Production Efficiency and Salary Distribution in Major League Baseball

R. Todd Jewell
Department of Economics
University of North Texas
P.O. Box 311457
Denton, TX 76203
(940) 565-3337
fax: (940) 565-4426
email: tjewell@unt.edu

and

David J. Molina
Department of Economics
University of North Texas
P.O. Box 311457
Denton, TX 76203
(940) 565-4543
fax: (940) 565-4426
email: molina@unt.edu

August 2001

I. Introduction

Two separate but related sport issues have attracted the attention of economists recently. First, there is the notion that teams in large markets have an advantage over those in smaller markets. It is assumed that the ability of large market teams to hire greater "talent" gives them undue advantage. This results in the issue of payroll inequality to which the Major League Baseball (MLB), the media, an economists have given much attention. In 1998, MLB Commissioner Bud Selig formed a Blue Ribbon Panel (hereafter, the Report) with the purpose of describing and explaining the economic condition of MLB (Levin et al., 2000). The Report points out that team payrolls have become increasingly disparate; the gap between “rich” and “poor” teams is not only wide, but it is growing. The effect, according to the Report, is a dramatic decline in parity and competitiveness of MLB. The Report discusses various recommendations that may reduce payroll inequality among teams, leading to what might be called “convergence” in team payrolls and possibly increased competition among teams. But in an indication of the *common wisdom* of the advantage of the larger market teams dominance, Eckard (2001) points out that some of the reports premises are "simply assumed, not demonstrated." Nonetheless, the distribution of salary between teams is an important issue for the future of MLB and other professional sports as well.

Another topic that while related is a separate issue is within-team payroll inequality. The focal point is whether a team’s own payroll distribution affects team production separately from the level of payroll relative to other teams. Two hypotheses have been discussed and tested. First, the relationship between within-team payroll inequality and team production may be positive, since a wider distribution of salaries can induce greater worker performance, as is the case in a “tournament” (Lazear and Rosen, 1981). Other examples of this are Ehrenberg and Bognanno (1990a, 1990b) who examine professional golf in the US and Europe and find that players’ performances are related to the size of the payoff. Specifically, larger prizes lead to lower (better) scores. Also, larger prizes appear to attract better players to professional golf events. Using data from the National Basketball League, Berri (2001) finds that an increase in payroll inequality within a team actually leads to an increase in wins.[1] Second, the relationship between within-team payroll inequality and team production may be negative, since salary inequality may create morale problems that lead to less team cohesion and thereby reduce team production (Lazear, 1989). Additional examples are Depken (2000) who finds that MLB teams with greater wage disparity have fewer wins and Sommers (1998) who finds similar results using National League data. These contradictory results may be attributed to the substantial differences among the institutions in the different sports. This paper advances the literature in both fronts by placing the discussion of payroll inequality and success in a stochastic production frontier framework. Using a panel data model discussed by Schmidt and Sickles (1984), we analyze the effect of salary dispersion on team winning percentage in MLB, *and* we measure how payroll inequality affects a team's ability to reach its production potential. If within-team payroll inequality affects production in MLB, then payroll inequality may be an important determinant of between-team payroll inequality, since we expect wins to be correlated with more revenue and teams with more revenue can pay higher salaries. Thus, MLB may also need to consider within-team payroll inequality when making changes designed to "level the playing field" in terms of team revenues.

In addition to the income distribution studies mentioned above, there are numerous others that estimate production functions for professional sports teams without including measures of payroll inequality. The outcome measures in these production models vary from wins and points scored to attendance and revenues. The professional sports studied include, but are not limited to,

[1] Other related studies include Fort (1992) and Jewell et al. (2001), who measure the salary distribution for the entire population of a sport's athletes; these studies, however, do not analyze within-team payroll inequality.

