2017

A Game-Level Analysis: How Does Trade Affect Team Performance in NBA?

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A Thesis Submitted to

Department of Economics

Skidmore College

In Partial Fulfillment of the Requirement for the B.A Degree

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May 2, 2017

Abstract

Using game-level panel data on the National Basketball Association for 2015-2016 season, I examine the relationship between trade and team performance. In my study, trade is measured by a game-minute-adjusted salary dispersion. I construct a fixed effect model to analyze the effect of salary dispersion on team performance. The results show that salary dispersion is negatively related to team performance. To verify whether different team characteristics will affect this relationship, I categorize the teams into two groups twice based on their playoff likelihood and number of trades made. The results provide additional evidence that salary dispersion influence team performance negatively. The findings suggest that a compressed salary structures lead to more productivity in the NBA.

Acknowledgement

I am indebted to Professor Qi for his support and guidance. I thank Jiebei Luo for her assistance on data collection. I also thank Professor Von Allmen, Mackenzie Nelson, and Ziao Zhang for their helpful suggestions and comments.

I. Introduction

Empirical investigations have shown that the uncertainty of the outcome of games or the league championship is a significant factor explaining a league's total revenue (Kesenne 2000). To guarantee a more balanced competition, league authorities have always tried to regulate the player labor market and to prevent the concentration of talent on one team (Michie and Oughton 2004). A salary cap, as one of the institutional regulations, was introduced in the NBA during the 1984-1985 season, and was used to limit the ability of high revenue teams to acquire the more talented players. In recent years, salary caps have continuously increased in size in the NBA since the 2013-2014 season. Consequently, most players are not willing to sign long contracts because they will lose the opportunities to gain higher salaries in the future of their career. This phenomenon causes an instability of team rosters, and as such, trades between teams happen more frequently than before. In 2015-2016 season, 43 players (including four currently overseas) switched teams. That sum accounts for nearly 10% of the entire league, and represents almost a 50% increase from 2005. While salary caps in other North American sports leagues, such as the NFL, also increased in recent years, this distinct trading trend only occurred in the NBA. One potential explanation is that NBA payrolls have a soft cap that allows more flexibility for trading than the hard cap in the NFL. Therefore, it is important to know how trading trends affect the league. Specifically, I will study the relationship between trade and team performance in the NBA and test whether trade will hurt the competitive balance.

In terms of measuring trade, none of the sports economic papers in the current literature provide any methodology. Katayama and Nuch (2011) provides evidence that trades affect the salary structures of the team and therefore change the salary dispersion, which implies the wage distribution of the team. Therefore, although with limitation, I believe that variation in salary dispersion can represent the trade, at least to some degree. I collect a dataset that contains player's salary and game-level statistics for the 2015-2016 season to study the balancing effect of trading for the National Basketball Association (NBA). In the first step, I formulate an estimation model similar to Katayama and Nuch (2011) and test the relationship between salary dispersion and team performance in NBA for the 2015-2016 season. My empirical results confirm that better performance is associated with lower salary dispersion which is consistent with the results from the fixed effects model in Katayama and Nuch (2011), but against the results from Frick, Prinz, and Winkelman (2003) and Berri and Jewell (2004).

Literature suggests that the owners of sports teams can be either profit maximizers or win maximizers (e.g. Ferguson et al., 1991 and Zimbalist, 2003). Therefore, teams in different situations tend to trade players for different purposes. For instance, on one hand, teams that are less likely to get into the playoffs may sacrifice talented players for draft picks and young players so they may be able to improve team performance in future seasons. As better performance leads to better win-loss ratios and higher attendance (Cebula, 2013), teams are able to maximize profits through better performance. On the other hand, teams that are more likely to get into the playoffs or win a title look for talented players to improve team performance and thereby maximize their wins. I believe the relationship between salary dispersion varies for teams in different situations. I categorized 30 teams into two groups based on the odds that they would get into the playoffs. The first group includes 6 teams that have less than 5% chance to get into the playoffs, namely lower potential ranked group, according to FiveThirtyEight's NBA forecast before the season starts. The second group includes the remaining 6 teams whose chances to get into the playoffs are greater than 90%, namely higher potential ranked group. Then I analyzed the relationship between salary dispersion and team performance separately for two groups in the same regression model with fixed effects. Results show that effects of salary dispersion are not clear for the teams in these two groups. Considering trade will affect the relationship between salary dispersion and team performance, I also categorize 30 teams into two groups based on the number of transactions each of them made during 2015-2016 season. The first group includes 15 teams that trade less than 5 times during that season. The second group includes the remaining 15 teams that trade more than 5 times during that season. Results show that trade might enhance the effect of salary dispersion on team performance.

