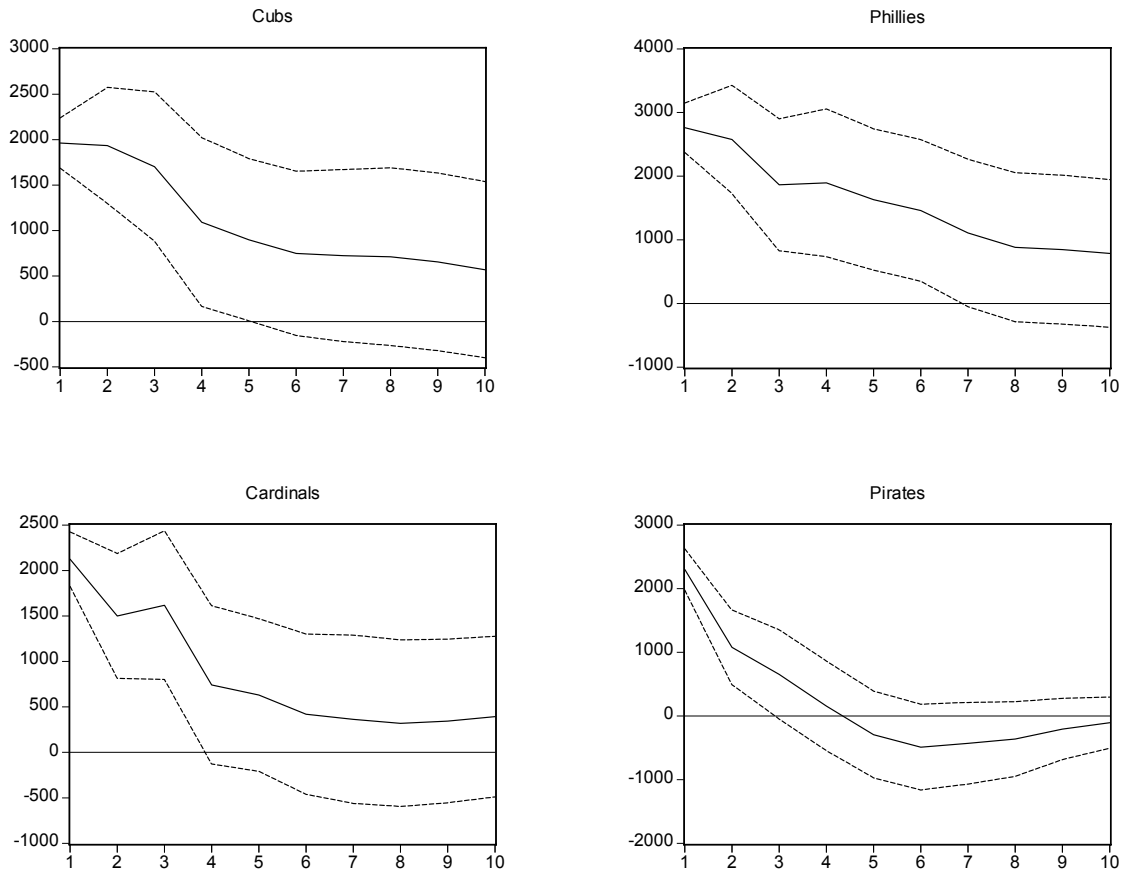in Winning Percentage (NL Teams)
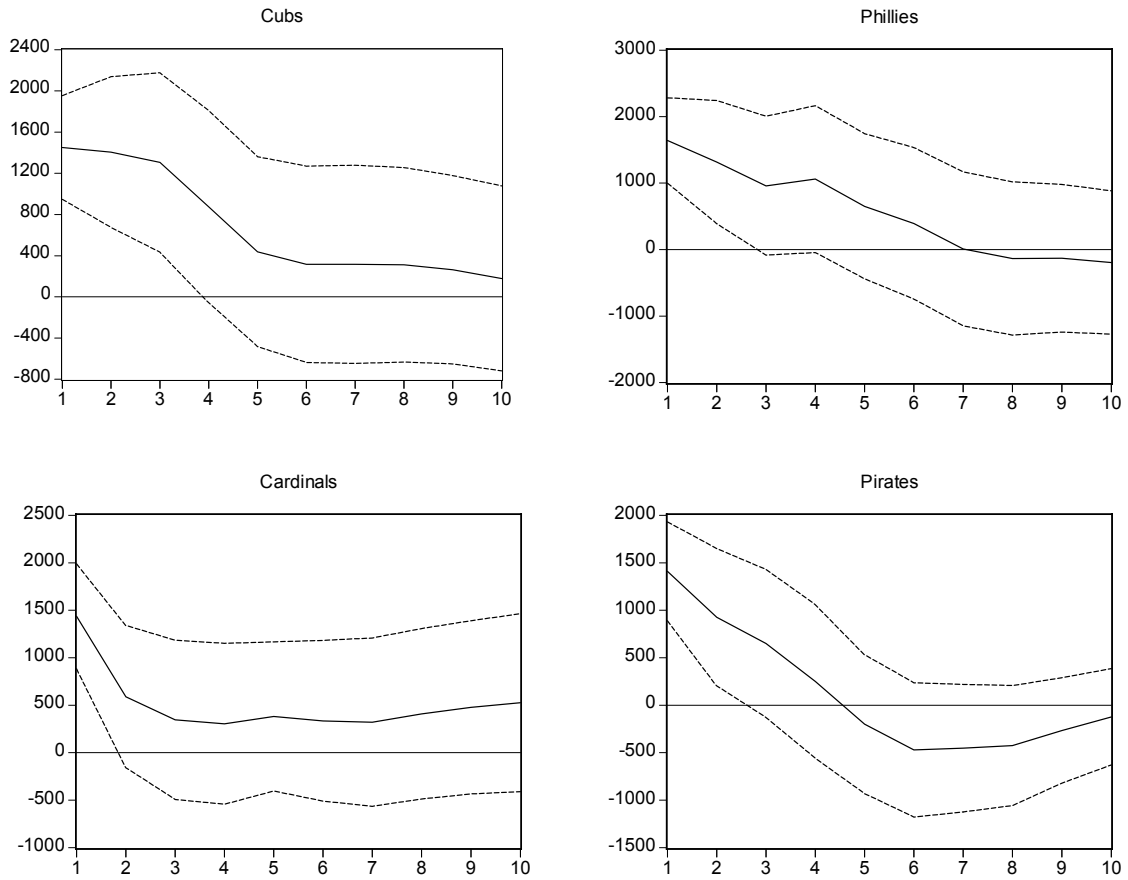
Solid line represents impulse responses. Dashed line represents two standard error bounds. Figures show responses to a one standard deviation shock. Y-axis represents years.

