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PRODUCTIVE EFFICIENCY AND SALARY DISTRIBUTION: THE CASE OF US MAJOR LEAGUE BASEBALL

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Abstract

Recent theoretical research suggests that a firm's salary structure can affect the firm's productivity. We investigate the relationship between payroll inequality and production using US Major League Baseball data. Employing panel data methods, this study finds that salary inequality has a significantly negative effect on team success. A general result is that team success in term of wins does not seem to be correlated with efficiency; specifically, some of the least successful teams are also some of the most efficient. In addition, salary inequality does not appear to be correlated with efficiency. Furthermore, revenues generated by teams are not necessarily correlated with team efficiency.

I Introduction

Recent additions to economic theory suggest that the distribution of salaries can affect the productivity of workers and firms. The most visible examples of this theoretical literature are Akerlof and Yellen (1990) and Levine (1991) who suggest that firms may be able to increase efficiency by equalizing salaries, since a more equal salary distribution will increase 'cohesion' within the firm. The implication is that firms with more equal salary distributions will be more productive than similar firms with less equal salary structures. Relatively few studies have attempted to validate this proposition empirically.[1] This paper attempts to shed light on the question of the connection between salary structure and productivity using professional sports data. Specifically, this paper analyses the possible effect of a US Major League Baseball (MLB) team's payroll distribution on production in terms of wins and efficiency. The professional sports industry, and MLB in particular, has proven to be a fruitful area for salary-related studies, since detailed data exists on player and team quality and, thus, the determinants of both salaries and production can be observed, which is not the case in most other industries.

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[1] For instance, Hibbs and Locking (2000) examine the salary structure of Swedish industry and find no evidence that more equal salary structures lead to greater productivity.

The inequality of payrolls within professional sports teams has recently become a topic of interest to researchers. For example, Sommers (1998) discovers a negative relationship between team success and within-team payroll inequality using US National Hockey League data. 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 seem to induce greater effort. Using data from the US National Basketball League, Berri (2001) shows that an increase in payroll inequality within a team actually leads to an increase in wins. Richards and Guell (1998) give evidence that MLB teams with greater salary variance have lower winning percentages and that salary dispersion seems to have no effect on the probability of winning championships. Bloom (1999) tests whether increases in salary dispersion within MLB teams have a positive or a negative effect on performance. The author finds that greater salary inequality is correlated with lower individual and team performance. Depkin (2000) shows that MLB teams with greater wage disparity have lower winning percentages, while those with larger total payrolls have higher winning percentages.[2]

This paper advances the literature by placing the discussion of MLB payroll inequality and team success in a stochastic production frontier framework. In addition, we correct for the fact that any salary measure will be correlated with performance measures. Using a panel data model developed by Schmidt and Sickles (1984), we analyze the effect of salary dispersion on team regular-season winning percentage in MLB, and we measure how payroll inequality affects a team's ability to reach its production potential. Measuring salary inequality using the Gini coefficient, we find support for the 'cohesion hypothesis': We find a strong, negative relationship between salary inequality and win percentage. In addition, we also analyze the relationship between salary distribution, production efficiency, and revenues generated by MLB teams as presented in the report of MLB's 1998 Blue Ribbon Panel (Levin *et al.*, 2000).[3]

[2] Other studies estimate the determinants of production for professional sports teams without including measures of payroll inequality. The professional sports studied include 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, 2002; Carmichael *et al.*, 2001), and rugby (Carmichael *et al.*, 1999). Our study is closest in spirit to Hofler and Payne (1996, 1997) who estimate stochastic production frontier models for US National Football League and US National Basketball Association teams.

[3] The panel's 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 since teams from larger markets can afford to buy up all the 'talent.' 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. Contrary to the findings of MLB's Panel, Eckard (2001) gives evidence that competitive balance has not radically changed recently in MLB and that there is a weak positive relationship between market size and wins that has not become stronger over time.

