HIRED TO BE FIRED: THE PUBLICITY VALUE OF MANAGERS

John Charles Bradbury*
Kennesaw State University

Abstract

Sports teams frequently fire and hire managers when they experience losing. However, determining managerial responsibility for player performance is difficult to measure. This study examines how major-league baseball players perform under different managers and estimates that managers have little effect on performance. The study further investigates whether or not replacing managers serves as a signal to fans that the team is improving, which boosts attendance. The results indicate that new managers were associated with increased attendance in the 2000s; however, such effects were not present in the 1980s and 1990s.

* Address correspondence to J.C. Bradbury, Department of HPS, Kennesaw State University, MD# 0202, 1000 Chastain Road, Kennesaw, GA, 30144-5591 (e-mail: jbradbu2@kennesaw.edu).

Buck Showalter is ratings gold. First 6 games for new O's manager rated 52% higher than MASN's season avg in Baltimore and 57% higher in DC. (John Ourand, August 10, 2010)

I. Introduction

Managerial inputs to production have long been a subject of interest to economists. Sports have served as a frequent laboratory for analyzing manager effects, because sports offer the opportunity to separate labor contributions of workers from manager/coach influences that are more difficult to disentangle in typical everyday workforces.

In the seminal study using baseball to measure managerial efficiency, Porter and Scully (1982) uses a frontier production approach to measure the efficiency with which baseball managers win, given their talent. The authors find evidence of some managers having rather large effects on winning beyond the talent given. However, it is not clear whether the managers themselves are responsible for the differences between each other or whether they just happened to benefit from excellent or sub-standard play during their tenures.

Horowitz (1994) compared team performance in wins relative to expected wins based on runs scored and runs allowed, a technique dubbed the "Pythagorean" method by James (1982). Managers' teams who consistently over- or under-performed win projections based on runs scored and runs allowed may be supplying inputs that contribute to winning beyond what players contribute on the field. Horowitz hypothesizes that managers may distribute runs in a manner that is more or less effective than the average projection. This black box theory of credit assigns managers responsibility for residual wins that occur. However, deviations from expectations may occur in bunches for managers naturally from random variation without managerial input; and, Horowtiz's estimates of managerial over- and under-performance are not statistically significant.

Furthermore, Ruggiero, Hadley, Ruggiero, and Knowles (1997) identify a misspecification with Horowitz's approach for measuring team performance.

Khan (1993) uses a "market-based" approach to value managers according the quality of players, measuring managerial quality as a function of previous winning percentage and experience. First, predicting managerial skills using these two inputs is not ideal and may not properly differentiate future and past success from roster talent (for example, a manager who continues managing good players will continue to win). Second, the performance measures used to proxy player ability are not the measures most-strongly associated with winning according to Bradbury (2008).

Observing how player performances change as players move from coach to coach is another method that researchers employ to analyze managing ability. Bradbury (2007) looks at the impact of major-league pitchers who pitched for famed Atlanta Braves pitching coach Leo Mazzone during the 1990s and 2000s. The results indicate that Mazzone's pitchers tended to perform approximately 0.5 runs better with Mazzone than without him. A downside of this approach is that it focuses on one particular individual; if Atlanta Braves scouts identified pitchers who were being mismanaged, then the observed improvements may overstate the impact of coaching.

Berri, et. al. (2009) looks at a sample of NBA players who played under many different coaches to identify the impacts of coaches. The authors find that most coaches are not associated with changes in player performance, and the impacts of the few coaches associated with improved performance are small and diminish over time.

Another technique for evaluating the capability of managers is to examine choices managers make when compared to a theoretical optimum for within-game decisions. Even if talent is properly allocated, and managers get the most out of their players, managers who make better strategic decisions than other managers will win more games. Albert and Bennett (2001), Lindsey (1963) and Thorn and Palmer (1984) have identified optimal strategies in baseball according to game situations. Hakes and Sauer (2004) finds that managers tend to make choices that are consistent with the costs and benefits of game situations, adjusting their strategies according to the context of the game. Thus, managers tend to make choices consistent with an economic model of decision making, which should not be surprising given that past studies, along with proverbial wisdom, have made the optimal choices widely known. Though there is some deviation in tendencies across managers, those differences are small; and, it is unclear whether those differences are the result of managerial mistakes or responses to different roster constructions.[1]

Even if managers have no direct impact on improving team performance, the perception that managers do impact performance may be sufficient to justify replacing the manager on a struggling team. There is a strong correlation between winning and revenue among Major League Baseball teams; thus, losing teams typically experience fan attrition.[2] A failing team may not be able to acquire talent quickly enough to keep fans interested in the team. By replacing the manager, the team can signal that the team has replaced an ineffective manager with a more productive manager who will "cause" the team to win more games. Even if the perception of improvement is mistaken, the shift in expectations generated by replacing a manager may increase team revenue, at least in the short term.

In Section II, I examine the impact of major-league managers on the performances of individual players. In Section III, I estimate the impact of managerial changes on team attendance.

[1] The authors state that their analysis is preliminary and is in need of further examination.
[2] See Scully (1974) and Bradbury (2010) for estimates of the relationship between winning and revenue.