Figure 3: Impulse Responses of Attendance to Shock
in Winning Percentage (AL Teams)
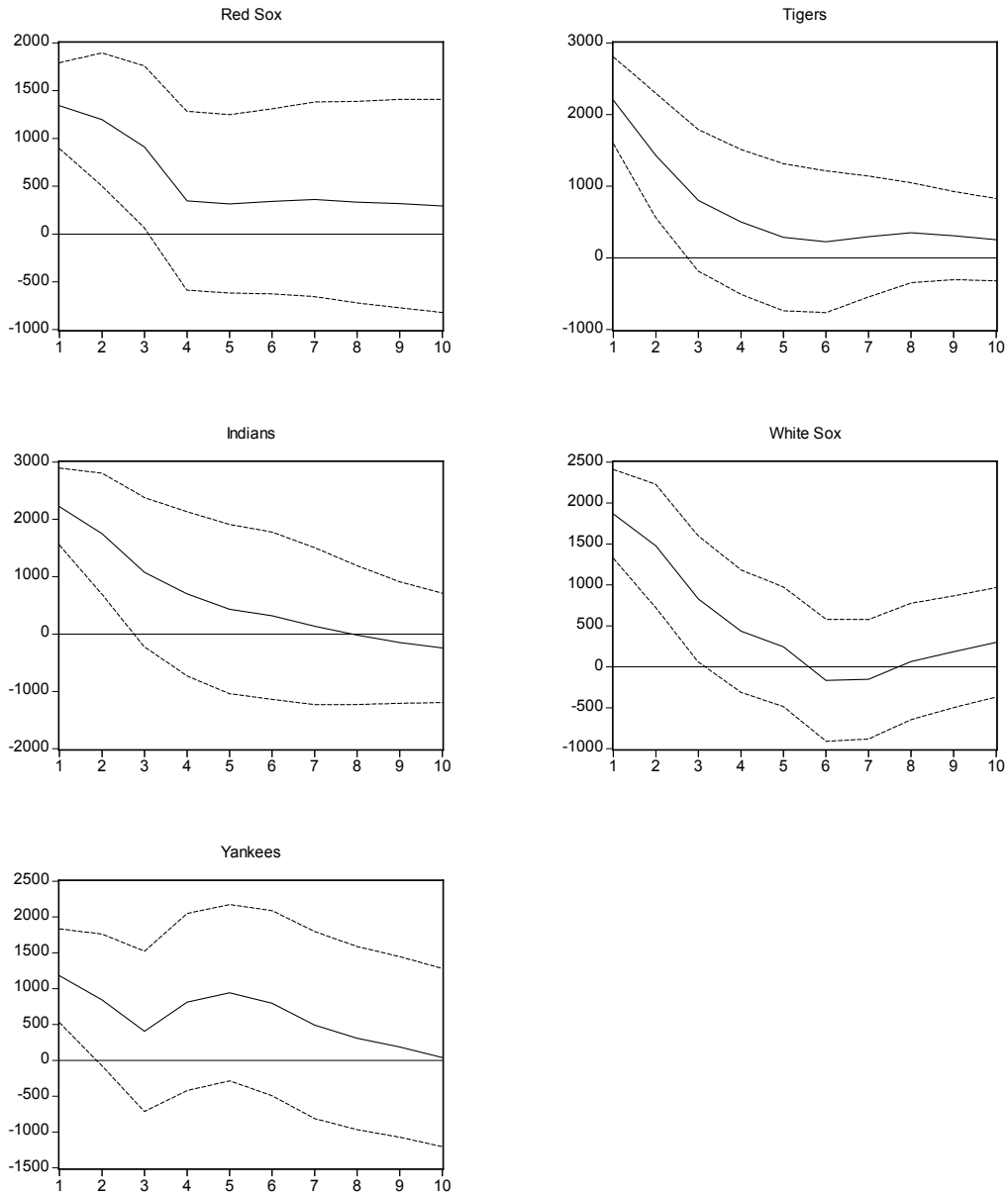
Solid line represents impulse responses. Dashed line represents two standard
error bounds. Figures show responses to a one standard deviation shock. Y-axis
represents years.

