Cohesion vs Hierarchy: The Impact of Roster Composition on Team Performance in the National Basketball Association

Shadi Chamseddine – 100937807

Christopher Lee – 100937241

Carleton University

Abstract

Our paper explores the optimal roster composition in terms of team performance for National Basketball Association (NBA) teams within the leagues roster composition constraints. Competing economic theories pit hierarchical pay structures against more homogeneous pay structures to determine which elicits the greatest incentive to boost worker productivity. Our results suggest different levels of salary dispersion among a team’s players has no causal impact on team performance. In contrast, analysis on team composition shows higher rates of within-team Marginal Revenue Product (MRP) dispersion results in better team performance. Given salary cap constraints and the high impact of star players on team performance, it is optimal to fill your team with a few top productive players and the remainder with minimum salary players.

Keywords: wage inequality, marginal revenue product

Impact of Salary and Marginal Revenue Product Dispersion on Team Performance in the National Basketball Association

In the context of roster composition and its impact on team performance, our paper explores two main questions. First, we examine the individual impact of salary dispersion and Marginal Revenue Product (MRP) dispersion on team performance in the National Basketball Association (NBA). Second, we determine which measure is a better indicator for team performance.

The primary focus of team owners, stakeholders, and front office management is maximizing team profitability. Better performing teams generate greater revenues through increased fan interest, merchandise sales and ticket revenues. As such, to maximize profits, teams attempt to attract and sign the best players which often improves team performance. Prior to 1984, NBA teams located in the largest and most prosperous basketball markets had the financial resources to unfairly assemble teams composed of the league's best players. In an effort to reduce the geographical disadvantage between teams, the NBA introduced the “salary cap” in 1984, which imposed a constraint on roster assembly by implementing a homogenous ceiling on total player payroll for all NBA teams. Since NBA management has the ability to form their roster in any way within the constraints of the salary cap, they have the option of adopting a homogenous pay structure by composing their roster primarily of average level players with similar salaries, or they can adopt a hierarchical pay structure by composing their roster of a few top level star players with large salaries, and filling out the remainder of the roster with low level, small salaries players. As players are the primary factor affecting team performance, team management is interested in understanding how roster composition with respect to the salary cap from the standpoint of salary dispersion impact team performance.

The relationship between pay structures and worker performance has been studied extensively in economics. There are competing economic theories with regards to salary dispersion and worker performance, namely tournament theory (Lazear and Rosen, 1981) and pay compression theory, (Levine, 1991). Tournament theory states hierarchical pay structures provide incentives for increased worker productivity. The idea is a system which provides opportunities for promotions encourages workers to increase effort and performance to try and achieve a higher salary, while a system with a homogenous salary structure provides no such incentive. In fact, it is argued the larger the salary dispersion, the greater the incentive to raise effort and performance, since the potential returns to productivity are higher. In contrast, the pay compression theory states equal pay structures foster group cohesion in organizations which could raise worker productivity. The idea is unequal pay structures cause workers to become resentful towards their co-workers and employers. This results in decreased motivation, teamwork and job satisfaction, leading to losses in individual and overall team productivity.

A few papers have tackled this question in the NBA setting with mixed results. Berri and Simmons (2011) find NBA players exhibit behaviour consistent with tournament theory, whereas, Berri and Jewell (2004), and Katayama and Nuch (2011) find salary dispersion has no causal effect on team performance and therefore supports neither theory. In the literature attempting to answer this question, there exists an endogeneity problem which results in inconsistent estimators. The endogeneity problem arises when better team performance in the previous season leads to higher or lower within-team salary dispersion in the following season. Berri and Simmons (2011) attempt to deal with the endogeneity problem using a Difference in Differences analysis with the 1996 Collective Bargaining Agreement (CBA) as a quasi-natural experiment. This method serves its purpose of dealing with endogeneity for their specific paper, however there are drawbacks. CBA's change every few seasons, so analysis using these agreements becomes outdated and may no longer hold for future agreements based on the conditions reached between the players and owners. Further, there is judgement in picking the treated and non-treated groups, which may result in selection bias. We deal with this endogeneity problem in a different manner accounting for these drawbacks.

