TESTING THE DETERMINANTS OF INCOME DISTRIBUTION IN MAJOR LEAGUE BASEBALL

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Using data from U.S. Major League Baseball, this article compares parametric and nonparametric Gini coefficients for each team and year. We employ a panel-data model to investigate the time-series and cross-sectional factors affecting the Gini coefficients and the parameters of the preselected distribution. We find that much of within-team income distribution is determined by time-related variables, with the 1994 MLB strike having an especially strong effect. A team's market potential does not seem to affect its salary distribution, but the average age of the players on a team's roster does. Furthermore, inequality first increases with team payroll, then decreases before increasing again. (*JEL* D31, L83)

I. INTRODUCTION

Income of professional athletes is a frequent topic of discussion of fans, sportscasters, and the general public. Economists have also increasingly been attracted to this topic, because the distribution of income of these players has both policy and business implications. As a consequence, the report of Major League Baseball's (MLB) Blue Ribbon Panel, formed in 1998 by MLB commissioner Bud Selig, received quite a lot of attention. This panel was charged with describing and explaining the economic condition of MLB. Comprised of such dignitaries as former Federal Reserve Chairman Paul Volker, Senator George Mitchell, Yale University President Richard Levin, and columnist George Will, this panel reported that team payrolls have become increasingly disparate; the gap between "rich" and "poor" teams is not only wide but is growing (Levin *et al.* 2000). A case in point is the fact that the salary of the highest-paid player in the 2000 season (Los Angeles' Kevin Brown at $15.7 million) was 95% 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 five largest payrolls had an average winning percentage of 0.557, whereas the five 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.

This article examines the distribution of income in MLB for 1985 to 2000. We revive (and extend) a technique first suggested by Thurow (1970) and show how it can be used to test for time trends versus cross-sectional demographic and economic aspects influencing income distribution. Thurow (1970) discusses the impact of various measures on median income. In the present case, by calculating the Gini coefficient, we

*We wish to thank Rod Fort for assistance in finding and cleaning the salary data. We also thank David Berri, Rod Fort, Brad Humphreys, Daniel Slottje, Steve Walters, and two anonymous referees for helpful comments and suggestions. The usual caveats hold.

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ABBREVIATIONS

AL: American League
DH: Designated Hitter
MLB: Major League Baseball
MSA: Metropolitan Statistical Area
NL: National League

Economic Inquiry
(ISSN 0095-2583)
Vol. 42, No. 3, July 2004, 469–482

DOI: 10.1093/ei/cbh074

can discuss the impact that the explanatory variables have on income inequality. In the context of MLB, we attempt to shed light on the reasons why teams have greater or lesser payroll disparity. We leave the question of the effect of between-team payroll inequality on team wins and team revenues for future research.

The issue of whether to use an inequality measure that is based on a particular distribution or one that is distribution-free has been widely discussed in the income distribution literature (Silber 1999). Ryu and Slottje (1999), in advocating the use of parametric distributions, point to several benefits of estimating the Lorenz curve in this manner. These benefits include the ability to summarize thousands of observation points with a few parameters, the ability to estimate the density function at any point, an enhanced ability to construct inequality measures, and the ability to formulate possible "laws" that would otherwise not be possible to detect. However, there are problems associated with the use of a parametric Lorenz curve, such as the choice of a suitable distribution. The problem is compounded by the fact that income data are often grouped and have an open-ended highest income category, making it difficult to obtain accurate estimates. One advantage of using professional sports data is the fact that the salary is available per individual and is not grouped; consequently, an actual number is available for the highest income.

This study analyzes payroll inequality in a professional sport by team. That is, for each year we calculate a measure of inequality for each MLB team and consider the characteristic differences in within-team payroll distributions. Our study is not, however, the first to consider income inequality within professional team sports. Depken (2000) and Jewell and Molina (2004) find that MLB teams with greater wage disparity have fewer wins. Furthermore, Sommers (1998) finds a negative relationship between team success and within-team payroll inequality using National Hockey League data. However, using data from the National Basketball Association, Berri (2001) finds that an increase in payroll inequality within a team actually leads to an increase in wins. Although the direction and magnitude of the effect of payroll inequality on team performance are still debated, it is clear that it is important to determine and analyze the factors that influence payroll inequality within professional sports teams.[1]

In the context of the present study, the large Kuznets curve body of literature that has emerged in development economics is of particular interest. Kuznets (1955) finds evidence of an inverted U-shaped relationship between the level of development (usually measured by per capita income) and various measures of inequality. That is, Kuznets and others find that income inequality rises with per capita income at low-income levels and then falls as countries move from middle-income to high-income status. Various explanations for this relationship have been given, mostly involving the nature of structural change in the economy.[2] In contrast, Gary Fields (1987, 1998) suggests that a U-shaped pattern is more plausible than an inverted U-shape. In particular, Fields demonstrates that if average income in a population increases due to a steady growth in the relative number of wealthy individuals, then measures of income inequality will first decrease before eventually increasing. Because this may indeed be the situation in MLB, it will be important to consider this in our study.

With our data, we are able to test whether the relationship proposed by Kuznets or the one proposed by Fields best describes MLB. In addition, we can evaluate the possibility that both the Kuznets and the Fields effects occur in MLB. If the Kuznets effect occurs at low average salary levels and is followed by the Fields effect at higher average salary levels, then the MLB Kuznets curve will exhibit an N-shape or, more precisely, a sideways, mirrored S-shape. Conversely, if the Fields effect occurs at low average salary levels and the Kuznets effect occurs at high average salary

1. Related studies include Fort (1992) and Jewell et al. (2001), who measure the overall Gini coefficients for the entire population of a sport's athletes in a given year. These studies, however, do not calculate or analyze team Gini coefficients. MacDonald (1988) discusses the impact of talent on the distribution of earnings. Rottenberg (2000) discusses the distribution of income in the production allocation sense. In another use of the Gini coefficient in sports economics, Schmidt (2001) and Schmidt and Berri (2001) study the impact of competitive-balance inequality in MLB.

