Salary Dispersion and Team Performance in Major League Baseball: A Quantile Regression Analysis

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Abstract:

This paper investigates the relationship between salary dispersion and team performance in Major League Baseball. Player salary data is collected to calculate each team's annual Gini coefficient from 1998-2016, which is used to represent a team's level of wage inequality in a given year. The study incorporates a fixed and random effects model, and distinguishes itself from previous research by employing multiple quantile regressions to analyze how the impact of salary dispersion differs depending on a team's performance level. The results find that the fixed effects model is preferred, and that there is consistently a negative relationship between wage differentials and team performance across all models used. Further, the quantile regressions completed reveal that salary dispersion has a greater impact on lower performing teams than it does for higher performing teams. This finding profoundly adds to existing research because it indicates that the relationship between salary dispersion and team performance is not uniform. This helps to advance the application of the regression results, where MLB teams can use these results to adjust their player selection and compensation decisions more effectively depending on which performance quantile their team falls within.

JEL Classification: J31, J33, J44, Z22

Keywords: Salary dispersion, Team performance, Major League Baseball, Gini coefficients

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1.0 INTRODUCTION

Total payroll and salary dispersion are both significant contributors to a team's overall level of success. With the nation's income inequality gap widening substantially since the 1980s, the effect of inter-organizational wage disparity on a firm's overall performance has become a contemporary and relevant area of study (Tao et al., 2016). This discussion of organizational performance has also been extended to analyze the determinants of team performance in professional sports. As the nation's infatuation with sports entertainment continues to increase, so will the overall revenues of sports teams and in turn the average salary of individual players (Heitner, 2015).

Nevertheless, whether payroll increases should be concentrated amongst a small group of players, or instead more evenly distributed between all team members has been debated in the fields of sports and labor economics. Therefore, this study aims to enhance the understanding of the relationship between salary dispersion and team performance in Major League Baseball (MLB). This research is especially prevalent in the modern baseball era, where record setting contracts seem to be offered every offseason, apparent in the recent signings of Bryce Harper and Mike Trout to contracts worth $330 Million and $430 Million respectively. With 8 of the top 10 largest MLB contracts being given out in this decade alone (Adler, 2019), it is surely important to analyze whether concentrating a team's total payroll amongst a few highly paid players reaps the returns of greater success.

Indeed, in accordance to the tournament theory (Lazear and Rosen, 1981), salary dispersion can have a positive effect on team performance. This theory states that wage inequality creates competition between teammates, motivating them to perform at higher levels in order to achieve a greater relative salary. However, supporting empirical research in this domain has mainly studied team performance in professional basketball and hockey (Frick et al., 2003; Marchand et al., 2006). Berri and Jewell (2004) actually find the possibility of either a positive or non-existent relationship between these two variables in the National Basketball Association (NBA). In these sports though, there are only 5 to 6 players per team performing at a time, where an individual player with strong offensive skills can have the considerable ability to dominate the game. While team cohesion is still important in these sports, teams can be fairly successful with high levels of salary inequality if they have a highly payed, highly skilled player that can generate wins through substantial offensive success.

Conversely, in professional baseball, team chemistry and a greater overall skill level across all players is more essential to team performance. The nature of the sport simply does not allow for one player to dominate and single-handily drive team success. Especially on offense, one player can only provide so much run production to win games, where in reality, multiple players must get on base and score runs for continued success to occur throughout a season. As a result, in accordance to the "equity-pay theory" and "team- cohesiveness hypothesis" (Lazear, 1989; Levine, 1991), several studies suggest that narrow wage differentials positively affect team performance in the MLB. More equitable inter-team pay has not only been found to increase performance and entice players to act less selfishly, but also to generate greater team chemistry and organizational efficiency, all of which positively impact team performance.

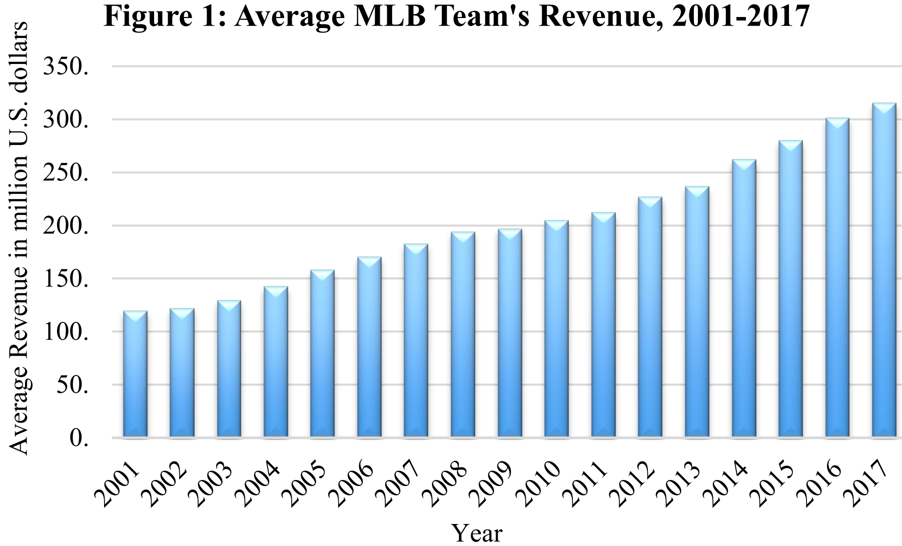
Consequently, this paper strives to build upon existing research, being guided by research objectives that differentiate it from past studies. First, it investigates the relationship between salary dispersion and team performance using dynamic panel data from all 30 MLB teams, with the most recent team statistics and individual salary data from 1998 to 2016 being utilized. Second, it analyzes this data using a fixed effects and random effects model, with team specific effects; and it uses the Hausman test to determine which model is preferred. Finally, it applies a quantile regression method to compare how the impact of salary dispersion on team performance differs depending on a team's winning percentage, where total team payroll is also an independent variable to capture its effect at varying levels of performance. There has been limited empirical work analyzing the effect of salary dispersion at different performance quantiles in professional baseball, and professional sports in general. This paper successfully fills this void.