Figure 4: Impulse Responses of Winning Percentage to
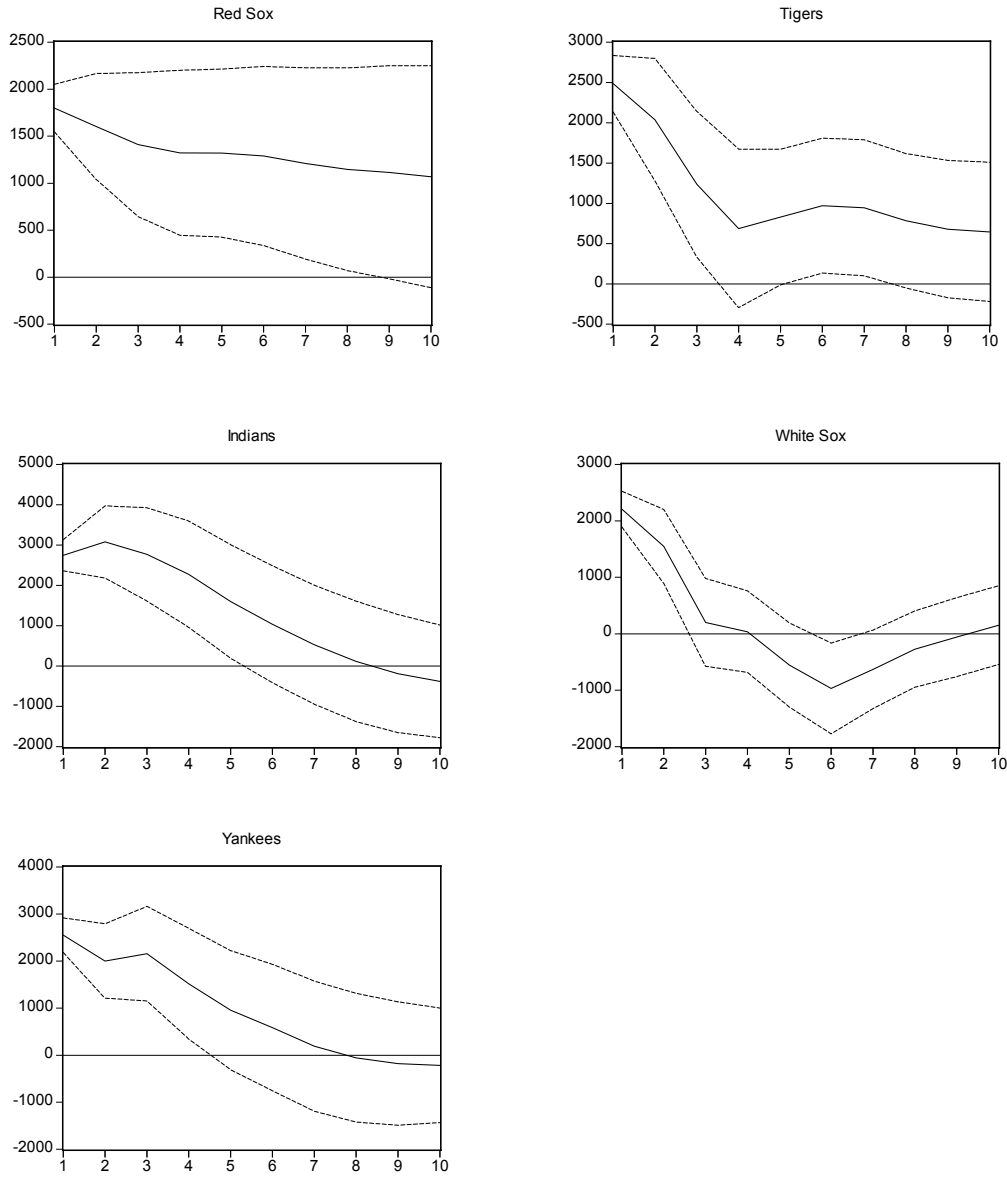Shock in Attendance (NL Teams)