2. In the development literature, the existence of a Kuznets relationship has not been firmly established. Paukert (1973), Papenek and Kyn (1986), Tsakloglou (1988), List and Gallet (1999), and Burger (2001) are examples of studies that have found empirical and theoretical support for the inverted U-shaped Kuznets curve. Saith (1983) and Ram (1991) are among those who have found evidence against this relationship.

levels, then the MLB Kuznets curve will be sideways S-shaped.[3]

We will compare a distribution-free Gini coefficient for each team and year with a Gini calculated from a distribution selected from the Pearson family of distributions by means of an a priori selection test. We then discuss the implications of both sets of Gini coefficients, including possible reasons why within-team payroll inequality has changed over time. Employing a random effects panel-data model, we investigate the time-series and cross-sectional factors that affect the Gini coefficients and the parameters of the preselected distribution. We find that much of within-team income distribution is determined by time-related variables, with the most interesting result being that the 1994 MLB strike significantly increased the dispersion of salaries within teams. We also find that a team's market potential does not seem to affect its salary distribution, but the average age of the players on a team's roster does have a significant effect on how salaries are distributed. Finally, we find that the effects postulate by both Fields and Kuznets occur at different average salary levels in MLB.

II. METHODOLOGY

We use a nonparametric as well as a parametric approach in constructing the Gini coefficients. Once the inequality measurements are constructed, the Gini coefficient and the parameters of the underlying distribution (if applicable) are regressed on a set of team-specific data that include team performance variables as well as economic and demographic information of the metropolitan area in which the team is located. The purpose of the regression is to determine what variables have the tendency of increasing or decreasing income inequality within the team. In addition, we analyze a measure of skewness based on the parameters of the underlying distribution. In the remainder of this section, we present the main functions used in our analysis. Further derivations and estimation techniques can be found in Appendix A.

3. We note that it would be difficult to generalize our results to developing countries. Rather, this study is intended only as an application of existing Kuznets curve theory to MLB.

Nonparametric Gini Coefficients

In the nonparametric approach, we use traditional Gini coefficients based on nongrouped data, which can be computed using equation (1):

$$(1) \quad Gini = 1 - (1/N)\left\{1 + (2/N\bar{y}) \times \sum_{i=1}^{N}(N-i)y_i\right\},$$

where y_i is the ith individual's income, $\bar{y}$ is mean population income, and N is population size.

Parametric Gini Coefficients

To obtain the Gini coefficient based on a parametric distribution, we select one from the Pearson family of distributions (Kendall and Stuart 1977). One advantage of this distribution family is that most of the functional forms commonly used to analyze the distribution of income (such as the beta I, the gamma, and the beta II) belong to this family. Furthermore, this particular distribution family allows discarding certain distributions a priori by the use of the kappa criterion ($\mathcal{K}$-criterion) (Elderton and Johnson 1969). The value of $\mathcal{K}$ is constructed from the empirical moments and compared to the magnitude and sign of $\mathcal{K}$ constructed from the theoretical moments of a known distribution to determine which distributions are inappropriate for the data in question. Hirschberg et al. (1988–89) list the value of $\mathcal{K}$ for the major income distribution functions.

The results of estimating the $\mathcal{K}$-criterion for each MLB team between 1985 and 2000 show that in the majority of the cases the $\mathcal{K}$-criterion is negative.[4] As shown in Hirschberg et al. (1988–89), a negative value of $\mathcal{K}$ suggests that the beta I distribution cannot be rejected a priori.[5] Equation (2) gives the three-parameter beta I distribution:

$$(2) \quad F(u;p,q,y) = (1/B[p,q]_u)\int_{u=0}^{Y}[u^{p-1}(y-u)^{q-1}]/[y^{p+q}]_{du},$$

where $B(p,q)$ is the complete beta function with parameters p and q (Rainville 1960) and where

4. In one case, the $\mathcal{K}$-criterion could not be estimated due to insufficient observations (Texas in 1987); in another case, the $\mathcal{K}$-criterion was positive (Baltimore in 1985).

5. The beta I distribution used by Thurow (1970) is a two-parameter distribution (p, q). The properties of this distribution are presented in MacDonald (1984). We use a three-parameter distribution (p, q, y). See Appendix A.

both p and q are greater than zero. The Gini coefficient for the three-parameter beta I distribution (2) is as follows:

$$(3)\quad Gini_{beta\,I} = [\Gamma(p+q)\Gamma(p+1/2)\Gamma(q+1/2)] / [\Gamma(p+1)\Gamma(q)\Gamma(1/2)\Gamma(p+q+1/2)],$$

where Γ is the gamma function.[6] Equation (3) is estimated for each MLB team using the method of moments.

Note that the Gini coefficient in equation (3) depends only on the parameters p and q and not on the scalar parameter y. We evaluate the impact that changes in the parameters p and q have on the Gini coefficient by plotting all relevant values of $p, q \in \mathscr{R}^2$. The results of this sensitivity analysis indicate that as p increases, the Gini coefficient decreases, whereas as q increases, the Gini coefficient increases (i.e., $\partial G/\partial p < 0$ and $\partial G/\partial q > 0$). Furthermore, there is a strong dominance of the p over the q parameter. That is, large changes in the q parameter lead to small changes in the Gini coefficient, and small changes in the p parameter lead to large changes in the Gini coefficient (i.e., $\partial G/\partial_p > \partial G/\partial_q$). This observation becomes crucial when examining the results of regressing these p and q on team-specific independent variables.[7]

Finally, we evaluate skewness for the beta I distribution in equation (2). Note that as in the case of the Gini coefficient, the skewness measure given in equation (4) is only a function of p and q and not the scalar parameter y.

$$(4)\quad SK = [2(q-p)/(2+p+q)] \times \sqrt{(1+p+q)/pq}.$$

The signs of the derivatives of equation (4) with respect to p and q are $\partial SK/\partial p < 0$ and $\partial SK/\partial q > 0$. Furthermore, unlike the Gini coefficient, for equivalent changes in q and p the overall effect will be zero. That is, if $\Delta q = \Delta p$, then $\partial SK/\partial q = \partial SK/\partial p$.

III. DATA AND RESULTS

A review of MLB salary figures using 1985–2000 data provides the interesting result that the type of inequality the Blue Ribbon Panel discussed is a relatively recent phenomenon: From 1985 to 1994, the between-team Gini coefficients measuring the inequality of total payrolls among all MLB teams averaged 0.148, whereas from 1995 to 2000, that same figure was 0.205. Although this payroll inequality between teams is certainly an interesting and important issue, there are other matters of equal import not addressed in the panel's report. Our focus is on payroll inequality *within* teams. Between-team payroll inequality affects MLB in that reduced parity between teams may result in a loss of interest on the part of fans of small-market teams, resulting in lower attendance and a widening of the payroll gap. Changes in within-team payroll inequality will have different and equally important effects. For example, a more equal distribution of payroll within a team may promote team cohesiveness, translating into team success. Alternatively, a less equal payroll distribution may signal the presence of a few high-quality players that increase the probability of a successful season.[8]

Table 1 lists descriptive statistics for the entire sample. Individual player salary data used in this study are available from a number of Internet sources.[9] The first two variables presented in this table correspond to two

6. MacDonald (1984) presents the Gini coefficient for the two-parameter beta I distribution. In Appendix A, we show it to be the same as the three-parameter beta I shown in equation (2).

