Does Salary Inequality Affect Team Success? Evidence from Major League Baseball

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I. Introduction

The New York Yankees Hall of Fame catcher Yogi Berra once stated, “A nickel ain’t worth a dime anymore.” This is one of his classic Yogi-isms, funny but also a statement on inflation. It is a reminder that the value of money continues to change over time and it impacts how firms choose to allocate it. This is especially true in Major League Baseball (MLB), where salary dynamics have reflected broader economic trends, including rising payrolls and widening pay gaps among players. Rising revenues and evolving labor markets have produced substantial disparities in player compensation within MLB teams. Understanding whether these internal salary inequalities influence on-field performance and ultimately team success is therefore critical to evaluating team strategy. This paper examines whether intra-team salary dispersion affects team success, using panel data covering multiple decades of MLB franchises.

Salary structures in professional sports provide a unique opportunity to study the relationship between inequality and performance. Major League Baseball (MLB) has a long history with detailed payroll records and statistics. This offers a data-rich setting for analyzing whether disparities in player salaries translate into differences in team success. Some franchises concentrate resources on a few star players, while others distribute payroll more evenly across their roster and have fewer if any superstar players. This variation raises the econometric question: does intra-team salary dispersion affect team success?

Since the 1980s and 1990s, superstar players have commanded multimillion-dollar contracts, while average and minimum salaries increased at a slower pace, producing a widening gap between elite and regular players. In 2025, the average MLB player salary increased to $5,160,245 going over $5 million for the first time. (Associated Press, 2025) The median salary, the level at which an equal number of players are above and below, is often a more realistic indicator of what a regular (not superstar) roster player might earn in each season. In 2025, the MLB median

salary was $1.35 million. (Associated Press, 2025) MLB is characterized by significant salary disparities. While the minimum salary in 2025 was $760,000 (Major League Baseball Players Association, 2025), superstars Shohei Ohtani signed a $700 million contract averaging $70 million annually and Juan Soto signed a $765 million contract averaging $51 million annually. (Baseball-Reference, 2025) The emergence of multimillion-dollar contracts, contrasted with slower growth in average and minimum salaries, emphasizes the increasing intra-team salary dispersion central to this econometric analysis.

II. Data and Summary Statistics

The data was taken from several sources, all of which are publicly available for download. All the raw data was downloaded in csv format and extracted and cleaned in Stata. The following section will describe this process and data in more detail. The unit of observation is team-year. While baseball statistics often resemble time series when tracking a single team or player across seasons, the dataset here is structured as panel data, combining multiple teams observed over many years.

The main source of data is the Lahman Baseball Database. This database was created by Society for American Baseball Research (SABR) member Sean Lahman and contains complete major league batting and pitching statistics plus fielding, won-loss records, manager history and more back to 1871. This database was also used for annual player salary data. The salary data was limited to the years 1985 through 2016, so this paper will only include these years for the analysis. The salary data contained missing observations. For example, only four players were provided for the 1987 Texas Rangers. Missing values were supplemented with data from Baseball Almanac (2025). Expansion teams (Diamondbacks, Marlins, Rockies, Rays/Devil Rays) were excluded so the study could include the same number of teams for all years. There are 26 teams and 32 years for a

total of 832 observations. The teams are based on franchise, so the data cleaning included aligning the Montreal Expos to the current Washington Nationals and similarly, the California and Anaheim Angels to the now current Los Angeles Angels. Team winning percentage (TWP) is our primary measure of team success. TWP, despite being labeled as percentage, is expressed as a proportion ranging between 0 and 1 rather than 0 and 100.

Manager quality is measured by manager career wins at the observation year. This incorporates manager experience into the control variable as well. If there were multiple managers in the year, the value is the sum of the prorated wins based on the percentage of games managed in that year for each manager.

Defensive statistical data includes runs allowed per game and fielding percentage. MLB.com defines fielding percentage as "How often does a fielder or team make the play when tasked with fielding a batted ball, throwing a ball, or receiving a thrown ball for an out. The formula is simple: the total number of putouts and assists by a defender, divided by the total number of chances (putouts, assists and errors)."

Offensive statistical data includes runs scored per game and On-Base Percentage (OBP). OBP is the statistical measurement that was used by Billy Beane and the Oakland Athletics to find players undervalued by the market but critical to winning games, and was the focus in Michael Lewis's Moneyball: The Art of Winning an Unfair Game. Defined by MLB.com, "OBP refers to how frequently a batter reaches base per plate appearance. Times on base include hits, walks and hit-by-pitches, but does not include errors, times reached on a fielder's choice or a dropped third strike." This was not provided with the raw data and instead was calculated in the Stata code.

WAR (wins above replacement) data was obtained from the FanGraphs website. Defined by MLB.com, "WAR measures a player's value in all facets of the game by deciphering how many more wins he's worth than a replacement-level player at his same position (e.g., a Minor League

replacement or a readily available fill-in free agent)." This data was used to determine the number of top players on a team for a given year. For starting pitchers and position players, top-rated players will be considered players with 4.0 rating or above. For relief pitchers it is 2.0 or above. These ratings were selected based on FanGraphs "good rule-of-thumb" chart describing WAR rating with 4 or above considered an all-star player. (FanGraphs, 2025) Top-rated relief pitchers are identified using a lower rating since they pitch much fewer innings.

Gini coefficient will be used to measure salary dispersion. This statistical measurement is one of the most common ways to measure income inequality. A coefficient of 1 represents total inequality, in which a single person has all the money, while a coefficient of 0 indicates perfect equality. A common measure of market concentration used in economics is the Herfindahl–Hirschman index (HHI). HHI < 1,500 indicates an unconcentrated market or more balanced salaries, HHI > 2,500 indicates a highly concentrated market or a small number of players account for a larger proportion of the total team salary. As a robustness check, I have included HHI as an alternate measure for salary dispersion.

Table 1 displays the summary statistics for the dependent variables, independent variables and the control variables. The TWP dependent variable has a good amount of variation between a minimum value of 26.5% and maximum value of 71.6% team winning percentage. The Gini coefficient independent variable also has a good amount of variation from the minimum value of 0.286 to maximum of 0.723. A second Gini coefficient is also shown which measures the salary inequality within the whole league, which shows less variation than by team which is expected.