The rest of the paper is organized into 5 remaining sections as follows: Section 2 provides the historical trends of salary compensation and dispersion in Major League Baseball to give reviewers the necessary background information on these subjects. Section 3 is the literature review which discusses the theoretical explanations surrounding this topic, as well as past research that either supports or rejects such theories. Section 4 outlines the empirical model. This contains the description of the data and the estimation methodology, which includes the fixed effects and random effects model, the Hausman (1978) test, and the quantile regression method. Section 5 then presents and discusses the empirical results of these tests. Finally, a conclusion is provided in Section 6, with descriptions of the variables being provided in the Appendices A and B.

2.0 TREND OF SALARY COMPENSATION AND DISPERSION

Baseball player's salaries have experienced an increasing trend over the past three decades. For one, this is a result of media revenues increasing substantially from 1985 to 2004 in the MLB, which allowed for significant increases in total payroll (Annala and Winfree, 2011). Figure 1 shows that this trend has only continued since 2004, as technological advances in sports coverage has allowed team revenue to consistently rise annually.

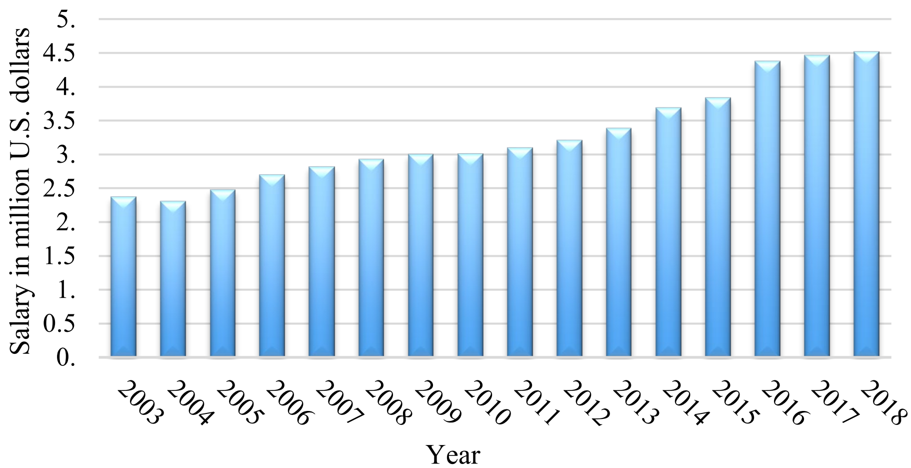
Figure 1: Average MLB Team's Revenue, 2001-2017



Source: Forbes Sports Statistics

This increase in team revenue has translated into higher salaries for players across all positions. As franchises earn more money, they have greater flexibility to spend additional funds on talented players, in the hopes that this will lead to greater team success and future returns. While not all of these extra profits have gone towards salaries, players have still experienced an increase in compensation. This is because owners have recognized that their players' performances, both individually and as a team, have helped drive such revenue increases (Brown and Jepsen, 2009). Additionally, in 2007, there was also a new collective bargaining agreement between MLB team owners and players, which changed the rules of revenue sharing in favor of the players. The tax rates associated with revenue sharing were decreased following this agreement, which in turn increased the salaries of both position players and pitchers (Hill and Jolly, 2017). The consistent increase in the average MLB player's salary can be seen on the following page in Figure 2.