7. This method of analyzing the sensitivity of a Gini coefficient to its parameters has been used by Parker (1999) for the beta II distribution. Following Parker, we use Mathematica (Wolfram 1999) to plot the Gini coefficient. The Mathematica program used for this analysis is available on request from the authors.

8. See Depken (2000) for a detailed discussion of the potential effects of within-team salary inequality. Also, see Ehrenberg and Bognanno (1990a, 1990b) for a discussion of salary inequality in the context of tournament theory and its application to an individual sport, professional golf.

9. We rely on the collections of Rod Fort (http://users. pullman.com/rodfort) and Sean Lahman (http://baseball1.com) as well as the archives of *USA Today* (http://usatoday.com). Whenever possible, we cross-checked figures from all of these sources. In addition, we cleaned the data so that the numbers reflect opening day salaries in most cases. 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. However, as is the case with some of the data stored on the Internet, there may be some errors in the data.

TABLE 1
Descriptive Statistics ($n = 433$)

Variable	Mean	SD
gini1	0.537	0.088
gini2[a]	0.565	0.100
trend	7.735	4.641
strike	0.397	0.490
real per capita salary/1 mil	0.882	0.447
age	28.556	1.181
wins	80.352	10.949
all-stars	2.185	1.363
national league	0.489	0.500
expansion team	0.050	0.219
population/1 mil	5.557	4.836
median household income/1000	35.390	4.412

[a]Sample size is 407.

different Gini coefficients. The first, *gini1*, is the Gini coefficient estimated nonparametrically as in equation (1). The second, *gini2*, is the Gini coefficient estimated parametrically based on the beta I distribution, calculated using equation (3). It is important to note that the number of Gini coefficients estimated under the two scenarios (nonparametric and parametric) is not the same. There are 20 teams with 26 years of data (416 observations), 2 teams with 8 years (16), and 2 teams with 3 years (6), for a total of 438 observations. However, in five instances the nonparametric Gini coefficients (*gini1*) could not be obtained because the data set did not contain information on enough players. In the case of the parametric Gini (*gini2*), the $\mathscr{K}$-criterion resulted in a negative number 436 times. However, in only 407 cases did we obtain parameters (p and q) that had the requisite positive sign despite the fact that the $\mathscr{K}$-criterion is negative. Nonetheless, it is clear that for this data set the beta I distribution is the least likely distribution of the Pearson family to be discarded.

The other variables included in our analysis can be separated into three categories. The first category contains time-trend variables. The two remaining categories contain team-specific cross-sectional variables and variables measuring the economic and demographic conditions of the markets in which teams are located. There are four time variables: a trend variable (*trend*), its square (*trend*^{2}) and cube (*trend*^{3}), and a dummy variable that controls for the effects of the 1994 strike (*strike*). *Strike* equals 1 if the year is 1995 or later and 0 otherwise; it is designed to ascertain whether the work stoppage of 1994 has had any impact on within-team inequality.

Our team-specific measures include per capita salary (in millions of constant 1990 dollars) along with its square and cube (to test for the Kuznets and the Fields effects), the number of regular season wins (*wins*), and the number of All-Star players on the team (*all-stars*). The average age of a team's players (*age*) is included to control for MLB's restraints on mobility and earnings power early in a player's career. Because MLB players with fewer than six years of experience have limited bargaining rights, players are generally paid less than their marginal revenue products in their first six years while they are ineligible for free agency. After free agency, players' salaries rise considerably (Blass 1992; Krautmann 1999). Increases in *age* should be associated with decreases in payroll inequality, because the older a team's players, the more of them are eligible for free agency and the tighter the salary distribution should be.

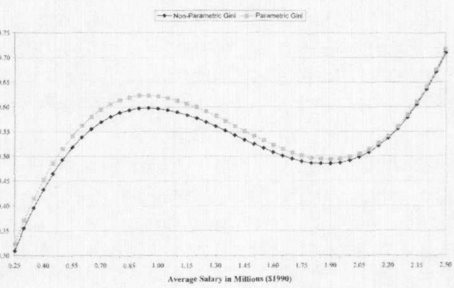
We include a dummy variable to control for the league in which the team played (*national league*), because there may be different institutional forces at work in the National League (NL) and the American League (AL). For instance, the AL uses a designated hitter (DH) instead of having the pitcher take his turn at bat, as is the case in the NL. For a given average salary, an AL team should have a different distribution of salaries than an NL team because the AL team must invest in a DH. Also, the level of competition is likely to be different in the AL and the NL. In a more competitive league, teams wishing to compete may need to invest in higher-priced talent, thus impacting within-team salary distribution. We include another dummy variable to control for differences between existing and expansion teams (*expansion team*). Expansion teams may operate under different cost structures or have different expectations for team success than existing teams. The market-specific variables include local metropolitan statistical area (MSA) population and median household income. Team-specific performance measures are collected from the Total Baseball Web site (http://totalbaseball.com), an online version of the official encyclopedia of MLB. MSA population and income measures are for 1990 from the U.S. Census Web site (http://census.gov).

TABLE 2
Pooled Regression Results: Kuznets Curves

	Nonparametric Gini (*gini1*) $n = 433$		Parametric Gini (*gini2*) $n = 407$	
Variable	**Coefficient**	**SE**	**Coefficient**	**SE**
real per capita salary/1 mil	1.518*	0.027	1.589*	0.032
(real per capital salary/1 mil)^2	−1.207*	0.040	−1.265*	0.047
(real per capital salary/1 mil)^3	0.285*	0.014	0.298*	0.016
Adjusted R-squared	0.9745		0.9697	

*Significant at 1%.

FIGURE 1
Simple Kuznets Curve



Estimating a Simple Kuznets Curve for MLB

Table 1 shows that for most of the time period, computing payroll inequality based on the parameters of the beta I distribution leads to larger Gini coefficients than for those computed using the nonparametric method, with *gini2* being on average about 5% more than *gini1*.[10] We begin by discussing the results from a pooled-data regression of the two Gini coefficients on average salary figures as reported in Table 2. This regression allows us to analyze a Kuznets curve for MLB. From the estimates presented in Table 2, we predict the Gini coefficients and graph them for different salaries in Figure 1.[11] Note that *gini2* is consistently above *gini1*, although the overall pattern with respect to salary levels is the same for both Gini coefficients.