Table 1: Summary Statistics

	Mean	Standard deviation	Minimum value	Maximum value
Dependent Variables				
Team Winning Percentage (TWP)	0.5028	0.0683	.265	.716
World Series champion (1=Yes, 0=No)	0.0337	0.1804	0	1
Independent Variables of Interest				
Gini coefficient	0.5607	0.0729	.286	.7227

Herfindahl–Hirschman Index	852.2001	204.5234	427.5004	2158.32
Control Variables				
TWP (prior year)	0.5027	0.0684	.265	.716
Estimated team payroll (millions)	61.7177	46.8440	4.613	265.1404
League (1=American, 0=National)	0.5204	0.4999	0	1
Manager career wins (at obs year)	608.0718	524.5647	41.4	2624.18
Gini coefficient (year)	0.5946	0.0563	.3923	.6786
Herfindahl–Hirschman Index (year)	849.1393	100.3430	630.7136	1010.086
On-base percentage	0.3291	0.0147	.292	.374
Runs per game	4.5677	0.5335	3.167	6.228
Fielding percentage	0.9819	0.0031	.971	.991
Runs allowed per game	4.5404	0.5533	3.241	6.809
# top rated players (High WAR)	2.2788	1.5665	0	8
Observations	832			

Figure 1 illustrates how the estimated team payroll increased both in total and in variance from 1985 to 2016. Both leagues (American League in blue, National League in red) display a similar pattern. The discrepancy between the high paying teams and low paying teams grew considerably since 1985. It is understandable that the historically low paying Oakland Athletics and other small market teams turned to statistical analysis to find undervalued players to win baseball games.

Figure 1: Distribution of Estimated MLB Team Payrolls, 1985-2016

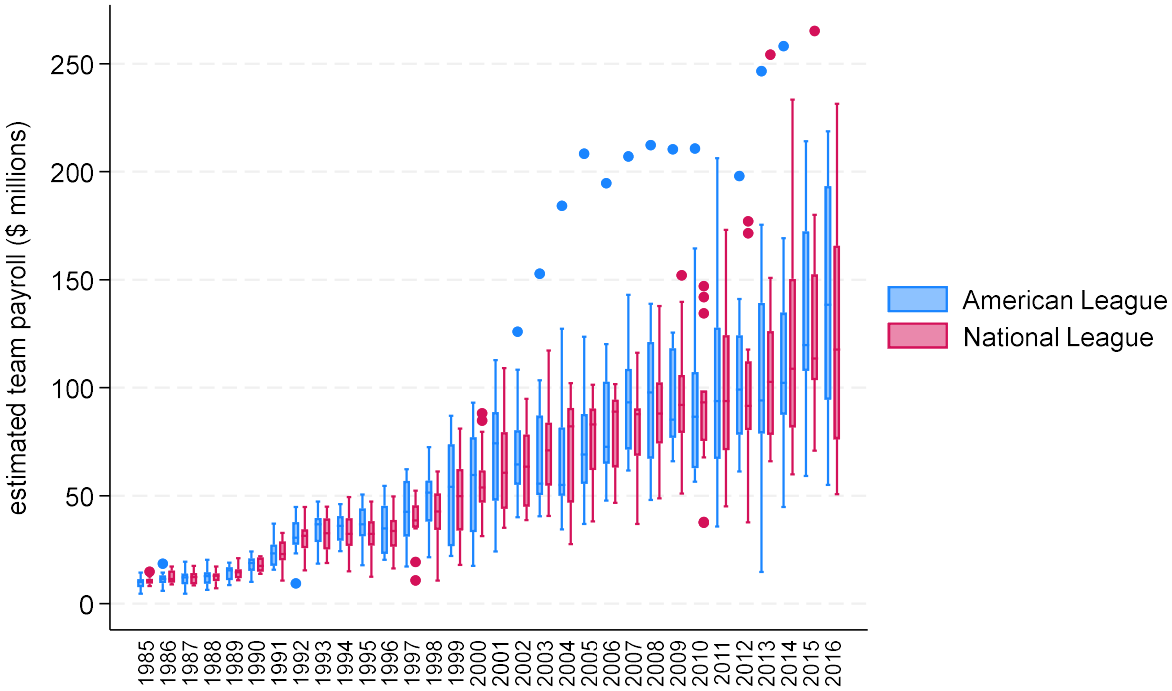


Figure 2 presents box plots of team-level Gini coefficients for payroll distribution across Major League Baseball (MLB) teams from 1985 to 2016, split by league (American League in blue, National League in red). The Gini coefficient measures intra-team salary inequality. Values range from 0 (perfect equality) to 1 (perfect inequality). Intra-team salary inequality rose steadily up to a peak in the mid-1990's. Then decreasing slightly and remaining somewhat constant on average to a level slightly under 0.6.

Figure 2: Distribution of MLB Team Gini Coefficients, 1985-2016

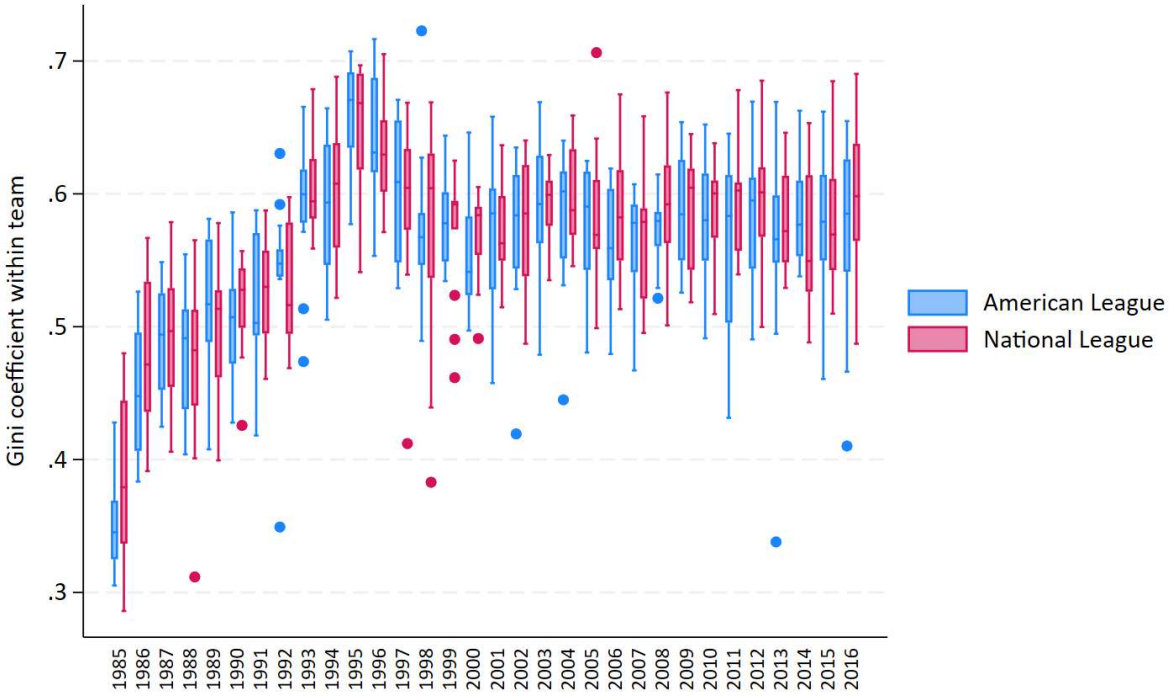


Figure 3 presents a scatter plot of our team-year observations from 1985 to 2016, showing the relationship between payroll inequality (measured by the Gini coefficient) and team winning percentage. Each dot represents a team each year, with World Series winners highlighted in blue and other teams in gray. A fitted regression line indicates a negative association between HHI and winning percentage. The slope of the fitted line is as expected, indicating a negative relationship between Gini coefficient and team winning percentage. Although the slope is relatively flat.