baseball (Scully, 1973, 1974; Zech, 1981; Porter and Scully, 1982; Bruggink and Eaton, 1996; Kahane and Shmanske, 1997), basketball (Zak et al., 1979; Kahn and Sherer, 1988; Burdekin and Idson, 1991; Hofler and Payne, 1997), American football (Hofler and Payne, 1996; Welki and Zlatoper, 1999), cricket (Schofield, 1988), soccer (Peel and Thomas, 1996; Baimbridge et al., 1996; Baimbridge, 1997; Jewell and Molina, 2001, Carmichael et al, 2001), and rugby (Carmichael et al., 1999).[2]

In the present study, we are examine changes in the distribution of salaries within teams in MLB from 1985 to 2000, concentrating on the effect that these changes have had on a the efficiency of a team's production in terms of winning percentage. Measuring salary inequality using the Gini coefficient, we find limited evidence that teams with more unequal payroll distributions are less efficient, although the magnitude of this effect is small and is only significant in recent years. We also compare are production efficiency results to the revenues generated by each team as presented in the Report for the years of 1995-1999.

II. Methodology

This study utilizes MLB data from the 1985 through 2000 seasons. During this time-period, there were two expansions, in 1993 and 1998. From 1985 to 1992, there were 26 teams in MLB, while there were 28 teams from 1993 to 1997 and 30 teams from 1998 to 2000. The total number of team-level observations for 1985 to 2000 is 438. Some data are missing for 1987: there is not enough salary data for Boston, Chicago (White Sox), Minnesota, Seattle, and Texas

[2] Our study is closest in spirit to Hofler and Payne (1996, 1997) who estimate stochastic production frontier models for National Football League and National Basketball Association teams respectively. The recent paper by Depken (2000) is similar to our study in the use of MLB data and the analysis of within-team payroll inequality. Our study differs from Depken's in two ways: we use a different measure of payroll inequality, and we expand the analysis by measuring the effect of payroll inequality on productive efficiency. Zech (1981) also estimates a production function for MLB, although the author makes no attempt to analyze salary inequality or productive efficiency. The paper by Porter and Scully (1982) is fundamentally different from our study, since the authors concentrate on an analysis of managerial efficiency.

to compute team Gini coefficients. Thus, the data set consists of 433 observations. The data are collected from several sources. The team performance measures are from the *Total Baseball* web site (totalbaseball.com), an online version of the official encyclopedia of MLB. Individual salaries are obtained from several internet sources, including the collections of Rodney Fort (users.pullman.com/rodfort) and Sean Lahman (baseball1.com), and from the *USAToday* web site (usatoday.com). Whenever possible, we crosschecked figures from each of these sources. In addition, we have cleaned the salary data, so that the numbers reflect opening day salaries in most cases.[3] However, as with much of the information stored on the internet, there may be some errors in the data.

Stochastic Production Frontier Model

MLB teams "produce" an output in terms of games over a season, where the quality and quantity of production can be measured by the number of wins or a team's winning percentage. Following Zech (1981) and Porter and Scully (1982), we assume that MLB wins are produced according to a Cobb-Douglas production model. In the manner of Hofler and Payne (1996, 1997) we measure productive efficiency using a stochastic production frontier model. In this context, "productive efficiency" describes how close a MLB team comes to its production potential. Specifically, the production function is of the following form:

(1) $$w_{it} = \alpha + X_{it}'\beta + v_{it} + u_i$$

where w_{it} is team *i*'s winning percentage in period *t*, α and the vector β are coefficients to be estimated, X_{it} are the win-producing characteristics of team *i* in period *t*, v_{it} is the white-noise error term, and all variables are measured in natural logs. In addition, u_i represents productive efficiency, is iid with mean $\mu < 0$ and variance σ^2_u, is uncorrelated with X_{it}, and is independent of

[3] For some years, we are unable to differentiate between yearly salaries and added bonuses. In the years in which we are able to separate out bonus payments, these payments do not significantly change teams' salary distributions. Thus, we are confident that the inclusion of bonuses in some years will not bias the Gini coefficients for those years.

v_{it}. For each team, u_i takes on only non-positive values and measures the distance by which the actual team winning percentage falls short of potential winning percentage.