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.[4] 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. However, it must be noted that winning percentage only measures production (and team quality) relative to other teams and is not an absolute measure of the quality of a team. 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:

$$w_{it} = \alpha + X'_{it}\beta + v_{it} + u_i \tag{1}$$

where w_{it} is team i's regular-season 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_u^2, is uncorrelated with X_{it}, and is independent of v_{it}. For each team, u_i takes on only non-positive values and measures the distance by which actual winning percentage falls short of potential winning percentage.

[4] 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.

We simplify the model by defining the following:[5]

$$\alpha^* = \alpha - \mu, \text{ and } u_i^* = u_i - \mu \tag{2}$$

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:

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

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.[6]

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

$$\alpha_i = \alpha^* + u_i^*, \text{ which implies that } \alpha_i = \alpha + u_i. \tag{4}$$

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% efficient in order to recover the one-sided individual effects. Thus, each team's estimated productive efficiency is not an absolute measure but, instead, is relative to the most efficient team.

Description of independent variables

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 (*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. Table 1 presents summary statistics.[7]

Gini will result from the salaries paid to players on a team, which will be correlated with the quality of players on a team. However, the quality of players also affects *winning percentage*. If the researcher can observe all dimensions of

[5] The discussion of the model follows Schmidt and Sickles (1984, pp. 368–69).

[6] 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.

[7] Other studies (e.g., Depken, 2000) include total team salaries as an independent variable. We do not include such a measure since it will be highly correlated with the included win-producing characteristics.

Table 1
Summary statistics $n = 433$

Variable	Mean	Standard deviation
winning percentage	0.4997	0.0665
gini	0.5370	0.0875
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
population/1,000,000	5.5575	4.8359

player quality that impact both salary distribution and team win production, then the relationship between salary inequality and team win production can be estimated with a single-equation regression. However, in the case of MLB, it is likely that there are some unobservable player-quality measures that impact both salaries and production, which implies *gini* will be an endogenous variable in a regression of equation (3). Take, for example, the issue of leadership. There are certain players that are seen as 'leaders,' implying that these players can inspire their teammates to play better than they would have otherwise. If leadership qualities have a value to teams in terms of more wins and if leadership is a scarce commodity in players, one would expect that MLB teams would reward players with superior leadership qualities with higher salaries, thereby affecting both salaries and win production. Thus, the unobservable 'leadership' would lead to a correlation between *gini* and the error term in equation (3). Since we expect some determinants of both *winning percentage* and *gini* to be unobservable, we treat *gini* as endogenous in the estimation discussed below.[8]

III Results and Discussion

Table 2 reports estimates from the stochastic production model given in equation (3) and discussed in the previous section. Later, we discuss the estimates of production efficiency. We remedy the endogeneity problem discussed above by using a predicted value for *gini*, computed from the regression reported in Appendix A. Identification of the salary-structure regression is accomplished through inclusion of a measure of market size

[8] A Hausman-Wu test for endogeneity (available on request from the authors) indicates that *gini* is endogenous at a 1% level of significance. Results treating *gini* as exogenous are presented in Appendix B.

Table 2
Cobb-Douglas stochastic production frontier random effects panel data estimation (variables in logs)
dependent variable = winning percentage n = 433

Variable	Coefficient	Std. error[a]
constant	– 0.0956	0.6443
gini[b]	– 0.2005***	0.0782
mean age	0.0450	0.1017
allstars	0.0188***	0.0057
runs per game	0.5870***	0.1654
on base percentage	0.4706**	0.2206
slugging percentage	0.3259*	0.1721
stolen bases per game	0.0222**	0.0092
complete games per game	– 0.0268***	0.0076
earned run average	– 0.7672***	0.0343
errors per game	– 0.0738***	0.0172
double plays per game	0.0208**	0.0097
$\chi^2(11)$	2577.8***	

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

(MSA *population*), a dummy variable equal to one if the team plays in the National League, and the square of *mean age*. Market size may affect a teams ability to generate revenues and pay higher salaries, which should affect *gini* but should not directly affect *winning percentage*.[9] In addition, there are characteristic differences between the National League and the American League (e.g, the designated hitter) that may lead to differences in salary structure. The square of *mean age* is included since it is standard in Mincer-type earnings equations. Since the estimation reported in Table 2 includes an instrumental variable (predicted *gini*), the standard errors of the *winning percentage* regression must be corrected. This correction is accomplished using bootstrapping methods; that is, the standard errors reported in Table 2 are bootstrapped from the original estimates.

