The Effect of Salary Distribution on Production: An Analysis of Major League Baseball

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I. Introduction

Efficiency wages models predict that higher wages lead to more productivity. This implies that the distribution of wages can affect worker performance, as is the case in a "tournament" (Lazear and Rosen, 1981). Tournaments reward players based on relative performance, and tournament payout schemes exist because they elicit more work than traditional payment schemes, especially when it is difficult to measure a worker's productivity. The tournament payment scheme describes the sports industry well, since sports salaries are based on how productive a player is relative to other players on a team or in a league. Ehrenberg and Bognanno (1990a, 1990b) 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. McClure and Spector (1997), however, find no significant relationship between prize amount and performance in US college basketball. This result may indicate the differences between professional athletes and those who cannot reap the rewards of a tournament.

A tournament may lead to a large spread in salaries, since a larger payoff spread can induce more effort from the competitors. Thus, a tournament can lead to an unequal distribution of salaries, and a more unequal salary distribution may actually reduce performance if it leads to resentment among workers. Specifically, salary inequality may create morale problems that lead to less team cohesion and reduce team production. Sommers (1998) investigates the relationship between production in the sports industry and salary inequality. The author estimates the following OLS model using 1996-97 US National Hockey League (NHL) data:

(1) $points = \text{constant} + \alpha gini + \beta salary + \varepsilon$,

where *points* measures team production, *gini* is the traditional Gini coefficient, and average *salary* is included to capture the impact of relative income between teams on performance. The author finds α to be negative and (marginally) significant, while β is positive and significant. These results suggest that an NHL team's success will vary inversely with salary inequality; they also suggest that teams with higher salaries are more successful.

The issue of salary inequality in US Major League Baseball (MLB) has recently received attention from the media and the league itself. In 1998, MLB Commissioner Bud Selig formed a Blue Ribbon Panel with the purpose of describing and explaining the economic condition of MLB. Comprised of such dignitaries as Paul Volker, Senator George Mitchell, and columnist George Will, this panel recently made its report (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. For example, the salary of the highest-paid player in the 2000 season (Los Angeles' Kevin Brown at $15.7 million) was 95 percent of the entire payroll of the "poorest" team, the Minnesota Twins. The effect, according to the panel's report, is a dramatic decline in parity and competitiveness of MLB: Since 1994, a team in the top payroll quartile has won every World Series game. In 1999, the teams with the 5 largest payrolls had an average winning percentage of 0.557, while the 5 poorest teams had a comparable figure of 0.444. The report discusses various recommendations that may narrow this gap, leading to what one might call "convergence" in team payrolls.

Interestingly, upon examination of MLB salary figures from 1985-2000, one can see that the increase in the type of inequality discussed by the panel is a relatively recent phenomenon: From 1985 to 1994, the Gini coefficient for the population of teams averaged 0.148, while from 1995 to 2000, that same figure was 0.205. The main contribution of the report is to suggest that teams with higher average salaries are more likely to be successful. That is, the report is concerned with salary inequality <u>between</u> different teams and ways to correct the inequality. The present study is concerned with the effect of salary inequality within teams and, thus, should add information to the discussion of salary distribution issues in MLB.

Numerous other studies in the economic literature estimate production functions for professional sports teams without including measures of income 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, 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, 2000), and rugby (Carmichael et al., 1999).

In the present study, we 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 team's success in terms of winning percentage. Measuring salary inequality using the Gini coefficient, we find that teams with more unequal salary distributions have less success, although the magnitude of this effect is small. We also present evidence indicating that the magnitude of this effect may be increasing over time. Our findings somewhat concur with those of MLB's Blue Ribbon Panel that teams with higher payrolls have greater success. Given increasing salary inequality in professional sports, the results imply that professional leagues and teams may soon need to consider within team salary inequality when making hiring decisions.

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 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.[1] However, as with much of the information stored on the internet, there may be some errors in the data.

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.[2] Specifically, the production function is of the following form:

$$(2) \qquad W_{it} = \Omega X_{it} + u_{it}$$

where W_{it} is team i's winning percentage in period t, Ω is a vector of coefficients, X_{it} are the win-producing characteristics of team i in period t, u_{it} is a random error term, and all variables are measured in natural logs.

[1] 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.

[2] The Cobb-Douglas production model has also been used to analyze other professional sports. For example, Hofler and Payne (1996, 1997) use this model to study production in the US National Football League and the US National Basketball Association.