One feature that distinguishes this study from those in the current literature is that we use individual game outcomes to measure variables such as team performance and salary dispersion. Season-level analysis of team performance may put too much weight on those players who did not play and only one salary structure per season is available. Salary structure of a team is believed to vary throughout the season. By using game-level data and thereby exploiting information not used in season-level analyses, I am able to gauge the exact extent of participation for each player and provide further insights into the effect of salary dispersion. Katayama and Nuch (2011) mention mid-season trades as a main factor that affect the salary structure of the team but haven't considered the trade as a control variable in the model. Berri and Jewell (2004) point out the importance of team stability as a determinant of team success. However, team stability is not able to measure trades since other factors such as injuries and age will also affect the team stability (Lee and Jeon 2009). Taylor and Trogdon (2002) provide evidence that tournament incentive will affect the team performance through two conditions: Strong teams that desire the title have tournament incentives to win and teams that are relatively weak have tournament incentives to lose since they will have higher draft orders as prizes for their low rankings. Therefore, I introduce four dummy variables to control tournament incentives in my study of salary dispersion which Katayama and Nuch (2011) have not taken into accounts. Moreover, by categorizing teams into different groups based on playoff likelihood and frequency of trade, my paper further studies the relationship between salary dispersion and team performance under different situations. Consequently, my study is more comprehensive than past studies based on a more accurate measure of salary dispersion, additional control variables and comparative studies. The results from this study can be used to explain the efficiency of policies related to total spending such as salary cap and luxury taxes and how these policies affect the salary dispersion and team performance.

This game-level study provides additional evidence for the relationship between salary dispersion and team performance in the NBA based on a more complete model which takes additional factors such as elimination effect and number of trades. However, it is difficult to interpret the trading effects efficiently according to the estimation results from my study. Further research is needed to investigate specifically the immediate effect of trade on salary dispersion and team performance. Therefore, I will then be able to further discuss the effect of trade on team performance and generate further implications for owners and the league.

The rest of the paper is organized as follows: Section 2 presents existing literature relevant to this study. Section 3 introduces an empirical model of salary dispersion and team performance and explains the construction of each variable. Section 4 describes the data used in the study. Section 5 demonstrates the empirical results. The implications are discussed in Section 6 and the conclusions are presented in Section 7. Section 8 presents the tables of summary statistics and estimation results.

II. Literature Review

Competitive Balance

Competitive balance refers to balance between the sporting capabilities of teams. The more evenly balanced strengths of teams will lead to a more uncertain outcome of each match and of the championship race. In a perfectly balanced league, each team would have an equal chance of winning each match and therefore have an equal chance of winning the league title (Zimbalist, 2002). Moreover, in a perfectly balanced league it would be impossible to predict which team is more likely to win or where the title is going with any certainty. The theory of competitive balance in team sports was first developed by Rottenberg (1956). He points out that the nature of the industry is such that competitors must be of approximately equal size if any are to be successful, which is a unique attribute of professional competitive sports. Since that time, economists have contributed rigorous theoretical and empirical work on various aspects of competitive balance. These contributions include formal measures of balance within a league (such as the standard deviation of win percentage and the concentration of championships); league rules regarding free agency, restricting entry, and expansion; cross-subsidization schemes such as reserve and draft systems, caps, and revenue sharing; and the connection between payroll and performance (Zimbalist, 2002).