Starting with a low average salary level, we observe the effect postulated by Kuznets followed by the effect postulated by Fields. That is, the relationship between the Gini coefficient and average salary (the Kuznets curve) is sideways, mirrored S-shaped. Based on the results in Table 2, payroll inequality within teams seems to increase as average salary increases to approximately $1 million. Payroll inequality then decreases slightly as average salary increases from $1 million to approximately $2 million. As average salary increases past $2 million, payroll inequity within MLB teams rises. Thus, for teams with low payrolls, any increase in average salary will tend to increase payroll inequality, whereas teams with mid-range payrolls will tend to have decreased payroll inequality. However, high-payroll teams will see a fairly dramatic increase in inequality with increases in average salary. In addition, a visual inspection of Figure 1 lends support to the hypothesis that within-team payroll inequality generally increases from the lowest to the highest paying teams.

The sideways, mirrored S-shaped MLB Kuznets curve can be explained by considering the potential effect on a team's payroll distribution from adding a star player. If a team signs such a player, we expect that its average salary will increase. Teams with low total payrolls (or low average salary levels) may have relatively equal within-team payroll distributions, because they may be unable to afford even one high-priced star player. For a low-payroll team, adding the star player surely means paying that player much more than the current average salary. Hence, payroll inequality increases. For a mid-range-payroll team, adding the star player may cause a decrease in inequality, because the team may already have one or two star players on their roster. The wealthiest MLB teams may be able

10. A complete listing of *gini1* and *gini2* by team and year is given in Appendix Table B-1.
11. We do not include a constant term because the Gini coefficient should be zero at a salary of $0.

TABLE 3
Panel Data Estimates: Gini Coefficients

	Nonparametric Gini (*gini1*) $n = 433$		Parametric Gini (*gini2*) $n = 407$	
Variable	**Coefficient**	**SE**	**Coefficient**	**SE**
constant	0.7267*	0.0846	0.9972*	0.0926
trend	0.0538*	0.0059	0.0491*	0.0064
$trend^2$	−0.0061*	0.0010	−0.0038*	0.0011
$trend^3$	0.0002*	0.0000	0.0001	0.0000
strike	0.1344*	0.0145	0.1126*	0.0153
real per capita salary/1 mil	0.5560*	0.0813	0.2495*	0.0974
$(real\ per\ capital\ salary/1\ mil)^2$	−0.4379*	0.0700	−0.2568*	0.0815
$(real\ per\ capital\ salary/1\ mil)^3$	0.1045*	0.0184	0.0677*	0.0209
age	−0.0178*	0.0030	−0.0220*	0.0031
wins	−0.0003	0.0003	−0.0006**	0.0003
all-stars	−0.0001	0.0024	0.0018	0.0025
national league	−0.0040	0.0058	−0.0045	0.0060
expansion team	0.0322*	0.0130	0.0350*	0.0135
population/1 mil	−0.0005	0.0006	0.0001	0.0006
median household income/1000	0.0004	0.0007	0.0002	0.0007
Chi square (14)	711.84*		913.65*	

*Significant at 1%.
**Significant at 5%.

to afford a number of expensive players, so these teams are expected to have the highest average salary levels. If a high-payroll team is to add another player and increase average salary, then said player would have to be an extremely highly paid star. Signing such a player may increase payroll inequality rather dramatically.

More Complete Estimates of Payroll Inequality in MLB

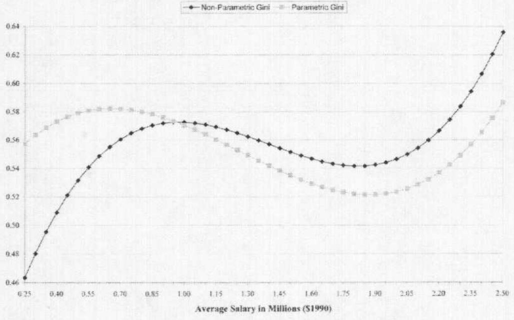
Table 3 reports the estimates from panel data regressions of Gini coefficients on the full set of determinants of payroll inequality. Note that the results using *gini1* and those using *gini2* are remarkably similar. We find a significant relationship between payroll inequality and the time trend, even after controlling for *strike* as a shift parameter. The implications of our results with respect to the MLB work stop page are especially interesting. The strike of 1994 increased within-team payroll inequality noticeably: Holding other factors constant, the Gini coefficient increased by between 0.11 (using *gini2*) and 0.13 (using *gini1*) from 1994 to 1995, which is an increase of approximately 20% to 25%. If, as some have stated (Staudohar 1997), the players were the "winners" of the strike, then the players who have reaped the greatest rewards are those who are the highest paid on each team.[12]

Table 3 also indicates that both *gini1* and *gini2* continue to exhibit a sideways, mirrored S-shaped relationship with average salary, similar to the results in Table 2. As expected, average player age is negatively correlated with payroll inequality. This result suggests that labor issues associated with player mobility and market power significantly affect within-team payroll inequality; this implication becomes even more obvious when one considers the coefficient on *strike* discussed. The number of wins decreases payroll inequality, indicating that better teams are those with less payroll inequality; however, the effect is small and insignificant when using *gini1*.[13]

12. We employ a random-effects, panel data estimator using the XTREG command in STATA (StataCorp 1999). A Hausman test (available from the authors) indicates that a random-effects model is more appropriate than a fixed-effects model. We include a constant term in these regressions because some included measures are dummy variables.

13. Due to the potential endogeneity of *wins*, we also estimate the models presented in this article without wins. These results show no significant differences from those presented herein and are available from the authors.

FIGURE 2
Kuznets Curve for Average Team



Expansion teams seem to have more payroll inequality than existing teams: Such teams have Gini coefficients about 0.03 points higher. This may indicate that expansion teams are impatient to be successful and have been willing to pay for that success by signing a few high-priced star players. Perhaps most interesting of all are the coefficients on market size. Market size, measured as population or income, appears to have no significant effect on within-team payroll inequality. Although MLB may be concerned about the gap between the payrolls of large- and small-market teams, we find no evidence that the small-market/large-market distinction affects how a team distributes salaries among its players.