X_{it} includes team-level measures that are inputs in the production of wins. The average 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 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.[3]

[INSERT TABLE ONE]

III. Results and Discussion

We present and discuss two sets of estimates. First, we replicate the estimation of Sommers (1998) using MLB data. Second, we present estimates from the more complete model given in equation (2) and discussed in the previous section.[4] The fact that the underlying

[3] The study that most closely resembles ours is Zech (1981), although Zech makes no attempt to analyze salary inequality. There are several differences between the independent variables used here and those used in the Zech study. First, Zech includes a league dummy and a measure of the contribution of the manager to team success; both these measures are found to be insignificant. We do not include either measure, since there is no indication that these variables are important in our sample of MLB. Second, Zech includes batting average and home runs, and we do not. Instead, we include *on base percentage* and *slugging percentage*, which should be more complete measures of offensive output. Third, we include more measures of team production ability than Zech. Porter and Scully (1982) is fundamentally different from our study, since the authors concentrate on an analysis of managerial efficiency.

[4] 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*,

production function in our model is Cobb-Douglas implies that the coefficients can be interpreted as elasticities.[5] Table Two reports the estimation results from the Sommers-type model. All else constant, MLB teams with greater Gini coefficients have less success in terms of wins. Thus, teams are less successful in the production of wins when they have greater salary inequality. The results indicate that a 1 percent increase in *gini* will decrease *winning percentage* by 0.143 percent, or the Gini coefficient would have to increase by 7 percent to decrease a team's *winning percentage* by 1 percent. The coefficient on *mean salary* is positive, indicating that teams with higher average salaries have better records. A 1 percent increase in salaries is shown to increase *winning percentage* by 0.08 percent. This last result is not surprising since a higher average salary probably implies higher quality players. Also, the findings of MLB's Blue Ribbon Panel are validated in that higher salaries do lead to greater success.

[INSERT TABLE TWO]

The estimated relationship between *gini* and *winning percentage* is visually represented in Figure One.[6] Gini coefficients in our sample range from a low of 0.273 (1985 Chicago Cubs) to a high of 0.884 (1995 Baltimore Orioles). Over that range, predicted *winning percentage* only drops from 0.545 (88 wins out of 162 games) to 0.461 (75 wins out of 162 games). Over this entire range, a 200 percent increase in salary inequality would result in a 15 percent decrease in *winning percentage*. Although the effect of increasing salary inequality on success is negative, the magnitude appears rather small.

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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 Census web site (census.gov). In addition, the square of *mean age* is included, as is standard in Mincer-type earnings equations.

[5] The model is estimated using a random-effects, panel data estimator and is performed using the XTREG command in STATA (StataCorp, 1997). 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 Tables Two and Three are bootstrapped from the original estimates.

[6] Predicted *winning percentage* is computed at the average *mean salary* of the sample, $881,568.

[INSERT FIGURE ONE]

It may be also instructive to analyze the predicted effects for an individual team. As an example, take the Cleveland Indians of 2000, the team that missed out on the playoffs by the smallest margin. The Indians finished with a record of 90 wins and 72 losses, while the Seattle Mariners earned the wild-card playoff berth with a record of 91 wins and 71 losses. The Indians missed the 2000 playoffs by 1 win, which surely had a negative effect on team revenue. In 2000, Cleveland had a 1.1 percent lower *winning percentage* than Seattle (0.556 to 0.562). The results from Table Two suggest that Cleveland could have had enough wins to get into the playoffs if the team had reduced its *gini* by 7.7 percent. Cleveland's *gini* for 2000 was 0.539, implying that the team would have been required to reallocate salaries to approximate the salary distribution of the Minnesota Twins (2000 *gini* 0.497), which would be an unlikely and potentially disruptive scenario. On the other hand, the change would have been less disruptive if Cleveland had reduced salary inequality and if Seattle had increased salary inequality simultaneously at the beginning of the year. However, the magnitude of the impact of salary distribution on team performance in MLB appears to be small, even though it is significant.

Our second set of estimates takes into account the fact that there are productive inputs other than salary inequality and average salaries that determine a team's success. Column A of Table Three reports the results from an estimation of the production model in equation 2 including team inputs to winning. The results indicate that *gini* is not significant. In addition, (predicted) *mean salary* is an insignificant determinant of team success. It appears that player and team production characteristics are more important than salary issues in producing wins in MLB.

[INSERT TABLE THREE]

According to the report by the MLB's Blue Ribbon Panel the "problems" associated with salary 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.[7] The results indicate that the negative effects found in Table Two are more pronounced after the strike; specifically, controlling for other determinants of team success, the relationship between *gini* and *winning percentage* is significant only 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.