We simplify the model by defining the following:[4]

(2) $\alpha^* = \alpha - \mu$, and $u_i^* = u_i - \mu$.

Notice that u_i^* is iid with mean 0, since $E(u_i) = \mu$. Substitute equation (2) into equation (1), and the stochastic production model becomes:

(3) $w_{it} = \alpha^* + X_{it}'\beta + v_{it} + u_i^*$.

Now both error terms have zero means and most of the standard issues regarding panel data estimation apply. Given the assumption that u_i is uncorrelated with X_{it}, the most appropriate method for estimating equation (3) is with a random effects, GLS estimator.[5]

After estimating equation (3), we need to recover estimates of production efficiency for each team. Define the following:

(4) $\alpha_i = \alpha^* + u^*$, which implies that $\alpha_i = \alpha + u_i$.

The intercept for each team, α_i, can be used to compare efficiency across teams. From the estimates of equation (4), we can obtain $\hat{\alpha}$, $\hat{u}_i$, and, therefore, $\hat{\alpha}_i$. Following Schmidt and Sickles (1984), we assume that the most efficient team in the sample is 100 percent efficient in order to recover the one-sided individual effects. Thus, each team's estimated productive efficiency is relative to an absolute standard of 100 percent efficiency.

Description of Included Variables

X_{it} includes team-level measures that are inputs in the production of wins. The average

[4] The discussion of the model follows Schmidt and Sickles (1984, pp. 368-369).
[5] The model is estimated using the XTREG command in STATA (StataCorp, 1999). A Hausman test, which is available from the authors, indicates that the individual effects are uncorrelated with the regressors.

player age (*mean age*) is included as a measure of experience, since teams with more experience should perform better. A player who plays in the All-Star Game in midseason is in the upper-echelon of players for that year: the number of players on a team who are All-Stars (*allstars*) is included to measure player quality. X_{it} also includes measures of offensive ability (*runs per game*, *on base percentage*, *slugging percentage*, and *stolen bases per game*), pitching ability (*saves per game*, *complete games per game*, and *earned run average*), and defensive ability (*errors per game* and *double plays per game*). In addition, X_{it} includes a team's Gini coefficient (*gini*) to measure the degree of salary inequality. The Gini coefficient can vary from 0 to 1, with 0 being complete salary equality and 1 being complete salary inequality. Following Sommers (1998), we also include average team salary in 1990 dollars (*mean salary*) to control for the effect of higher salaries on team performance. Table One presents summary statistics for the variables used in this study.

[INSERT TABLE ONE]

III. Results and Discussion

We begin this section with estimates from the stochastic production model given in equation (3) and discussed in the previous section. Later, we discuss the estimates of production efficiency. According to the Report, the "problems" associated with payroll inequality have been more severe after the strike of 1994 (Will, 2000). To test this hypothesis, we include an interaction term (*strike*) in Column B to test for the effect of within salary inequality before 1994 and after, while Column A does not include *strike*.[6] Concentrating on the relationship between

[6] Since a team's *mean salary* will be a function of the quality of players, which also affects *winning percentage*, *mean salary* will be endogenous. We remedy this potential problem by using a predicted value for *mean salary*, computed from the regression reported in the Appendix. Identification of the salary regression is accomplished through inclusion of measures of market size (MSA *median* (household) *income* and *population*), which should affect salaries but should not directly affect *winning percentage*. Information on market size is found on the US

payroll inequality and team success, the results in Column A of Table Two indicate that *gini* is not significant. However, the results in Column B indicate that the relationship between *gini* and *winning percentage* becomes significant after 1994. Among other things, this result may indicate that a fundamental change in the overall MLB salary distribution occurred as a result of the most recent labor strife. However, the magnitude of the coefficient on *gini*×*strike* is small; after 1994, a 1 percent increase in *gini* leads to a 0.02 percent decrease in *winning percentage*. To put this result in context, an average team with 81 wins would have to reduce its Gini coefficient by 60 percent to increase the number of wins by 1.