To further explore the Kuznets curve relationship, we predict *gini1* and *gini2* from Table 3, and graph these predictions at different average salary levels for an "average team."[14] The predicted Kuznets curves are presented in Figure 2. A visual inspection of the predicted Kuznets curves reveals some interesting facts. First, as expected from the numerical results, the curves are similarly shaped, both having the now-familiar sideways, mirrored S-shape. That is, controlling for time effects and other variables, we still observe both the Kuznets and Fields effects in MLB. Second, the two Kuznets curves track each other, with the largest differences occurring at low average salary levels. It appears that there is a small difference in the general predicted trend: Using the nonparametric Gini, there seems to be a slight upward trend in payroll inequality when moving from lowest to highest salary; using the parametric Gini, there seems to be no such trend from lowest to highest salary. Clearly, the results from the two estimations are different, but for the most part the differences are in terms of intercept shifts, not in the substantive relationship between average salary and payroll inequality.

Third, comparing Figure 2 to Figure 1 shows another intriguing result: There seems to be less of an upward trend in payroll inequality from low to high salaries in Figure 2 than was the case in Figure 1. The predictions shown in Figure 2 do not include the effect of time, because they show Kuznets curves for a representative team in a single year. However, time is a factor in Figure 2 because the data are pooled. Therefore, we might conclude that much of the upward trend is due to structural changes over time or due to changes in time-sensitive variables not included in our estimates, although it is possible that some other mechanism is at work.

The Determinants of the Beta I Parameters

Having established that we do not lose much information when using the parametric rather than the nonparametric Gini coefficients, we now turn to an analysis of the parameters of the beta I distribution. Table 4 reports results from panel data regressions of p and q on the same explanatory variables used in Table 3. The regressions provide further insight into the reasons for the observed changes in equality. As noted in section II, the Gini coefficient is inversely related to the parameter p and positively related to the parameter q. The first interesting observation to be made from Table 4 is the fact that the only variables that significantly affect p are *trend*, *trend*^{2}, *trend*^{3}, *strike*, and *age*, most of which are indicators of time.[15] As previously noted, p is the more dominant parameter. Therefore, it appears that time (or unobserved variables correlated with time) has had the most significant impact on payroll inequality

14. This average team has the following characteristics (as suggested by the sample averages in Table 1): the year is 1990, and the average player age is 28.5 years old; the team has 80 wins, has two All-Stars, and plays in the American League; the team is located in an MSA with a population of 5.6 million and a median household income of $35,390. The predictions will change somewhat with a change in any of these characteristics; however, the relative shapes of the predicted Kuznets curves will be the same and any difference will result from an intercept shift.

15. We find no evidence that there is a time trend in age for the league as a whole or for individual teams.

TABLE 4
Panel Data Estimates: Parameters of Beta I Distribution

	p $n = 407$		q $n = 407$	
Variable	**Coefficient**	**SE**	**Coefficient**	**SE**
constant	−0.1265	0.4031	35.0492***	10.7267
trend	−0.2915***	0.0278	−2.1493***	0.7994
trend^2	0.0324***	0.0048	0.3340**	0.1389
trend^3	−0.0010***	0.0002	−0.0127**	0.0058
strike	−0.3100***	0.0664	−1.4161	1.8887
real per capita salary/1 mil	−0.4995	0.4239	−32.8757***	11.9238
(real per capital salary/1 mil)^2	0.3148	0.3545	19.9295**	9.9920
(real per capital salary/1 mil)^3	−0.0618	0.0909	−3.7892	2.5667
age	0.0496***	0.0137	−0.6037*	0.3655
wins	0.0012	0.0014	0.0152	0.0382
all-stars	−0.0098	0.0109	0.0916	0.3016
national league	0.0251	0.0261	0.5998	0.5698
expansion team	−0.0569	0.0589	1.7824	1.4945
population/1 mil	−0.0009	0.0027	0.0670	0.0580
median household income/1000	0.0036	0.0032	0.0300	0.0685
Chi square (14)	482.10***		461.26***	

*Significant at 10%.
**Significant at 5%.
***Significant at 1%.

in MLB. This gives support to the tentative conclusion reached based on the time pattern of Gini coefficients in Figures 1 and 2. Furthermore, the time-motivated increase in inequality was accelerated by the strike in 1994. It is worthy of note that the other variables representing cross-sectional information (e.g., average salary levels) have no impact on p. In particular, this implies that the shape of the MLB Kuznets curve cannot be attributed to the dominant parameter p.

Turning our attention to estimates using the parameter q, it is interesting to note that the *trend* measures affect q but *strike* does not. Note that the coefficient signs on *trend*, *trend*^{2}, and *trend*^{3} are the same using p and q, and recall that p and q have different impacts on the parametric Gini. Consequently, the *trend* coefficients imply that over time there have been changes in MLB (not observed in other included variables) that have increased inequality, while at the same time there have been changes that have decreased inequality. That is, the coefficients on the *trend* variables are actually measuring different impacts of time on the distribution of income. Also interesting is the fact that changes in average salary do impact q. Thus, it appears that the Kuznets curve relationship between the beta I Gini coefficient and average salary comes primarily from the q parameter, which is less dominant than p. In addition, it appears that q varies with age and enhances the effect of age on payroll inequality observed when using p.

A Brief Discussion of Skewness

As indicated in equation (4), the skewness of the beta I distribution can be presented in terms of p and q. Therefore, using a parametric income inequality measure allows for more detailed analysis of the entire salary distribution than if one were to use a distribution-free measure. Table 5 presents the skewness based on the annual averages of p and q. Recall that a positive (negative) skewness measure indicates the function is skewed to the right (left). There seems to be a general upward trend in skewness from 1985 to 1990 and no consistent pattern after that. Note that the highest measures of skewness occurred in 1995 and 1996, directly after the 1994 strike, giving further evidence that labor strife affects the salary distribution of MLB and that the highest-paid players benefited most from the 1994 strike.

TABLE 5
Average Skewness (SK) for the Beta I Distribution

Year	*SK*
1985	−1.440
1986	0.176
1987	0.354
1988	0.375
1989	0.848
1990	1.088
1991	0.647
1992	0.546
1993	1.121
1994	0.651
1995	2.625
1996	2.025
1997	1.560
1998	0.931
1999	1.430
2000	1.167

IV. CONCLUSION

This study analyzes income distribution within teams in MLB. Specifically, we use a technique first suggested by Thurow (1970), extending it to test for the demographic and economic aspects that influence MLB income distribution. Our findings will be of interest to sports economists in general and to those interested in MLB in particular. We find, for example, that within-team payroll inequality has generally increased since 1985. It is also noteworthy that the strike of 1994 had the effect of dramatically increasing inequality. In addition, we find that the average age of players on a team has a significant effect on payroll inequality; specifically, teams with older players have tighter salary distributions. These findings raise a number of questions for future research. For instance, how will future labor strife and inevitable institutional changes affect income distributions in professional sports?