In the NBA context, player and team statistics, along with salary data are widely available, which means our salary and performance measures for productivity are observable. This data availability makes the NBA a prime target to conduct analysis on these pay dispersion theories. Using regular season win percentage as our measure for team performance, bootstrap variance and Theil's index as our measures for dispersion, and MRP as our individual player performance metric, we analyze NBA team and player performance data for the 2005 to 2019 NBA seasons, to understand the relationship between our dispersion measures and their impact on team performance.

In our paper, we make three primary contributions to the existing literature. First, we use Arellano-Bond Generalized Method of Moments (GMM) Dynamic Panel Data (DPD) estimator with lags to net out endogeneity in the model. The endogeneity problem is dealt with by using past observations of team performance as instruments. For our second contribution, since each NBA team typically has between 14-17 players on their roster each season, we must account for the low sample size to ensure we have a low margin of error when calculating our dispersion measures. Taking each team-year roster as a realization, we conduct a non-parametric bootstrap with replacement to estimate the true population dispersion in our data. For our third contribution, we analyze the relationship between MRP dispersion and team performance. We believe MRP dispersion is a better predictor of team performance, because MRP represents a player's actual productivity, whereas salary is typically based on a player's previous productivity combined with the team's expectation of what the player's future productivity will be. Our measure of MRP in this context is through a statistic referred to as Value Over Replacement Player (VORP). VORP acts as a single per season productivity score comparable across all players. Taking this information, we create a model which allows us to conduct inference on the impact of salary dispersion and MRP dispersion on NBA win percentage. We expect MRP dispersion to trend closer to team performance compared to salary dispersion.

When it comes to salary dispersion, our results are consistent with both Berri and Jewell (2004) and Katayama and Nuch (2011), who find salary dispersion has no causal effect on team performance. On the other hand, when testing our models with MRP dispersion, we find larger MRP dispersion among a team's roster has a statistically significant positive impact on team performance. Looking from an MRP perspective, our results are more in line with Berri and Simmons (2011) where teams with higher MRP dispersion have better team performance. We find a one percent increase in MRP dispersion is associated with on average an 11.0 percent increase in team performance. Our results suggest MRP dispersion is a better indicator of team performance than salary dispersion.

Literature Review

The literature examining this problem is divided on the likely impacts of increased salary dispersion on team performance. Berri and Simmons (2011) conduct a season level analysis on salary dispersion and team performance in the NBA, and find players exhibit behaviour consistent with tournament theory. On the other hand, Berri and Jewell (2004), and Katayama and Nuch (2011) both conduct a game level analysis on the salary structure within a team's roster and its impact on team performance in the NBA and find salary dispersion has no causal effect on team performance and therefore supports neither pay structure theory.

In their paper, Berri and Simmons (2011), use a difference-in-differences method to analyze the effect of the 1996 CBA on roster composition as it led some teams to increase payroll inequality. Using the 1996 CBA as a quasi-natural experiment, they split the teams into a treated group if the roster's income inequality rose following the CBA, or the control group if it did not. The researchers begin by creating a player salary model which uses a weighted average of the player's performance statistics. They then identify two measures of salary inequality in their analysis, one for dispersion of expected salaries and one for dispersion of salaries around their expected values. These two measures of pay inequality are inserted into a team-level regression model of team performance along with team effects and a dummy variable for before and after the 1996 CBA, with team performance measured by regular season winning percentage. They find teams and players respond positively to increased dispersion of expected salaries, which the authors confirm as supporting the tournament theory.

Katayama and Nuch (2011), take a different approach to modeling this problem. Their measure of salary dispersion is based on game level rosters while the outcome of the individual game is used as their performance measure. They test their model using three different roster specifications, which are active players, occasional players, and the entire player population. They find, regardless of the roster specification chosen, salary dispersion does not influence team performance. They find team performance is not affected by salary dispersion either among players who play in the game or among all players on the rosters. To compare to existing literature, Katayama and Nuch test their model at the season-level. The results at the season-level are consistent with the game-level results which show salary dispersion has no causal effect on team performance. Thus, this study does not support the tournament theory nor the cohesion theory.