Concentrating on the relationship between payroll inequality and regular-season team success, the results indicate that *gini* is negative and significant. The coefficient on *gini* implies that a 1% increase in *gini* leads to a 0.2% decrease in *winning percentage*.[10] To put our result in context, an average team with 81 wins would have to reduce its Gini coefficient by 6% to increase the number of wins

[9] Information on market size is found on the US Census web site (census.gov).

[10] Using a different methodology and a different measure of payroll distribution, Depken (2000) finds that a 1% increase in salary inequality will significantly decease winning percentage by 13%.

by one.[11] It may also be 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. In 2000, Cleveland had a 1.1% lower *winning percentage* than Seattle (0.556 to 0.562). The results from Table 2 suggest that Cleveland could have had enough wins to get into the playoffs if the team had reduced its *gini* by 5.3% (from 0.539 to 0.510), which is a 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.

Examining the remaining coefficients reported in Table 2, it appears that issues other than payroll inequality are important in determining success in MLB success. Among the most important is pitching. This is, of course, not surprising since good pitching is essential to success: A 1% increase in *earned run average* leads to a 0.77% decrease in *winning percentage*. However, the coefficient on *complete games* is negative and significant, although the magnitude is small. This result may indicate that teams with more complete games are forced to have their starting pitchers finish games due to inconsistent or poorly-performing relief pitching. A team's offensive production is also extremely important: A 1% increase in *runs* increases winning percentage by 0.59%; a 1% increase in *on base percentage* leads to a 0.47% increase in *winning percentage*; a 1% increase in *slugging percentage* results in at least a 0.33% increase in *winning percentage*; and a 1% increase in *stolen bases* results in a 0.02% increase in *winning percentage*. The experience level of the team does not appear to be an important factor in team success, since the coefficient on *mean age* is insignificant. However, it is more likely that experience is important, but the average age measure is not picking up this information. Defence is clearly important since a 1% increase in *errors* decreases *winning percentage* by 0.07%, and an increase in *double plays* turned increases *winning percentage* by 0.02.

When assessing the relative importance of salary distribution in wins production, we see that there are some factors that are not as important as salary inequality. For instance, a 1% increase in *stolen bases* or *double plays* increases a team's *winning percentage* by a smaller absolute value than a 1% increase in salary inequality decreases *winning percentage*. The 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 approximately 10%. This player will not increase team win production unless the player's salary increases inequality by less than 1%. Nonetheless, it appears that salary

[11] According to the report of MLB's Blue Ribbon Panel, the 'problems' associated with payroll inequality have been more severe after the strike of 1994 (Will, 2000). To test this hypothesis, we also estimate the model including an interaction term for years after 1994. The interaction term is insignificant, and the remaining coefficients are similar to those reported in Table 2. Among other things, this result may indicate that the effect of salary distribution on MLB teams' ability to generate wins has not changed as a result of the most recent labour strife.

inequality is a statistically significant variable, but one with a small effect in absolute terms and relative to most other measures of performance.[12]

Estimates of productive efficiency

Table 3 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 observation years for each team, *Predicted Wins* is the estimated productive (wins) capacity for each team per year, 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% efficiency (a situation that no doubt exists in MLB), then all teams will exhibit greater inefficiency than is listed here. Thus, similar to Schmidt and Sickles (1984, p. 371), we cannot be certain of the absolute measures of efficiency presented here, but we have confidence in the relative measures.