As a further indication of the small effect of within team salary inequality on MLB win production, take the case of Alex Rodriguez, the new shortstop for the Texas Rangers. Starting in 2001, Rodriguez will be paid $250 million over 10 years; he is currently the highest paid player on the team and in MLB. The Gini coefficient for the Texas Rangers increased from 0.552 in 2000 to 0.657 in 2001, a 19 percent increase. According to the results in Column B of Table Three, this rather large increase in salary inequality should decrease Texas' wins by 0.44 percent, which is less than one game. Although statistically significant, the magnitude of the coefficient on *gini*×*strike* clearly shows that within team salary inequality is probably a less important

[7] Although not reported here, the model in Table Three 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 Three. These estimates are available from the authors.

component of the decision-making process of MLB teams than other factors related to team and player performance.

The result with respect to average team salary is also interesting. In both columns of Table Three, the coefficient on *mean salary* is insignificant. The implication here is that teams with higher salaries do not have an advantage in terms of winning, after controlling for team quality. This result does not imply that the Blue Ribbon Panel's 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 <u>by itself</u> 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 Column B of Table Three, many other determinants appear to be more important to MLB success than salary inequality. 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 0.47 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 a 0.34 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 0.20 percent. Defense is clearly important since a 1 percent increase in *errors per game* decreases *winning percentage* by 0.04 percent.

[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.

Interpreting the coefficient on *allstar* requires a closer review. Column B of Table Three shows that a 1 percent increase in *allstar* leads to an increase in *winning percentage* of 0.0089 percent. At first glance, this appears to be of extremely small magnitude. However, this variable cannot be increased in a continuous manner. For instance, if a team already has one All-Star player and increases its number of All-Stars (marginally) by one, then this team sees a 100 percent increase in *allstar*, which leads to an increase in *winning percentage* of 0.89 percent. Depending on a team's current number of All-Star players, adding additional high-quality players may be the most effective way of increasing wins production in MLB. Furthermore, as the Blue Ribbon Panel will tell you, these All-Star-quality players can only be hired if a team has sufficient revenue.

There are some factors of production in MLB that do not appear to be as important as salary inequality. A 1 percent increase in *stolen bases per game*, *complete games per game*, and *double plays per game* all increase a team's *winning percentage* by a smaller absolute value than a 1 percent increase in salary inequality decreases *winning percentage*. The policy implication of this result can be seen in the following example. Assume a team is considering hiring a player who is predicted to increase stolen bases by 1 percent. This player will not increase team win production unless the player's salary increases inequality by less than 1 percent. Nonetheless, it appears that salary inequality at present is a statistically significant variable, but one with a small effect in absolute terms.

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).[9] 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.

IV. Conclusion

Salaries in MLB are rising as salary 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.

Although this paper deals with salary inequality within teams, MLB seems to be more concerned with the issue of salary inequality between teams. Our results give limited evidence that teams with higher salaries have more success. At the very least, we are unable to give strong evidence that salary inequality between teams does not affect team success. From our results, it

[9] 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.

appears that MLB have paid higher salaries to obtain higher-quality players. Due to the Blue Ribbon Panel's observation that between team salary 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 Wins Production Estimation: Sommers-Type Model
(variables in logs)
dependent variable = *winning percentage*
n = 433

Variable	Coefficient	Standard Error[a]
constant	-0.7762***	0.0260
gini	-0.1430***	0.0420
mean salary/1,000,000[b]	0.0834***	0.0154