Figure 3: Relationship between Team Winning Percentage and Payroll Inequality (Gini), years 1985-2016

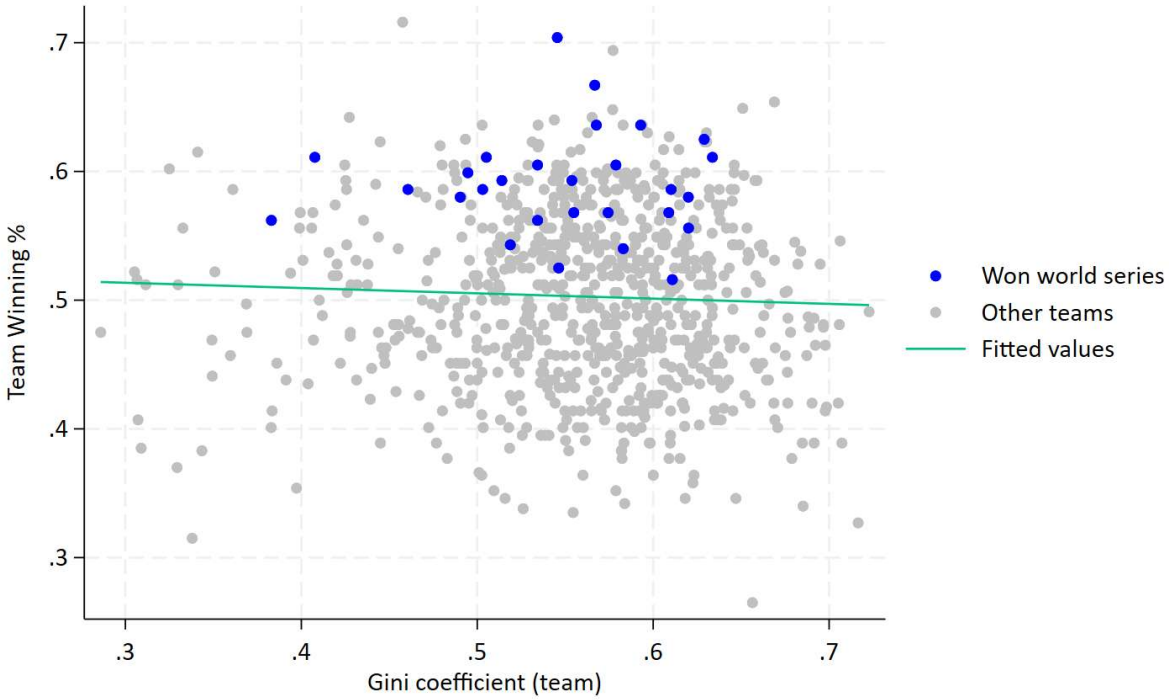


Figure 4 presents a scatter plot of team-year observations from 1985 to 2016, showing the relationship between payroll inequality measured by the Herfindahl–Hirschman Index (HHI) and team winning percentage. Each dot represents our team-year observations, with World Series winners highlighted in blue and other teams in gray. A fitted regression line indicates a negative relationship between HHI and winning percentage. The results are consistent with Figure 3 for Gini coefficient and winning percentage. An interesting thing to note is that the HHI has observations concentrated toward the lower HHI index whereas our Gini figure above indicates greater concentration of observations toward the higher coefficient value. And the HHI fitted line is slightly steeper which could indicate a stronger relationship between salary inequality and team success.

Figure 4: Relationship between Team Winning Percentage and Payroll Inequality (HHI), years 1985-2016

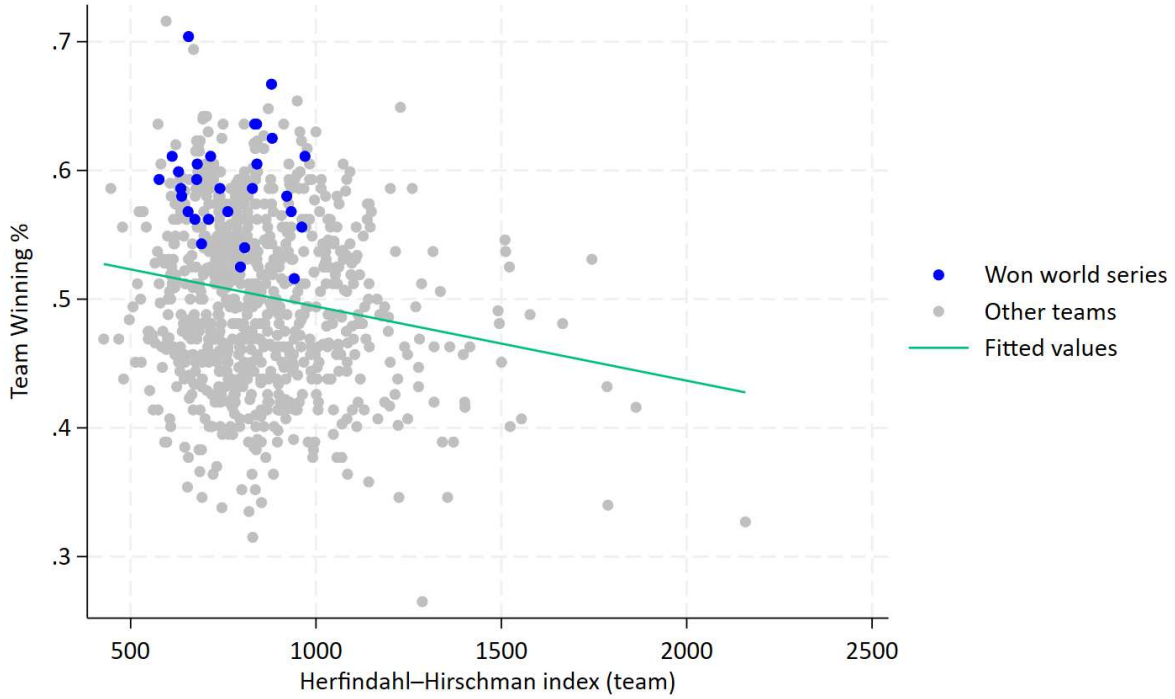
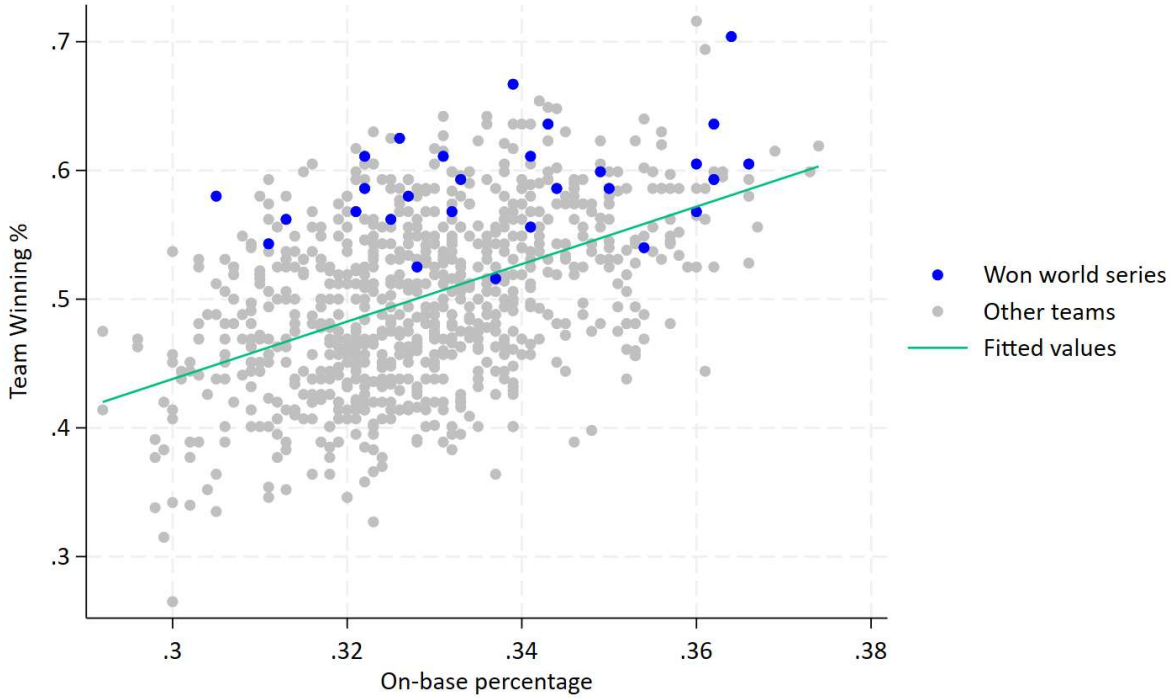


