The Impact of Labor Strikes on Consumer Demand: An Application to Professional Sports

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The primary bargaining power of organized labor is its ability to withdraw labor from the firm in the form of a strike. From the workers' perspective, a strike is intended to impose substantial costs upon the firm. Over time, as these costs accumulate, the firm develops an appreciation of the solidarity of labor and may eventually surrender to the demands of the workers. Orley C. Ashenfelter and George E. Johnson (1969) note that the strike also serves the function of informing the workers to the reality of the firm's position. Although the union leadership may recognize early in negotiations that the firm cannot or will not meet the workers' demands, the rank and file of the union often do not understand the impracticality in their position until the workers have struck and the firm fails to surrender.

Whether strikes ultimately serve as a lesson to workers or firms is partially impacted by the extent to which such events impart costs upon both the firm and the industry. For example, Brian E. Becker and Craig A. Olson (1986) examined the relationship between worker strikes and changes in shareholder equity. These authors found that on average, a strike of at least 1,000 workers would reduce shareholder equity by 4.1 percent. Richard A. De Fusco and Scott M. Fuess, Jr. (1991) examined airline carriers and found that strikes tended to redistribute wealth from shareholders of those airlines which experienced a strike to shareholders of airlines that had management-labor peace. Furthermore, Richard McHugh (1991) investigated the impact of a labor strike on both the firm and organizations linked as purchasers or suppliers. Surprisingly, the impact of the strike was greater for the linked firm than it was for the firm directly experiencing the worker strike.

Each of the aforementioned studies found that strikes impose costs on the firm. These costs generally centered on the loss of output the firm experienced during the duration of the management-labor conflict. Previous studies have largely neglected the possible extended costs associated with the reactions of the remaining party impacted by the worker strike, the consumer. Although in many industries firms can increase inventories prior to a worker strike, this is not true in all industries. Within the airline industry, for example, labor strikes temporarily force consumers to either consume the production of other suppliers or live without the particular good or service. This outcome leads to the question we investigate: Do work stoppages permanently impact consumer demand when the struck firm is unable to meet demand during the labor strike?

A natural setting to explore this issue is the professional sports industry. In such an industry, worker strikes can completely remove the output from the consumer's consumption basket. Unlike strikes in other industries, though, consumers of the output from the professional team sports industry frequently threaten to withdraw all future demand if worker strikes are not avoided or ended quickly.[1] This threat has led industry insiders to claim that labor strikes might destroy the professional sports league experiencing management-labor difficulty.

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[1] As noted by an anonymous referee, strikes in professional sports differ from the majority of industries since strikes generally tend to occur at the firm level. Hence consumers generally have the option of choosing output from competing firms. In contrast, strikes in professional sports generally are at the industry level. In this sense, these strikes are most similar to strikes in the public sector, i.e., busing strikes.

TABLE 1—MAJOR LEAGUE BASEBALL, NATIONAL LEAGUE FOOTBALL, AND NATIONAL HOCKEY LEAGUE WORK STOPPAGES

Major League Baseball			National League Football			National Hockey League		
Year	Work stoppage	Games canceled	Year	Work stoppage	Games canceled	Year	Work stoppage	Games canceled
1981 (50 days)	Player strike	712	1982 (57 days)	Player strike	98	1994 (103 days)	Lock out	442
1994–1995 (232 days)	Player strike	920	1987 (24 days)	Player strike	56			

We consider three North American professional team sports leagues: Major League Baseball (MLB), the National Football League (NFL), and the National Hockey League (NHL). As detailed below, each of these sports experienced at least one worker strike during the last 30 years. With the use of time-series and panel data, we investigate how quickly aggregate league attendance recovers from the loss of output. In general, our results suggest that labor-management conflicts in professional sports do not have permanent effects. In fact, the analysis suggests that the strike cost is limited to the strike period and that consumer demand returns in force immediately after the strike ends. Given the low cost of strikes, we suspect that we are not likely to see a reduction in strike activity within professional sports in the future.

The paper is organized as follows: Section I briefly reviews the recent history of management-labor strife in these sports leagues. Section II reports our time-series and panel data investigation of the impact strikes have upon league attendance. Finally, Section III provides a brief conclusion.

I. Owner–Labor Strife

Conflict between owners and labor is not new to North American sports.[2] Table 1 summarizes the recent events in professional team sports that led to a loss of regular season games. As Table 1 highlights, both MLB and the NFL have each had two worker stoppages that led to a shortened regular season, while the NHL has had one.[3] Given the frequency of these events, one might conclude that labor-management relationships in these sports has been relatively peaceful. However, as James Quirk and Rodney Fort (1999) point out, work stoppages in professional sports are much more common than for the economy as a whole.[4] We follow with a brief review of the history of each sport to illustrate the extent of the conflict between these two parties.

As noted by Staudohar (1997), since the removal of the reserve clause, work stoppages have occurred in baseball at the expiration of each collective bargaining agreement, i.e., 1972, 1973, 1976, 1980, 1981, 1985, 1990, and 1994.[5] Baseball does not have a monopoly on contentious management-labor relationships. Staudohar (1988, 1996) also notes the difficulties management in the NFL has had with the NFL Players Association (NFLPA). Prior to 1994, the NFL and NFLPA were never able to reach an accord without a period of acrimony.

In comparison to MLB and the NFL, the NHL has been relatively free of labor-management conflict. The exception to the trend occurred during the 1994–1995 season. Fearing

[2] For example, the so-called "Brotherhood Revolt" of 1890 and the Detroit Tigers strike of 1912 (Paul D. Staudohar, 1997).

[3] The NBA also experienced a shortened season due to management-labor conflict during the 1999–2000 season. Given the nature of our analysis, though, too little time has passed for us to adequately access the long-term impact of this event. Consequently, our analysis will only focus on the NHL, NFL, and MLB.

[4] We thank an anonymous referee for bringing our attention to the Quirk and Fort (1999) observation.

[5] The reserve clause was written into each Major League Baseball player's contract prior to 1976. This clause gave the team "the right to renew this contract for the period of one year on the same terms" (Quirk and Fort, 1999, p. 185). As noted by Quirk and Fort, this clause effectively tied a player to the team he initially signed with for the duration of the player's career.

a potential player strike prior to the commencement of the NHL playoffs, NHL owners locked the players out at the beginning of the regular season.[6] After 103 days and the loss of 442 regular season games, an agreement was reached.[7] The fact that labor peace in professional sports has been elusive provides cursory evidence that strikes impose minimal long-term costs.

In general, labor-management conflicts have centered over how the two sides would divide the substantial revenues generated in these industries. These revenues are generated by the millions of people who pay attention, both in person and via broadcast media, to the actions of a relatively small portion of the population. Unlike work stoppages in other industries, the consumers of sport output take a very active interest in the conflict between labor and management. In fact, many of these consumers express such disgust with the bickering between two sets of very wealthy individuals that these customers promise to never purchase the industries' outputs again.