The fact that *gini* becomes significant only after the 1994 strike indicates that the negative effect of within team salary inequality is a relatively recent phenomenon. Although not reported here, the wins production model was also estimated with interaction terms for each year after the strike (1995 through 2000).[7] These results indicate that changes in *gini* had the strongest effect in 1999 and 2000, where an increase of 1 percent in a team's *gini* would have reduced winning percentage by 0.03 and 0.08 percent respectively; the coefficients for both years are significant at the 5 percent level. Therefore, there is some evidence that this recent effect is becoming stronger over time and may very well become even more important in the future.

[INSERT TABLE TWO]

The results with respect to average team salary are also interesting. In both columns of Table Two, the coefficient on *mean salary* is insignificant. The implication here is that teams

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Census web site (census.gov). In addition, the square of *mean age* is included, as is standard in Mincer-type earnings equations. Since the estimation includes an instrumental variable (predicted *mean salary*), we need to correct the standard errors of the *winning percentage* regressions. This correction is accomplished using bootstrapping methods; that is, the standard errors reported in Table Two are bootstrapped from the original estimates. Although not reported here, the model in Table Two was also estimated with an interaction term for *mean salary* and *strike*. No significant effect was found for team salaries after the 1994 strike, and the remaining coefficients are similar in significance and magnitude to those presented in Table Two. These estimates are available from the authors

[7] The remaining coefficients of this estimation are similar in significance and magnitude to those presented in Table Three. These estimates are available from the authors.

with higher salaries do not have an advantage in terms of winning, after controlling for team quality. This result does not imply that the Report is incorrect, because teams with higher salaries can afford the best players.[8] However, the result does imply that the distribution of salaries between teams does not by itself affect *winning percentage*. In the context of MLB, we know that just because the New York Yankees can afford to pay high salaries does not guarantee success unless the team also gets high-quality players.

From the coefficients in Column B of Table Two, it appears that other determinants are more important to MLB success than payroll inequality, even after 1994. Among the most important is pitching. This is, of course, not surprising since good pitching is essential to success: A 1 percent increase in *earned run average* leads to a 0.66 percent decrease in *winning percentage*, and a 1 percent increase in *saves per game* increases *winning percentage* by 0.20 percent. A team's offensive production is also extremely important: a 1 percent increase in *runs per game* increases winning percentage by 0.48 percent; a 1 percent increase in *on base percentage* leads to a 0.41 percent increase in *winning percentage*; and a 1 percent increase in *slugging percentage* results in at least a 0.32 percent increase in *winning percentage*. The experience level of the team also appears to be an important factor in team success, since a 1 percent increase in *mean age* will increase *winning percentage* by approximately 0.17 percent. Defense is clearly important since a 1 percent increase in *errors per game* decreases *winning percentage* by about 0.04 percent.

Estimates of Productive Efficiency

Table Three presents an alphabetical listing of teams, along with predictions from the model. *Average Wins* is the actual number of wins averaged over the number of observations for

[8] Although not the focus of this paper, the salary equation results in the Appendix do show an interesting fact: Teams in larger MSAs have higher salaries. It seems that during our sample period, teams in larger markets had the highest salaries. MLB's Blue Ribbon Panel would have no trouble agreeing with this result.

each team, *Predicted Wins* is the estimated productive (wins) capacity for each team, and *Relative Efficiency* is a measure of actual production (wins) relative to potential production. Recall that our measure of productive efficiency is relative to the most efficient team, thus the estimate of efficiency actually represents the upper bound for each team. For instance, if no team is reaching 100 percent efficiency (a situation that no doubt exists in MLB), then all teams will exhibit greater inefficiency than is listed here. Thus, we cannot be certain of the absolute measures of efficiency presented here, but we are confident in the relative measures.