Figure 5 presents a scatter plot of team-year observations from 1985 to 2016, illustrating the relationship between on-base percentage (OBP) and team winning percentage. The fitted regression line reveals a clear positive relationship, indicating that teams with higher OBP tend to achieve higher winning percentages. Figure 5 confirms a positive relationship between OBP and winning percentage, although OBP does not appear to be correlated winning the World Series as shown by the blue dots. The figure reiterates the importance of offensive statistics in explaining team performance and supports their inclusion as key controls in panel regressions assessing the impact of salary structure. On-Base Percentage (OBP) is the statistic emphasized in Michael Lewis's Moneyball as a source of competitive advantage. While Major League Baseball teams continue to rely on data and analytics to gain a competitive advantage, it has evolved into much more complex forms of analysis.

Figure 5: Relationship between Team Winning Percentage and On-Base Percentage, year 1985-2016



III. Preliminary Analysis

This analysis attempts to understand the relationship between salary dispersion on Major League Baseball teams and team performance. Variations on the following model are estimated using ordinary least squares (OLS),

Equation (1):

$$TWP_{it} = \beta_0 + \beta_1 Gini_{it} + \beta_2 TWP_{i(t-1)} + \ln(Payroll)_{it}\beta_3 + \beta_4 X_{\boldsymbol{it}} + League_i\delta + u_{it}$$

where the dependent variable TWP_{it} is team winning percentage for team i in year t. The primary independent variable is $Gini_{it}$ which is the Gini coefficient for team i in year t. A secondary independent variable is $Payroll_{it}$ which is the total payroll for team i in year t. As indicated in figure 1 team payrolls are highly skewed and show an increasing variance, therefore a log transformation will be used. $TWP_{i(t-1)}$ is a control variable for the team winning percentage from the prior year. X_{it} is a vector of control variables that are likely correlated with team success such as manager quality,

Gini coefficient for the whole league in the year, on-base percentage, runs per game, fielding percentage, runs allowed per game, and number of all-star quality players. Finally, $League_i$ is a dummy variable to control for differences between the American league and National League. The data is panel data, using many units (teams) over many points in time (years). We will use team winning percentage from the prior year to control for the momentum factor going into a new season. Estimated payroll is a control variable to account for how overall payroll impacts winning percentage. The other variables control for offensive performance and player/manager quality on team success. To mitigate omitted variable bias, defensive statistics were included in the regressions.

The analysis will also include two additional regressions. Equation (2) will test winning the World Series as the outcome variable. This is a binary variable and a rare event so a logit regression will be used. For Equation (3) we substitute Gini coefficient with HHI as the independent variable of interest in our original OLS regression.

Equation (2):

$$WorldSeriesWin_{it} = \beta_0 + \beta_1 Gini_{it} + \beta_2 TWP_{i(t-1)} + \ln(Payroll)_{it}\beta_3 + \beta_4 X_{it} + League_i\delta + u_{it}$$

Equation (3):

$$TWP_{it} = \beta_0 + \beta_1 HHI_{it} + \beta_2 TWP_{i(t-1)} + \ln(Payroll)_{it}\beta_3 + \beta_4 X_{it} + League_i\delta + u_{it}$$

Equation (1) regression results for the outcome variable team winning percentage are reported in Table 2, heteroskedastic robust standard errors are reported in parenthesis. The first specification in Column 1 is a simple regression of Gini coefficient on team winning percentage. We find the coefficient of the Gini coefficient is -0.041. We interpret this as an increase in the Gini coefficient by 0.10 (increase in inequality) is associated with a decrease in winning percent of 0.0041 (on a proportional scale). For a 162-game season, this is approximately 0.66 fewer wins.

However, the effect is neither statistically significant nor economically significant. When team payroll is added as shown in Column 2, the coefficient becomes larger in magnitude and statistically significant, suggesting that payroll inequality matters conditional on overall payroll size. The coefficient of -0.158 indicates an increase in the Gini coefficient by 0.10 (increase in inequality) is associated with a decrease in winning percent of 0.0041 (on a proportional scale). For the 162-game season, this is approximately 2.5 fewer wins. This is economically significant since 2-3 wins might impact a team qualifying for or missing the playoffs. However, when the model is expanded to include more comprehensive control variables as shown in Columns 3 and 4, the effect of salary dispersion disappears. This indicates that the relationship is absorbed by direct measures of team quality such as runs scored, runs allowed, manager quality, and the presence of top-rated players. Among the control variables, runs scored per game, runs allowed per game, and the number of top-rated players are statistically significant predictors of team winning percentage, which is consistent with expectations given their direct relationship to team performance. The league dummy variable (American League = 1, National League = 0) has a coefficient of –0.000 with a standard error of 0.002, indicating no statistically or economically significant difference in winning percentage between leagues.