Finally, Berri and Jewell (2004), find wage inequality and team performance are not related in the NBA setting. The 1996 CBA was projected to raise team payroll by 45 percent prior to its implementation, thus in anticipation of the increase in the salary cap, many teams strategically prepared to enter the offseason with relatively empty rosters to maximize the salary cap room they had available to spend on players. Similar to Berri and Simmons (2011), they use the 1996 CBA as a quasi-natural experiment to examine how wage inequality impacts the performance of a team. The researchers use the Herfindahl-Hirschman Index for salary dispersion at the team level. They find salary dispersion is not a statistically significant determinant of team wins. They state players will not react negatively to salary dispersion by playing poorly because shirking can be punished very quickly with the large number of idle players.

Methodology

Our model uses the Arellano-Bond Generalized Method of Moments (GMM) Dynamic Panel Data (DPD) estimation technique. The Arellano-Bond estimator deals with endogeneity, heteroskedasticity, and autocorrelation in panel-data problems. To overcome the endogeneity problem, the model uses past observations of team performance as instruments. Since better team performance can lead to higher or lower salary dispersion in the following season, instruments of past team performance are used to control for this impact. Additionally, autocorrelation is accounted for by controlling for lagged versions of team performance on current year team performance. In our case, we only account for a couple of seasons of lags, because the short length of NBA contracts and player trades between teams, creates high roster turnover which mitigates the autocorrelation between current team performance and lagged versions. Finally, the Arellano-Bond estimator accounts for the issue of heteroskedasticity as it is consistent and asymptotically efficient in the presence of heteroskedasticity. Overall, Arellano-Bond allows us to obtain consistent estimators for our coefficients of interest.

As our measure of salary dispersion is based at the team level, it needs to be computed from the individual player salaries on each team. We convert player salaries in each season to 2019 USD using the yearly Consumer Price Index for the United States, allowing us to account for inflation and normalize player salaries across seasons. As salaries increase each year for inflation, the difference between two equivalent salaries will widen as you move through time. In our case we used two different measures of salary dispersion, bootstrap variance and Theil's index. The bootstrap variance is to account for the fact an NBA team may have a maximum of 17 players on its active roster. The small sample size causes the calculation of variance to be larger. Our bootstrap process is replicated 499 times to create 499 bootstrap samples. From these bootstrap samples we are able to create a sampling distribution and obtain a bootstrap variance for each team. Theil's index is used for our second measure of salary dispersion as it can be decomposed into inequality within and between differently defined population subgroups.

Due to small NBA team rosters, it is easy for a team to have a small number of players available to play in games, whether due to numerous injuries or other factors to players. There exist two contract types allowing team to maintain full rosters on a short-term basis to overcome these issues. These two types of contracts are 10-day contracts and 2-way contracts, which allows for a player to temporarily play for the NBA team as well as their minor league team. Players on these contracts make less than the NBA minimum salary for a "full-time" roster player, which would skew the dispersion measures. Thus, they are omitted from our analysis as we are focused on “full-time” players on NBA teams.

Our model for the relationship between salary dispersion on team performance is as follows:

$$TEAM\ PERFORMANCE_{it} = \beta_0 + \beta_1 LOG\ SALARY\ DISPERSION_{it} + \beta_2 TEAM\ EFFECTS + \varepsilon_{it} \quad (1)$$

where $TEAM\ PERFORMANCE_{it}$ is the regular season win percentage for a team in a given season. $LOG\ SALARY\ DISPERSION_{it}$ is the within-team player log salary bootstrap variance/Theil’s index for a given season. As $TEAM\ PERFORMANCE_{it}$ is in a percentage form, we log transform our salary dispersion measure to compare them across the same units. $TEAM\ EFFECTS$ is a vector of control variables including conference and average age. The conference variable is to account for team schedules because a team located in the Eastern Conference will play teams within its own conference more than teams in the Western Conference, and vice versa. The average age of players on a team is included because of contracts and productivity. A player’s contract is partially dictated by what portion of their career they are in. Players at the peak age of their career are typically paid more money based on production, whereas young players on rookie contracts and older players reaching the end of their careers have these factors taken into account when being offered a contract.