II. The Impact of Managers on Performance

If managers directly improve players, then managerial impacts should be observable in individual player performances as players and managers turn over. I estimate the impact of managers on player performance using a sample of major-league baseball players from 1980 to 2009, available from Baseball-Databank.org. I estimate Equation 1 using the Baltagi and Wu (1999) random-effects method, which corrects for detected first-order serial correlation.

$$(1)\quad \text{Performance}_{iy} = \boldsymbol{\gamma}\,\textbf{Manager}_{iy} + \beta_1\,\text{League Performance}_{y} + \beta_2\,\text{Career Performance}_{i} + \beta_3\,\text{Age}_{iy} + \beta_4\,\text{Age}_{iy}^{2} + \boldsymbol{\theta}\,\textbf{Park}_{iy} + \nu_i + \varepsilon_{iy}$$

Performance is the individual performance of player *i* in year *y*. To ensure an adequate sample size to gauge true performance, only hitters with at least 200 plate appearances and pitchers who threw at least 50 innings are included in separate samples. In order to separate effects of switching teams and managers within seasons, the samples include only players who played on one team in the season and teams that had only one manager for the season. For hitters, performance is measured using on-base-plus-slugging (OPS), which is a simple metric for measuring how effective a hitter is at producing runs. For pitchers, performance is measured using earned run average (ERA).[3]

Manager is a vector of individual manager dummy variables. The coefficients for the dummy variables in vector $\boldsymbol{\gamma}$ should reflect the impact that individual managers have on player output. In addition, a model with manager dummies can be compared to a model without manager dummies to measure the overall influence of managers on player performance.

[3] While ERA is more influenced by factors beyond pitcher control than OPS is for hitters, one of the potential outside factors is managerial influence through structuring defense. Therefore, ERA is preferred to "defense-independent" pitching metrics in this case. Bradbury (2008) discusses the pros and cons of using these metrics to proxy performance.

League Performance is the league average OPS for hitters and league average ERA for pitchers. The league average controls for fluctuations in run scoring in the leagues may cause deviations in performance across leagues and over time. Career Performance measures the quality of the observed players by averaging the performance of each player over his entire career, which normally spans several managers. In addition, Age (measured as year minus birth-year) and Age^2 control for the rise and decline of performance with age, which Bradbury (2009) estimates to have a quadratic shape. The player-specific control variables are important for separating talent and managerial impacts on performance. **Park** is a vector of dummies for each park to control for the unique characteristics of individual parks. ν is a player-specific error term, and ε is a standard error term. Table 1 reports the summary statistics for all variables in the model.

Due to the size of the model, the results are reported in Tables 2, 3, 4, and 5. Table 2 reports the coefficient estimates for the control variables and overall summary statistics. For both hitters and pitchers, I report estimates of an unrestricted model (including the manager dummy variables) and a restricted model (excluding the manager dummy variables). An F-ratio test reveals that the differences between R^2s are statistically significant; however, the size of the differences—0.0142 for hitters and 0.0219 for pitchers—indicates the impact of managers on player performance is small.

Tables 3 and 4 report the coefficient estimates for all managers in the sample. Long-time manager Tony La Russa is excluded to serve a comparison. In addition, the statistical analysis software excludes Ron Gardenhire in the pitcher and hitter estimates, and Ron Washington is excluded in the pitcher estimates. Table 5 highlights the managers whose impacts are statistically significant according to the lenient ten-percent level benchmark. Of the 134 managers in the sample, the estimates for 25 managers are statistically significant at the ten-percent level for hitters.

21 managers are associated with improvement and four managers are associated with a decline. For pitchers, the estimates for 24 managers are statistically significant at the ten-percent level. 15 managers are associated with player improvement and nine managers are associated with a performance decline. Five managers are associated with improvement and decline for both groups; however, in all cases, the managers are associated with the opposite effect for the two groups of players. Thus, no manager is associated with improving performance for both offense and defense.

The results indicate that if managers have some influence on player performance, the impact is small and difficult to identify. While Table 5 includes managers with good and bad reputations, it also includes managers who are not recognized typically as being exceptionally good or bad. The small differences between models that include and exclude the manager dummy variables further support the notion that managers have only a small impact on player performance.

III. The Impact of Managerial Changes on Attendance

> *Baseball managers are much maligned. Indeed, when a club is slipping in the standings, it is the manager who will usually be fired. The implication of this maneuver is that another manager can organize the existing player inputs in a somewhat different fashion to produce more output (wins). If this is possible, it is a less costly solution for a club owner going into the players' market for additional expensive playing talent.* (Scully 1989, p. 182).

As Scully notes above, managers represent a single input that can be replaced more easily and cheaply than a roster of underperforming players. However, if managers have little effect on performance, then replacing a losing manager will not cause improvement. Why do teams frequently replace managers following poor performance if their impact is small? An alternate hypothesis for why teams replace managers is that the mere perception that managers affect performance offers an avenue for owners to stimulate demand for their teams. Replacing a manager sends a signal that the team has improved by removing an ineffective manager and installing a superior leader. The managerial change translates to increased demand for attending games as expectations for winning increase with a new manager.

In order to test the hypothesis that fans respond to managerial turnover, I examine the impact of managerial changes on fan attendance. I focus on changes within the season, because rosters are more likely to remain constant than when managers are changed between seasons. Therefore, observed changes in attendance after replacing manager are likely a response to fan perceptions of managerial influence.

Equation 2 estimates the impact of adding a new manager on attendance while controlling for several likely contributing factors. I estimate the equation using the Baltagi and Wu (1999) fixed-effect method to control for unique properties of each market and to correct for detected serial correlation.

$$\text{(2)}\quad \text{Attendance}_{tg} = \beta_1\text{New Manager}_{tg} + \beta_2\text{Wins in Last 10 Home Games}_{tg} + \beta_3\text{ Team W\%}_t + \beta_4\text{ Manager Career W\%}_{tg} + \boldsymbol{\theta}\mathbf{X}_{tg} + \nu_t + \varepsilon_{tg}$$

Attendance is official game attendance as reported by Retrosheet game logs for team *t* in game *g*. New Manager is a dummy variable equal to one after a new manager joins a club during the season. New Manager is equal to zero prior to a team firing a manager or when a team does not change managers during the season. When a new manager joins a team was determined by analysis of Retrosheet game logs and Baseball-Databank.org's managerial database.[4]

[4] The information used here was obtained free of charge from and is copyrighted by Retrosheet. Interested parties may contact Retrosheet at "www.retrosheet.org".