Table 2: Panel regression results for Gini coefficient and winning percentage

	1	2	3	4
Gini coefficient	-0.041	-0.158***	0.012	0.012
	(0.035)	(0.037)	(0.017)	(0.017)
Estimated team payroll (log)		0.022***	0.001	0.001
		(0.003)	(0.002)	(0.002)
Team winning percentage (prior year)			0.020	0.020
			(0.015)	(0.015)
Manager career wins (at obs year)			0.000	0.000
			(0.000)	(0.000)
Gini coefficient (year)			-0.029	-0.029
			(0.033)	(0.034)
On-base percentage			0.166	0.163
			(0.134)	(0.135)
Runs per game			0.090***	0.091***

			(0.004)	(0.004)
Fielding percentage			0.571	0.582
			(0.394)	(0.398)
Runs allowed per game			-0.096***	-0.096***
			(0.002)	(0.002)
# top rated players (WAR)			0.002***	0.002***
			(0.001)	(0.001)
League (1=American, 0=National)				-0.000
				(0.002)
Observations	832	832	806	806
Adjusted R^2	0.001	0.057	0.868	0.868

Heteroskedasticity-robust standard errors reported in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Now we examine our results for Equation (2) which uses winning the World Series as the dependent variable. The regression results are reported in Table 3a, heteroskedastic robust standard errors are reported in parenthesis. The Gini variable has a negative value for all four columns indicating a negative relationship as expected. But salary inequality within a team is statistically significant only in the specification controlling for team payroll only (Column 2). Once the model is expanded to include more comprehensive control variables (Columns 3 and 4), the effect disappears. By contrast, runs scored per game and runs allowed per game remain strong and statistically significant predictors of winning the World Series, further evidence that actual performance metrics, rather than payroll distribution, drive championship outcomes. These results are consistent with Equation (1) for winning percentage. Table 3b reports average marginal effects from a logit regression of World Series win probability. The estimated average marginal effect of the team Gini coefficient on World Series win probability is -0.015979. This implies that a one-unit increase in salary inequality reduces the likelihood of winning the championship by 1.6 percentage points. However, the effect is not statistically significant (p = 0.901) and economically trivial, as even a 0.1 increase in inequality corresponds to less than a 0.2 percentage point change in win probability. These results suggest that salary dispersion does not meaningfully influence the probability of winning the World Series. Payroll inequality within teams, overall payroll size, prior-

year performance, and manager success all yield statistically insignificant effects. By contrast, scoring more runs per game significantly increases championship probability, while allowing fewer runs per game strongly reduces the likelihood of defeat, which is expected. These results emphasize that direct measures of team quality, rather than intra-team payroll distribution, impact winning the World Series.

Table 3a: Regression results for Gini coefficient and winning the World Series

	1	2	3	4
Gini coefficient	-2.321	-6.138**	-1.419	-0.551
	(1.992)	(2.867)	(4.538)	(4.455)
Estimated team payroll (log)		0.653**	0.602	0.578
		(0.292)	(0.485)	(0.488)
Team winning percentage (prior year)			0.602	0.552
			(3.820)	(3.819)
Manager career wins (at obs year)			0.000	0.000
			(0.000)	(0.000)
Gini coefficient (year)			-12.321	-11.609
			(10.165)	(10.279)
On-base percentage			28.883	32.159
			(29.857)	(30.117)
Runs per game			1.914**	1.709**
			(0.788)	(0.796)
Fielding percentage			-4.376	-19.701
			(94.596)	(97.175)
Runs allowed per game			-2.871***	-3.019***
			(0.714)	(0.761)
# top rated players (WAR)			-0.205	-0.207
			(0.168)	(0.166)
League (1=American, 0=National)				0.448
				(0.409)
Observations	832	832	806	806

Heteroskedasticity-robust standard errors reported in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3b: Average Marginal Effects from Logit Regression on World Series Win Probability

	dy/dx	Delta-method Std. err.	z	P> |z|	[95% conf. interval]	dy/dx
Gini coefficient	-0.015979	0.1290518	-0.12	0.901	-0.2689158	0.2369578
Team winning percentage (prior year)	0.0159989	0.1108211	0.14	0.885	-0.2012064	0.2332043
Estimated team payroll (log)	0.0167421	0.0138774	1.21	0.228	-0.0104572	0.0439414
Manager career wins (at obs year)	9.51E-06	0.000011	0.87	0.386	-0.000012	0.000031
Gini coefficient (year)	-0.3363965	0.2973837	-1.13	0.258	-0.9192579	0.2464649
On-base percentage	0.9318615	0.8590813	1.08	0.278	-0.7519069	2.61563
Runs per game	0.0495108	0.0245359	2.02	0.044	0.0014214	0.0976002
Fielding percentage	-0.5708854	2.802081	-0.20	0.839	-6.062863	4.921093

Runs allowed per game	-0.087479	0.023543	-3.72	0.000	-0.1336224	-0.0413357
# top rated players (WAR)	-0.0059911	0.0048261	-1.24	0.214	-0.01545	0.0034679
League (1=American, 0=National)	0.0129816	0.0118737	1.09	0.274	-0.0102905	0.0362537
Observations	806					

Table 4 presents regression results using the Herfindahl–Hirschman Index (HHI) for team payroll concentration. The results here are similar in pattern to our first test although the HHI results are not as economically significant. In fact, as shown the HHI coefficient results are at or nearly zero. By contrast, runs scored per game, runs allowed per game, and the number of top-rated players remain strong and statistically significant predictors of winning percentage and when these additional control variables were added the R^2 jumped from 0.079 to 0.868. This indicates that runs per game, runs allowed per game and number of star players most likely fully absorb the explanatory power of the full model. These results reinforce the conclusion that direct measures of team quality, rather than payroll concentration, affect team success.

Table 4: Regression results for HHI and team winning percentage

	1	2	3	4
Herfindahl–Hirschman Index	-0.000***	-0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Estimated team payroll (log)		0.019***	0.001	0.001
		(0.003)	(0.002)	(0.002)
Team winning percentage (prior year)			0.021	0.021
			(0.015)	(0.015)
Manager career wins (at obs year)			0.000	0.000
			(0.000)	(0.000)
Herfindahl–Hirschman Index (year)			-0.000	-0.000
			(0.000)	(0.000)
On-base percentage			0.154	0.152
			(0.135)	(0.135)
Runs per game			0.091***	0.091***
			(0.004)	(0.004)
Fielding percentage			0.563	0.573
			(0.400)	(0.402)
Runs allowed per game			-0.096***	-0.096***
			(0.002)	(0.002)
# top rated players (WAR)			0.002***	0.002***
			(0.001)	(0.001)
League (1=American, 0=National)				-0.000

				(0.002)
Observations	832	832	806	806
Adjusted R^2	0.029	0.079	0.868	0.868

Heteroskedasticity-robust standard errors reported in parenthesis.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

These specifications treat the dataset as pooled panel data, estimated with ordinary least squares. Beyond the controls already discussed, several econometric concerns remain. Endogeneity between payroll distribution and team success, unobserved heterogeneity across teams, and serial correlation in panel data may bias estimates. These considerations highlight the importance of robustness checks and alternative specifications in the advanced analysis. While the unit of observation is the team-year, the model does not yet exploit the full panel structure, for example team-specific fixed effects or random effects. The analysis assumes independence across team-years, which may overlook unobserved heterogeneity at the team level. The next section leverages advanced techniques to address these concerns.