Michie and Oughton (2004) use several measures, such as Herfindahl index and C5 index to study the competitive balance in English soccer league for the period 1947-2003. They indicate the importance of competitive balance, arguing that uncertainty of outcomes generate interest from supporters and increases demand for watching matches both live and on television. An increase in competitive balance has the effect of shifting the demand curve for viewing matches outward. Therefore, maintaining and promoting competitive balance becomes one of the priority goals for both clubs and leagues to maximize profits. Additionally, their study illustrates that competitive balance is important to ensure league stability. Unbalanced leagues will face increased risks of bankruptcy of lagging clubs and threats of league break-up from new or rival leagues. They also find that the decline in competitive balance experienced by the English Premier League is associated with a widening income gap between the leading and lagging clubs. Given the existence of a positive relationship between wage expenditure and league performance (e.g. Hall et al. 2002), the increasing gap between rich and poor has enabled the top clubs to increase their dominance of the league (as measured by, for example, share of points) and has resulted in a decline in competitive balance. They suggest that the Premier League and UEFA can guard against these risks by re-examining their redistribution rules. A more egalitarian distribution of income will help the lagging clubs increase their shares of total revenue and thereby increase the competitive balance.

While the sports leagues always want to prevent themselves from unbalancing, team owners' objectives are sometimes inconsistent with that of the league. There has been some empirical work attempting to decipher the true objective function of team owners, but results from different literature are inconclusive. Zimbalist (2003) has a theoretical study on the owner's objective. He finds that the team itself is often not managed as a profit center, but rather as a vehicle for promoting the owner's other investments. For instance, George Steinbrenner used his New York Yankees to create the YES regional sports network in the nation's largest media market, which had a market value upward of $850m in 2001. Therefore, owners may find that the best way to profit maximize globally is to win maximize at the team level. In summary, one conclusion to draw from the discussion of Zimbalist (2003) is that owners maximize global long-term returns rather than team's reported annual operating profits. However, the author fails to further apply the results to owner's behaviors. For instance, how will owners with different objectives made transaction decisions differently. In my paper, I will specifically study how different situations affect the relationship between trade and team performance. Zimbalist (2003) also points out that when owner investment in player's yields returns to both the ball club and to other businesses of the owners, the revenue gap between clubs can become larger; this may be a significant additional source of league imbalance. Team's win maximization or profit maximization behaviors will hurt the league's goal of competitive balance. Consequently, institutions are introduced to limit the ability of concentration talent and protect the balance of the league.

Institutions to protect competitive balance

Sanderson and Siegfried (2003) list the potential factors including many institutions and off-the-field rules that may affect the degree of competitive balance in any professional sports league. Policies related to salary cap have been introduced to all four North American major sports leagues and are now an integral part of the regulation system in those same leagues. Salary caps emerged from the NBA's collective bargaining agreement with the players' union in 1998 and early 1999 in reaction to the league's leaky team payroll cap. A salary cap is a direct restriction, setting both a ceiling and a floor on the amount of salaries paid by a club to all its players, and thereby limits the ability of high revenue teams to acquire the more talented players. The big difference between the salary restrictions in the NBA and the NFL is that NBA payrolls have a soft cap, which has exceptions to the limits imposed by cap. This fact implies the phenomenon that more transactions happened only in the NBA as the salary cap increased. Because all of the exceptions have undermined the soft cap, the NBA developed a number of supplemental measures to reinforce the policy, which includes luxury tax and individual salary cap. The NBA is the only U.S men's professional sports league currently using individual player salary caps. Results from Sanderson and Siegfried (2003) show that the individual salary caps are likely to increase competitive imbalance because they encourage players to rely more on their preference for joining a winning team than on differences between salary offers.