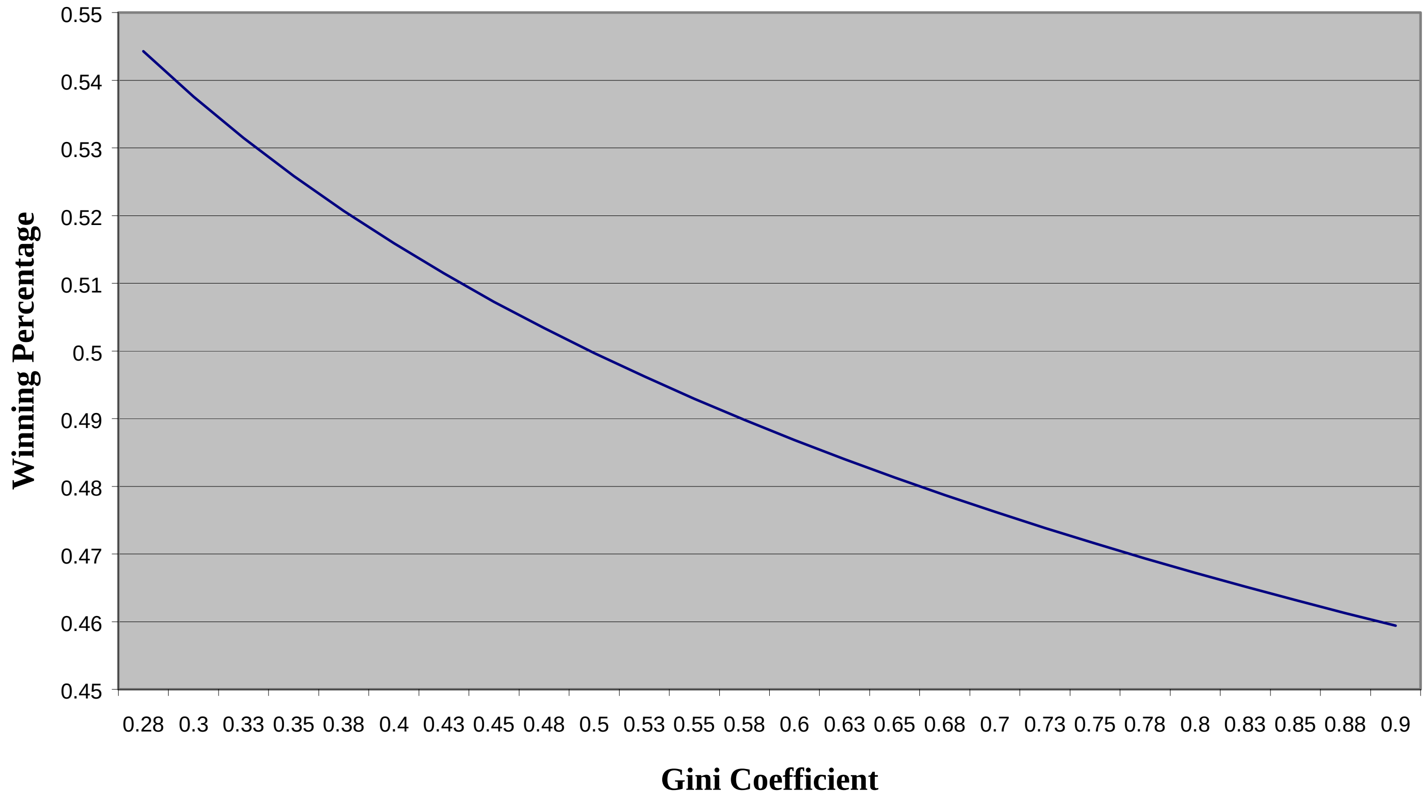
[a] The standard errors are bootstrapped from the second stage estimates presented in this table.
[b] Mean salary is predicted based on the regression presented in the Appendix.
*** Significant at the 1 percent level based on a t-test.

Table Three
Cobb-Douglas Wins Production Estimation: Full Set of Regressors
(variables in logs)
dependent variable = *winning percentage*
n = 433

	A		B	
Variable	**Coefficient**	**Std. Error** [a]	**Coefficient**	**Std. Error** [a]
constant	-0.0652	0.5643	-0.1076	0.5571
gini	0.0048	0.0141	0.0020	0.0142
gini×strike			-0.0232**	0.0111
mean salary/1,000,000 [b]	-0.0047	0.0079	-0.0083	0.0081
mean age	0.1982***	0.0749	0.2039***	0.0750
allstars	0.0077*	0.0046	0.0089*	0.0047
runs per game	0.4753***	0.1502	0.4749***	0.1509
on base percentage	0.4182**	0.1897	0.4110**	0.1865
slugging percentage	0.3574**	0.1536	0.3406**	0.1526
stolen bases per game	0.0141*	0.0074	0.0140*	0.0078
saves per game	0.1941***	0.0163	0.1960***	0.0164
complete games per game	0.0170***	0.0049	0.0200***	0.0053
earned run average	-0.6559***	0.0279	-0.6566***	0.0280
errors per game	-0.0329***	0.0121	-0.0408***	0.0130
double plays per game	0.0043	0.0080	0.0047	0.0076

[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.

Figure One
Predicted Winning Percentage



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

Variable	**Coefficient**	**Standard Error**
constant	-7.2123	5.2968
time	0.0788***	0.0054
strike	-0.2898***	0.0451
mean age	0.2494	0.3694
$(\textit{mean age})^2$	-0.0018	0.0064
allstars	0.0323***	0.0109
runs per game	-0.1899***	0.0652
on base percentage	3.3634*	1.7843
slugging percentage	4.2847***	1.0137
stolen bases per game	0.1013*	0.0581
saves per game	-0.6941**	0.3392
complete games per game	0.2101	0.3457
earned run average	-0.0266	0.0350
errors per game	-0.0619	0.0999
double plays per game	-0.0661***	0.0225
median income/10,000	0.0398	0.0478
population/1,000,000	0.0101**	0.0044

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