Table Four presents rankings of MLB teams (from the estimate in Column B of Table Three) in terms of *Relative Efficiency*, *Average Wins*, and *Predicted Wins*. The teams are listed in order of their ability to produce with relatively little inefficiency. *Average Wins* and *Predicted Wins* appear to be positively related (correlation coefficient = 0.98); that is, those teams that have the most productive capacity also tend to be the most successful teams, which is not surprising. However, there seems to be no obvious correlation between *Predicted Wins* and *Relative Efficiency* (correlation coefficient = -0.16). The later observation implies that a MLB team's production function is unrelated to its ability to efficiently produce wins. Take, for example, the five most productively efficient MLB teams: Texas, Kansas City, Colorado, Los Angeles, and Milwaukee. The only one of these teams that is even in the top half of teams in a ranking of *Predicted Wins* is Los Angeles. The same can be said for these five teams and their ranking in terms of *Average Wins*. In addition, the only team in this list of five that can be called a "large-market" team for the entire sample period is Los Angeles.[9] It might be that these teams have had to make due with fewer financial resources, and thus have been forced to be more efficient to be competitive on the field. Conversely, the New York Yankees are ranked number one in terms of

[9] It can be argued that Texas is currently a large-market team given the population growth in Dallas/Ft. Worth and given the new, revenue-producing Ballpark at Arlington. However, for most of the sample period, Texas was considered a small- to medium-market team.

productive capacity (*Predicted Wins*) and in terms of on-the-field success (*Predicted Wins*), but are only the 23rd most efficient team. Clearly, the Yankees have many resources, and they are able to waste some of their resources while still being extremely successful.

In Table 5a, we compare our results with those from the Report in terms of revenues generated by the teams for the years of 1995-1999 the years that the Report covers. Notice that while it is true that during this period, the teams that won generally had the highest winning ratios, 73.33%, that does not translate to efficient teams. In particular, teams in the upper half of total revenues (i.e. larger market teams) accounted for less than half, 46.67%, of the top half of efficient teams. And teams with in the lower half of the revenues accounted for more than half, 53.33%, of the efficient teams. In Table 5b the information is presented in quartiles. Here it is apparent that the division is even greater for the middle quartile teams. It is noticeable that teams with very high revenue account for 42.86% of the first quartile of efficient teams. On the other hand, teams with the second highest quartile in revenues account for half, 50.0%, of the least efficient teams. Furthermore, teams in the third quartile of revenues account for nearly 43% of the two top most efficient quartiles. It appears than that with the very efficient teams need not be those with the highest revenues. This could indicate that those teams that with moderate revenues, 3rd quartile, are using their resources to their best in order to maintain their fans interested where as those teams in the lower upper half of revenues, i.e. 2 quartile, are attracting their fans by their roster rather than by using their resources in the most efficient manner.

IV. Conclusion

Salaries in MLB are rising as payroll inequality within and between teams is increasing. MLB observers and participants have shown concern that this rising inequality may affect the success of individual teams and the league as a whole. This study finds that the distribution of salaries within MLB teams does have a significantly negative effect on team success as measured by a team’s winning percentage. The magnitude of this effect may be too small to have an impact on the current hiring and salary decisions of MLB teams. However, salary inequality is a more important determinant of wins in MLB than some team quality measures. In addition, the evidence suggests that the negative effect of inequality on wins is strongest after the recent work stoppage and that it may be getting stronger. If this trend continues, MLB may be forced to explore ways to equalize salaries within teams. This implication alone merits further evaluation of the impact of salary inequality on wins production in MLB (and other sports) in future studies.

Due to the Blue Ribbon Panel’s observation that between-team payroll inequality has had a particularly strong effect on competitive balance in MLB in recent years, this area should be more completely analyzed in future research.

Table One
Summary Statistics
n = 433

Variable	Mean	Standard Deviation
winning percentage	0.4997	0.0665
gini	0.5370	0.0875
mean salary/1,000,000	0.8816	0.4474
time	8.7352	4.6412
strike	0.3973	0.4899
mean age	28.5563	1.1805
allstars	2.2032	1.3402
runs per game	4.6115	0.5641
on base percentage	0.3298	0.0152
slugging percentage	0.4060	0.0314
stolen bases per game	0.7333	0.2422
saves per game	0.2505	0.0476
complete games per game	0.0910	0.0511
earned run average	4.2123	0.5965
errors per game	0.6613	0.1345
double plays per game	2.2296	0.5661
median income/10,000	3.5390	0.4412
population/1,000,000	5.5575	4.8359