II. The Impact of Worker Strikes on Attendance

The Data and Basic Methodology.—In order to examine the impact these strikes had on consumer demand, we investigate the strikes' impact on league attendance. The present analysis therefore requires time-series data on total attendance for all teams in MLB, the NFL, and the NHL. For MLB, the attendance data was obtained for the years 1901–2000 from *The Sporting News Complete Baseball Record Book* (2000). The NFL data begins in 1935 and concludes in 1999 and was obtained from *The Sporting News Pro Football Guide* (1999). Finally, attendance data for the NHL was obtained for the period 1960–2000 from *Total Hockey* (2000).

In order to simplify the interpretation of the attendance series, we modified these in two ways. First, we adjusted the data for periods of expansion. These periods would increase attendance without imparting any endogenous fan response. Specifically, we deflated the attendance series by the number of teams to produce an average attendance figure.[8] Second, we scaled the data in terms of the 1992 attendance figure. The graphs presented in Figure 1 depict the scaled average MLB, NFL, and NHL attendance series. Each of the events listed in Table 1 led to a large negative spike in the attendance time series.[9] In addition, the following year's response foreshadows the lack of permanent effect.

In order to ascertain the impact strikes have on league attendance, we followed the interven-

[6] As noted by Michael Leeds and Peter von Allmen (2001), the timing of a work stoppage is crucial to the leverage of each side in the management-labor negotiations. Toward the end of the season players have collected much of their salary. Hence a strike is not particularly costly. However, owners reap much of their revenues from the playoffs, hence a work stoppage toward the end of the season is especially expensive. Given the nature of the revenue and cost streams, owners would much prefer a work stoppage at the beginning of the season. Consequently, lockouts are generally imposed at the beginning of a season, worker strikes tend to come toward the end of the campaign.

[7] Similarly, the loss of regular season games had also generally been avoided in the NBA. However, during the 1998–1999 campaign, the owners followed the lead of the NHL and locked the players out at the onset of the season. After 191 days and the loss of 464 regular season games, an agreement was reached between the two parties.

[8] Specifically, MLB has expanded six times from the original 16 teams. In 1961, 1962, 1977, 1993, and 1998, the league expanded by two teams, while four teams were added in 1969. The NFL had nine teams in 1934, 11 teams in 1935. The NFL has expanded and lost teams many more times. Specifically, they lost two teams in 1935, gained one team in 1937, lost two teams in 1943, gained two teams in 1944, gained three teams in 1950, lost one team in 1951, gained one team in 1960, gained one team in 1961, and another in 1966 and 1967. The NFL further expanded by ten teams in 1970, two teams in 1976, two teams in 1994, and one team in 1999. The NHL has expanded 11 times and lost one franchise over the period investigated. Specifically, the NHL doubled to 12 teams in 1967, added two teams in 1970, 1972, and 1974. It lost one team in 1978 and added four teams in 1979. Finally, one team was added in 1991, 1998, and 1999 and two teams were added in 1992, 1993, and in 2000.

[9] In addition, the leagues have altered the number of games played by a member team within a season. In general, we captured these effects through the use of dummy variables. We chose this option because creating per game average attendance figure would not capture the loss of games caused by the strike. We could, however, have created a *hypothetical* per game average for the strike year. This approach lead to similar conclusions as those presented below.

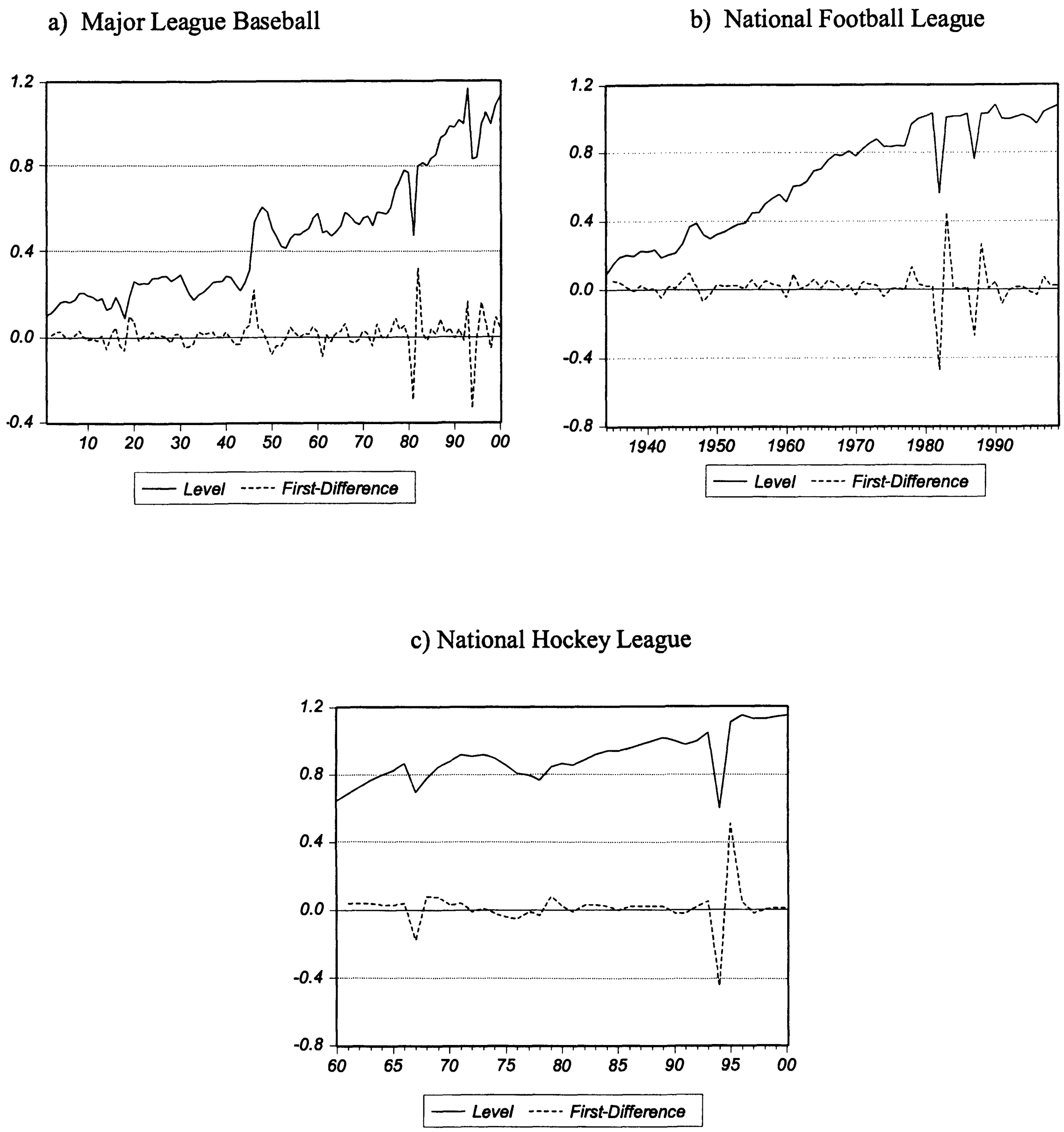

FIGURE 1. AGGREGATE YEARLY ATTENDANCE—SCALED

tion analysis methodology outlined in Walter Enders (1995).[10] Intervention analysis allows for a formal test of a change in the mean of a series, given an intervention (i.e., an exogenous shock).[11] The approach may be highlighted within this simple AR(1) representation:

$$(1)\quad y_t = \alpha_0 + \alpha_1 * y_{t-1} + \alpha_2 * z_t + \varepsilon_t$$

[10] Our analysis follows from the work of Schmidt and Berri (2002).