Performance in the Last 10 Home Games controls for recent local excitement regarding the team. Team W% is the team's winning percentage for the entire season, which controls for the quality of the club. Though it is an imperfect proxy, career winning percentage of the manager (Manager Career W%) serves as a control for managerial quality (actual and perceived). Vector **X** includes month dummy variables to control for seasonal shifts in attendance, day-of-week dummy variables to capture daily fluctuations, and year dummy variables to capture the impact of individual seasons. ν is a player-specific error term, and ε is a standard error term.

Over the range of the sample, baseball attendance grew dramatically. As a normal good, baseball consumption increased along with the wealth of the U.S. economy. In the 1980s, Major League Baseball teams averaged 23,716 fans per game; but by the 2000s, average attendance increased by 30 percent to 30, 975 fans per game. In addition, baseball's revenue sources grew through increased television broadcasts and sponsorship. As the revenue potential from winning increased, clubs may have become more sensitive to fan interest in winning. Therefore, I examined the impact of managerial changes in the three decades separately in the sample.

Table 7 reports the results of the estimates, which differ by decade. In the most recent decade of the 2000s, adding a new manager was associated with increased game attendance by approximately 1,000 fans a game. In the 1990s, the estimated effect was smaller (approximately 140 fans per game); however, the effect was not statistically significant. In the 1980s, the effect of adding a new manager on attendance was negative, with a new manager being associated with a decline in attendance by approximately 1,000 fans per game. For robustness, I also estimated the model using random effects. The random-effects estimates reported in Table 8 are similar to the fixed-effects estimates for the 2000s and 1990s; for the 1980s, the effect is close to zero and not statistically significant.

The identified bump in attendance from hiring a new manager during the season in the 2000s offers some support the managers-as-signals hypothesis. Fan interest in the game was certainly greater in the 2000s than in the preceding decades, and it is possible that the signaling effect did not manifest until recently as fans became more fervent in their demand for a winning team. However, the lack of the effect in the preceding decades makes it difficult to say for certain that the signaling effect is the primary cause for the rise in attendance associated with managerial turnover.

IV. Discussion and Conclusion

Baseball managers are charged with overseeing valuable labor inputs in order to maximize wins. How well managers perform at their job is difficult to distinguish from player performance. Using a sample of major-league baseball players from 1980 to 2009, this study finds little impact of managers on player performance.

Though the estimated impact of managers on improving clubs directly through winning is small, changing managers may still benefit a team by sending a signal to fans that the team will improve. It is possible that managers are paid handsomely as compensation for serving as a potential scapegoat and the reputational damage that might occur after a firing. Estimates from the 2000s indicate that new managers boosted attendance by approximately 1,000 fans a game, though this effect was not observed in the two prior decades. Hiring managers so that their firings can be used as signals of impending improvements, even if managers are benign, may be a strategy employed by private businesses to retain the confidence of customers and shareholders.

The results do not mean that managers play no role on baseball clubs. To the contrary, no team could operate without the aid of a manager. Organizing players, settling disputes, and controlling the media are managerial duties that must be handled, and have the potential to be handled poorly. The results of this study indicate that managers who have served at the major-league level do not differ greatly from one another in their ability to handle these important responsibilities in a way that improves or dampens player performance.

Table 1. Summary Statistics (Performance)

Hitters	Mean	S.D.	Minimum	Maximum
OPS	0.757	0.107	0.398	1.422
League OPS	0.741	0.030	0.673	0.795
Career OPS	0.753	0.082	0.454	1.055
Age	29.370	4.073	20.000	47.000
Age^2	879.190	248.403	400.000	2209.000
Pitchers	Mean	S.D.	Minimum	Maximum
ERA	4.061	1.146	0.610	10.640
League ERA	4.234	0.377	3.454	4.999
Career ERA	4.148	0.708	1.836	8.858
Age	28.940	4.310	19.000	47.000
Age^2	856.078	264.428	361.000	2209.000

Table 2. Comparison of Unrestricted and Restricted Estimates

	Hitters			Pitchers	
	Unrestricted	Restricted		Unrestricted	Restricted
League OPS	0.76328	0.62866	League ERA	0.7210763	0.5067653
	[0.05367]**	[0.04218]**		[0.06081]**	[0.04763]**
Career OPS	0.93924	0.92929	Career ERA	0.8682692	0.854856
	[0.01373]**	[0.01370]**		[0.02261]**	[0.02236]**
Age	0.03648	0.03619	Age	-0.1453761	-0.1393654
	[0.00293]**	[0.00291]**		[0.03434]**	[0.03440]**
Age^2	-0.00061	-0.00060	Age^2	0.0027121	0.0025792
	[0.00005]**	[0.00005]**		[0.00056]**	[0.00056]**
Observations	7446	7446		6680	6680
R^2	0.5941	0.5799	R^2	0.3929	0.3710
R^2u -R^2r	0.0142		R^2u -R^2r	0.0219	
F-statistic	1.92**		F-statistic	1.75**	

Standard errors in brackets; **significant at 1%; park effects not reported.