Table Two
Cobb-Douglas Stochastic Production Frontier
(variables in logs)
dependent variable = *winning percentage*
n = 433

	A		***B***	
Variable	**Coefficient**	**Std. Error [a]**	**Coefficient**	**Std. Error [a]**
constant	-0.0045	0.5560	-0.0112	0.5474
gini	0.0005	0.0145	-0.0046	0.0151
gini×*strike*			-0.0230**	0.0115
mean salary/1,000,000 [b]	-0.0013	0.0058	-0.0025	0.0076
mean age	0.1739**	0.0702	0.1649**	0.0738
allstars	0.0074*	0.0044	0.0080*	0.0045
runs per game	0.4783***	0.1463	0.4812***	0.1450
on base percentage	0.4135**	0.1824	0.4058**	0.1822
slugging percentage	0.3489**	0.1493	0.3243**	0.1463
stolen bases per game	0.0140*	0.0075	0.0141**	0.0073
saves per game	0.1947***	0.0164	0.1957***	0.0165
complete games per game	0.0176***	0.0049	0.0209***	0.0053
earned run average	-0.6539***	0.0279	-0.6550***	0.0275
errors per game	-0.0346***	0.0133	-0.0437***	0.0139
double plays per game	0.0046	0.0076	0.0051	0.0080
χ^2 (13)	3722.4***		χ^2 (14)	3753.6***

[a] The standard errors are bootstrapped from the second stage estimates presented in this table.
[b] Mean salary is predicted based on the regression presented in the Appendix.
* Significant at the 10 percent level based on a t-test.
** Significant at the 5 percent level based on a t-test.
*** Significant at the 1 percent level based on a t-test

Table Three
Productive Efficiency Estimates

Team	N	Average Wins[c]	*Model A Estimates* Predicted Wins	*Model A Estimates* Relative Efficiency	*Model B Estimates* Predicted Wins	*Model B Estimates* Relative Efficiency
Anaheim	16	79.49	80.66	98.55%	80.76	98.43%
Arizona	3	83.33	85.83	97.09%	86.31	96.55%
Atlanta	16	86.61	87.39	99.11%	87.57	98.90%
Baltimore	16	79.33	81.91	96.85%	82.16	96.56%
Boston	15	85.59	87.56	97.75%	87.54	97.77%
Chicago (NL)	16	76.73	78.97	97.16%	79.08	97.03%
Chicago (AL)	15	82.99	84.54	98.17%	84.56	98.14%
Cincinnati	16	84.50	86.42	97.78%	86.63	97.54%
Cleveland	16	81.92	84.55	96.89%	84.66	96.76%
Colorado	8	77.94	78.55	99.22%	78.50	99.29%
Detroit	16	76.69	78.51	97.68%	78.56	97.62%
Florida	8	72.65	73.32	99.09%	73.50	98.84%
Houston	16	84.03	85.03	98.82%	85.13	98.71%
Kansas City	16	79.05	79.08	99.96%	79.24	99.76%
Los Angeles	16	83.09	83.57	99.43%	83.72	99.25%
Milwaukee	16	78.29	79.03	99.06%	79.13	98.94%
Minnesota	15	75.73	77.23	98.06%	77.41	97.83%
Montreal	16	81.11	83.28	97.39%	83.43	97.22%
New York (NL)	16	86.23	88.26	97.70%	88.42	97.52%
New York (AL)	16	88.42	90.92	97.25%	91.04	97.12%
Oakland	16	83.21	85.56	97.25%	85.52	97.30%
Philadelphia	16	75.02	76.68	97.84%	76.82	97.66%
Pittsburgh	16	77.07	78.07	98.72%	78.33	98.39%
San Diego	16	78.46	81.01	96.85%	81.15	96.69%
San Francisco	16	82.96	84.10	98.64%	84.21	98.52%
Seattle	15	77.97	80.49	98.55%	80.57	96.75%
St. Louis	16	82.46	83.99	98.18%	84.10	98.05%
Tampa Bay	3	67.01	71.03	94.34%	71.25	94.05%
Texas	15	80.76	80.76	100.00%	80.76	100.00%
Toronto	16	85.63	87.97	97.34%	88.01	97.30%