Figure 2: Average MLB Player's Salary, 2003-2018

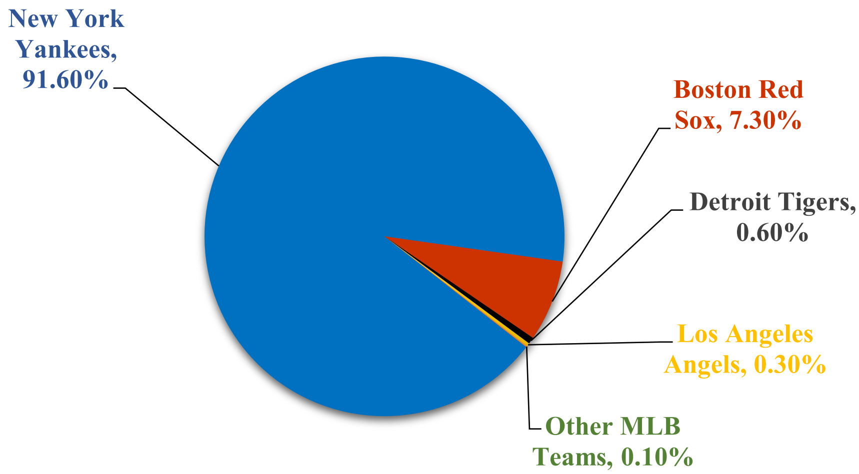


Source: USA Today Salaries Database

Generally, Major League Baseball players earn higher salaries than most other players in professional leagues, such as the NBA, NHL, and NFL. Mainly, this is because there is no salary cap imposed upon MLB franchises. A salary cap is an agreement that places a monetary limit on the amount that a team can spend on players' salaries, and it can either be imposed on a per-player basis or as a total limit for the entire team. As an alternative, the MLB has imposed a predetermined payroll threshold since 2003, in an attempt to level the amount a team can spend on their roster annually. Yet, teams are still allowed to exceed this threshold, but they must pay a Competitive Balance Tax, or "luxury tax…on each dollar above the threshold" (MLB, 2019). The fact that there is no salary cap in the MLB is important in the discussion of wage disparity between players because it has allowed organizations the opportunity to spend large amounts on a small group of players if they are willing and able to pay the luxury tax. For instance, in the 2000s, the New York Yankees were notoriously known around the league for using their massive revenue stream to acquire the league's top players. As see in figure 3, the Yankees actually paid 91.6% of the total luxury taxes paid in the MLB from 2003-2010.

That being said, this does not necessarily mean that every team has been able to take advantage of the absence of a salary cap, nor does it mean that going beyond the predetermined payroll threshold inevitably has led to greater team performance. For example, while the Red Sox and Yankees won a combined 3 World Series from 2003-2010, the other 5 World Series winners do not even appear in Figure 3 for their total luxury taxes paid during this period.

Figure 3: Percentage of Total MLB Luxury Tax Paid, 2003-2010



Source: Business Insider Database

Thus, even though team payrolls and players' salaries have seen an increasing trend, this does not necessarily mean that every team has had the objective of signing a few highly talented players to expensive contracts. In fact, while this appeared to be the traditional, growing trend at the start of the 21st century, many teams were subsequently influenced by an alternative strategy adopted by the Oakland Athletics in 2003, commonly known as "Moneyball" (Lewis, 2004). This was a new sabermetric approach that encouraged teams to change the way they valued players in terms of player selection and compensation. Rather than paying players for "power" statistics, given that most of the top contracts were being awarded based on such figures, this theory called teams to focus on "reaching base" statistics when deciding which player's to sign and for how much (Congdon-Hohman and Lanning, 2018).

Under the traditional approach, a wider salary dispersion was more likely given that teams prioritized the compensations of only a few players. Yet, this new attitude instead placed a greater focus on building a group of 25 players whom all contribute to the team's success. This has ultimately led teams who have adopted this strategy more towards a narrow salary distribution. Currently, both strategies are apparent amongst organizations in Major League Baseball, where one has yet to be proven more effective than the other. While not its primary purpose, this study aims to also educate baseball personnel on the relationship between salary dispersion and team performance to help guide their decision-making approaches towards player selection and compensation in the future.

3.0 LITERATURE REVIEW

The relationship between an organization's level of wage disparity and their overall performance has been greatly researched and analyzed. Several studies utilize conceptual theories and econometric models to discuss the effect of pay inequality on an individual's performance and motivation level, along with overall team cohesiveness. Both of these factors have been found to contribute to an organization's ability to succeed. Likewise, research has also been conducted surrounding the impact of salary dispersion on player performance within the realm of professional sports, such as basketball, football, and hockey (Frick et al. 2003). Most notably and predominantly has been the application of these models and theories to examine the relationship between wage disparity and team performance in Major League Baseball. Indeed, the "tournament theory" (Lazear & Rosen, 1981) predicts that salary dispersion positively influences organizational performance, because this creates a level of healthy competition between team members that pushes all members to strive towards greater productivity. Whereas this may be true in corporate settings or individually dominated sports like basketball and hockey (Berri and Jewell, 2004; Marchand et al., 2006), numerous studies support the assertion that in a more team-oriented sport like baseball, there is instead a negative relationship between wage differentials and team performance.

One theoretical framework for understanding this relationship examines the adverse effect that perceived wage disparity has on an individual's effort and performance, which in turn impacts the team's overall performance. According to the "equity theory," (Adams, 1963) the effort provided by workers, in this case professional baseball players, in an organization is based on their compensation for such effort. This effort decision is centered on the relative effort-compensation ratios of their fellow team members. Adams (1963) finds that when team members are not satisfied with their relative effort-compensation ratio, they will either reduce their work productivity, seek a wage increase, or leave the organization. In professional baseball though, it is fairly difficult to simply leave an organization or receive an increase in salary upon request, due to rules governing player movement and free agency. This indicates that players are more likely to lower their productivity if they are dissatisfied with their relative salaries, which is an explanation for why greater payroll disparity is found to lower a team's winning percentage (Annala and Winfree, 2011). A study by Bloom (1999) also finds that there is a robust relationship between a team's calculated Gini coefficient, and both individual and team performance, where each is negatively impacted by high levels of salary dispersion. This dual effect supports the claim that lower individual performance, due to a high intra-team salary inequality, adversely impacts a team's overall performance as well.