Dietl et al. (2011) analyze the effects of salary cap in a league with win-maximizing clubs and flexible talent supply based on a game-theoretic model. The results show that a percentage-of revenue salary cap increases competitive balance and decreases overall salary payments in the league, thereby contributing to financial stability and more balance. The study further highlights the potential conflicts between the league and society that the effect of salary cap on social welfare depends on fans' preference because fans determine the talent allocation in the unregulated league. In general, a salary cap increases social welfare if fans have high preferences for aggregate talent or favor an unbalanced league. In contrast, if fans have high preference for competitive balance, the salary cap policy will reduce social welfare. One of the limitations of this paper is that the authors simply assume that clubs try to maximize wins. However, according to Zimbalist (2003), there are some clubs try to maximize profits instead of wins. Therefore, further study needs to consider whether the effects of salary cap will change if profit maximizing clubs are involved in the league. Also, further studies can focus on whether different types of salary caps in NBA affect the competitive balance differently.

Kesenne (2000) sets up a two club model and analyzes the impacts of payroll cap and individual cap on competitive balance in a professional team sports league. Without the regulation of any salary cap, the model shows that the big club will hire more players with high talent than the small club because bigger market size will generate more marginal revenue to pay the payrolls. Also, the salary difference between the star players and grass-roots players can be very large if top players are in short supply. When introducing the payroll salary cap into the model, the results show that this salary cap policy does improve the competitive balance in a league through the improvement of player salary distribution. The payroll cap holds down the excessive top player salaries which guarantee the club owners of both small and big clubs a reasonable profit rate to attract new investments. They use the same model to test the impact of the individual cap and compare the outcomes with and without the individual cap. Under regulation of an individual cap, the top players will prefer to play for the bigger clubs, since bigger clubs are able to offer them more non-wage or fringe benefits on top of their salary. Therefore, the individual cap actually makes the competitive balance become more unequal. The study provides evidence to support the assumption about the impacts of salary caps in Sanderson and Siegfried (2003). Moreover, it confirms that it is necessary to have these regulations because agents and owners might be irrational that either ignoring the negative external effect of an unbalanced league or bidding up top players' salaries in a free agency market.

Sanderson and Siegfried (2003) believe that the reverse-order entry draft may also impact the competitive balance. This policy allows teams to select players according to their order of finish in the previous season. The team with the worst record chooses first, followed by the second-worst team and so forth. The draft policy is believed to promote competitive balance by allocating the best new players to the weakest teams. The NBA, as a special tournament, offers rewards for both winning and losing. Therefore, weaker teams are believed to have incentives for losing in order to get higher draft orders. Taylor and Trogdon (2002) examine three NBA seasons to determine whether team performance responds to changes in the underlying tournament incentives provided by the NBA’s introduction and restructuring of the lottery system to determine draft order. They build up an empirical model to test the effects of the tournaments incentives on winning percentage. A dummy variable that determined the home-away factor is included in the model to control for the effect that venue has on the outcome of any particular game. The results on the elimination variable confirm their presumption that non-playoff teams are incentivized to lose in order to gain higher draft positions. Although the league adjusted the draft policy from reverse-order to weighted-lottery in 1989-1990, the eliminated teams were still found to lose approximately twice as often as playoff-bound teams. Once eliminated from contention, teams could do better by decreasing winning efforts and moving down in the league standings. Although the reverse-order draft policy is introduced as a promoter of competitive balance, the study shows that it may also worsen competitive balance since it rewards failure with high draft picks. If teams are forward looking, the elimination effect may exist before teams are statistically eliminated from playoff consideration. However, the study estimates a model, which includes a variable that captures a team's (and its opponent's) relative playoff likelihood, and finds no evidence to support this hypothesis. Further research needs to re-examine this hypothesis and find more implications related to this elimination effect. For instance, it is interesting to study whether elimination effect will affect transaction behaviors among teams. According to the results from this paper and Zimbalist (2003), I assume that some eliminated teams or teams with high possibilities to be eliminated might trade star players or players with high salaries for young players or draft picks. In my study, I am going to take tournament incentives into account when analyzing the relationship between trade and performance.