[11] Enders et al. (1990) use the approach to estimate the impact of the U.S. bombing of Libya in 1986 on terrorist activity.

TABLE 2—AUGMENTED DICKEY-FULLER (ADF) AND PHILLIPS-PERRON UNIT ROOT TESTS

Major League Baseball Sample: 1901–2000			National League Football Sample: 1937–1999			National Hockey League Sample: 1960–2000		
Average attendance	ADF statistic (p)	Phillips-Perron statistic (l)	Average attendance	ADF statistic (p)	Phillips-Perron statistic (l)	Average attendance	ADF statistic (p)	Phillips-Perron statistic (l)
MLB	−0.165 (2)	−0.486 (3)	NFL	−1.008 (2)	−1.291 (3)	NHL	−1.910 (1)	−2.797 (3)
d(MLB)	−7.166 (2)*	−6.749 (3)*	d(NFL)	−7.123 (2)*	−16.247 (3)*	d(NHL)	−6.909 (1)*	−11.785 (3)*

Notes: The ADF (augmented Dickey-Fuller) statistics were computed using (p) lags and a constant. The choice of p was based upon minimization of the Schwartz-Bayesian criteria (SBC). The Phillips-Perron statistics were computed using the AR(1) regression including a constant. The choice of truncation lag (l) is based upon Newey-West. In addition, * represents significance at the 1-percent critical level.

where y_t is the variable of interest and z_t is the intervention variable. Specifically, z_t takes a value of one when the intervention occurs. The initial impact of the *intervention* is designated by the value of α_2. Given the AR(1) representation, the long-run impact is defined by $\alpha_2/(1 - \alpha_1)$. When $\alpha_1 = 0$, α_2 represents both short- and long-run impacts. Specifically, the approach allows us to investigate whether a strike, an intervention, fundamentally altered the behavior of league attendance, y_t.

The Prelabor Conflict Models.—The first step in the process is to estimate an ARMA model which represents the *preintervention* period. As has been well documented, spurious regression concerns require us to examine whether the data are stationary. Therefore, Table 2 reports the results of both the augmented Dickey-Fuller (ADF) and Phillips-Perron tests to determine the integrated level of the attendance series. Given these results, we estimate the behavior of the three data series as $I(1)$ and incorporate the variables' first-differences in the analysis.

In addition, the prestrike periods were influenced by several large outliers. Figure 1 suggests that both the MLB and NFL series were subject to a large positive spike in 1946, which coincides with the end of WWII and the return of U.S. soldiers, removal of travel restrictions, etc. The effect was quite large with more than a 20-percent increase in attendance for MLB and nearly a 10-percent increase for the NFL. In order to control for these outliers, we included a dummy variable $z(46)$ in both models. In addition, the NFL has spikes at 1961 and 1978. These represent expansion in the number of games each team played within the regular season.[12] Specifically, the NFL schedule was expanded to 14 games in 1961 and 16 games in 1978. We therefore included two dummy variables, $z(61)$ and $z(78)$, within the NFL analysis. Finally, the NHL experienced a significant negative spike in 1967 due to expansion. In 1967, the NHL doubled its size to 12 teams. However, aggregate total attendance only increased by 50 percent. We therefore included a dummy variable, $z(67)$, within the NHL analysis.[13]

As a point of comparison, our analysis of the prelabor conflict period is captured by the following three white noise representations, where y_t represents the (differenced) average attendance. The estimation of these univariate Box-Jenkins specifications is reported in the initial row of Table 3 [panels (a)–(c)].

$$(2) \quad y_{MLBt} = \alpha_{MLB0} + \alpha_{MLB1} * z(46) + \varepsilon_{MLBt}$$

$$y_{NFLt} = \alpha_{NFL0} + \alpha_{NFL1} * z(46) + \alpha_{NFL2} * z(61) + \alpha_{NFL3} * z(78) + \varepsilon_{NFLt}$$

$$y_{NHLt} = \alpha_{NHL0} + \alpha_{NHL1} * z(67) + \varepsilon_{NHLt}.$$

In order to examine whether the equation was properly specified, the Breusch-Godfrey test for serial correlation, the Jarque-Bera test for nor-

[12] The incorporated lag structure was determined by minimization of the Schwartz-Bayesian Criterion (SBC) for the ADF test and by the lag truncation suggested by Newey-West for the Phillips-Perron statistic. Use of the Akiake Information Criteria (AIC) produced similar results.

[13] The coefficients were positive and highly significant. These are available from the authors upon request.