Table 3. Manager Coefficient Estimates (Hitters)

Manager	Coefficient	SE	Z-statistic	P-value	Manager	Coefficient	SE	Z-statistic	P-value
Alan Trammell	-0.00539	0.02194	-0.25	0.81	Jim Fregosi	0.00590	0.01343	0.44	0.66
Art Howe	-0.00329	0.01071	-0.31	0.76	Jim Frey	0.07095	0.01999	3.55	0.00
Bill Plummer	-0.00134	0.02450	-0.05	0.96	Jim Lefebvre	0.00798	0.01711	0.47	0.64
Bill Russell	0.03890	0.02871	1.35	0.18	Jim Leyland	-0.00224	0.01541	-0.15	0.89
Bill Virdon	0.02587	0.01932	1.34	0.18	Jim Riggleman	0.00560	0.01620	0.35	0.73
Billy Gardner	0.02955	0.01731	1.71	0.09	Jim Tracy	0.03008	0.01846	1.63	0.10
Billy Martin	0.02784	0.01372	2.03	0.04	Jimy Williams	-0.00852	0.01538	-0.55	0.58
Bob Boone	-0.03009	0.02095	-1.44	0.15	Joe Altobelli	0.05059	0.03109	1.63	0.10
Bob Brenly	0.01786	0.02209	0.81	0.42	Joe Girardi	-0.01421	0.02127	-0.67	0.50
Bob Geren	-0.04349	0.02865	-1.52	0.13	Joe Maddon	0.00241	0.02145	0.11	0.91
Bob Lillis	0.05089	0.02137	2.38	0.02	Joe Morgan	0.01005	0.01998	0.50	0.62
Bob Melvin	-0.01670	0.01882	-0.89	0.38	Joe Torre	-0.00164	0.01056	-0.15	0.88
Bobby Cox	-0.00460	0.01583	-0.29	0.77	Joey Amalfitano	0.01313	0.03005	0.44	0.66
Bobby Mattick	-0.04281	0.02366	-1.81	0.07	John Boles	-0.04448	0.02717	-1.64	0.10
Bobby Valentine	0.01248	0.01399	0.89	0.37	John Felske	0.01495	0.02145	0.70	0.49
Bruce Bochy	-0.01822	0.01951	-0.93	0.35	John Gibbons	-0.00843	0.03702	-0.23	0.82
Buck Martinez	-0.01937	0.02985	-0.65	0.52	John McNamara	0.02833	0.01469	1.93	0.05
Buck Rodgers	0.01049	0.01606	0.65	0.51	John Russell	0.03608	0.03054	1.18	0.24
Buck Showalter	0.01115	0.01455	0.77	0.44	John Wathan	0.04249	0.02414	1.76	0.08
Bud Black	-0.03591	0.02750	-1.31	0.19	Johnny Oates	0.02850	0.01641	1.74	0.08
Buddy Bell	-0.00450	0.02062	-0.22	0.83	Ken Macha	-0.04117	0.01997	-2.06	0.04
Butch Hobson	-0.03022	0.01919	-1.57	0.12	Kevin Kennedy	0.00956	0.01661	0.58	0.57
Cal Ripken	0.02864	0.03273	0.88	0.38	Larry Bowa	-0.02591	0.01717	-1.51	0.13
Carlos Tosca	0.03629	0.03092	1.17	0.24	Larry Dierker	0.00351	0.02229	0.16	0.88
Cecil Cooper	-0.00847	0.02820	-0.30	0.76	Larry Parrish	-0.00633	0.03318	-0.19	0.85
Charlie Manuel	0.00622	0.02485	0.25	0.80	Larry Rothschild	-0.02361	0.02194	-1.08	0.28
Chuck Cottier	0.04913	0.02645	1.86	0.06	Lee Elia	0.01878	0.02655	0.71	0.48
Chuck Tanner	0.00568	0.01676	0.34	0.74	Lee Mazzilli	0.01807	0.02566	0.70	0.48
Cito Gaston	0.01426	0.02439	0.58	0.56	Lloyd McClendon	0.05645	0.02882	1.96	0.05
Clint Hurdle	-0.04758	0.02162	-2.20	0.03	Lou Piniella	0.01494	0.01302	1.15	0.25
Dallas Green	0.01219	0.01691	0.72	0.47	Manny Acta	0.00672	0.03492	0.19	0.85
Dave Bristol	0.00284	0.02729	0.10	0.92	Marcel Lachemann	0.03680	0.02551	1.44	0.15
Dave Garcia	0.01615	0.02221	0.73	0.47	Mike Hargrove	-0.00344	0.01605	-0.21	0.83
Dave Miley	0.01082	0.02950	0.37	0.71	Mike Scioscia	0.05403	0.03042	1.78	0.08
Dave Trembley	0.01732	0.02346	0.74	0.46	Ned Yost	-0.01688	0.02527	-0.67	0.50
Davey Johnson	0.03552	0.01316	2.70	0.01	Nick Leyva	-0.01977	0.02466	-0.80	0.42
Davey Lopes	0.01543	0.02331	0.66	0.51	Ozzie Guillen	0.01484	0.03071	0.48	0.63
Dick Howser	0.06530	0.01872	3.49	0.00	Pat Corrales	0.02688	0.01648	1.63	0.10
Dick Williams	0.02093	0.01593	1.31	0.19	Paul Owens	0.05760	0.02466	2.34	0.02
Doc Edwards	0.02205	0.02686	0.82	0.41	Pete Rose	0.02039	0.02070	0.99	0.33
Don Baylor	0.00252	0.01827	0.14	0.89	Phil Garner	-0.00407	0.01561	-0.26	0.79
Don Wakamatsu	0.00977	0.02928	0.33	0.74	Phil Regan	0.01741	0.02584	0.67	0.50
Don Zimmer	0.03538	0.01765	2.00	0.05	Ralph Houk	0.04230	0.01902	2.22	0.03
Doug Rader	0.00394	0.01749	0.23	0.82	Ray Knight	-0.00208	0.02410	-0.09	0.93
Dusty Baker	-0.00067	0.01584	-0.04	0.97	Ray Miller	0.03744	0.02184	1.71	0.09
Earl Weaver	0.04010	0.02902	1.38	0.17	Rene Lachemann	0.02823	0.01719	1.64	0.10
Eric Wedge	-0.03625	0.02165	-1.67	0.09	Roger Craig	0.00297	0.02100	0.14	0.89
Felipe Alou	-0.00650	0.01652	-0.39	0.69	Ron Washington	0.03091	0.04223	0.73	0.46
Frank Howard	0.03357	0.02704	1.24	0.21	Russ Nixon	-0.02587	0.02029	-1.27	0.20
Frank Robinson	0.01373	0.02066	0.66	0.51	Sam Perlozzo	0.03022	0.02859	1.06	0.29
Fredi Gonzalez	-0.00749	0.02566	-0.29	0.77	Sparky Anderson	0.03291	0.02783	1.18	0.24
Gene Lamont	-0.00882	0.01724	-0.51	0.61	Steve Boros	0.01831	0.01668	1.10	0.27
Gene Mauch	0.04293	0.01835	2.34	0.02	Stump Merrill	0.00106	0.02338	0.05	0.96
George Bamberger	0.00883	0.01814	0.49	0.63	Terry Bevington	-0.01639	0.02511	-0.65	0.51
Grady Little	0.00977	0.01698	0.58	0.57	Terry Collins	0.02047	0.02018	1.01	0.31
Greg Riddoch	-0.01536	0.02799	-0.55	0.58	Terry Francona	-0.01549	0.01499	-1.03	0.30
Hal Lanier	0.04031	0.02092	1.93	0.05	Tim Johnson	-0.01344	0.02939	-0.46	0.65
Hal McRae	0.00204	0.01890	0.11	0.91	Tom Kelly	0.01113	0.01125	0.99	0.32
Harvey Kuenn	0.08728	0.02693	3.24	0.00	Tom Trebelhorn	0.01777	0.01666	1.07	0.29
Jack McKeon	-0.01107	0.01937	-0.57	0.57	Tommy Lasorda	0.03179	0.01719	1.85	0.06
Jackie Moore	0.02990	0.02212	1.35	0.18	Tony Muser	-0.02929	0.02297	-1.28	0.20
Jeff Torborg	-0.01228	0.01423	-0.86	0.39	Tony Pena	-0.02127	0.02528	-0.84	0.40
Jerry Coleman	-0.02444	0.02975	-0.82	0.41	Trey Hillman	-0.03327	0.02424	-1.37	0.17
Jerry Manuel	-0.01571	0.02195	-0.72	0.47	Whitey Herzog	0.01398	0.01259	1.11	0.27
Jerry Narron	0.00846	0.02163	0.39	0.70	Willie Randolph	0.00385	0.01772	0.22	0.83
Jim Fanning	0.05804	0.02948	1.97	0.05	Yogi Berra	0.03438	0.02360	1.46	0.15