Sanderson and Siegfried (2003) also discuss the impact of revenue sharing on competitive balance. Revenue sharing is believed to improve the balance in the league by equalizing teams' profits and demand for talent. Additionally, they list other rules such as relocation restrictions and revenue enhancements that may also affect the competitive balance in different ways. However, my study analyzes the competitive balance at the game level using only data from one season, and these factors will not be taken into account in my model since rules and institutions are unlikely to change during the season.

Factors affect team performance

Hall et al. (2002) use data on team payrolls in MLB between 1980 and 2000 to examine the causality between payroll and team performance. The result shows that cross-section correlation between payroll and performance increased significantly in the 1990s. As a comparison, the paper also examines the relationship between pay and performance in English soccer, and it is shown that higher payrolls will lead to better performance. This study provides evidence that supports the reversible causality between payroll and performance. While payroll of each player is determined by the individual performance, the allocation of better individual performance always leads to better team performance. The evidences from Hall et al. supports Kesenne (2002) that the revenue gaps will make the league more unbalanced as richer clubs tend to generate more revenues and thereby hire more talented players. This fact highlights the importance of salary cap related policy and the reexamination of distribution rules, which are mentioned in Michie and Oughton (2004).

Although evidences show that higher payroll will lead to higher performance. Under the restriction of salary cap, it is unclear which salary structure leads to better performance. Economic theories of the firm provide two differing predictions on the effect of different salary structures. Some argue that a compressed salary structure leads to harmony among group members, thereby increasing productivity (e.g. Akerlof and Yellen, 1988). On the contrary, others suggest that greater salary disparity elicits higher levels of efforts among group members and therefore increases productivity (e.g. Lazer and Rosen, 1981). These differing opinions motivate further study on this topic.

Frick et al. (2003) use Gini-index as the disparity measure to study the relationship between win percentage and salary dispersion on a fixed effects model for the North American major leagues. According to their estimates, a higher degree of intra-team wage dispersion is beneficial to the performance of professional basketball teams. This implies that a single "star player" may be of paramount importance for the team's performance, which will lead to a highly skewed distribution of player salaries. On the contrary, since the size of the squad is significantly higher in baseball and football, an individual player's impact on the performance of his team is likely to be much smaller than in basketball. The results show a higher degree of inequality is associated with a poorer performance, which is consistent with their hypothesis. Combining the results from different professional sports leagues, they conclude that a higher degree of wage inequality can have a positive as well as negative influence on team performance depending on the specific circumstances of the production process, especially the size of the team. One omission of this study pointed out by the authors is that they have not explicitly controlled for changes in the composition of teams over time. Changes in the composition of teams affect their team performance: the higher the turnover rate, the poorer is the performance. Moreover, they argue that it is interesting to take a closer look at different policies that used to curtail total spending and to ask whether these have any influence on intra-team salary structures and, therefore, also on team performance.

Berri and Jewell (2004) use Herfindahl index to measure dispersion and estimate the relationship between wage dispersion and team performance with six seasons of data in the NBA. The authors believe that team chemistry is also an important determinate of team success, while the roster stability will promote the level of team chemistry. Conversely, worker turnover is believed to undermine the level of team chemistry and thereby reduce the team performance. Consequently, they construct a measure of roster stability to control team chemistry by calculating the percentage of team minutes played by players who played for a team in both the current and prior seasons. Change in the stability of the team's roster is not found to statistically impact the change in team winning percentage. Salary dispersion is also not found to be a significant determinant of team wins. Results suggest that only the quality of players and quality of coaching matter in terms of team wins. Therefore, the authors argue that further research could investigate how changes in salary dispersion directly impact player performance rather than investigating the phenomenon through the lens of firm performance.