TABLE 3—INTERVENTION ANALYSIS MLB, NFL, AND NHL PRELABOR CONFLICT UNIVARIATE REPRESENTATIONS

Dependent variable: $y_t - d(attendance)_t$

y_{t-1}	y_{t-2}	ε_{t-1}		Diagnostic tests
(a) Major League Baseball—Sample: 1901–1980				
—	—	—	adjR^2 = 0.319 SSE = 0.096	B-G(4) = 1.648 (0.17) J-B(2) = 0.970 (0.62)
			AIC = −3.823 SBC = −3.763	ARCH(4) = 1.218 (0.31) Q(10) = 11.074 (0.35)
0.176	—	—	adjR^2 = 0.329 SSE = 0.093	B-G(4) = 1.067 (0.38) J-B(2) = 2.107 (0.35)
(1.524)			AIC = −3.813 SBC = −3.722	ARCH(4) = 0.540 (0.67) Q(10) = 9.355 (0.41)
—	−0.211	—	adjR^2 = 0.121 SSE = 0.092	B-G(4) = 0.767 (0.25) J-B(2) = 0.235 (0.89)
	(1.825)		AIC = −3.817 SBC = −3.726	ARCH(4) = 1.392 (0.25) Q(10) = 9.199 (0.42)
—	—	−0.285*	adjR^2 = 0.344 SSE = 0.091	B-G(4) = 2.975 (0.23) J-B(2) = 1.168 (0.33)
		(−2.551)	AIC = −3.848 SBC = −3.758	ARCH(4) = 0.362 (0.84) Q(10) = 7.121 (0.63)
−0.255	—	0.506	adjR^2 = 0.342 SSE = 0.090	B-G(4) = 0.893 (0.42) J-B(2) = 1.753 (0.47)
(−0.626)		(1.382)	AIC = −3.820 SBC = −3.699	ARCH(4) = 0.367 (0.83) Q(10) = 6.018 (0.65)
(b) National Football League—Sample: 1935–1981				
—	—	—	adjR^2 = 0.373 SSE = 0.037	B-G(4) = 1.179 (0.34) J-B(2) = 5.087 (0.08)
			AIC = −6.983 SBC = −6.825	ARCH(4) = 0.611 (0.66) Q(10) = 6.049 (0.81)
0.045	—	—	adjR^2 = 0.376 SSE = 0.035	B-G(4) = 1.528 (0.21) J-B(2) = 5.393 (0.07)
(0.271)			AIC = −6.965 SBC = −6.767	ARCH(4) = 0.704 (0.59) Q(10) = 6.150 (0.73)
—	0.093	—	adjR^2 = 0.389 SSE = 0.034	B-G(4) = 1.210 (0.32) J-B(2) = 5.014 (0.08)
	(0.615)		AIC = −6.970 SBC = −6.769	ARCH(4) = 0.604 (0.66) Q(10) = 6.747 (0.66)
—	—	0.040	adjR^2 = 0.359 SSE = 0.037	B-G(4) = 1.731 (0.16) J-B(2) = 5.122 (0.08)
		(0.242)	AIC = −6.942 SBC = −6.745	ARCH(4) = 0.659 (0.62) Q(10) = 6.058 (0.73)
0.372	—	−0.386	adjR^2 = 0.370 SSE = 0.034	B-G(4) = 1.220 (0.32) J-B(2) = 5.053 (0.08)
(0.668)		(−0.672)	AIC = −6.937 SBC = −6.699	ARCH(4) = 0.631 (0.64) Q(10) = 6.478 (0.59)
(c) National Hockey League—Sample: 1960–1993				
—	—	—	adjR^2 = 0.501 SSE = 0.032	B-G(4) = 1.620 (0.20) J-B(2) = 0.233 (0.89)
			AIC = −6.819 SBC = −6.728	ARCH(4) = 1.503 (0.23) Q(10) = 14.62 (0.15)
0.022	—	—	adjR^2 = 0.486 SSE = 0.031	B-G(4) = 2.693 (0.05) J-B(2) = 0.097 (0.95)
(0.168)			AIC = −6.739 SBC = −6.601	ARCH(4) = 1.059 (0.40) Q(10) = 15.38 (0.12)
—	0.271	—	adjR^2 = 0.520 SSE = 0.029	B-G(4) = 1.076 (0.39) J-B(2) = 0.247 (0.88)
	(1.488)		AIC = −6.785 SBC = −6.646	ARCH(4) = 0.156 (0.96) Q(10) = 12.945 (0.17)
—	—	0.212*	adjR^2 = 0.569 SSE = 0.027	B-G(4) = 0.529 (0.72) J-B(2) = 0.484 (0.78)
		(−7.619)	AIC = −6.937 SBC = −6.801	ARCH(4) = 0.673 (0.62) Q(10) = 6.552 (0.68)
−0.101	—	0.432	adjR^2 = 0.563 SSE = 0.026	B-G(4) = 0.474 (0.75) J-B(2) = 0.183 (0.91)
(−0.761)		(2.041)	AIC = −6.874 SBC = −6.691	ARCH(4) = 0.936 (0.46) Q(10) = 7.311 (0.61)

Notes: All attendance figures have been first-differenced. Each equation includes a constant. The coefficients are reported with their associated t-statistic for the null hypothesis that the estimated value is equal to zero. In addition, * represents significance at the 1-percent critical level. B-G(q) reports the Breusch-Godfrey statistic for serial correlation within the residuals obtained from the estimated model, with lag order of q. J-B(q) reports the Jarque-Bera statistic for normality of the residuals obtained from the estimated model, with lag order of q. ARCH(q) reports the Engle ARCH statistic for heteroskedastic errors within the residuals obtained from the estimated model, with lag order of q. Q(n) reports the Ljung-Box Q-statistic for the autocorrelations of the n residuals of the estimated model. P-values are in parentheses.

mality, and an ARCH test for heteroskedasticity were performed. Each statistic was well outside its 10-percent critical level. Finally, the reported Ljung-Box Q-test also suggests that each equation's estimated residuals, ε_t, approximated white noise.

In order to find a parsimonious ARMA representation, we examined each series' autocorrelation functions (ACF, PACF) and its associated Ljung-Box Q-test statistics. These revealed remarkably similar behavior. Specifically, each series yielded a marginally significant spike at lag one, i.e., suggestive of an AR(1) or an MA (1). In addition, some oscillating behavior in the residuals for both equations was evident, i.e., perhaps suggestive of AR(2) processes. However, these were generally insignificant. We, therefore, estimated these alternative ARMA representations.

The remaining rows of Table 3 report the results of these univariate Box-Jenkins representations. Overall the AR(1), AR(2), and ARMA(1, 1) representations were less attractive by all measures, relative to the white noise representation, for all three leagues. While the white noise specification was always preferred by the NFL data, both the NHL and MLB analysis suggest the existence of an MA(1) term (row 4). Indeed, the moving average coefficients were significant at the 1-percent critical level. Overall, however, there is little difference between these two specifications. Therefore, we estimated the impact of the strikes with both specifications for both the NHL and MLB. The intervention analysis reported in Tables 4 and 5 was not sensitive to the choice, as both specifications produced similar results. In the end, we opted for the white noise specification due to its parsimony and because the moving average term became insignificant as the data was updated.

The Postlabor Conflict Models.—The next step in the intervention analysis is to reestimate the optimal specification over the extended sample period and examine the importance of the intervention variable(s). This analysis was completed for each of the labor conflicts that occurred in MLB, the NFL, and the NHL. The results of this analysis are reported in Tables 4–6.