We also show that employing parametric measures of income inequality in MLB allows for a more detailed analysis of the determinants of the distribution of income than simply using nonparametric measures. This finding could also be of interest to development and labor economists who are concerned about the ongoing discussion of the value of parametric versus nonparametric measures. Although our results do not suggest which approach is better, we do give evidence of the relative usefulness of parametric income inequality measures as compared to nonparametric measures. Specifically, analysis of a parametric Gini coefficient allows the researcher to regress the parameters of the distribution on independent variables, providing greater insight into the determinants of income distribution. In our sample of MLB teams, the dominant parameter, p, is mainly affected by time-trend variables; thus, we can infer that time is the strongest determinant of changes in payroll inequality within MLB teams. Salary measures seem to impact a team's payroll distribution only through changes in q, implying that the MLB Kuznets curve is a result of changes in q. Furthermore, we find evidence for the effects proposed by both Kuznets and Fields with respect to income inequality and average salaries. Although our results are not easily generalized to other industries or to country-level analysis, it is clear that both effects need not be mutually exclusive.

APPENDIX A

$\mathcal{K}$-Criterion Test

The test begins by computing the value of $\mathcal{K}$ using the empirical moments. The value of $\mathcal{K}$ constructed from the empirical moments is then compared to the magnitude and sign of $\mathcal{K}$ constructed from the theoretical moments of a known distribution to determine which distributions are inappropriate for the data in question. Hirschberg et al. (1988–89) list the value of $\mathcal{K}$ for the major income distribution functions. The moments about the mean are the following (Kendall and Stuart 1997):

$$\text{(A-1a)} \qquad \mu_2 = \mu_2' - (\mu_1')^2,$$

$$\text{(A-1b)} \qquad \mu_3 = \mu_3' - 3\mu_1'\mu_2' + 2(\mu_1')^3, \quad \text{and}$$

$$\text{(A-1c)} \qquad \mu_4 = \mu_4' - 4\mu_1'\mu_3' + 6(\mu_1')^2\mu_2' - 3(\mu_1')^4,$$

where μ_j is the jth empirical raw moment of the data under observation. The $\mathcal{K}$-criterion is presented in equation (A-2) (Elderton and Johnston 1969):

$$\text{(A-2)} \qquad \kappa = [\beta_1(\beta_2 + 3)^2]/[4(4\beta_2 - 3\beta_1) \times (2\beta_2 - 3\beta_1 - 6)],$$

where

$$\text{(A-3a)} \qquad \beta_1 = \mu_3^2/\mu_2^3, \quad \text{and}$$

$$\text{(A-3b)} \qquad \beta_2 = \mu_4/\mu_2^2.$$

The distribution that best fits the $\mathscr{K}$-criterion for our MLB data is the beta I distribution. We use a flexible three-parameter distribution function,

$$\text{(A-4)}\quad F(u;p,q,y) = (1/B[p,q])\int_{u=0}^{Y}[u^{p-1}(y-u)^{q-1}]/y^{p+q}\,du,$$

where $B(p,q)$ is the complete beta function with parameters $p>0$ and $q>0$ (Rainville 1960). The parameters of this distribution are estimated using the method of moments. The raw moments of this distribution are

$$\text{(A-5)}\quad \mu'_j = [y^j B(p+q,j)]/B(p,j),$$

where j indicates the relevant moment.

The beta function is related to the gamma function in the following manner (Rainville 1960):

$$\text{(A-6)}\quad B(\alpha,\beta) = \Gamma(\alpha)\Gamma(\beta)/\Gamma(\alpha+\beta).$$

Therefore, equation (A-5) can be rewritten as follows:

$$\text{(A-7)}\quad \mu'_j = [y^j(\Gamma[p+q]/\Gamma(p+q+j))] /[\Gamma(p)/\Gamma(p+j)].$$

Furthermore, recalling the factorial function,

$$\text{(A-8)}\quad (\alpha)_n = \prod_{k=1}^{n}(\alpha+k-1),$$

and that the factorial function and the gamma function are related (Rainville 1960),

$$\text{(A-9)}\quad (\alpha)_n = [\Gamma(\alpha+n)/\Gamma(\alpha)],$$

it is clear that (A-5) can be rewritten as follows:

$$\text{(A-10)}\quad \mu'_j = y^j(p)_j/(p+q)_j.$$

The first three raw moments of this distribution are

$$\text{(A-11a)}\quad \mu'_1 = yp/(p+q);$$

$$\text{(A-11b)}\quad \mu'_2 = [y^2p(p+1)] /[(p+q)(p+q+1)]; \quad \text{and}$$

$$\text{(A-11c)}\quad \mu'_3 = [y^3p(p+1)(p+2)]/[(p+q) \times (p+q+1)(p+q+2)].$$

The parameters p, q, and y are estimated by solving the system of equations (A-11a–c) for each team and year. In addition, with the use of equations (A-1a–c) and (A-11a–c), it is easy to show that for the three parameter beta I used here, the ratios in (A-3a–b) do not contain the scalar parameter y. Therefore, the $\mathscr{K}$-value is the same as that from Thurow's (1970) standard two-parameter beta I.

Gini Coefficient

The Gini coefficient for the beta I distribution function is shown to be (A-12) in MacDonald (1984).

$$\text{(A-12)}\quad G = [B(p+q,1/2)B(p+1/2,1/2)] /B(q,1/2)\pi$$

As Rainville (1960) shows:

$$\text{(A-13)}\quad \sqrt{\pi} = \Gamma(1/2).$$

With the use of (A-6) and (A-13), (A-12) can be written as

$$\text{(A-14)}\quad G_{Beta\ I} = [\Gamma(p+q)\Gamma(p+1/2)\Gamma(q+1/2)] /[\Gamma(p+1)\Gamma(q)\Gamma(1/2)\Gamma(p+q+1/2)].$$

Skewness

The square root of equation (A-3a) is a measure of skewness (Kendall and Stuart 1977). Using equations (A-1a–c) and (A-11a–b), the skewness can be expressed as the following.