Table 4 presents rankings of MLB teams in terms of *Relative Efficiency*, *Average Wins*, and *Predicted Wins*, where teams are listed from most to least efficient. *Average Wins* and *Predicted Wins* appear to be positively related (correlation coefficient = 0.97); 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 = 0.12). The later observation implies that a MLB team's production function is generally unrelated to its ability to efficiently produce wins. Take, for example, the ten most productively efficient MLB teams: Texas, Chicago (AL), Anaheim, Montreal, Chicago (NL), Kansas City, Oakland, Milwaukee, New York (AL), and Minnesota. The only two of these teams, New York (AL) and Oakland, are in the top ten in a ranking of *Average Wins*. In addition, only New York (AL), Anaheim, and both Chicago teams are located in 'large-markets.'[13] It might be that most of 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 Mets are ranked number three in terms of productive capacity (*Predicted Wins*) and in terms of on-the-field success (*Average Wins*), but are only the 19th most efficient

[12] The results from Appendix B show that treating *gini* as exogenous results in an insignificant coefficient on salary inequality. Although this OLS estimation is probably inappropriate, it suggests that the effect of salary inequality on team win production is small or even non-existent. Additionally, these results highlight the need to correct for unobservable measures of player quality such as leadership. For instance, positive correlations between leadership and *winning percentage* and between leadership and *gini* would bias the estimated coefficient on *gini* upward, i.e., from the negative and significant coefficient shown in Table 2 to the insignificant coefficient shown in Appendix B. Note that although we use leadership as an example, the actual unobserved player-quality measures cannot be pinpointed, because they are (by definition) unobservable and unknown to the researcher.

[13] Texas might be considered 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.

Table 3
Productive efficiency estimates

Team	*N*	Average wins	Predicted wins	Relative efficiency %
Anaheim	16	79.49	80.69	98.51
Arizona	3	83.33	87.21	95.55
Atlanta	16	86.61	89.14	97.16
Baltimore	16	79.33	82.58	96.06
Boston	15	85.59	88.10	97.15
Chicago (NL)	16	76.73	78.25	98.06
Chicago (AL)	15	82.99	84.22	98.54
Cincinnati	16	84.50	86.84	97.31
Cleveland	16	81.92	85.95	95.31
Colorado	8	77.94	80.12	97.28
Detroit	16	76.69	80.52	95.24
Florida	8	72.65	74.74	97.20
Houston	16	84.03	87.09	96.49
Kansas City	16	79.05	80.74	97.91
Los Angeles	16	83.09	85.81	96.83
Milwaukee	16	78.29	80.17	97.65
Minnesota	15	75.73	77.76	97.39
Montreal	16	81.11	82.61	98.18
New York (NL)	16	86.23	89.00	96.89
New York (AL)	16	88.42	90.71	97.48
Oakland	16	83.21	85.02	97.87
Philadelphia	16	75.02	77.17	97.21
Pittsburgh	16	77.07	79.46	96.99
San Diego	16	78.46	81.52	96.25
San Francisco	16	82.96	85.94	96.53
Seattle	15	77.97	82.39	94.64
St. Louis	16	82.46	84.88	97.15
Tampa Bay	3	67.01	72.10	92.94
Texas	15	80.76	80.76	100.00
Toronto	16	85.63	88.42	96.84

team. Clearly, the Mets have many productive resources, and they are able to waste some of their resources while still being successful.[14]

Salary distribution and efficiency

As discussed above, salary distribution appears to have an effect on wins production in MLB. It may also be interesting to examine the correlation between a team's ability to efficiently produce wins and the teams salary structure.[15] Table 5 presents a ranking of teams by (average) *gini* and *Relative*

[14] For the better teams in MLB, the 'waste' of resources may occur at the end of the season, when they have clinched a spot in the post-season and they are preparing for it by resting some of their best players. Although this might be rational for a MLB team, it still represents a waste of resources and inefficiency in terms of producing regular-season wins.

[15] The correlation coefficient between *gini* and *Relative Efficiency* is -0.12.