This is reinforced by the "equity-pay theory" (Lazear, 1989), which states that a more equitable pay scheme within a firm leads to better individual performance, since this reduces uncooperative behavior by employees that may be detrimental to the firm. In complement, Jane (2010) confirms from her study that there is one-way negative causality between the dispersion of salary payment and team performance in Major League Baseball. Bose et al. (2010) even find that within a team setting, high levels of wage dispersion lead to sabotage by those individuals who feel underpaid. This sabotage activity mostly comes in the form of decreased effort, which then lowers their team's overall performance, as explained by the equity-pay theory. In fact, while much of this research uses season-level performance as the dependent variable, a study by Breunig et al. (2014) examines game-level performance as well; and they also find a negative relationship between inequality and team performance. Evidently, salary dispersion has been found to decrease individual effort levels within a team, under both a game and season-level analysis. This is clearly one possible explanation supporting the claim that a wider dispersion of salaries negatively effects an MLB team's overall performance.

In relation to this, the "team-cohesiveness hypothesis" (Levine, 1991) also suggests that narrow wage differentials positively affect team performance, as a result of improvements to team chemistry and organizational efficiency. On one hand, Jewell and Molina (2004) do find that team success in the MLB is not correlated with team efficiency, and that several teams with the lowest winning percentages are actually highly efficient. However, in accordance with the team-cohesiveness hypothesis, studies predominantly support the claim that there is a positive relationship between team efficiency and overall team performance. For instance, Levine (1991) finds that a lower wage gap in an organization reduces dissonance amongst employees, thus leading to greater team cohesion and performance. In support, Harder (1992) finds that in MLB teams with a greater level of salary dispersion, under-rewarded players perform more selfishly and less for the team's overall best interest. Moreover, a study by Debrock et al. (2004) concludes that "the most technologically efficient teams tend to have flatter salary distributions."

On a similar note though, the same study also finds that teams with above-average wages and payrolls achieve higher performance, which brings into question whether wage disparity or total payroll has a more robust impact on team performance (Debrock et al. 2004). In comparison, when a team's payroll level relative to the rest of the league is controlled for, Tao et al. (2016) find that while the team-cohesiveness hypothesis is supported, a team's payroll rank in the MLB "is a more robust explanatory variable" than salary dispersion. Therefore, it is unclear whether the positive effect of a flatter salary dispersion is a result of increased team-cohesiveness and efficiency, or whether teams with more equal salaries concurrently have higher payrolls, where payroll level is instead the driving factor behind team performance. Hence, this study contributes to this existing discussion by examining how the impact of salary dispersion differs between higher and lower performing teams. With this, total team payroll is also an independent variable in this analysis to capture its effect at varying levels of performance, as well as its correlation with a team's winning percentage.

4.0 DATA AND EMPIRICAL METHODOLOGY

4.1 Data

This study uses annual panel data from 1998 to 2016, covering salary, payroll, and performance statistics for all 30 MLB teams. The study does not use data before 1998, since there were less than 30 MLB teams prior to this year. In 1998, the Tampa Bay Devil Rays and the Arizona Diamondbacks were added to the league as expansion teams, where the number of teams in the league has not changed since this expansion. Annual team level data were obtained from the Sean Lahman's baseball database. The summary statistics for the data are provided in Table 1.

Table 1: Summary Statistics

Variable	Observations	Mean	Std. Dev.	Minimum	Maximum
TWP	570	.499986	.0710899	.2654321	.7160494
Gini	570	.5767672	.0527194	.3379976	.7501984
ln(TP)	570	18.10719	.4992808	16.18027	19.26216
ln(TR)	570	6.606892	.1153958	6.240276	6.916715
TWP(t-1)	568*	.4999836	.0708117	.2654321	.7160494
League	570	.4736842	.4997456	0	1

*Note: Tampa Bay Rays and Arizona Diamondbacks did not have a TWP for 1997

4.2 Empirical Model

Following Tao et al. (2016) and Annala and Winfree (2011), this study modifies and combines these models to include the independent variables *Gini*, *ln(TP)*, $TWP_{i(t-1)}$, and *League*. Further, this study adds the control variable *ln(TR)* to account for the effect of a team's offensive performance on their overall performance. This study applies a fixed effects and random effects model as well to test the possible impact of individual, team specific effects on a team's winning percentage. In the fixed effects model it is assumed that the independent variables are correlated with these individual, team specific effects. Rather, in the random effects model, the assumption is that the independent variables are not correlated with these individual, team specific effects (Annala and Winfree, 2011). This model can be written as follows:

$$TWP_{it} = \alpha + \beta_1 * TWP_{i(t-1)} + \beta_2 * Gini_{it} + \beta_3 * \ln(TP_{it}) + \beta_4 * \ln(TR_{it}) + \beta_5 * League_{it} + \eta\delta_{it} + \mu \quad \textbf{(1)}$$

This study employs a Hausman (1978) specification to test whether the individual, team specific effects are correlated with the independent variables. This is used to determine whether the fixed or random effect model is preferred given the dataset, in that the favored model it provides a stronger and more accurate estimation.