[c]Based on 162 games per year

Table Four
Rankings: Relative Efficiency and Wins
(Based on Model B Estimates from Table Three)

Team	Relative Efficiency	Predicted Wins	Average Wins[c]
Texas Rangers	1	18	16
Kansas City Royals	2	21	19
Colorado Rockies	3	25	23
Los Angeles Dodgers	4	14	10
Milwaukee Brewers	5	22	21
Atlanta Braves	6	4	2
Florida Marlins	7	29	29
Houston Astros	8	9	7
San Francisco Giants	9	12	12
Anaheim Angels	10	19	17
Pittsburgh Pirates	11	26	24
Chicago White Sox	12	11	11
St. Louis Cardinals	13	13	13
Minnesota Twins	14	27	27
Boston Red Sox	15	5	5
Philadelphia Phillies	16	28	28
Detroit Tigers	17	24	26
Cincinnati Reds	18	6	6
New York Mets	19	2	3
Oakland Athletics	20	8	9
Toronto Blue Jays	21	3	4
Montreal Expos	22	15	15
New York Yankees	23	1	1
Chicago Cubs	24	23	25
Cleveland Indians	25	10	14
Seattle Mariners	26	20	22
San Diego Padres	27	17	20
Baltimore Orioles	28	16	18
Arizona Diamondbacks	29	7	8
Tampa Bay Devil Rays	30	30	30

[c]Based on 162 games per year

Appendix
Predicted Salary Equation
(dependent variable = *mean salary*/1,000,000)
n = 433

Variable	**Coefficient**	**Standard Error**
constant	-8.7885*	5.4890
time	0.0555***	0.0051
mean age	0.3805	0.3828
$(\textit{mean age})^2$	-0.0042	0.0067
allstars	0.0321***	0.0115
runs per game	-0.2148***	0.0688
on base percentage	4.3346**	1.8650
slugging percentage	4.0757***	1.0509
stolen bases per game	0.0595	0.0592
saves per game	-0.6901**	0.3537
complete games per game	0.1739	0.3623
earned run average	-0.0634*	0.0353
errors per game	-0.1174	0.1030
double plays per game	-0.0780***	0.0236
median income/10,000	0.0389	0.0367
population/1,000,000	0.0096***	0.0033
χ^2 (13)	879.3***	

TABLE 5a
By Halfs
1995-1999 Data
Comparison of Wins and Efficiency to Local Revenues

	Actual win rank	
Local Revenues	Upper Half	Lower Half
Upper Half	73.33%	26.67%
Lower Half	26.67%	73.33%
	Efficiency rank	
Local Revenues	Upper Half	Lower Half
Upper Half	46.67%	53.33%
Lower Half	53.33%	46.67%

TABLE 5a
By Quatiles
1995-1999 Data
Comparison of Wins and Efficiency to Local Revenues

	Percent in terms of Actual win rank			
Local Revenues	*First Quartile*	Second Quartile	*Third Quartile*	*Fourth Quartile*
First Quartile	57.14%	28.57%	14.29%	0.00%
Second Quartile	28.57%	28.57%	28.57%	14.29%
Third Quartile	12.50%	25.00%	37.50%	25.00%
Fourth Quartile	0.00%	12.50%	25.00%	62.50%
	Percent in terms of Efficiency rank			
Local Revenues	*First Quartile*	Second Quartile	*Third Quartile*	*Fourth Quartile*
First Quartile	42.86%	14.29%	14.29%	28.57%
Second Quartile	14.29%	28.57%	0.00%	57.14%
Third Quartile	25.00%	50.00%	12.50%	12.50%
Fourth Quartile	12.50%	0.00%	75.00%	12.50%

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