In general, our analysis followed several steps. Initially, we extended the white noise representation to examine whether the work stoppages had any effect on average attendance. These are reported in the first row of Tables 4(a), 4(b), 5(a), 5(b), and 6. As expected, the estimates all had low R^2s and large standard errors, and we easily rejected normality within the errors. We therefore examined three alternative representations. The second row of these tables introduces the intervention (i.e., strike) dummy variable. For example, in order to capture the impact of the 1981 player strike, the strike intervention variable, $z(81)$, appears in the second row of Table 4(a). The strike intervention variable takes a value of unity in the year of the conflict, and zero otherwise. Not surprisingly, these variables were consistently negative and highly significant. Specifically, while the two MLB strikes led to a 30-percent and 35-percent reduction in MLB attendance, the two NFL strikes led to reductions of 50 percent and 29 percent. The NHL lost nearly 50 percent of its attendance due to the work stoppage. Moreover, while the variables increased R^2s, all equations continue to produce large *nonnormal* errors.[14]

As these dummy variables capture only the initial impact of the strikes, the large errors may be associated with a continuing or permanent strike effect. In order to examine whether the

[14] Within the poststrike estimation, we introduced an additional dummy variable for both MLB and the NFL. Specifically, MLB expansion in 1993 was followed by an increase in attendance unequaled in the post-WWII period. Aggregate National League attendance increased by nearly 13 million fans, or an increase of roughly 33 percent. The increase was well above the 1983–1992 average of slightly more than a million a year. In part, the rise may be attributed to the unique behavior of the two expansion teams which began play in 1993, the Colorado Rockies and the Florida Marlins. Specifically, the two teams had a total attendance of nearly 7.5 million, accounting for more than half of the overall increase. Moreover, the Colorado Rockies, playing in Mile High stadium, set a major league attendance record in their debut year with more than 4.4 million. While the "expansion effect" was controlled for by the use of the average measure, the effect of the 1993 expansion was significantly larger than in any other expansion period, where average attendance actually decreased by an average of 1 percent. Therefore, we included $z(93)$ within the MLB equations. In addition, a dummy variable, $z(91)$, was introduced for the NFL due to a large exogenous shock. It should be noted that none of the results in the paper was sensitive to the inclusion or exclusion of these dummy variables.

TABLE 4—INTERVENTION ANALYSIS: MLB

Dependent variable: $y_t - d(attendance)_t$

(a) The 1981 Strike—Sample: 1901–1992

z(81)	z(82)	z(81–92)		Diagnostic tests
—	—	—	adjR^2 = 0.125 SSE = 0.297	B-G(4) = 2.654 (0.04) J-B(2) = 1,010.86 (0.00)
			AIC = −2.844 SBC = −2.789	ARCH(4) = 10.819 (0.00) Q(10) = 11.963 (0.29)
−0.306*	—	—	adjR^2 = 0.390 SSE = 0.204	B-G(4) = 0.854 (0.50) J-B(2) = 1,475.20 (0.00)
(−0.048)			AIC = −3.195 SBC = −3.112	ARCH test (4) = 0.064 (0.99) Q(10) = 6.294 (0.79)
—	—	0.014	adjR^2 = 0.121 SSE = 0.298	B-G(4) = 6.176 (0.00) J-B(2) = 1,036.96 (0.00)
		(0.754)	AIC = −2.829 SBC = −2.746	ARCH(4) = 10.666 (0.00) Q(10) = 13.529 (0.20)
−0.302*	0.316*	—	adjR^2 = 0.681 SSE = 0.106	B-G(4) = 0.999 (0.41) J-B(2) = 1.611 (0.45)
(−8.611)	(8.997)		AIC = −3.831 SBC = −3.721	ARCH(4) = 1.370 (0.25) Q(10) = 11.378 (0.33)
	H_0: $z(81) = (-1) * z(82)$			Wald statistic = 0.074 (0.41)

(b) The 1994–1995 Strike—Sample: 1901–2000

z(81)	z(82)	z(93)	z(94)	z(94–00)	z(96)		Diagnostic tests
−0.303*	0.315*	—	—	—	—	adjR^2 = 0.436 SSE = 0.285	B-G = (4) = 2.37 (0.06)
							J-B(2) = 1,117.89 (0.00)
(−5.491)	(5.710)					AIC = −2.929 SBC = −2.824	ARCH(4) = 1.045 (0.39)
							Q(10) = 17.270 (0.07)
−0.301*	0.317*	0.160*	—	—	—	adjR^2 = 0.480 SSE = 0.260	B-G(4) = 1.902 (0.12)
							J-B(2) = 1,526.11 (0.00)
(−5.690)	(5.981)	(3.027)				AIC = −3.001 SBC = −2.870	ARCH(4) = 0.744 (0.56)
							Q(10) = 17.946 (0.06)
−0.305*	0.313*	0.157*	−0.345*	—	—	adjR^2 = 0.713 SSE = 0.142	B-G(4) = 1.203 (0.32)
							J-B(2) = 21.172 (0.00)
(−7.745)	(7.952)	(3.978)	(−8.777)			AIC = −3.585 SBC = −3.427	ARCH(4) = 0.437 (0.78)
							Q(10) = 9.165 (0.52)
−0.302*	0.316*	0.159*	—	−0.013	—	adjR^2 = 0.477 SSE = 0.259	B-G(4) = 1.886 (0.12)
							J-B(2) = 1,182.67 (0.00)
(−5.687)	(5.941)	(2.998)		(−0.612)		AIC = −2.985 SBC = −2.828	ARCH(4) = 1.194 (0.31)
							Q(10) = 18.435 (0.05)
−0.303*	0.315*	0.158*	−0.344*	—	0.152*	adjR^2 = 0.756 SSE = 0.120	B-G(4) = 0.500 (0.74)
							J-B(2) = 1.385 (0.50)
(−8.365)	(8.680)	(4.364)	(−9.486)		(4.203)	AIC = −3.740 SBC = −3.557	ARCH(4) = 1.898 (0.12)
							Q(10) = 10.300 (0.42)
H_0: $z(81) = (-1) * z(82)$					Wald statistic = 0.488 (0.84)		
H_0: $z(94) = (-1) * z(96)$					Wald statistic = 13.808 (0.00)		
H_0: $z(94) = (-1) * [z(93) + z(96)]$					Wald statistic = 0.2756 (0.60)		

Notes: See Table 3. The equations also contained a constant and a dummy variable for 1946. Wald statistic(s) are for the null hypothesis that the associated coefficients are equal. Wald t-values are in parentheses.

strikes and lockouts had a permanent impact on league attendance, we introduced an intervention variable that was unity for the strike period and for all remaining years. These results are reported in the third row of Tables 4(a), 4(b), 5(a), 5(b), and 6. Each of these were inferior to the single-year dummy representation. For example, the pulse specification, $z(87–99)$, in Table 5(b) suggests the existence of serial correlation, nonnormality of the errors, and heteroskedasticity.