Table 4. Manager Coefficient Estimates (Pitchers)

Manager	Coefficient	SE	Z-statistic	P-value	Manager	Coefficient	SE	Z-statistic	P-value
Alan Trammell	0.52317	0.31408	1.67	0.10	Jim Fregosi	0.00051	0.19166	0.00	1.00
Art Howe	-0.23906	0.15297	-1.56	0.12	Jim Frey	0.19897	0.27003	0.74	0.46
Bill Plummer	0.42595	0.34035	1.25	0.21	Jim Lefebvre	-0.24308	0.24036	-1.01	0.31
Bill Russell	-0.15098	0.35379	-0.43	0.67	Jim Leyland	0.32924	0.21251	1.55	0.12
Bill Virdon	-0.34161	0.26659	-1.28	0.20	Jim Riggleman	-0.34704	0.22307	-1.56	0.12
Billy Gardner	0.63410	0.23737	2.67	0.01	Jim Tracy	-0.24818	0.24795	-1.00	0.32
Billy Martin	0.12103	0.22370	0.54	0.59	Jimy Williams	-0.26954	0.21467	-1.26	0.21
Bob Boone	-0.41435	0.29543	-1.40	0.16	Joe Altobelli	0.02962	0.43219	0.07	0.95
Bob Brenly	0.02894	0.32987	0.09	0.93	Joe Girardi	-0.35835	0.30378	-1.18	0.24
Bob Geren	-0.42814	0.40569	-1.06	0.29	Joe Maddon	-0.04241	0.29793	-0.14	0.89
Bob Lillis	-0.08376	0.28468	-0.29	0.77	Joe Morgan	0.35570	0.26557	1.34	0.18
Bob Melvin	0.23267	0.27166	0.86	0.39	Joe Torre	0.12193	0.14526	0.84	0.40
Bobby Cox	-0.37108	0.22117	-1.68	0.09	Joey Amalfitano	0.80512	0.39986	2.01	0.04
Bobby Mattick	-0.50135	0.33009	-1.52	0.13	John Boles	0.03270	0.38390	0.09	0.93
Bobby Valentine	-0.40529	0.19736	-2.05	0.04	John Felske	0.27447	0.30602	0.90	0.37
Bruce Bochy	-0.61141	0.27081	-2.26	0.02	John Gibbons	-0.70544	0.49018	-1.44	0.15
Buck Martinez	-0.89035	0.39780	-2.24	0.03	John McNamara	0.15950	0.20761	0.77	0.44
Buck Rodgers	0.00157	0.22314	0.01	0.99	John Russell	-0.14739	0.39655	-0.37	0.71
Buck Showalter	0.19106	0.20892	0.91	0.36	John Wathan	-0.05814	0.34917	-0.17	0.87
Bud Black	-0.24874	0.37750	-0.66	0.51	Johnny Oates	-0.06932	0.22972	-0.30	0.76
Buddy Bell	-0.49395	0.28669	-1.72	0.09	Ken Macha	-0.46648	0.27918	-1.67	0.10
Butch Hobson	-0.14882	0.29709	-0.50	0.62	Kevin Kennedy	0.06055	0.23855	0.25	0.80
Cal Ripken	0.57218	0.46369	1.23	0.22	Larry Bowa	-0.27218	0.23882	-1.14	0.25
Carlos Tosca	-0.17019	0.41532	-0.41	0.68	Larry Dierker	-1.10645	0.30583	-3.62	0.00
Cecil Cooper	-0.15041	0.37431	-0.40	0.69	Larry Parrish	-0.26770	0.46411	-0.58	0.56
Charlie Manuel	0.50046	0.33367	1.50	0.13	Larry Rothschild	-0.60616	0.31100	-1.95	0.05
Chuck Cottier	0.69322	0.36582	1.89	0.06	Lee Elia	-0.02592	0.35038	-0.07	0.94
Chuck Tanner	0.59927	0.23400	2.56	0.01	Lee Mazzilli	-0.07610	0.33981	-0.22	0.82
Cito Gaston	-0.44898	0.34087	-1.32	0.19	Lloyd McClendon	-0.40278	0.38129	-1.06	0.29
Clint Hurdle	-0.99185	0.29265	-3.39	0.00	Lou Piniella	-0.16036	0.18063	-0.89	0.38
Dallas Green	-0.09054	0.23012	-0.39	0.69	Manny Acta	-0.16476	0.43995	-0.37	0.71
Dave Bristol	-0.19521	0.38279	-0.51	0.61	Marcel Lachemann	-0.36543	0.36839	-0.99	0.32