Solid line represents impulse responses. Dashed line represents two standard
error bounds. Figures show responses to a one standard deviation shock. Y-axis
represents years.

Figure 5: Impulse Responses of Winning Percentage to
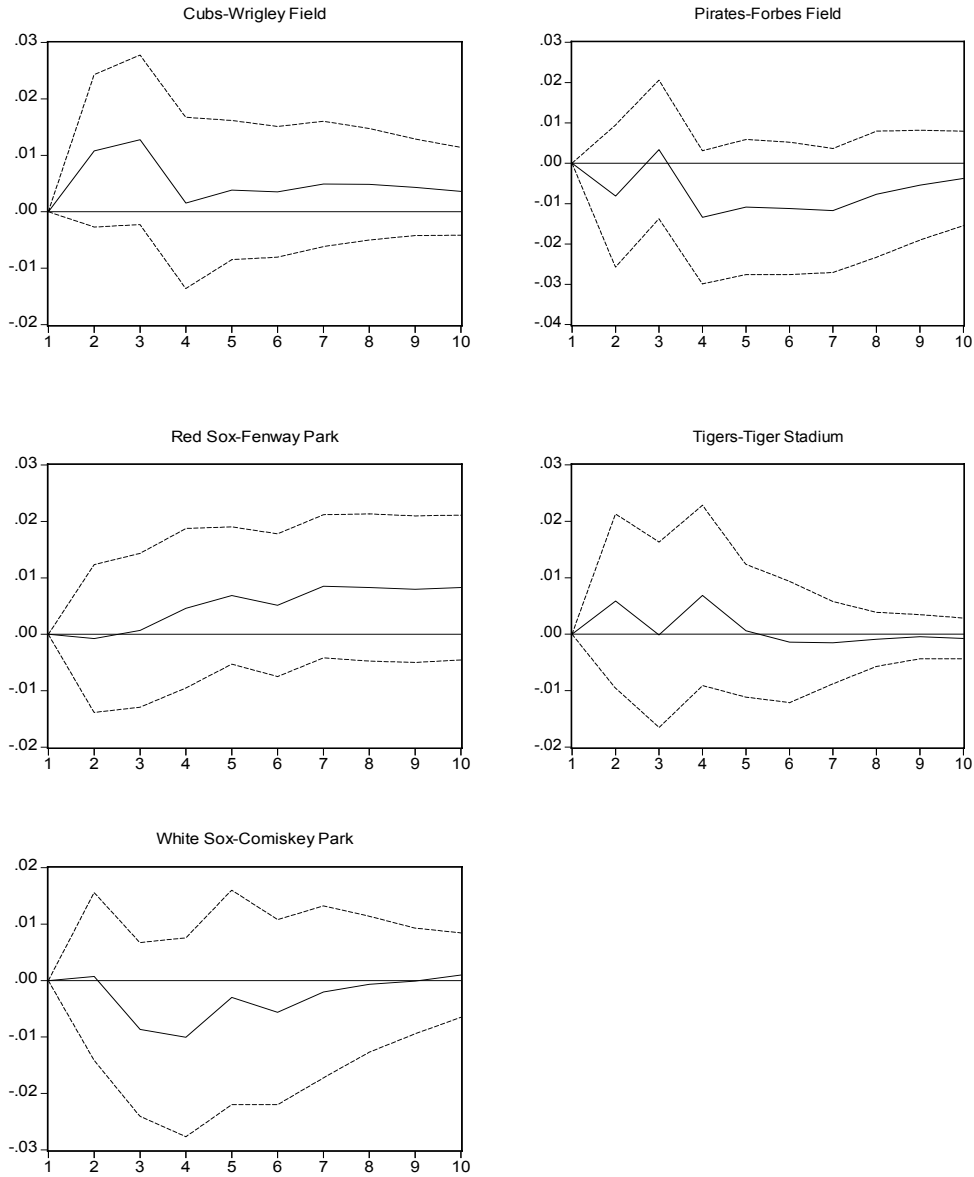Shock in Attendance (AL Teams)

Solid line represents impulse responses. Dashed line represents two standard
error bounds. Figures show responses to a one standard deviation shock. Y-axis
represents years.

Figure 6: Impulse Response of Attendance to shock in
Attendance (NL teams)

Solid line represents impulse responses. Dashed line represents two standard
error bounds. Figures show responses to a one standard deviation shock. Y-axis
represents years.