A cursory examination of Figure 1 suggests

TABLE 5—INTERVENTION ANALYSIS: NFL

Dependent variable: $y_t - d(attendance)_t$

(a) The 1982 Strike—Sample: 1935–1986

z(82)	z(83)	z(82–86)		Diagnostic tests
—	—	—	adjR^2 = −0.004 SSE = 0.464 AIC = −4.564 SBC = −4.414	B-G(4) = 5.753 (0.00) J-B(2) = 776.308 (0.00) ARCH(4) = 6.595 (0.00) Q(10) = 12.192 (0.27)
−0.497* (−7.143)	—	—	adjR^2 = 0.508 SSE = 0.223 AIC = −5.261 SBC = −5.073	B-G(4) = 0.056 (0.99) J-B(2) = 2,333.27 (0.00) ARCH(4) = 0.100 (0.982) Q(10) = 1.283 (0.999)
—	—	−0.014 (−0.303)	adjR^2 = −0.024 SSE = 0.464 AIC = −4.528 SBC = −4.340	B-G(4) = 6.626 (0.00) J-B(2) = 756.355 (0.00) ARCH(4) = 8.273 (0.00) Q(10) = 11.611 (0.31)
−0.488* (−17.020)	0.436* (15.120)	—	adjR^2 = 0.917 SSE = 0.037 AIC = −7.018 SBC = −6.793	B-G(4) = 1.277 (0.29) J-B(2) = 6.431 (0.04) ARCH(4) = 0.324 (0.86) Q(10) = 6.639 (0.76)
	H_0: z(82) = (−1) * z(83)			Wald statistic = 1.023 (0.21)

(b) The 1987 Strike—Sample: 1935–1999

z(82)	z(83)	z(87)	z(87–99)	z(88)		Diagnostic tests
−0.486* (−8.300)	0.438* (7.483)	—	—	—	adjR^2 = 0.671 SSE = 0.199 AIC = −5.606 SBC = −5.406	B-G = (4) = 4.122 (0.00) J-B(2) = 565.936 (0.00) ARCH(4) = 8.073 (0.00) Q(10) = 17.554 (0.06)
−0.490* (−10.78)	0.433* (9.521)	−0.286* (−6.298)	—	—	adjR^2 = 0.801 SSE = 0.118 AIC = −6.097 SBC = −5.863	B-G(4) = 1.762 (0.15) J-B(2) = 783.082 (0.00) ARCH(4) = 0.222 (0.93) Q(10) = 10.355 (0.41)
−0.488* (−8.269)	0.436* (7.385)	—	−0.103 (−0.549)	—	adjR^2 = 0.667 SSE = 0.198 AIC = −5.581 SBC = −5.347	B-G(4) = 4.264 (0.01) J-B(2) = 559.424 (0.00) ARCH(4) = 8.863 (0.00) Q(10) = 17.227 (0.06)
−0.488* (−17.02)	0.436* (15.20)	−0.284* (−9.900)	—	0.253* (8.830)	adjR^2 = 0.921 SSE = 0.045 AIC = −6.994 SBC = −6.693	B-G(4) = 0.906 (0.47) J-B(2) = 5.082 (0.08) ARCH(4) = 0.279 (0.89) Q(10) = 5.436 (0.86)
H_0: z(82) = (−1) * z(83) H_0: z(87) = (−1) * z(88)					Wald statistic = 1.208 (0.27) Wald statistic = 0.381 (0.54)	

Notes: See Table 3. The equations also contained a constant and a dummy variable for 1946, 1961, 1978. In addition, part (b) contains a dummy variable for 1991.

an alternative explanation: the strike year was always followed by an upward adjustment of total attendance. We therefore included an intervention variable for the year immediately following each of the strikes. For example, we included two intervention variables for the NHL, one for the lockout of 1995, *z(95)*, and one for the readjustment the following year, *z(96)*. Including the second intervention variable dramatically increases the R^2, reduces the standard errors, and eliminates the *nonnormality* of the errors. Therefore, including both the 1995 strike and the 1996 correction dummies provides the strongest representation of attendance behavior for the NHL. Similar results exist for **all** strike representations.

Finally, while these specifications suggest some readjustment upwards of attendance during the period directly following the strike, the specification in the fourth row of Tables 4(a), 4(b), 5(a), 5(b), and 6 may still imply long-term impacts if the correction dummies were signif-

TABLE 6—INTERVENTION ANALYSIS: NHL

Dependent variable: $y_t - d(attendance)_t$
The 1994–1995 Strike—Sample: 1961–2000

z(94)	*z(95)*	*z(94–01)*		Diagnostic tests
—	—	—	adjR^2 = 0.039 SSE = 0.495 AIC = −4.291 SBC = −4.207	B-G(4) = 3.015 (0.03) J-B(2) = 325.37 (0.00) ARCH(4) = 4.733 (0.00) Q(10) = 8.944 (0.54)
−0.479* (−5.526)	—	—	adjR^2 = 0.459 SSE = 0.271 AIC = −4.843 SBC = −4.716	B-G(4) = 0.181 (0.95) J-B(2) = 1,220.67 (0.00) ARCH(4) = 0.033 (0.99) Q(10) = 1.712 (0.99)
—	—	−0.004 (−0.073)	adjR^2 = 0.014 SSE = 0.495 AIC = −1.404 SBC = −1.277	B-G(4) = 2.848 (0.04) J-B(2) = 348.31 (0.00) ARCH(4) = 4.655 (0.01) Q(10) = 8.809 (0.55)
−0.466* (−14.92)	0.494* (15.79)	—	adjR^2 = 0.930 SSE = 0.034 AIC = −6.863 SBC = −6.694	B-G(4) = 1.742 (0.17) J-B(2) = 0.028 (0.99) ARCH(4) = 1.697 (0.18) Q(10) = 13.63 (0.19)
	H_0: $z(94) = (-1) * z(95)$			Wald statistic = 0.364 (0.55)

Notes: See Table 3. The equations also contained a constant and a dummy variable for 1967.

icantly smaller. However, the estimated coefficients **all** suggest that the responses are similar in magnitude. We used Wald tests to test the null hypothesis that the coefficients on z (*strike year*) and z (*strike year* + 1) were equal in absolute value.[15] Interestingly, **all** Wald statistics fail to reject the null hypothesis. In the end, the strikes had little permanent impact on the attendance series.

Two Extensions.—A criticism of the preceding analysis is that it fails to incorporate economic theory.[16] Specifically, the construction of equation (2) failed to recognize the many factors that may influence an individual's choice to attend games, such as price, team quality, income, and size of the market. A second criticism is the results represent the aggregate behavior of attendance and may neglect individual team variation. In order to examine these issues, we need to add cross-sectional variation to our analysis. Therefore, we next turn to two panel data sets for MLB.

There are several reasons for limiting our analysis to MLB. The first reason is that we were able to obtain, for a subset of periods, data on the price of admission. A second factor, as was explained previously, is that the owner-labor relationship has been the most contentious within MLB. Therefore, one would expect that long-term impacts are most likely to exist here. A final reason is that baseball is the least likely to sell out games and, therefore, is the least likely to have significant excess or pent-up demand.