Team and player performance data is extracted from Basketball Reference, which is a professional basketball statistics website. Player salary data is retrieved from Basketball Reference and HoopsHype, which is a basketball news outlet. Salary cap and salary structure is extracted from Basketball Reference and RealGM, which is a sports reporting website. Consumer Price Index data is retrieved from the Minneapolis Federal Reserve Board.

As players can sign multi-year contracts with teams, it means team performance for the current season can be affected by salaries determined in a past season. When looking at these contracts across seasons they can be considered static in a sense, as salary for a player across multiple seasons is constant. Measures encompassing a player's overall value to a team in a season is dynamic across seasons, one such measure is the MRP of a player in a season. Economic theory states in a competitive market, workers are paid according to their MRP. As the NBA is a competitive market within the scope of top-level basketball players, we believe MRP dispersion is a better predictor of team performance. We use VORP as our basketball measure for MRP. VORP is calculated for each player by converting their Box Plus/Minus (BPM) statistic into an estimate of each player's overall contribution to their team. BPM is a box score-based statistic to measure a basketball player's skill level and contribution to their team. The VORP value is a comparison to a "replacement player", where a "replacement player" is a player paid the league minimum salary.

Our model for the relationship between MRP dispersion on team performance is as follows:

$$TEAM\ PERFORMANCE_{it} = \beta_0 + \beta_1 LOG\ MRP\ DISPERSION_{it} + \beta_2 TEAM\ EFFECTS + \varepsilon_{it} \qquad (2)$$

The difference between model (2) and model (1) is MRP dispersion replaces salary dispersion as our variable of interest in the regression. We do this substitution to study the impact of each dispersion measure individually on team performance across the same model specifications. This provides the proper baseline to compare the two dispersion measures to determine which one acts as a better predictor of team performance. It also gives us two different ways to model our relationship, which provides different results and intuition to the problem.

Results

The effect of salary dispersion on team performance tells a different story than the effect of MRP dispersion on team performance. Our model shows salary dispersion has an insignificant impact on team performance while increased MRP dispersion has a significant positive impact on team performance. We see a one percent increase in salary dispersion is associated with on average a 0.9 percent point increase in team performance, when using our first measure of salary dispersion, bootstrap salary variance, as shown below in Table (1). This relationship is not statistically significant at any level.

Table 1[1]

Salary Dispersion Impact on Win Percentage

Win Percentage	Coef.
Constant	-0.518
	(0.333)
Log Bootstrap Salary Variance	0.009
	(0.010)
Win Percentage L1	0.584***
	(0.116)
Conference	0.000
	(Omitted)
Average Age	0.018**
	(0.008)

[1] Standard errors are shown in parenthesis. ,* ,** ,*** represent statistical significance at the 10%, 5% and 1% levels, respectively.

With our second measure of salary dispersion, Theil's index, we see a one percent increase in salary dispersion is associated with on average a 3.1 percent decrease in team performance, as shown below in Table (2). This relationship is not statistically significant at any level.

Table 2

Salary Dispersion Impact on Win Percentage

Win Percentage	Coef.
Constant	-0.302
	(0.198)
Log Theil's Index Salary	-0.031
	(0.024)
Win Percentage L1	0.559***
	(0.115)
Conference	0.000
	(Omitted)
Average Age	0.018**
	(0.008)

In both cases, our measures of salary dispersion do not have a statistically significant impact on team performance. Our two dispersion measures give us contradicting results, with bootstrap variance showing a positive relationship between salary dispersion and team performance, whereas the Theil index shows the opposite. Our results are consistent with both Berri and Jewell (2004) and Katayama and Nuch (2011), who find salary dispersion has no causal effect on team performance. We argue since the NBA is the top-level basketball association in the world, any form of shirking due to resentment stemming from unequal pay structures can be punished easily, as poor performing players can have their contracts canceled and replaced with a player from the minor league pool. To this point, any incentives associated with the pay compression theory no longer apply. We also argue in an NBA setting, player performance is not necessarily tied to how hard a player works, but rather star players are gifted with the talent level other players cannot reach no matter how hard they train, which mitigates the incentives driving tournament theory. Therefore, we conclude for these reasons, salary dispersion follows neither the tournament theory nor the pay compression theory.