IV. Advanced Analysis

In panel datasets, correlation in the error terms over time can result in inconsistent heteroskedasticity-robust standard errors, and ordinary least squares (OLS) may not be the most efficient estimator. To address these concerns, I begin by reporting cluster-robust standard errors at the team level, which account for arbitrary serial correlation and heteroskedasticity within teams. I then estimate a random-effects (RE) model, which can be more efficient than pooled OLS when the RE assumptions hold and unobserved heterogeneity is uncorrelated with the regressors. A further concern is omitted variable bias arising from unobserved, time-invariant team characteristics, such as franchise strategy, general manager quality, or minor league player-development advantages, that may influence both payroll structure and team success. To reduce the impact of this source of bias, I estimate a fixed-effects (FE) model that removes all time-invariant team-level heterogeneity

and provides a more credible basis for causal interpretation when the strict exogeneity assumption holds. A Hausman test will be used to check if the RE assumption is violated, which implies that the RE estimates are inconsistent and the FE estimates are preferred.

Before turning to these alternative estimators, I first assess the degree of multicollinearity among the control variables. Variance Inflation Factors (VIFs) were calculated for all covariates, and the results are reported in Table 5. All VIF values fall well below the conventional threshold of 10. Runs per game and on-base percentage exhibit moderate VIFs of 5.93 and 5.49, respectively, but remain within acceptable thresholds. The mean VIF of 2.49 indicates that multicollinearity is not a major concern for the subsequent analysis.

Table 5: Test for multicollinearity among control variables

Variable	VIF	1/VIF
Runs per game	5.93	0.168768
On-base percentage	5.49	0.182171
Gini coefficient (year)	2.62	0.382400
Estimated payroll (log)	2.44	0.409163
Runs allowed per game	2.06	0.485409
Gini coefficient (team)	1.72	0.582863
Top players on team	1.66	0.600909
Fielding percentage	1.66	0.602571
Prior year team winning percentage	1.41	0.710376
League Id	1.29	0.778198
Manager wins (as of obs year)	1.17	0.857311
Mean VIF	2.49	

Table 6 reports pooled OLS, fixed effects, and random effects estimates of the relationship between salary inequality and team winning percentage. The RE and FE estimates indicate different results, the FE estimate has a Gini coefficient result very close to 0, the RE estimate is low as well but at 0.007. The RE estimate and POLS estimate results are almost identical. A Hausman test rejects the null hypothesis that the RE assumption holds at the 5% level and even the 1% level with p-value = 0.0000. This indicates that I should use the FE estimate since the RE estimate is

inconsistent. As mentioned above this indicates that my regressors are correlated with team-level, time-constant unobserved characteristics. All the coefficients on the Gini coefficient are not statistically significant. This was unexpected, and it indicates there is no evidence that the Gini coefficient (salary inequality within a team) is associated with team winning percentage. Even if the FE estimate coefficient for the Gini coefficient was statistically significant, since it is nearly zero it would not be economically significant.

Table 6: Panel regression results for Gini and winning percentage

	POLS	FE	RE
Gini coefficient	0.007	-0.000	0.007
	(0.019)	(0.021)	(0.019)
Team winning percentage (prior year)	0.010	-0.002	0.010
	(0.019)	(0.021)	(0.019)
Estimated team payroll (log)	0.006	0.010***	0.006
	(0.004)	(0.003)	(0.004)
Manager career wins (at obs year)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Gini coefficient (year)	-0.112	-0.182***	-0.112
	(0.072)	(0.064)	(0.072)
On-base percentage	0.177	0.141	0.177
	(0.156)	(0.167)	(0.156)
Runs per game	0.089***	0.089***	0.089***
	(0.004)	(0.004)	(0.004)
Fielding percentage	0.742	0.747	0.742
	(0.543)	(0.526)	(0.543)
Runs allowed per game	-0.096***	-0.097***	-0.096***
	(0.002)	(0.002)	(0.002)
# top rated players (WAR)	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
League (1=American, 0=National)	-0.000	-0.008**	-0.000
	(0.002)	(0.003)	(0.002)
Observations	806	806	806
Adjusted R^2	0.865	0.852	

Heteroskedasticity-robust standard errors clustered by team reported in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 reports pooled OLS, fixed effects, and random effects estimates of the relationship between salary inequality and winning the World Series. Like my previous test, OLS and RE are

nearly identical. FE and RE/OLS are slightly different. The Hausman test again rejects the null hypothesis with p-value=0.000, indicating I should use the FE estimate since the RE estimate is inconsistent. All the coefficients on the Gini coefficient are not statistically significant. Again, this was unexpected, and it indicates there is no evidence that the Gini coefficient (salary inequality within a team) is associated with winning the World Series. The values are negative, which is the direction expected but again not statistically significant.

Table 7: Panel regression results for Gini and world series win

	POLS	FE	RE
Gini coefficient	-0.057	-0.035	-0.057
	(0.134)	(0.142)	(0.134)
Team winning percentage (prior year)	-0.066	-0.078	-0.066
	(0.119)	(0.132)	(0.119)
Estimated team payroll (log)	0.040**	0.022	0.040**
	(0.017)	(0.027)	(0.017)
Manager career wins (at obs year)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Gini coefficient (year)	-0.626	-0.274	-0.626
	(0.480)	(0.611)	(0.480)
On-base percentage	0.861	0.507	0.861
	(1.008)	(0.994)	(1.008)
Runs per game	0.038*	0.041*	0.038*
	(0.021)	(0.023)	(0.021)
Fielding percentage	-0.437	-2.322	-0.437
	(2.138)	(2.042)	(2.138)
Runs allowed per game	-0.061***	-0.066**	-0.061***
	(0.021)	(0.025)	(0.021)
# top rated players (WAR)	-0.003	-0.002	-0.003
	(0.006)	(0.007)	(0.006)
League (1=American, 0=National)	0.010	-0.001	0.010
	(0.010)	(0.017)	(0.010)
Observations	806	806	806
Adjusted R^2	0.013	-0.007	

Heteroskedasticity-robust standard errors clustered by team reported in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8 reports pooled OLS, fixed effects, and random effects estimates using the Herfindahl–Hirschman Index (HHI) as an alternate measure of salary inequality. This time the OLS and RE are still nearly identical, but the FE and RE/OLS are much closer in value. The Hausman test

again rejects the null hypothesis with p-value=0.000, I should use the FE estimate since the RE estimate is inconsistent. Like the previous two tests all the coefficients on the Gini coefficient are not statistically significant. This is consistent with my Gini regression and indicates there is no evidence that salary inequality within a team is associated with team winning percentage.