Table 7 reports our analysis of two panel data sets for MLB. In the initial rows, we extended the earlier approach to examine the impact of the two strikes for all 30 MLB teams for the 1901–2000 period. In addition to the earlier variables, we included several additional variables that are generally thought to affect attendance. Specifically, we included individual team winning percentage, the number of games the individual team finished behind the first-place

[15] Specifically, our null is that z (*strike year*) + z (*strike year* + 1) is equal to zero. As has been noted by several authors, e.g., Donald W. K. Andrews (1989), tests such as these, while common within empirical work, lack power. Specifically, acceptance of the null is usually associated with high probability of a Type II error. We, therefore, investigated alternative null hypotheses, ranging from (1, −1), to examine the sensitivity of our conclusions. The results of this exercise continue to highlight the lack of long-term impact of strikes. For example, we were able to reject, at the 95-percent level, the null for all values above 0.025 and for all values less than −0.005. It would, therefore, be more accurate to say that the 1981 MLB strike produced, at the 90-percent level, a 1982 attendance response ranging from a decrease of 0.5 percent to an increase of 2.5 percent. Similar results exist for the remaining strikes. We thank an anonymous referee for raising this issue.

[16] We thank an anonymous referee for raising these issues.

TABLE 7—INTERVENTION ANALYSIS: MLB—PANEL EXTENSIONS

Dependent variable: $y_{it} - d(attendance)_{it}$
Sample: 1901–2000

$z(81)$	$z(82)$	$z(93)$	$z(94)$	$z(96)$	Winning percent	Games back	Excess capacity	Dummy: New park	Dummy: New city
−0.235*	0.304*	0.092*	−0.303*	0.134*	0.273*	−0.193*	0.002*	0.022*	0.255*
(−5.541)	(11.86)	(2.267)	(−8.622)	(5.026)	(3.526)	(−2.671)	(−5.723)	(2.250)	(4.023)

H_0: $z(81) = (-1) * z(82)$ Wald statistic = 2.003 (0.16)
H_0: $z(94) = (-1) * [z(93) + z(96)]$ Wald statistic = 1.746 (0.19)

Sample: 1975–1988

$z(81)$	$z(82)$	Price	Pop	Y/Pop	Winning percent	Games back	Excess capacity	Dummy: New park	Dummy: New city
−0.363*	0.295*	−0.020*	−0.006*	0.010*	0.872*	−0.243	0.060*	0.038	—
(−1.794)	(11.76)	(1.914)	(−2.554)	(1.721)	(3.342)	(−0.991)	(−3.333)	(0.676)	

H_0: $z(81) = (-1) * z(82)$ Wald statistic = 0.112 (0.74)

Notes: The unbalanced panel estimates were estimated using weighted generalized least squares that incorporated individual team-specific fixed effects. The coefficients are reported with their associated t-statistic for the null hypothesis that the estimated value is equal to zero. In addition, * indicates significance at the 10-percent critical level. Wald p-values are reported in parentheses.

team,[17] dummies for moving to a new park and a new city, and a measure of excess capacity.[18,19]

The unbalanced panel data was estimated using weighted generalized least squares (GLS) that incorporated team-specific fixed effects.[20] In general, the results are consistent with our expectations and continue to highlight the lack of a long-term impact of strikes. Specifically, while a higher winning percentage increases team attendance, the further back a team is within the division the lower is the team's attendance. Moving to a new city and/or ballpark also increases team attendance. Finally, as with the earlier results, we cannot reject the null hypothesis of no long-term impact for either strike.

While team price data is not available for the entire 1901–2000 sample, we were able to obtain individual team ticket prices for a subset of MLB history. Specifically, Quirk and Fort (1992) provide a measure of ticket prices for 12 American and 11 National League teams for the period 1975–1988.[21] The individual ticket prices represent a weighted average in order to capture the variety of seats available for purchase and were deflated to represent 1991 dollars. Finally, we also included real income and

[17] This is included to capture the fact that fan interest may be raised when their team has a greater chance of making the playoffs.

[18] More successful teams may dip into their pool of excess demand to replenish any disenchanted fans. In order to partially control for this we included a variable which measured the availability of seats, excess capacity. In the aggregate, the variable was constructed by multiplying stadium seating capacity by total games played and dividing total team attendance by this number. This number was subtracted from one to create a measure of available seating. Interestingly, only two teams, Toronto, in 1994, and San Francisco, in 1999, had total attendance equal to capacity. All other teams had attendance rates smaller than capacity. However, many teams sell out a large number of games, in which case an increase in seating capacity would free up seats, especially for the most popular visiting teams (i.e., the Yankees, Red Sox, etc.), and would therefore increase attendance. In this case, one would expect team attendance and the available seating to be positively related.

[19] The data on winning percentage and games behind came from www.baseball-almanac.com/. The stadium data on capacity came from www.ballparks.com/baseball/. These two dummies were zero prior to the move and one afterward.

[20] One possible reason for a team "fixed effect" is the possible brand recognition of teams. Both domestically and internationally, the Yankees are more recognized than the Royals.

[21] Actually, Quirk and Fort (1992) only report ticket prices from 1975–1980. We thank Rodney Fort for providing the additional 1981–1988 data. The 12 AL teams are Baltimore, Boston, California, Chicago, Cleveland, Detroit, Kansas City, Milwaukee, Minnesota, New York, Oakland, and Texas. The 11 NL teams are Atlanta, Chicago, Cincinnati, Houston, Los Angeles, New York, Philadelphia, Pittsburgh, St. Louis, San Diego, and San Francisco.

TABLE 8—INTERVENTION ANALYSIS: MLB—Individual Teams
[Dependent variable: $y_{it} - d(attendance)_{it}$]