Dave Garcia	0.32143	0.31662	1.02	0.31	Mike Hargrove	0.06918	0.21692	0.32	0.75
Dave Miley	0.41607	0.42638	0.98	0.33	Mike Scioscia	-0.53865	0.40714	-1.32	0.19
Dave Trembley	0.28200	0.29951	0.94	0.35	Ned Yost	-0.78783	0.35505	-2.22	0.03
Davey Johnson	-0.11231	0.18304	-0.61	0.54	Nick Leyva	0.25404	0.33453	0.76	0.45
Davey Lopes	-1.11130	0.32346	-3.44	0.00	Ozzie Guillen	0.16343	0.44656	0.37	0.71
Dick Howser	0.11466	0.27452	0.42	0.68	Pat Corrales	0.17961	0.23994	0.75	0.45
Dick Williams	-0.05449	0.22623	-0.24	0.81	Paul Owens	-0.07325	0.37659	-0.19	0.85
Doc Edwards	-0.07604	0.40688	-0.19	0.85	Pete Rose	0.27373	0.27635	0.99	0.32
Don Baylor	-0.46090	0.24839	-1.86	0.06	Phil Garner	-0.21978	0.21568	-1.02	0.31
Don Wakamatsu	-0.32518	0.35808	-0.91	0.36	Phil Regan	-0.07807	0.36373	-0.21	0.83
Don Zimmer	0.07294	0.24858	0.29	0.77	Ralph Houk	0.62027	0.25877	2.40	0.02
Doug Rader	-0.43537	0.25823	-1.69	0.09	Ray Knight	-0.06940	0.34737	-0.20	0.84
Dusty Baker	-0.09597	0.21792	-0.44	0.66	Ray Miller	0.14858	0.29459	0.50	0.61
Earl Weaver	-0.03581	0.40188	-0.09	0.93	Rene Lachemann	0.01578	0.24098	0.07	0.95
Eric Wedge	0.29427	0.29971	0.98	0.33	Roger Craig	-0.12183	0.28560	-0.43	0.67
Felipe Alou	-0.25917	0.22906	-1.13	0.26	Russ Nixon	0.50231	0.27791	1.81	0.07
Frank Howard	0.36227	0.36932	0.98	0.33	Sam Perlozzo	0.26195	0.36723	0.71	0.48
Frank Robinson	-0.15271	0.27939	-0.55	0.59	Sparky Anderson	-0.00410	0.38509	-0.01	0.99
Fredi Gonzalez	-0.41686	0.36992	-1.13	0.26	Steve Boros	0.06888	0.24246	0.28	0.78
Gene Lamont	0.03825	0.23592	0.16	0.87	Stump Merrill	0.24261	0.30230	0.80	0.42
Gene Mauch	-0.36354	0.27049	-1.34	0.18	Terry Bevington	0.44784	0.34922	1.28	0.20
George Bamberger	0.36305	0.25679	1.41	0.16	Terry Collins	-0.22236	0.29250	-0.76	0.45
Grady Little	-0.20206	0.23662	-0.85	0.39	Terry Francona	0.01863	0.20603	0.09	0.93
Greg Riddoch	-0.33363	0.35556	-0.94	0.35	Tim Johnson	-0.58048	0.41740	-1.39	0.16
Hal Lanier	-0.33945	0.29441	-1.15	0.25	Tom Kelly	0.49529	0.14938	3.32	0.00
Hal McRae	-0.05085	0.26748	-0.19	0.85	Tom Trebelhorn	-0.13115	0.23354	-0.56	0.57
Harvey Kuenn	-0.10099	0.33556	-0.30	0.76	Tommy Lasorda	0.21094	0.23390	0.90	0.37
Jack McKeon	-0.70688	0.26552	-2.66	0.01	Tony Muser	-0.31678	0.32426	-0.98	0.33
Jackie Moore	-0.08873	0.33614	-0.26	0.79	Tony Pena	-0.31506	0.35641	-0.88	0.38
Jeff Torborg	0.04562	0.19892	0.23	0.82	Trey Hillman	-0.21535	0.35105	-0.61	0.54
Jerry Coleman	0.13040	0.36439	0.36	0.72	Whitey Herzog	0.44332	0.16292	2.72	0.01
Jerry Manuel	0.16082	0.30337	0.53	0.60	Willie Randolph	-0.51843	0.24223	-2.14	0.03
Jerry Narron	-0.14016	0.32127	-0.44	0.66	Yogi Berra	-0.01408	0.31497	-0.04	0.96
Jim Fanning	-0.03696	0.36057	-0.10	0.92					