Table 4
Rankings: efficiency and wins (based on estimates from Table 3)

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

Efficiency. What becomes obvious at first glance is that the four expansion teams have the highest degrees of salary inequality. Since these teams have fewer observations, an abnormally high *gini* in a single year could drive this result. However, we could be observing this outcome if all gini coefficients in MLB are increasing over time and these teams are forced to have unequal salary structures to compete.[16] Next, Texas has the fifth highest gini coefficient, but is able to produce wins in a more efficient manner than all other MLB teams. Although salary inequality clearly appears to impact *winning percentage* as shown by the results in Table 2, there seems to be no clear relationship between salary inequality and a team's ability to produce wins efficiently.

[16] The correlation coefficient between *gini* and a linear time trend is 0.59. Clearly, there seems to be an upward trend in *gini*; specifically, the salary structure of MLB is changing such that salary inequality is getting worse over time. An analysis of the causes of this trend is beyond the scope of this paper.

Table 5
Rankings: gini and efficiency (based on estimates from Table 3)

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

Revenue and efficiency

As MLB's Blue Ribbon Report argues, MLB teams in larger markets tend to have more local media revenues. Larger revenues enable teams to hire better players, but the results presented in Eckard (2001) imply that this ability may not directly translate to more on-the-field success. Our results discussed above suggest that productive capacity and productive efficiency in MLB are not highly correlated, which supports Eckard's conclusion to the extent that teams with less talent can become more competitive by increasing efficiency. In fact, our results indicate that this is exactly the way some small-market/low-revenue teams are able to compete. In addition, this result may directly reflect on the efficiency of management (either on the field or in the general manager's office); the management of smaller-market teams must be more efficient to compete with larger-market teams that have more resources at their disposal. For example, some teams have specialized in the development of relatively low-cost, young

Table 6
Rankings: local revenues, wins, and efficiency (based on estimates using 1995–1998 data)

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

athletes who are allowed to leave the team when they are able to demand higher salaries upon eligibility for free agency.[17] There undoubtedly exist other management practices that allow some teams to produce wins at a lower cost.

Further evidence supporting the argument that smaller-market teams are often more efficient can be seen with the use of data from the report of MLB's Blue Ribbon Panel. The report presents data on local media revenues generated by teams for the years 1995 to 1999. In Table 6, we present a ranking of teams by local media revenues as reported by MLB; we then compare the revenue ranking of teams to a ranking of teams in terms of *Average Wins* and *Relative Efficiency* over the same time period.[18] Over the time period 1995 to 1999, a team's revenue

[17] The most obvious example is that of the Montreal Expos, a team that regularly has young, talented players but few older, established players. The prevailing wisdom is that the Montreal organization does a better job of scouting and developing young players than other MLB teams.

[18] Note that the rankings presented in Table 6 differ from those presented in earlier tables since the time period is different.

ranking appears to be a fairly good predictor of on-the-field success (correlation coefficient = 0.66). However, the amount of revenues and *Relative Efficiency* do not seem to be related, either positively or negatively (correlation coefficient = 0.05). Teams in the top half of the revenue ranking are in the top half of a win ranking 75% of the time. However, these same teams are not always the most efficient teams. In particular, teams in the upper half in terms of revenues (i.e. larger-market teams) account for only about 50% of the top half of most efficient teams, implying that teams in the lower half of the revenue ranking account for about 50% of the most efficient teams.