$$\text{(A15-a)}\quad SK = \mu_3/\mu_2^{3/2}$$

$$\text{(A15-b)}\quad SK = [2(q-p)/(2+p+q)]\sqrt{(1+p+q)/pq}$$

The impact of changes in p and q on SK are the following:

$$\text{(A-16a)}\quad \partial SK/\partial q = (p+q)(3[p+q+pq]+p^2+2) /[pq^2\sqrt{(1+p+q/pq)} \times (2+q+p)^2] > 0, \quad \text{and}$$

$$\text{(A-16b)}\quad \partial SK/\partial p = -(p+q)(3[p+q+pq]+q^2+2) /[p^2q\sqrt{(1+p+q)/pq} \times (2+q+p)^2] < 0.$$

Furthermore, if we compare the value of these two derivates, then for equivalent changes in q and p, the overall effect on SK will be zero.

$$\text{(A-17a)}\quad |\partial SK/\partial q| - |\partial SK/\partial p| = [(p^2-q^2)([p+q]^2+3[p+q]+2)] /[p^2q^2\sqrt{(1+p+q)/pq}(2+p+q)^2]$$

If $\Delta p = \Delta q$, then

$$\text{(A-17b)}\quad |\partial SK/\partial q| - |\partial SK/\partial p| = 0.$$

APPENDIX TABLE B-1
Gini Coefficients by Team and Year

		1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	*Average*	*Difference*
Anaheim	*gini1*	0.340	0.440	0.441	0.475	0.435	0.493	0.505	0.552	0.647	0.570	0.684	0.630	0.561	0.572	0.588	0.642	*0.536*	*0.019*
	gini2	0.343	0.424	0.448	0.487	0.441	0.502	0.514	0.561	0.686	0.595	0.736	0.682	0.584	0.596	0.621	0.664	*0.555*	
Arizona**	*gini1*														0.649	0.575	0.562	*0.595*	*0.031*
	gini2														0.715	0.595	0.571	*0.627*	
Atlanta	*gini1*	0.298	0.437	0.454	0.526	0.550	0.560	0.461	0.490	0.501	0.521	0.620	0.650	0.623	0.645	0.564	0.574	*0.530*	*0.016*
	gini2	0.308	0.445	0.461	0.542	0.588	0.601	0.469	0.502	0.516	0.527	0.637	0.672	0.640	0.664	0.572	0.584	*0.546*	
Baltimore	*gini1*	0.297	0.388	0.524	0.555	0.624	0.427	0.554	0.522	0.586	0.555	0.884	0.605	0.545	0.460	0.494	0.547	*0.535*	*0.025*
	gini2	****	0.389	0.531	0.567	0.683	****	0.607	0.536	0.609	0.570	0.666	0.619	0.554	0.468	0.497	0.550	*0.560*	
Boston	*gini1*	0.368	0.462	***	0.550	0.514	0.537	0.471	0.491	0.554	0.534	0.646	0.616	0.576	0.567	0.539	0.533	*0.531*	*0.011*
	gini2	0.373	0.452	***	0.560	0.526	0.552	0.479	0.500	0.571	0.544	0.694	0.636	0.588	0.576	0.546	0.527	*0.542*	
Chicago (NL)	*gini1*	0.273	0.375	0.456	0.563	0.578	0.559	0.555	0.574	0.577	0.564	0.676	0.623	0.602	0.570	0.401	0.591	*0.533*	*0.032*
	gini2	0.275	0.388	0.469	0.577	0.623	0.614	0.574	0.603	0.598	0.579	0.743	0.653	0.622	0.579	0.539	0.602	*0.565*	
Chicago (AL)	*gini1*	0.396	0.501	***	0.487	0.483	0.512	0.575	0.590	0.505	0.491	0.608	0.626	0.666	0.708	0.516	0.646	*0.554*	*0.041*
	gini2	0.401	0.514	***	0.509	0.497	****	0.606	0.617	0.515	0.496	0.618	0.639	0.692	0.761	0.748	0.723	*0.595*	
Cincinnati	*gini1*	0.444	0.492	0.490	0.455	0.524	0.533	0.520	0.514	0.541	0.505	0.608	0.631	0.634	0.603	0.593	0.570	*0.541*	*0.026*
	gini2	0.456	0.492	0.509	0.466	0.545	0.573	0.531	0.520	0.553	0.554	0.619	0.667	0.661	0.687	0.646	0.602	*0.567*	
Cleveland	*gini1*	0.318	0.473	0.473	0.467	0.485	0.484	0.564	0.341	0.429	0.493	0.579	0.567	0.542	0.482	0.558	0.539	*0.487*	*0.036*
	gini2	****	0.489	0.483	0.484	****	0.501	0.586	****	0.437	0.501	0.594	0.577	0.547	0.486	0.570	0.549	*0.523*	
Colorado*	*gini1*									0.409	0.575	0.642	0.628	0.622	0.567	0.535	0.542	*0.565*	*0.028*
	gini2									0.433	0.607	0.674	0.654	0.643	0.586	0.554	****	*0.593*	
Detroit	*gini1*	0.308	0.400	0.425	0.443	0.504	0.538	0.401	0.597	0.549	0.432	0.699	0.717	0.548	0.491	0.542	0.536	*0.508*	*0.019*
	gini2	0.313	0.407	0.432	0.449	0.513	0.560	0.409	0.617	0.565	0.437	0.736	0.840	****	0.517	0.561	0.546	*0.527*	
Florida*	*gini1*									0.622	0.634	0.684	0.639	0.613	0.728	0.609	0.605	*0.642*	*0.081*
	gini2									0.676	0.693	0.773	0.670	0.632	0.796	0.755	0.789	*0.723*	
Houston	*gini1*	0.330	0.398	0.407	0.426	0.431	0.477	0.590	0.453	0.575	0.565	0.695	0.649	0.631	0.611	0.522	0.586	*0.522*	*0.024*
	gini2	0.335	0.402	0.418	0.433	0.439	0.488	0.641	0.469	0.597	0.587	0.747	0.700	0.684	0.649	0.532	0.614	*0.546*	
Kansas City	*gini1*	0.374	0.445	0.543	0.494	0.508	0.522	0.520	0.544	0.532	0.508	0.691	0.629	0.613	0.602	0.593	0.532	*0.541*	*0.025*
	gini2	0.379	0.449	0.555	0.500	0.524	0.534	0.527	0.563	0.542	0.513	0.773	0.690	0.643	0.630	0.655	0.573	*0.566*	
Los Angeles	*gini1*	0.361	0.457	0.493	0.490	0.504	0.525	0.496	0.468	0.557	0.491	0.660	0.588	0.573	0.601	0.535	0.581	*0.524*	*0.012*
	gini2	0.367	0.460	0.503	0.503	0.509	0.541	0.504	0.472	0.569	0.504	0.691	0.609	0.590	0.622	0.543	0.590	*0.536*	
Milwaukee	*gini1*	0.301	0.508	0.544	0.523	0.560	0.586	0.423	0.543	0.587	0.559	0.635	0.631	0.599	0.549	0.566	0.587	*0.544*	*0.031*
	gini2	0.307	0.526	0.580	0.547	0.588	0.630	0.512	0.556	0.609	0.584	0.723	****	0.666	0.572	0.582	0.635	*0.574*	