Using game-level panel data on the NBA, Katayama and Nuch (2011) examine the causal effect of within-team salary dispersion on team performance. According to the study, a sporting team in a professional sports league, like the NBA, can have a number of salary structures throughout the season as the team rosters are continually updated and players may experience injuries and mid-season trades. As a result, the study analyzes at a game level in order to catch the exact extent of participation for each player. The study builds up a unique dataset, which covers five regular seasons from 2002 to 2006, while the variables used in the study are calculated from a reduced dataset that includes the first game of each season for each match-up of teams. The variable of salary dispersion is measured by three different methods. The first measure is adjusted for the number of minutes played by each player in each game, thereby accounting for the heterogeneous level of participation among players within a game. The second measure is the Herfindahl index, which is constructed using only those who played more than half of their team’s games in a season. The third measure is the Gini coefficient, which is constructed using team rosters of all players who had participated in at least one game during a season. The authors first construct a fixed effects model. Then, they argue that the fixed effects estimator may be inconsistent because of the endogeneity of average salary measure and salary dispersion measure. Both measures depend on the number of game-minutes played by players and therefore is determined jointly with the game outcome. Consequently, they eliminate the fixed effects by differencing the equation of the fixed effect model and estimate the average salary and salary dispersion in the Generalized method of moments (GMM) framework. The GMM method requires that a certain number of moment conditions were specified for the model. These moment conditions are functions of the model parameters and the data, such that their expectation is zero at the true values of the parameters. The GMM method then minimizes a certain norm of the sample averages of the moment conditions and provides the most efficient estimates on the basis of moment conditions available. The study finds that team average salaries are an important determinant of team performance, since the coefficient on average salary measure is positive and significant at the 1% level. When the average salary among active players is high, the team is more likely to actualize a win. Results based on GMM estimator indicate that salary dispersion is unrelated to season winning percentage whichever dispersion measure is used, which is consistent with the results from the season-level analysis. However, since the coefficient of salary dispersion measures based on the fixed effects estimator are negative and significant, they argue that a bigger dataset could provide more accurate estimates and their GMM estimates might turn out to be significant.

Just as firms must consider the impact of changes in management, sports teams must consider whether a coaching change will improve the team performance. Coaching turnover has been considered in a variety of team sport settings. Roach (2013) examine the effects of coaching changes for NFL teams between the 1995 and 2012 seasons on a regression model including team-specific fixed effects. The author finds that firing a coach reduces a team's expected performance during the next season and the team's average performance over the next two seasons. He provides a potential explanation for the results that the productivity and efficiency are determined by experience according to the learning curve. Coaches and players with more experiences tend to have higher productivities.

Staw and Hoang (1995) study the sunk-cost effect in the context of professional basketball. In this case, sunk costs are operationalized by the order in which players were selected in the college draft. They believe that draft order can be used to predict playing time, being traded and survival in the NBA. They use the NBA draft to determine the initial cost of players and then examine whether this cost influences the amount players are utilized by teams and the length of time they are retained by NBA franchises. The sample included 241 players selected from the 1980-1986 drafts who eventually received contracts and played at least two years in the NBA. Additionally, they create three indices of player performance: scoring, toughness, and quickness, and control additional variables such as injuries, illness, and trade, which might also affect player's performance. Scoring factor consists of points per minute, field-goal percentage, and free-throw percentage. This factor explains 30 percent of the variance in the sample of forwards and centers, whereas it accounts for 23 percent of the variance in the sample of guards. Results show that a player's scoring is the primary performance variable associated with greater playing time over the five years' data, while the occurrence of an injury or being traded are also consistent predictors of minutes played. The draft order is a significant predictor of minutes played since teams are more willing to develop players with high potentials; this effect is above and beyond any other effects of a player's performance such as scoring.