Team sample	$z(81)$	$z(82)$	$z(93)$	$z(94)$	$z(96)$	Team sample	$z(81)$	$z(82)$	$z(93)$	$z(94)$	$z(96)$
	H_0: $z(81) = (-1) * z(82)$			H_0: $z(94) = (-1) * [z(93) + z(96)]$			H_0: $z(81) = (-1) * z(82)$			H_0: $z(94) = (-1) * [z(93) + z(96)]$	
Anaheim	−0.362	0.459	0.114	−0.138	0.163	Minnesota	−0.178	0.358	−0.189	−0.435	0.176
1962–2000	0.051 (0.823)			0.094 (0.761)		1902–2000	0.312 (0.578)			1.965 (0.166)	
Atlanta	−0.095	0.574	0.204	−0.663	0.064	Montreal	−0.536	0.339	−0.111	−0.391	0.091
1902–2000	**4.050 (0.048)**			1.869 (0.176)		1970–2000	0.116 (0.737)			0.458 (0.506)	
Baltimore	−0.377	0.226	−0.082	−0.630	0.125	New York Mets	0.115	0.378	0.276	−0.116	0.168
1902–2000	0.846 (0.360)			**9.239 (0.003)**		1963–2000	0.769 (0.388)			0.390 (0.538)	
Boston	−0.455	0.372	−0.053	−0.319	0.012	New York Yanks	−0.454	0.185	0.264	−0.348	0.199
1902–2000	0.385 (0.536)			**5.058 (0.027)**		1902–2000	**3.238 (0.075)**			0.444 (0.507)	
Chicago Cubs	−0.097	0.372	0.183	−0.269	0.139	Oakland	0.241	0.192	−0.236	−0.369	−0.040
1902–2000	1.473 (0.228)			0.002 (0.967)		1902–2000	**8.661 (0.001)**			**12.501 (0.001)**	
Chicago WS	0.014	0.258	−0.130	−0.370	0.008	Philadelphia	−0.358	0.324	0.506	−0.293	−0.070
1902–2000	1.939 (0.167)			**4.369 (0.034)**		1902–2000	0.047 (0.829)			0.740 (0.392)	
Cincinnati	−0.410	0.192	0.084	−0.286	0.005	Pittsburgh	−0.320	0.224	−0.087	−0.077	0.210
1902–2000	1.446 (0.233)			1.143 (0.288)		1902–2000	0.188 (0.667)			0.044 (0.834)	
Cleveland	−0.083	0.173	0.443	−0.096	0.104	San Diego	−0.603	0.497	−0.080	−0.313	0.434
1902–2000	0.151 (0.699)			**3.393 (0.069)**		1970–2000	0.116 (0.737)			0.024 (0.879)	
Detroit	−0.306	0.220	0.379	−0.249	0.275	San Francisco	0.055	0.255	0.355	−0.178	0.118
1902–2000	0.243 (0.623)			0.005 (0.945)		1902–2000	2.142 (0.147)			1.483 (0.227)	
Houston	−0.526	0.086	0.379	−0.249	0.275	Seattle	0.004	0.067	0.034	−0.057	0.421
1963–2000	0.861 (0.362)			0.799 (0.379)		1978–2000	0.046 (0.835)			1.328 (0.272)	
Kansas City	−0.393	0.404	0.026	−0.239	0.126	St. Louis	−0.127	0.475	0.126	−0.439	0.344
1970–2000	0.001 (0.975)			0.092 (0.765)		1902–2000	**4.481 (0.037)**			0.029 (0.864)	
Los Angeles	−0.617	0.525	0.393	−0.621	0.153	Texas	−0.746	0.165	−0.043	0.886	0.309
1902–2000	0.162 (0.689)			0.084 (0.773)		1902–2000	**6.544 (0.016)**			**12.900 (0.001)**	
Milwaukee	−0.338	0.330	0.009	0.103	0.046	Toronto	−0.389	0.316	−0.201	−0.776	−0.029
1902–2000	0.001 (0.986)			0.133 (0.719)		1978–2000	0.009 (0.928)			**3.711 (0.078)**	

Notes: The individual team estimates incorporated a constant and where appropriate a dummy variable for 1946. Wald p-values are reported in parentheses and boldface indicates rejection of the null at the 10-percent level.

size of the market variables.[22,23] The latter rows of Table 7 report our analysis of this second panel data set.

As with the earlier panel results, the 1975–1988 results are generally consistent with our

[22] The Survey of Current Business (various years) provided estimates of each city's per capita income. A common proxy for a team's market is the size of each team's metropolitan statistical area (MSA), which was obtained from the Statistical Abstract (various years).

[23] As with the earlier attendance measures, there is some concern over the stationarity of these variables. We, therefore, computed ADF and Phillips-Perron tests for both the per capita income and individual team MSA data. Overall, the results of these tests were mixed. Specifically, at the 5-percent level, 12 of the 23 teams rejected the hypothesized unit root in the individual team attendance data, 10 of the 23 teams for the per capita income data, 13 of the 23 for the population data, 12 out of 23 for the team price data, and 13 of the 23 teams for the winning percentage data. Therefore it appears that the majority of the data are $I(0)$. However, the choice is quite close. One of the factors reducing the concern over nonstationarity is the fact that only 14 years of data are incorporated. Such a short time period does limit the power of these tests. Therefore we completed the following section incorporating both the levels and the differences of the data. Either approach produced qualitatively similar results. The individual team ADF and Phillips-Perron tests, as well as the differenced results are available from the authors upon request.

expectations. Specifically, while a higher price reduces demand, increased per capita income increases attendance. The one difficulty is population where the estimate is the opposite sign of what one would expect. However, it is unlikely that the MSA population data adequately captures the size of the market. This is due to the fact that teams generally draw from a much larger area. Furthermore, if population increases are associated with new births it may be many years before such an impact would be felt. In any event, the lack of a permanent impact from the 1981 strike continues.

The individual team strike responses and associated Wald tests are also reported in Table 8. Specifically, we replicated the analysis of Table 7 (the nonprice approach) for the individual teams.[24] While there exists several degree of freedom issues, as some teams have fewer than 25 observations, these results continue to highlight the lack of long-term effects. For example, only five teams (Atlanta, New York Yankees, Oakland, St. Louis, and Texas) reject the null of no impact for the 1981 strike. Furthermore, for three of these teams (Atlanta, Oakland, and St. Louis) the rejection is an outgrowth of *too large* a rebound in 1982. While the number of teams for which we reject the null for the 1994–1995 strike increases, only five teams did not immediately rebound in 1996: Baltimore, Boston, Chicago White Sox, Oakland, and Toronto. Given the idiosyncratic nature of individual team attendance and fan rhetoric, one might have expected more.

One final piece of cursory evidence is available: The impact of one sport's strike on other sports' attendance.[25] One might expect that if fans' sports dollars are transferable, most likely within the industry, a strike within one sport should positively impact attendance of competitors. If so, the long-term consequences maybe more serious. We, therefore, examined the impact of each sport's strike on attendance data for competing sports. Consistent with the results presented above, strikes had little or no impact on competing league attendance, as nearly all responses were insignificant. The only significant response was the 1987 NFL strike which increased 1988 MLB attendance by roughly 0.8 percent.

[24] We left out four teams (Arizona, Colorado, Florida, and Tampa Bay) due to degrees of freedom issues.

[25] We thank an anonymous referee for bringing this application to our attention.

III. Concluding Observations

The consumers of the output of professional sports leagues have often reacted with "disgust" to the management-labor conflict that has plagued this industry in the past three decades. Frequently, members of each side of the conflict wonder if the consumer will return after the conflict has been resolved. In fact, the threat of consumers rejecting this industry is cited frequently as a reason for management and labor to resolve their disputes peacefully.

Our analysis offers historic evidence that suggests the consumers' threat has not been credible. In general, none of the events we examined had a permanent impact upon attendance in these sports. In fact, in almost all instances attendance immediately rebounded in the year following the labor conflict. This explains why strikes and lockouts are happening with increasing frequency in professional sports. If the levels of attendance in the postconflict era are equivalent to the preconflict time period, only short-run costs are imposed upon the conflict participants. Given the millions at stake in each dispute, our analysis would indicate that labor conflicts that disrupt the regular seasons of these sports are likely to occur again in the future.

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