Minnesota	***gini1***	0.362	0.478	***	0.496	0.590	0.549	0.471	0.556	0.599	0.582	0.706	0.706	0.657	0.518	0.537	0.497	*0.554*	*0.034*
	gini2	0.365	0.487	***	0.506	0.620	****	0.483	0.575	0.626	0.596	0.767	0.792	0.705	0.530	0.584	****	*0.587*	
Montreal	***gini1***	0.351	0.548	0.531	0.485	0.493	0.527	0.613	0.599	0.630	0.637	0.541	0.607	0.573	0.407	0.502	0.594	*0.540*	*0.054*
	gini2	0.354	0.571	****	0.497	0.500	0.547	0.662	0.652	0.714	0.687	****	0.680	0.631	****	0.574	0.646	*0.594*	
New York (NL)	***gini1***	0.477	0.536	0.527	0.493	0.547	0.522	0.461	0.536	0.574	0.637	0.697	0.621	0.646	0.533	0.484	0.506	*0.550*	*0.019*
	gini2	0.512	0.523	0.538	0.499	0.564	0.543	0.468	0.544	0.585	0.665	0.767	0.663	0.681	0.545	0.491	0.509	*0.569*	
New York (AL)	***gini1***	0.325	0.407	0.527	0.438	0.557	0.488	0.471	0.551	0.559	0.497	0.600	0.574	0.529	0.487	0.515	0.594	*0.508*	*0.010*
	gini2	0.333	0.415	0.546	0.448	0.571	0.496	0.475	0.560	0.570	0.502	0.613	0.583	0.542	0.496	0.520	0.605	*0.517*	
Oakland	***gini1***	0.366	0.537	0.516	0.427	0.408	0.500	0.424	0.558	0.574	0.552	0.698	0.701	0.671	0.578	0.550	0.580	*0.540*	*0.031*
	gini2	0.369	0.560	0.527	0.431	0.412	0.513	0.435	0.568	0.594	0.568	0.738	0.817	0.817	****	0.597	0.616	*0.571*	
Philadelphia	***gini1***	0.432	0.550	0.531	0.472	0.512	0.506	0.524	0.570	0.522	0.454	0.687	0.699	0.669	0.609	0.588	0.559	*0.555*	*0.039*
	gini2	****	****	0.543	0.481	0.534	0.532	0.541	0.599	0.537	0.461	0.733	0.762	0.725	0.644	0.651	0.581	*0.595*	
Pittsburgh	***gini1***	0.360	0.568	0.489	0.401	0.425	0.432	0.498	0.593	0.595	0.617	0.626	0.636	0.412	0.451	0.440	0.524	*0.504*	*0.053*
	gini2	0.363	0.592	0.519	****	****	0.440	0.517	0.609	0.617	0.662	0.691	0.681	****	****	0.455	0.544	*0.558*	
San Diego	***gini1***	0.433	0.458	0.499	0.506	0.508	0.512	0.566	0.575	0.655	0.620	0.677	0.583	0.528	0.509	0.546	0.606	*0.549*	*0.025*
	gini2	0.447	0.465	0.508	0.527	0.517	0.525	0.587	0.592	0.696	0.691	0.741	0.611	0.551	0.525	0.557	0.637	*0.574*	
San Francisco	***gini1***	0.345	0.386	0.424	0.312	0.399	0.530	0.529	0.517	0.586	0.498	0.692	0.705	0.590	0.522	0.562	0.602	*0.513*	*0.010*
	gini2	0.347	0.398	0.431	0.313	0.404	0.548	0.538	0.523	0.599	0.509	0.739	0.750	****	****	0.589	0.619	*0.522*	
Seattle	***gini1***	0.319	0.365	***	0.520	0.500	0.469	0.441	0.556	0.546	0.615	0.680	0.677	0.640	0.589	0.525	0.522	*0.531*	*0.037*
	gini2	****	0.372	***	0.562	0.514	0.492	0.457	0.572	0.556	0.651	0.725	0.713	0.670	0.603	0.529	0.529	*0.568*	
St. Louis	***gini1***	0.453	0.545	0.579	0.536	0.516	0.556	0.544	0.510	0.566	0.552	0.605	0.578	0.607	0.577	0.586	0.550	*0.554*	*0.019*
	gini2	0.464	0.570	0.603	0.548	0.523	0.578	0.564	0.524	0.597	0.565	0.627	0.594	0.631	0.588	0.612	0.569	*0.572*	
Tampa Bay**	***gini1***														0.644	0.617	0.618	*0.626*	*0.045*
	gini2														0.713	0.659	0.642	*0.671*	
Texas	***gini1***	0.303	0.634	***	0.412	0.535	0.536	0.548	0.640	0.639	0.574	0.659	0.606	0.661	0.548	0.497	0.552	*0.556*	*0.028*
	gini2	0.306	****	***	****	0.559	0.576	0.569	0.672	0.668	0.602	0.691	0.633	0.694	0.558	0.503	0.560	*0.584*	
Toronto	***gini1***	0.335	0.426	0.481	0.505	0.545	0.469	0.470	0.519	0.553	0.543	0.692	0.689	0.618	0.539	0.553	0.601	*0.533*	*0.018*
	gini2	0.339	0.432	0.488	0.514	0.563	0.483	0.486	0.525	0.562	0.562	0.720	0.746	0.639	0.546	0.570	0.643	*0.551*	
Average	***gini1***	*0.357*	*0.470*	*0.493*	*0.479*	*0.509*	*0.513*	*0.508*	*0.537*	*0.563*	*0.549*	*0.663*	*0.636*	*0.598*	*0.564*	*0.541*	*0.569*	*0.534*	*0.026*
	gini2	*0.366*	*0.468*	*0.505*	*0.498*	*0.532*	*0.538*	*0.528*	*0.561*	*0.586*	*0.572*	*0.703*	*0.679*	*0.641*	*0.602*	*0.580*	*0.601*	*0.560*	

*Expansion team in 1993.
**Expansion team in 1998.
***Observation missing due to limited sample size (less than one-half opening-day roster).
****Observation missing due to misfit of beta I distribution.

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