III. Methodology

Estimation model

In studying the performance of sports teams, performance levels are typically measured by the winning percentages of each team at the end of the season. In other words, team performance measures are an aggregate of the outcomes of individual games throughout the season. Consequently, a great deal of information tends to be discarded, including who participated in individual games and for how long they played. Such information may nonetheless be vitally relevant to the analysis of team performance and salary structures in sports that involve significant player turnover and mid-game interchange. The effect that salary structures have on team performance is potentially dependent on which players are active members of the team. Although two teams may have the same salary structure and the same number of players, the playing time distributions of them are different. For instance, a team may let their best players play longer time, the other team may have a more even spread of game time. If so, season-level analysis of team performance may put too much weight on those players who did not play. Additionally, as mentioned in the literature review section, a sporting league like the NBA can be considered to have a number of salary structures throughout the season. A season-level analysis only provides one salary structure for each team per season, which fails to capture the effects of trades during the mid-season. Thus, I analyze the case at game level where the measure of salary dispersion that is based on a more accurate depiction of team composition. My measure of salary dispersion is based on game level rosters and game outcomes are used as performance measures. My estimation model is inspired by Katayama and Nuch (2011) study on salary dispersion, in which a production function for team performance for a given season is considered first:

$$y_i = A_i(disper_i, X_i, \mu_i, \varepsilon_i,) f(a_{1i}l_{1i}, \dots, a_{ki}l_{ki}) \quad (1)$$

where y_i is the team performance of team i, $l_{ki}$is the labor input of player k (k=1,...K), a_{ki} is the player's skill level, A_i is the scale of production which is assumed to be a function of salary dispersion ($disper_i$), team characteristics such as coaching quality (X_i), team-specific time-invariant unobserved factor (μ_i), and an idiosyncratic error (ε_i). On the basis of the relationship in the Equation 1 above, the following estimation model for game-level data is considered:

$$Y_{ijt} = \beta_0 + \beta_1 avesal_{ijt} + \beta_2 disper_{ijt} + \beta_3 record_{ijt} +$$

$$\beta_4 exp_{ijt} + \beta_5 clinch_{i,ijt} + \beta_6 Oclinch_{i,ijt} + \beta_7 \Delta elim_{i,ijt} + \beta_8 \Delta Oelim_{i,ijt} + \mu_{ij} + \varepsilon_{ijt} \quad (2)$$

where $Y_{ijt} = Y_{i,ijt}/Y_{j,ijt}$ is the ratio of the point scored by team *i* to that by team *j* in the game where *i* is at home against *j* in season *t*, $avesal_{ijt} = avesal_{i,ijt}/avesal_{j,ijt}$ is the ratio of measures of average salaries, $disper_{ijt} = disper_{i,ijt}/disper_{j,ijt}$ is the ratio of salary dispersion measures, $record_{ijt} = record_{i,ijt}/record_{j,ijt}$ is the ratio of coaches' records, $exp_{ijt} = exp_{i,ijt}/exp_{j,ijt}$ is the ratio of coaches' experiences, $clinch_{i,ijt}$ is the dummy variable which determines whether the team *i* has clinched playoff berth at the time team *i* versus home against team *j* in season *t* , $elim_{i,ijt}$ is the dummy variable which determines whether the team *i* has been eliminated from playoff at the time team *i* at home against team *j* in season *t*, μ_{ij} is an unobserved fixed effect for matches of team *i* at home against *j* and $\varepsilon_{ijt}$is an idiosyncratic error. Note that match-ups *ij* and *ji* are not the same, as the former indicate *i* being at home and the latter denotes *j* at home. Additionally, since my study only uses data for 2015-2016 season, I do not need to include the *t* in my model, which represents change in seasons. The Equation 2 is a general form that can apply to study on this topic across season.

I apply this fixed effect regression model to study the relationship between salary dispersion and team performance at game level. I first run the regression for all thirty teams.