Table 8: Panel regression results for HHI and winning percentage

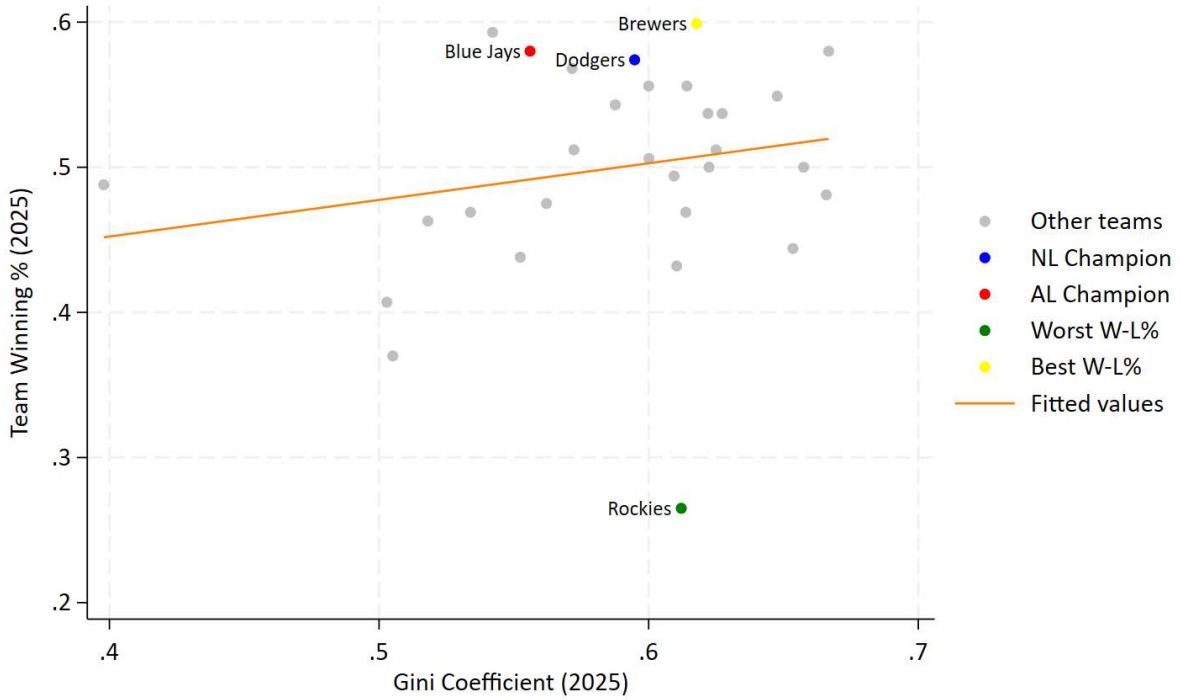
	POLS	FE	RE
Herfindahl–Hirschman Index	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Team winning percentage (prior year)	0.011	0.000	0.011
	(0.019)	(0.021)	(0.019)
Estimated team payroll (log)	0.007*	0.011***	0.007*
	(0.004)	(0.003)	(0.004)
Manager career wins (at obs year)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Herfindahl–Hirschman Index (year)	-0.000*	-0.000***	-0.000**
	(0.000)	(0.000)	(0.000)
On-base percentage	0.179	0.143	0.179
	(0.155)	(0.166)	(0.155)
Runs per game	0.089***	0.089***	0.089***
	(0.004)	(0.004)	(0.004)
Fielding percentage	0.727	0.735	0.727
	(0.544)	(0.525)	(0.544)
Runs allowed per game	-0.096***	-0.097***	-0.096***
	(0.002)	(0.002)	(0.002)
# top rated players (WAR)	0.002**	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
League (1=American, 0=National)	-0.000	-0.008***	-0.000
	(0.002)	(0.002)	(0.002)
Observations	806	806	806
Adjusted R^2	0.865	0.852	

Heteroskedasticity-robust standard errors clustered by team reported in parenthesis.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results of these regression tests are not what I expected, I was expecting measures of salary inequality to impact team success. In the following pages I performed additional data analysis based on 2025 MLB season data. Each figure highlights four teams. The Los Angeles Dodgers (won World Series), the Toronto Blue Jays (lost World Series), the Colorado Rockies (worst W-L%), and the Milwaukee Brewers (best W-L%) in 2025. Figure 6 displays The Gini coefficient and

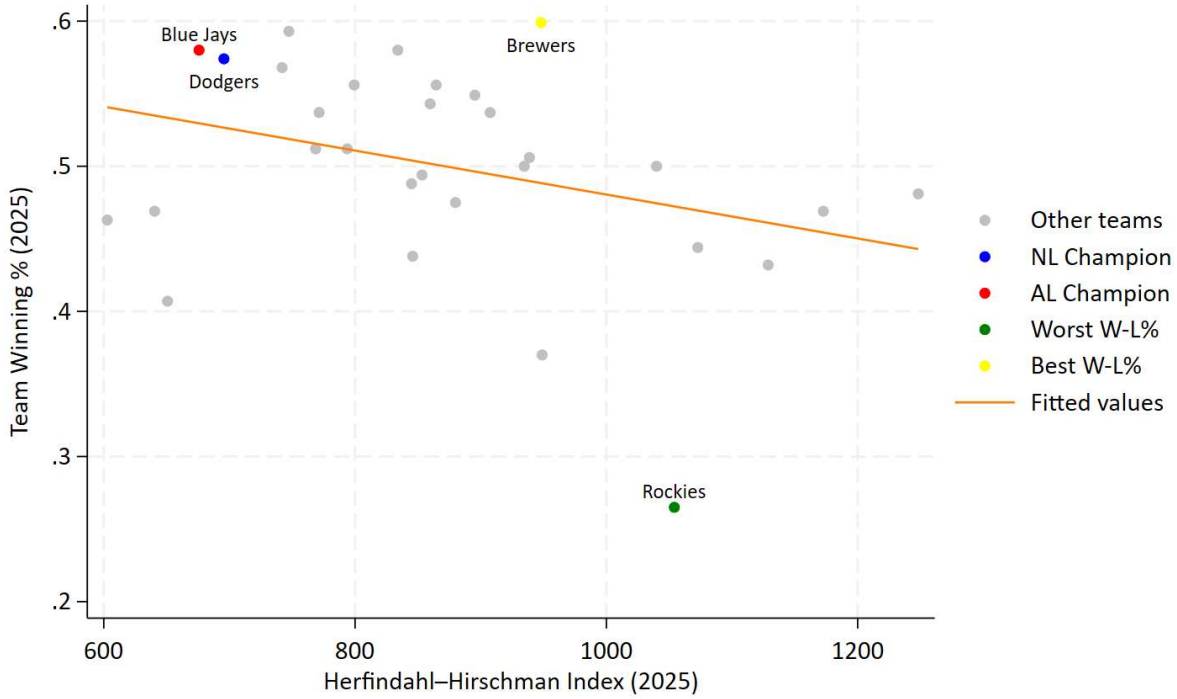
team winning percentage. Surprisingly the Dodgers and Blue Jays appear to be in the middle to lower half of all observations for Gini coefficient. And the Brewers and Rockies have somewhat similar Gini coefficients but were at opposite ends of team winning percentage. This is further evidence that salary inequality is not a big driver in team success. Figure 7 offers similar analysis using HHI as the salary inequality measurement. The Dodgers and Blue Jays are even lower on the HHI scale, indicating lower inequality. Figure 8 displays total team payroll and team winning percentage. The Dodgers are far and away higher than any other team and the Blue Jays are in the top 5. So, although they have high payrolls, the salary inequality measurement was around the league average. The Brewers had a very low payroll but had the best record in baseball this year. Figure 8 is evidence that overall payroll does affect team success, but smaller-market teams like the Brewers can still win with comparatively lower payrolls.