Table 5. Estimated Manager Effects with P-Values Less than Ten Percent

Hitting

Improve	Coefficient	SE
Harvey Kuenn	0.09	0.03
Jim Frey	0.07	0.02
Dick Howser	0.07	0.02
Jim Fanning	0.06	0.03
Paul Owens	0.06	0.02
Lloyd McClendon	0.06	0.03
Mike Scioscia	0.05	0.03
Bob Lillis	0.05	0.02
Chuck Cottier†	0.05	0.03
Gene Mauch	0.04	0.02
John Wathan	0.04	0.02
Ralph Houk†	0.04	0.02
Hal Lanier	0.04	0.02
Ray Miller	0.04	0.02
Davey Johnson	0.04	0.01
Don Zimmer	0.04	0.02
Tommy Lasorda	0.03	0.02
Billy Gardner†	0.03	0.02
Johnny Oates	0.03	0.02
John McNamara	0.03	0.01
Billy Martin	0.03	0.01

Decline	Coefficient	SE
Eric Wedge	-0.04	0.02
Ken Macha†	-0.04	0.02
Bobby Mattick	-0.04	0.02
Clint Hurdle†	-0.05	0.02

Pitching

Improve	Coefficient	SE
Davey Lopes	-1.11	0.32
Larry Dierker	-1.11	0.31
Clint Hurdle†	-0.99	0.29
Buck Martinez	-0.89	0.40
Ned Yost	-0.79	0.36
Jack McKeon	-0.71	0.27
Bruce Bochy	-0.61	0.27
Larry Rothschild	-0.61	0.31
Willie Randolph	-0.52	0.24
Buddy Bell	-0.49	0.29
Ken Macha†	-0.47	0.28
Don Baylor	-0.46	0.25
Doug Rader	-0.44	0.26
Bobby Valentine	-0.41	0.20
Bobby Cox	-0.37	0.22

Decline	Coefficient	SE
Whitey Herzog	0.44	0.16
Tom Kelly	0.50	0.15
Russ Nixon	0.50	0.28
Alan Trammell	0.52	0.31
Chuck Tanner	0.60	0.23
Ralph Houk†	0.62	0.26
Billy Gardner†	0.63	0.24
Chuck Cottier†	0.69	0.37
Joey Amalfitano	0.81	0.40

† Manager associated with statistically significant opposite effect for other area.

Table 6. Summary Statistics (Attendance)

	Mean	S.D.	Minimum	Maximum
2000s				
Attendance	30,975	11,211	2,134	61,068
New Manager	0.077	0.266	0	1
Wins in Last 10 Home Games	5.44	1.69	0	10
Team W%	0.50	0.07	0.27	0.72
Manager Career W%	0.50	0.04	0.27	0.58
1990s				
Attendance	29,064	12,084	1,695	73,957
New Manager	0.075	0.264	0	1
Wins in Last 10 Home Games	5.38	1.68	0	10
Team W%	0.50	0.07	0.33	0.70
Manager Career W%	0.50	0.03	0.33	0.80
1980s				
Attendance	23,716	11,908	1,171	73,303
New Manager	0.119	0.324	0	1
Wins in Last 10 Home Games	5.41	1.60	0	10
Team W%	0.50	0.07	0.34	0.67
Manager Career W%	0.50	0.04	0.00	0.58

Table 7. The Impact of a New Manager on Attendance (Fixed Effects)

	2000s	1990s	1980s
New Manager	953.476	138.675	-1,014.60
	[409.239]*	[486.697]	[384.251]**
Wins in Last 10 Home Games	200.085	185.54	531.667
	[50.588]**	[60.898]**	[65.574]**
Team W%	33,085.14	59,397.21	50,764.81
	[2,040.376]**	[2,256.453]**	[2,351.422]**
Manager Career W%	25,893.21	-1,178.03	-16,584.81
	[2,326.345]**	[2,740.403]	[2,640.348]**
May	-2,191.95	-303.222	1,035.77
	[598.329]**	[726.457]	[605.888]
June	-222.627	1,867.86	3,506.92
	[590.481]	[706.858]**	[587.582]**
July	396.569	3,483.65	4,642.52
	[589.383]	[707.827]**	[594.745]**
August	-295.677	2,497.53	3,506.21
	[585.995]	[706.373]**	[582.493]**
September	-2,177.46	-250.418	-1,231.13
	[557.128]**	[678.441]	[553.691]*
Sunday	4,888.03	5,704.64	7,198.82
	[162.921]**	[202.022]**	[236.073]**
Monday	-809.9	-679.952	669.62
	[177.954]**	[210.392]**	[244.723]**
Tuesday	-1,131.67	-1,609.51	-844.775
	[152.651]**	[192.291]**	[226.689]**
Wednesday	-466.78	-645.842	-171.058
	[125.550]**	[166.123]**	[200.511]
Friday	4,035.93	3,802.25	4,572.55
	[132.016]**	[164.717]**	[196.732]**
Saturday	7,450.11	8,051.25	8,503.55
	[153.184]**	[190.398]**	[223.553]**
R^2	0.43	0.38	0.33
Observations	18,614	16,455	14,834