Large-market teams will certainly have an advantage over smaller-market teams in terms of acquiring talent. According to our analysis, smaller-market teams may be able to overcome some of the disadvantage they face by producing wins more efficiently. If this is so, how much does efficient production actually matter in term's of increasing wins? A general answer to this question can be arrived at by examining Table 6 in more detail. Specifically, we want to compare a team's revenue rank with its win rank; i.e., if a team is able to increase its win rank relative to its revenue rank, then we can assume it has overcome any disadvantage it had *vis-à-vis* the revenue-generating power of larger-market teams. First, look at the top five teams in terms of *Relative Efficiency* (Texas, Atlanta, San Francisco, Colorado and Milwaukee). With the exception of Colorado, each of these teams is ranked higher in terms of wins than in terms of revenues. Second, concentrate on the two most efficient teams from 1995 to 1999: Texas and Atlanta. Texas was able to move up four spots from tenth ranked in revenues to sixth ranked in wins, while Atlanta was able to jump three spots from fourth in revenues to first in wins. Although we cannot be certain that efficient production led to the increase in rankings, it probably had a major impact. The news is not all good for smaller-market teams: The sixth, eighth, and ninth ranked teams in terms of *Relative Efficiency* (Florida, Anaheim and Philadelphia) are all in the lower half of the revenue ranking, and these teams are actually ranked lower in terms of wins than in terms of revenues. Clearly, just because efficient production can overcome revenue constraints does not mean it always will allow a team to overcome any disadvantage in revenue-generating potential.

IV Conclusion

Salaries in MLB are rising as payroll inequality within teams is increasing. 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 production, where production is measured by regular-season winning percentage. However, salary distribution does not appear to have a negative effect on team efficiency. Also with respect to efficiency, our results indicate that weaker teams can, and do, become more competitive by becoming more efficient. If within-team payroll inequality continues to increase, this may limit the ability of smaller-market teams to increase efficiency, thereby making revenue disparities more difficult to overcome.

The results presented in this study are consistent with the 'cohesion hypothesis.' However, there is another plausible explanation that should be considered: The correlation between salary inequality and winning percentage could be a result of management behaviour, arising from either mismanagement or rational, profit-maximizing behaviour. For instance, the enormous amounts of money spent on superstar players by certain teams may lead to increased salary inequality without a corresponding increase in winning percentage. This 'mismanagement' may simply occur because players are generally paid based on past, not current, performance. On the other hand, profit-maximizing teams may not care as much about winning as they do about attendance or revenues. Thus, while hiring a superstar player may not maximize winning percentage, it may maximize profit. In any case, our results indicate that there is a negative correlation between wins and salary inequality in US Major League Baseball.

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Appendix A

Predicted gini equation random effects panel data estimation (dependent variable = gini) n = 433

Variable	Coefficient	Standard error
constant	– 3.5137**	1.6278
mean age	0.2832**	0.1135
(mean age)^2	– 0.0052***	0.0020
allstars	0.0016	0.0034
runs per game	0.0293	0.0206
on base percentage	0.1728	0.5563
slugging percentage	– 0.1433	0.3118
stolen bases per game	0.0018	0.0176
complete games per game	– 0.5075***	0.0872
earned run average	0.0316***	0.0095
errors per game	– 0.0739**	0.0311
double plays per game	0.0080	0.0071
population/1,000,000	0.0008	0.0009
national league	0.0189*	0.0102
$\chi^2(13)$	153.65***	

Notes:
*Significant at the 10% level based on a *t*-test.
**Significant at the 5% level based on a *t*-test.
***Significant at the 1% level based on a *t*-test.

Appendix B

Cobb-Douglas stochastic production frontier random effects panel data estimation treating gini as exogenous (variables in logs)
dependent variable = winning percentage n = 433

Variable	Coefficient	Std. error
constant	– 0.2665	0.3478
gini	– 0.0023	0.0161
mean age	0.1935***	0.0670
allstars	0.0175***	0.0054
runs per game	0.5404***	0.0635
on base percentage	0.4669***	0.1219
slugging percentage	0.3410***	0.0840
stolen bases per game	0.2042***	0.0079
complete games per game	– 0.0097**	0.0049
earned run average	– 0.8032***	0.0254
errors per game	– 0.0552***	0.0145
double plays per game	0.0176**	0.0090
$\chi^2(11)$	2524.4***	

Notes:
*Significant at the 10% level based on a *t*-test.
**Significant at the 5% level based on a *t*-test.
***Significant at the 1% level based on a *t*-test.

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