Along with using a fixed and random effects model, this study incorporates a model that is used to run multiple quantile regressions, at each quantile that is a multiple of 10. While also running a pooled OLS regression, unlike previous research, this study employs a quantile regression to test the effect of salary dispersion at different levels of team performance. The model adopted can be written as follows:

$$TWP_{it} = \alpha + \beta_1 * TWP_{i(t-1)} + \beta_2 * Gini_{it} + \beta_3 * \ln(TP_{it}) + \beta_4 * \ln(TR_{it}) + \beta_5 * League_{it} + \mu \quad \textbf{(2)}$$

4.3 Description of Variables

In both models, the dependent variable is TWP_{it} which represents the winning percentage of a given individual team *i* in year *t.* This can be calculated by dividing a team's total wins by total games played in a given year *t.* This variable directly corresponds with a team's overall annual performance.

The independent variables consist of five baseball measures and statistics that can contribute to a team's level of performance. All variables are measured annually, so each is listed at year *t. Gini* represents a team's level of wage disparity. It can be calculated by imputing a team's players' salaries into a Gini macro function, where a value is generated that ranges from 0 to 1. The second variable, $\ln(TP_{it})$, is the natural logarithm of a team's total payroll. It can be calculated by taking the natural logarithm of the sum of individual player salaries on a given team. Next, $\ln(TR_{it})$ is the natural logarithm of a team's total runs scored in a given year. This represents the contribution of offensive success to a team's performance. $TWP_{i(t-1)}$ is a lag variable that represents a team's winning percentage in the previous year. It signifies the momentum factor that a previous year's performance can have on the current year's performance. Further, $League_{it}$ is a dummy variable to denote a team's league membership within the MLB, where a value of 1 is coded for the American League and 0 for the National League. Finally, δ_{it} is added to the fixed and random effects model to capture the individual, team specific effects. Appendices A and B provide the acronym, description, data source, and expected sign for each variable.

5.0 EMPIRICAL RESULTS

5.1 Fixed Effects and Random Effects Model

The primary objective of this study is to find the relationship between salary dispersion and team performance in Major League Baseball, which is meant to extend the existing research completed on this topic. Further, this study also seeks to analyze whether this estimated impact is a result of better team cohesiveness and efficiency, or instead a higher overall team salary that is evenly distributed amongst several highly skilled players. For this reason, several regressions were run to accurately capture the impact of the independent variables on the dependent variable, team winning percentage (*TWP*). First, complementing the research of Annala and Winfree (2011), the fixed and random effect model (1) was tested. The results of this regression can be found below in Table 2.

Table 2: Regression Results for Fixed and Random Effect Models

Variable/Measure	Coefficient Values	
	Fixed Effects Model	Random Effects Model
Gini	-0.125*** (0.046)	-0.094** (0.043)
ln(TP)	0.041*** (0.006)	0.033*** (0.005)
ln(TR)	0.326*** (0.023)	0.283*** (0.021)
TWP(t-1)	0.172*** (0.039)	0.282*** (0.037)
League	-0.001 (0.029)	-0.013*** (0.006)
Constant	-2.409*** (0.209)	-2.053*** (0.166)
Overall R-Squared	0.4463	0.4651
F-value/Wald Chi Squared	68.43***	488.69***
Number of Observations	568	568

Note: ***, **, and * denotes significance at the 1%, 5%, and 10% respectively.
Standard Errors in Parentheses

After running both regressions, the Hausman (1978) test was then be applied to determine whether the fixed or random effects regression results are preferred. The test led to the rejection of the null hypothesis that the random effects regression is preferred, leading to the conclusion that the fixed effects model is more applicable given the dataset used. This indicates that the independent variables are correlated with the individual, team specific effects. Indeed, a study by Depken (2000) instead found the Hausman test to support a random effects model when analyzing salary dispersion and team performance in the MLB. Yet, this study used data from 1985-1998, and the Herfindahl-Hirschman index (HHI) was also utilized rather of Gini coefficients to measure salary dispersion. This helps explain these contrasting results. It also reveals that the preference for estimating the determinants of team winning percentage in the MLB may have changed since 1998, where a fixed effects model is now preferred. This finding is especially important since Annala and Winfree (2011) did not use the Hausman test in their more recent study that applies a fixed and random effects model.

Likewise, the overall R-Squared of the fixed effects model is 0.4463. While this is below 0.5, it still indicates that the model is a decent fit for the dataset. Even so, the high f-statistic of 68.43 and p-value of approximately 0 indicate that at least one of the independent variables are statistically significant. As shown above in Table 2, the independent variables representing the level of salary dispersion, total payroll, total runs allowed, and team winning percentage in the previous year are all statistically significance at a significance level of 1%, given that their p-values are all less than 0.01. This shows that these variables all have an estimated effect on the dependent variable, team winning percentage. The magnitude of each variable's estimated impact corresponds with its coefficient values. On the other hand, the independent variable representing a team's league membership has a high p-value of .972, which suggests that a team's league does not have an estimated influence on their winning percentage.