Figure 7: Impulse Responses of Attendance to Shock
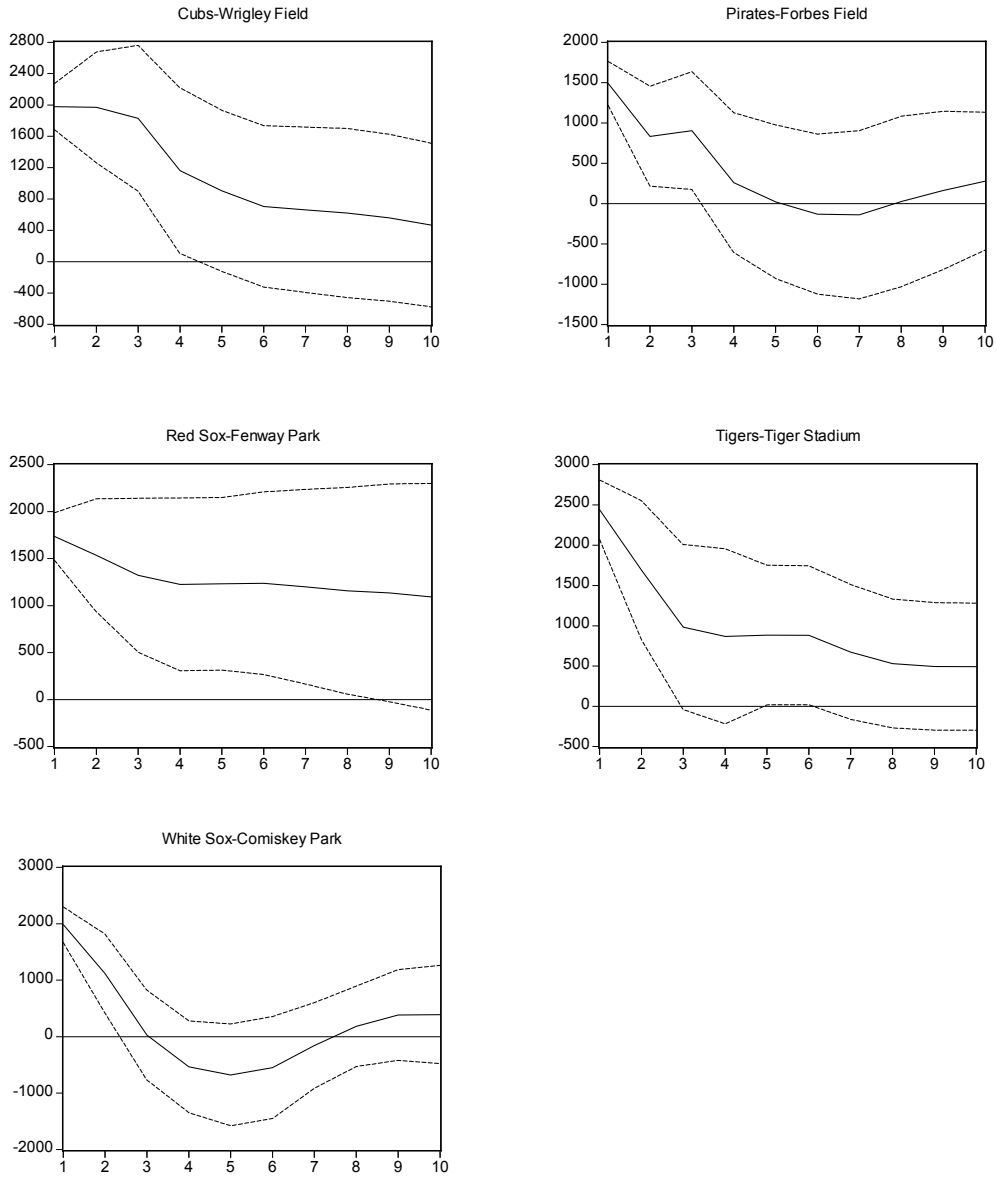in Attendance (AL Teams)

Solid line represents impulse responses. Dashed line represents two standard error bounds. Figures show responses to a one standard deviation shock. Y-axis represents years.

Figure 8: Impulse Response of Winning Percentage to shock
in Attendance (Team-Stadium Combinations)

Solid line represents impulse responses. Dashed line represents two standard
error bounds. Figures show responses to a one standard deviation shock. Y-axis
represents years.

Figure 9: Impulse Response of Attendance to shock
in Attendance (Team-Stadium Combinations)

Solid line represents impulse responses. Dashed line represents two standard
error bounds. Figures show responses to a one standard deviation shock. Y-axis
represents years.