Standard errors in brackets; * significant at 5%; ** significant at 1%; year effects not reported.

Table 8. The Impact of a New Manager on Attendance (Random Effects)

	2000s	1990s	1980s
New Manager	1,643.49	206.319	6.484
	[424.023]**	[484.465]	[390.965]
Wins in Last 10 Home Games	203.404	176.609	531.597
	[49.663]**	[60.088]**	[64.932]**
Team W%	31,744.77	58,651.21	54,329.20
	[2,051.107]**	[2,257.879]**	[2,364.774]**
Manager Career W%	37,547.18	4,891.89	12,172.80
	[3,774.175]**	[4,910.357]	[3,676.943]**
May	-1,205.71	421.259	3,398.98
	[614.121]*	[743.956]	[629.237]**
June	704.485	2,462.14	5,724.48
	[607.141]	[726.312]**	[610.449]**
July	1,345.34	4,059.34	6,788.41
	[606.124]*	[726.460]**	[614.974]**
August	600.071	2,986.99	5,682.83
	[602.452]	[722.571]**	[604.910]**
September	-1,341.15	257.442	813.148
	[571.705]*	[691.680]	[573.965]
Sunday	4,815.99	5,625.63	7,176.91
	[158.778]**	[197.044]**	[231.202]**
Monday	-694.315	-635.849	931.18
	[173.601]**	[207.920]**	[242.837]**
Tuesday	-985.914	-1,599.68	-667.529
	[148.524]**	[189.988]**	[224.850]**
Wednesday	-444.099	-692.758	-183.586
	[123.447]**	[163.260]**	[197.162]
Friday	4,112.98	3,859.23	4,797.31
	[129.385]**	[162.572]**	[194.891]**
Saturday	7,432.84	8,016.84	8,543.57
	[150.344]**	[187.330]**	[220.787]**
R^2	0.29	0.27	0.39
Observations	18,645	16,486	14,859

Standard errors in brackets; * significant at 5%; ** significant at 1%; year effects not reported.

References

Albert, Jim and Jay Bennett (2001). *Curve Ball: Baseball, Statistics, and the Role of Chance in the Game*. New York: Copernicus.

Baltagi, B.H. and P.X. Wu (1999). "Unequally Spaced Panel Data Regressions with AR(1) Disturbances," *Econometric Theory*, 15: 814-823.

Baseball-Databank (2009). (http://www.baseball-databank.org/). November 29, 2009.

Berri, David J., Michael A. Leeds, Eva M. Leeds, and Michael Mondello (2009). "The Role of Managers in Team Performance," *International Journal of Sport Finance*, 4(2): 75-93.

Bradbury, John C. (2007). *The Baseball Economist: The Real Game Exposed*. New York: Dutton.

Bradbury, John C. (2008). "Statistical Performance in Sport," in Brad R. Humphreys and Dennis R Howard, *The Business of Sports*, 3: 41-56. Westpotr, CT: Praeger.

Bradbury, John C. (2009). "Peak Athletic Performance and Ageing: Evidence from Baseball," *Journal of Sports Sciences*, 27: 599-610.

Bradbury, John C. (2010). *Hot Stove Economics: Understanding Baseball's Second Season*. New York: Copernicus.

Hakes, Jahn K. and Raymond D. Sauer (2004). "Measurement and Evaluation of Managerial Efficiency in MLB," Unpublished manuscript, Clemson University.

James, Bill (1982). *The Bill James Baseball Abstract*. New York: Ballantine.

Kahn, Lawrence M. (1993). "Managerial Quality, Team Success, and Individual Player Performance in Major League Baseball," *Industrial and Labor Relations Review*, 46(3): 531-547.

Lindsey, George R. (1963). "An Investigation of Strategies in Baseball," *Operations Research*, 11(4): 477-501.

Ourand, John (2010). (http://twitter.com/#!/Ourand_SBJ/status/20808349466), August 10, 2010.

Porter , Philip K. and Gerald W. Scully (1982). "Measuring Managerial Efficiency: The Case of Baseball," *Southern Economic Journal*, 48(3): 642-650.

Retrosheet (2010). (http://retrosheet.org/).

Ruggiero, John, Lawrence Hadley, Gerry Ruggiero, and Scott Knowles (1997). "A Note on the Pythagorean Theorem of Baseball Production," *Managerial and Decision Economics*, 18(4): 335-342.

Scully, Gerald W. (1974). "Pay and Performance in Major League Baseball," *American Economic Review*, 64 (6): 915-930.

Scully, Gerald W. (1989). *The Business of Major League Baseball.* Chicago: The University of Chicago Press.

Thorn, John and Pete Palmer (1984). *The Hidden Game of Baseball: A Revolutionary Approach to Baseball and Its Statistics*. New York: Doubleday.