Furthermore, looking at the results from the fixed effects regression, the Gini variable has a coefficient value of -0.125, which means that an increase of its value by .01 or 1% is estimated to decrease a team's winning percentage by 0.125, or by 12.5%. This demonstrates a negative relationship between salary dispersion and team performance, which supports both the "equity-pay theory" (Lazear, 1989) and the "team-cohesiveness hypothesis" (Levine, 1991). In addition, these findings help reinforce the previous research that also conclude a similar negative relationship. However, Tao et al. (2016) find the impact of salary dispersion on team winning percentage to be approximately half as substantial as this study's results; and Annala and Winfree

(2011) actually find salary dispersion to have a larger effect on team winning percentage. Evidently, the magnitude of salary dispersion's effect on team performance found in this study is approximately the arithmetic average of the respective results from Tao et al. (2016) and Annala and Winfree (2011). This is reasonable given that this paper combines the empirical models used in each of these previous studies.

5.2 Quantile Regression Method

Next, a quantile regression method was employed to test the effect of salary dispersion at different levels of team performance. Using model (2), a regression was run at each quantile that is a multiple of 10. This is meant to see how the estimated impact of the independent variables differ as a team's winning percentage changes. In this scenario, the 10^{th} Quantile represents the teams with the worst performance, since their winning percentages are only greater than 10% of the teams in the MLB. Conversely, the 90^{th} Quantile represents the teams with the best performance, since their winning percentages are greater than 90% the teams in the MLB. This is surely an area where limited empirical research has been conducted, what differentiates this study from previous works. The results of each quantile regression, as well as the pooled OLS regression, can be found on the next page in Table 3.

For a quantile regression, the R-squared is not as useful of a measure to determine a model's goodness of fit because many of the properties of the R-squared in an OLS regression are not applicable for in a quantile regression. That being said, the R-squared for the pooled OLS regression is 0.4651, which is similar to the overall R-squared of the fixed effects model. This indicates that the model used is still a decent fit for the given dataset. Next, looking at results for the variable of interest, the variable that represent a team's salary dispersion is statistically significant: at a significance level of 1% for the 20th, 30th, 40th, and 50th quantile; at a significance level of 5% for the 10th and 60th quantiles; and at a significance level of 10% for the 70th quantile. This variable is not statistically significant for the 80th and 90th quantiles.

For those quantiles where this Gini variable is statistically significant, there is consistently a negative relationship found between salary dispersion and team performance, as is found when using the fixed effects model. Additionally, the coefficient values shown in Table 3 represent the magnitude of salary dispersion's effect on team winning percentage, and this magnitude decreases as the quantile increases. For example, for a team in the 10th quantile, a 1% increase in their Gini coefficient is estimated to result in a 18.9% decrease in their overall winning percentage; while for

Table 3: Regression Results for Quantile and Pooled OLS

Variable	Coefficient Values									
	Pooled OLS	10th Quantile	20th Quantile	30th Quantile	40th Quantile	50th Quantile	60th Quantile	70th Quantile	80th Quantile	90th Quantile
Gini	-0.094** (0.043)	-0.189** (0.078)	-0.168*** (0.061)	-0.155*** (0.052)	-0.140*** (0.046)	-0.127*** (0.044)	-0.122** (0.047)	-0.010* (0.056)	-0.081 (0.066)	-0.056 (0.089)
ln(TP)	0.033*** (0.005)	0.034*** (0.010)	0.036*** (0.008)	0.038*** (0.008)	0.040*** (0.006)	0.041*** (0.006)	0.043*** (0.006)	0.044*** (0.007)	0.046*** (0.009)	0.049*** (0.011)
ln(TR)	0.283*** (0.021)	0.332*** (0.040)	0.330*** (0.031)	0.330*** (0.031)	0.330*** (0.023)	0.326*** (0.022)	0.324*** (0.024)	0.323*** (0.028)	0.322*** (0.033)	0.319*** (0.045)
TWP(t-1)	0.282*** (0.037)	0.169** (0.070)	0.170*** (0.055)	0.170*** (0.055)	0.171*** (0.041)	0.172*** (0.039)	0.172*** (0.042)	0.173*** (0.050)	0.174*** (0.060)	0.175** (0.079)
League	-0.013*** (0.005)	0.004 (0.052)	0.002 (0.041)	0.002 (0.041)	0.000 (0.031)	-0.001 (0.029)	-0.002 (0.032)	-0.037 (0.037)	-0.004 (0.044)	-0.006 (0.059)
Observations	568	568	568	568	568	568	568	568	568	568

Note: ***, **, and * denotes significance at the 1%, 5%, and 10% respectively. Standard Errors in Parentheses a team in the 70th quantile, this same 1% increase is estimated to result in only an 8.1% decrease in their winning percentage. In fact, the significance level for which the Gini variable is statistically significant increases beyond the 10^{th} quantile, as seen by the increasing p-values at each quantile. This demonstrates that as a team's performance increases, the effect of salary dispersion becomes weaker, to the point where this variable's impact is not statistically significant for the teams with the highest winning percentages in the 80^{th} and 90^{th} quantiles. These results indicate that salary dispersion has a greater effect on team performance for lower performing teams than it does for higher performing teams.