When looking at MRP dispersion, we see a one percent increase in MRP dispersion is associated with on average an 11.0 percent increase in team performance, as shown below in Table (3). This relationship is statistically significant at the one percent level.

Table 3

MRP Dispersion Impact on Win Percentage

Win Percentage	Coef.
Constant	0.206
	(0.132)
Log Bootstrap VORP Variance	0.11***
	(0.007)
Win Percentage L1	0.114
	(0.007)
Conference	0.000
	(Omitted)
Average Age	0.019***
	(0.005)

In the case of MRP dispersion, our results show MRP dispersion has a positive relationship with team performance, and the relationship is highly statistically significant. Our results are more in line with Berri and Simmons (2011), as we find teams with higher MRP dispersion tend to perform better on average. We argue since only five players are on the court at any given time in the NBA, the impact of a star player is much larger than a star player in any other sports league. Our data shows the VORP of star players in the NBA is typically around 12 times higher than the average player, which means they have a significant impact on their team’s ability to win. Therefore, when MRP dispersion is higher, teams have more star players, who are able to impact the game in terms of winning to a much greater degree than any group of average players can.

Overall, given our results, we argue MRP dispersion is a better predictor of team performance, because MRP represents a player's actual productivity, whereas our data shows salary is based on a player's previous productivity combined with the team's expectation of what the player's future productivity will be. Therefore, MRP dispersion tends to explain more of the variation in team performance compared to salary dispersion.

Conclusion

The main questions explored in this paper are the impact of salary dispersion and MRP dispersion on team performance in the NBA. Within the branch of the salary dispersion analysis, we use bootstrap salary variance and Theil's index as our measures for dispersion. Both measures show there is no causal relationship between salary dispersion and team performance in the NBA, and therefore support neither tournament theory nor pay compression theory. Turning our attention to the MRP dispersion analysis, we find a one percent increase in MRP dispersion is associated with on average an 11.0 percent increase in team performance. The result is statistically significant at the one percent level. Our results suggest MRP dispersion is a better indicator of team performance than salary dispersion. Thus, NBA team management should structure their rosters with the largest MRP dispersion possible which will allow them to increase team performance and generate greater revenues as a result.

References

2018-19 NBA Standings. (n.d.). Retrieved from https://www.basketball-reference.com/leagues/NBA_2019_standings.html.

2018/19 NBA Player Salaries. (n.d.). Retrieved from https://hoopshype.com/salaries/players/2018-2019/.

2018-19 NBA Player Stats: Advanced. (n.d.). Retrieved from https://www.basketball-reference.com/leagues/NBA_2019_advanced.html.

About Box Plus/Minus (BPM). (n.d.). Retrieved from https://www.basketball-reference.com/about/bpm.html.

Arellano, M., & Bond, S. (1991). "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations." *The review of economic studies*, 58(2), 277-297.

Consumer Price Index, 1913-. (n.d.). Retrieved from https://www.minneapolisfed.org/about-us/monetary-policy/inflation-calculator/consumer-price-index-1913-.

Katayama, H., & Nuch, H. (2011). "A game-level analysis of salary dispersion and team performance in the National Basketball Association." *Applied Economics*, 43(10), 1193-1207.

Lazear, E. P., & Rosen, S. (1981). "Rank-order tournaments as optimum labor contracts." *Journal of political Economy*, 89(5), 841-864.

Levine, D. I. (1991). "Cohesiveness, productivity, and wage dispersion." *Journal of Economic Behavior & Organization*, 15(2), 237-255.

NBA Salary Cap History. (n.d.). Retrieved from https://basketball.realgm.com/nba/info/salary_cap.

NBA Salary Cap History. (n.d.). Retrieved from https://www.basketball-reference.com/contracts/salary-cap-history.html.

Simmons, R., & Berri, D. J. (2011). "Mixing the princes and the paupers: Pay and performance in the National Basketball Association." *Labour Economics*, 18(3), 381-388.

U.S. Department of Labor Bureau of Labor Statistic. (n.d.). Retrieved from https://data.bls.gov/cgi-bin/surveymost.