Figure 6: Relationship between Team Winning Percentage and Payroll Inequality (Gini), 2025



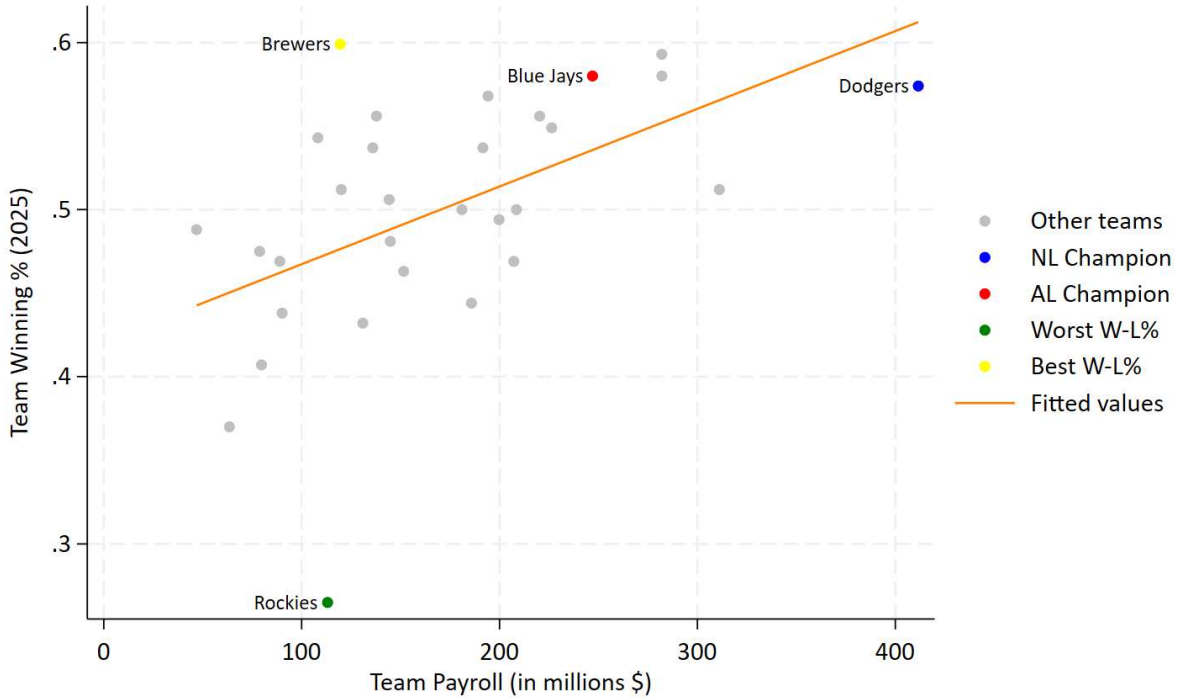
Note. MLB salaries from USA Today (2025), MLB W-L% from baseball-reference (2025).

Figure 7: Relationship between Team Winning Percentage and Payroll Inequality (HHI), 2025



Note. MLB salaries from USA Today (2025), MLB W-L% from baseball-reference (2025).

Figure 8: Relationship between Team Winning Percentage and Team Payroll, 2025



Note. MLB salaries from USA Today (2025), MLB W-L% from baseball-reference (2025).

V. Discussion

There have been many economic studies on salary inequality and impact to organizational success, including studies using MLB data. According to Breunig, et al., (2013), wider wage disparities diminish individual effort, which in turn lowers collective team performance. They used two empirical models, one utilizing the Gini coefficient and another using the Herfindahl-Hirschman Index (HHI). They found coefficients of Gini demonstrate a significant negative relationship between wage inequality and winning percentage. Although they only used one control variable, that being average team salary. Their HHI test also produced similar results.

Tao, Chuang, and Lin (2016) examined whether MLB team performance aligns more with tournament theory or the team-cohesiveness hypothesis. Tournament theory argues that larger pay gaps motivate effort (Lazear & Rosen, 1981), while the cohesive view holds that narrower wage differences improve teamwork and productivity. Because MLB players naturally earn different salaries by position, Tao, et al., reasoned that tournament incentives are unlikely to strongly influence performance. They state that large gaps, such as league minimum salary players outperforming highly paid teammates, could ultimately cause dissatisfaction. Their results support the team-cohesiveness hypothesis that salary dispersion within teams has limited explanatory power, and overall team payroll rank is a stronger predictor of performance.

My results align with Tao et al. (2016), as demonstrated both in this paper's regression analysis and in the examination of the 2025 Major League Baseball season, that intra-team salary inequality has limited explanatory value. Tao et al. incorporated a wide set of control variables, including team average salary, relative payroll position, league identifier, manager quality, market size, the salaries of the top three pitchers and top three batters, city tenure, and league average salaries. Similarly, the estimates in this paper include multiple control variables and utilizes more

advanced analytical techniques. This comprehensive approach positions both Tao et al.'s study and this paper's analysis as methodologically robust.

VI. Conclusion

This paper examined the relationship between salary dispersion and team performance in Major League Baseball using panel data. Across specifications, including models using the Gini coefficient, the Herfindahl-Hirschman Index (HHI), and outcome variables team winning percentage and winning the World Series, the results were neither statistically nor economically significant. These findings suggest that intra-team salary inequality may have limited explanatory power for both regular-season success and championship performance. While some prior studies have reported negative associations between salary dispersion and winning percentage, the lack of significance here underscores the importance of control variables and model specification.

Future analysis could incorporate fixed-effects specifications and more comprehensive covariates to better exploit the panel structure and isolate the independent effects of intra-team payroll inequality. Or more in-depth data analysis on which players to include on each team, such as only full-time players or starting players. And further examination of the division of pay by player position, player experience or whether a team is rebuilding or competing for a championship. Ultimately, this paper's results contribute to the ongoing debate of intra-team payroll inequality and MLB franchise success, highlighting the need for further econometric investigation into how compensation structures influence organization performance in professional sports and beyond.

In the spirit of Yogi Berra's remark that "a nickel ain't worth a dime anymore," the evidence presented here suggests that salary dispersion adds little explanatory value when it comes to understanding Major League Baseball team success.

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