While research has been conducted surrounding this relationship in Major League Baseball, this study distinguishes itself in that it finds how this relationship changes at different performance levels. Indeed, previous conclusions from Bloom (1999), Annala and Winfree (2011), and Tao et al. (2016) are supported by these quantile regression results, at least for teams besides those with the highest performances in the 80^{th} and 90^{th} quantiles. More notably though, these findings contribute meaningful insights to existing research because they indicate that the relationship between salary dispersion and team performance is not uniform, where its significance differs depending on a team's current performance level. With this knowledge, these regression results can be applied to guide player selection and compensation decisions more effectively than previous research has been able to do. Teams can now better and more accurately manage such decisions depending on which performance quantile their team falls within, since they know that salary dispersion's impact on their performance is contingent this relative factor.

As eluded to earlier as well, this relationship has been found to be positive or non-existent when it is analyzed in different, more individually dominated sports like hockey (Marchland et al., 2006) and basketball (Berri and Jewell, 2004). It would be interesting to look at how this relationship differs depending on a team's level of performance through using a quantile regression method. This could further contribute to the field of sports and labor economics by adding more specified insight into the effect that high wage differentials can have on a team's performance.

In fact, it also would be useful to examine whether this negative relationship is present in other more team-oriented sports, such as professional soccer where there are 11 players per team playing at a time whom all must effectively contribute for the team to consistently win and succeed. Studies conducted by Bucciol et al. (2014) and Coates et al. (2016) find that team production and performance are negatively responsive to increases in salary inequality in the Italian Soccer League and Major League Soccer (MLS). Yet, these studies do not analyze this topic using a quantile regression method either. It would thus be interesting then to see how the relationship between salary dispersion and team performance differs depending on a team's performance level in professional soccer. Such research could not only help uphold the findings in this study, but it would also further contribute to this area of research so that such results could be more effectively used to guide player selection and compensation decisions in professional sports.

5.3 Discussion and Limitations

Moreover, while salary dispersion is the primary determinant of interest in this study, total payroll is also important when analyzing the reasoning behind the estimated impact of wage differentials on team performance. According to the fixed effects model, a 1% increase in total payroll is estimated to result in a 4.1% increase in a team's winning percentage, where this relationship is statistically significant at a significance level of 1%. With this, the quantile regression results estimate that the effect of a 1% increase in total payroll on team performance ranges from 3.4% for the 10^{th} quantile, to 4.9% for the 90^{th} quantile. This relationship is also consistently significant at a significance level of 1% through all quantiles examined. This means that as a team's performance increases, so does the impact of total payroll on their winning percentage.

From here though, this actually displays that salary dispersion has a greater effect on team winning percentage than total payroll, which contrasts previous findings that total payroll is a more robust variable (Tao et al., 2016). Nevertheless, this does not necessarily mean that a higher payroll directly leads to a better winning percentage, especially because the correlation coefficient between these two variables in the study is only 0.34. In fact, even when the average player's salary is calculated for each MLB team in the dataset, the correlation coefficient between a team's average player's salary and their overall winning percentage is still 0.35, which is again a fairly low correlation.

Hence, while this study finds a negative relationship between salary dispersion and team performance in the MLB, it is inconclusive whether this estimated impact is a result of better team cohesiveness and efficiency, or instead a higher overall team salary that is evenly distributed to several highly skilled players. One of this study's primary limitations is that it is difficult to capture the combined skill level of a team of individuals in a quantifiable measure. There is no "golden" formula for determining the correct compensation for players either. Besides skill level, several other subjective opinions and biases amongst a team's upper management effect how MLB teams value players when making player selection and salary decisions. This is why it is misleading to use total payroll as the measure of a team's combined skill level, especially with the conflicting approaches in Major League Baseball in valuing and compensating players as discussed earlier. This makes it more difficult to determine the reasoning behind the negative relationship found between salary dispersion and team performance.

That being said, this study still consistently finds a wide salary dispersion to have an adverse effect on team performance, and a more robust impact than team payroll. This should be recognized by MLB organizations to improve their overall team performance and success. However, this relationship should not be taken in absolute terms, and it is important for MLB personnel to also consider their team's unique environment, culture, and characteristics when making player selection and compensation decisions. For instance, the fact that wage inequality has a more significant impact on team winning percentage for lower performing teams means that these teams should place a greater focus than their higher performing opponents on narrowing their level of salary dispersion. Perhaps there is a certain threshold of combined team skill level that makes a team perform in the highest quantiles, where if a team surpasses this threshold, salary dispersion is not as important in determining overall team performance. This would then indicate that even though lower performing teams have a combined skill level that falls below this threshold, they could instead still increase their performance by fostering greater team chemistry and efficiency via narrowing their level of wage differentials amongst players. This is certainly a plausible explanation behind this study's quantile regression results.

6.0 CONCLUSION

This study contributes to the existing research surrounding the relationship between salary dispersion and annual team performance in Major League Baseball. This is meant to further confirm the application of both the "equity-pay theory" (Lazear, 1989), along with the "team-cohesiveness hypothesis," to help explain the negative effect that a large salary dispersion has on an MLB team's performance. Additionally, unlike previous research, this study uses the most current MLB statistics and salary data, and applies a quantile regression method to analyze how the estimated impact of wage differentials differs between higher and lower performing teams.

Overall, the estimation results find that there is a negative relationship between salary dispersion and annual team winning percentage. The results also show that a team's calculated Gini coefficient has a greater effect on team performance than total payroll size, which contrasts previous findings that total payroll is the more robust independent variable. Further, the fixed effects model is concluded to be preferred and a better fit for the dynamic panel dataset. This indicates that the estimated impacts of the independent variables in the model are correlated with individual, team specific effects. Lastly, the quantile regression results reveal that as a team's annual performance increases, the effect of salary dispersion is weaker, where this variable's impact is in fact statistically insignificant for teams with winning percentages in the 80^{th} and 90^{th} quantiles. This leads to the conclusion that salary dispersion has a greater impact on lower performing teams than it does for higher performing teams, a question which has yet to be analyzed prior to this study.

This is an important finding that meaningfully adds to the existing research because it indicates that the relationship between salary dispersion and team performance is not uniform, where its significance differs depending on a team's current level of performance. This helps to advance the effectiveness of applying results in this field of study to better guide player selection and compensation decisions. Further research can surely be conducted by employing a similar quantile regression when studying other professional sports, such as hockey, basketball, and soccer, to analyze whether the effect of wage differentials differs depending on a team's performance level. This would help to cultivate a more comprehensive understanding of this phenomena in the fields of sports and labor economics.

Nonetheless, it is still inconclusive whether this estimated impact is a result of better team cohesiveness and efficiency, or instead a higher overall team salary that is evenly distributed amongst several highly skilled players. As a result, an avenue of future research could also be an analysis into MLB teams' skill levels based on their respective players' qualitative and quantitative performance attributes. This could be used to compare the relationships between a team's skill level differs, salary dispersion, and team winning percentage. A quantile regression method could also be used to see if a team's skill level varies, as well as its estimated impact, depending on their winning percentage relative to the rest of the league. This will help further explain the reasoning behind salary dispersion's negative relationship with team performance in Major League Baseball.

Baseball personnel and upper level management should not conclude from this study that there is a "golden" rule for compensating players and establishing their rosters. Indeed, salary dispersion is estimated to negatively affect team performance, but the magnitude of this impact differs depending on a team's winning percentage, as shown by the quantile regression results. For example, the results indicate that lower performing teams should perhaps strive to increase their overall performance via fostering greater team chemistry and efficiency by having a lower level of salary dispersion. Along with this, baseball personnel should also take into account the individual, unquantifiable characteristics of their team and organizational culture when deciding how to select and compensate players. Therefore, depending on a team's performance level and these unique team attributes, the optimal player selection and compensation strategy will differ on a team by team basis. This is an important reality to acknowledge and remember moving forward as further research is conducted in this field of study.

Appendix A – Variable Description and Data Source

Acronym	Description	Data source
TWP_{it}	Team *i* winning percentage in current year (= wins/games played)	Sean Lahman's Baseball Database
$Gini_{it}$	Level of wage disparity on team *i*, calculated using player salaries in current year (Range 0-1)	Sean Lahman's Baseball Database
$ln(TP_{it})$	Natural logarithm of team *i* total payroll in current year	Sean Lahman's Baseball Database
$ln(TR_{it})$	Natural logarithm of team *i* total runs scored in current year	Sean Lahman's Baseball Database
$TWP_{i(t-1)}$	Lag variable representing team *i* winning percentage in previous year *t*-1	Sean Lahman's Baseball Database
$League_{it}$	Dummy Variable coded 1 for American League, 0 for National League	Sean Lahman's Baseball Database
$\eta\delta_{it}$	Represents individual, team specific effects	Sean Lahman's Baseball Database

Appendix B – Variables and Expected Signs

Acronym	Variable Description	What it captures	Expected sign
$Gini_{it}$	Team Gini Coefficient	The pay equity and team-cohesiveness effects of salary dispersion on team performance	–
$ln(TP_{it})$	Natural Logarithm of Team Total Payroll	The positive effect that total payroll has on the skill level of a team's players	+
$ln(TR_{it})$	Natural Logarithm of Team Total Runs Scored	The positive effect that scoring runs has on team performance	+
$TWP_{i(t-1)}$	Team Winning Percentage in Previous Year	The momentum and persistence effect of past team performance on present team performance	+
$League_{it}$	Dummy Variable for Team League	Differences in performance based on relative league difficulty in a given year	+/–
$\eta\delta_{it}$	Individual, Team Specific Effects	Team specific attributes not captured in quantifiable variables that effect team performance	+/–

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