Taylor and Trogdon (2002) point out that the tournament in the NBA offers prizes to both winners and losers. I believe that teams will trade players for different purposes according to their situations measured by odds of getting into playoff. Consequently, I categorize 30 teams into two groups according to the pre-season playoff likelihoods prediction done by FiveThirtyEight's NBA forecast. FiveThirtyEight created CARMELO, a system that projects the careers of every current NBA player by identifying similar players throughout league history. They combined the CARMELO system with Elo ratings, which is a system for calculating the relative skill levels of players in competitor-versus-competitor games. They used this combined system called "CARM-Elo" to calculate win probabilities and point spread for every NBA game and determine which teams have the best shot to make the playoffs or win the finals. Additional factors that will affect the game outcomes such as fatigue, travel and altitude, were also taken into account in their calculation process. Then they simulated the regular season 10,000 times to find the average final record of each team and the percentage of simulations that each team makes the playoffs. They used the NBA tiebreaking rules to seed teams in the playoffs and then simulate the playoffs 10,000 times to find the winner of the finals. The odds of each team makes playoff vary from less than 1% to greater than 99% according to the forecast before the 2015-2016 season starts. The predication is closed to the final results in that season. All the teams that have more than 45% odds got into the playoffs except three teams, these teams being the Chicago Bulls, Washington Wizards and New Orleans Pelicans. Note that both Chicago Bulls and Washington Wizard fight for the entrance ticket until the end of the regular seasons. All the teams that that has less than 6% odds were eliminated from the playoffs. There are two teams, including Dallas Mavericks and Portland Blazers, that also clinched the playoff although their odds of making playoff are 29% and 23% respectively before the season started. The first group in my model includes 6 teams whose have more than 90% chances to get into the playoffs, namely higher potential ranked teams. These teams, including Cleveland Cavaliers, Golden State Warriors, Oklahoma City Thunders, San Antonio Spurs, Los Angle Clippers and Boston Celtics, look for talent players in the trading market in order to improve their performance and win more games. The second group in my model including 6 teams that have less than 5% chance to get into playoff, namely lower potential ranked teams. This six teams in this group are the Brooklyn Nets, Denver Nuggets, Los Angeles Lakers, Minnesota Timberwolves, New York Knicks and Philadelphia 76ers. These teams statistically understand that they are unlikely to get into the playoffs before the season starts. Therefore, according to the hypothesis mentioned in Taylor and Trogdon. (2002), these teams might prefer to get a lower rank so that they will have higher draft order for the next season. These teams may sacrifice their talented players for future draft picks and young potential players

In order to have a closer look at the effect of trade on performance, I also categorize 30 teams into two groups based on numbers of transactions done by each team during 2015-2016 season. Note that each time a team trades, waives, or signs a player, this counts as one transaction. The numbers of transactions among each team vary from 0 to 29 times in 2015-2016 season. I categorize 15 teams that made more than 5 transactions as group one, namely high trade group. Note that the Memphis Grizzlies made 29 transactions in that season. The second group includes the remaining 15 teams that made less than 5 transactions in that season, namely low trade group. The groups are categorized based on the distribution of number of transactions made in that season. I apply the same fixed effect model to these two groups and examine whether trading behavior will affect the relationship between salary dispersion and team performance.

Note that in Equation 2, several variables are made up of the ratio between two teams. The dependent variable represents not absolute but relative performance measures which is considered to be more relevant to the production of competitive sports teams according to Zak et al. (1979). Similarly, the independent variables represent ratios of relative inputs. For example, $disper_{ijt}$ measures the salary dispersion in their relative levels between team i and j. The estimation results should be interpreted accordingly. In order to clarify the roles of each independent variable in Equation 2, I will explain how these variables are constructed. The details will be discussed in the following section.

Variable construction

I construct these variables according to the methods provided by Katayama and Nuch (2011). The variable $avesal_{i,ij}$ is define as $avesal_{i,ij} = \frac{\sum sal_{ki} \cdot mp_{ki,ij}}{\sum mp_{ki,ij}}$, where sal_{ki} is the salary of player k in team i, $mp_{ki,ij}$ is the number of game-minutes played by player k in team i in match-up *ij* and *Ki* is the number of players in team *i*. That is, $avesal_{i,ij}$ is a weighted average of salaries of the team members in that game where the share of the minutes played by each player is used as a weight. This variable is considered to control for $f(a_{1i}l_{1i}, \ldots, a_{ki}l_{ki})$ in Equation 1, given that player salaries are associated with player-specific production statistics in past studies on NBA(e.g. Lee and Jeon, 2009). The variable $disper_{ij}$ is constructed on the basis of players who actually participated in a given game. It is the game-minute-adjusted coefficient of variation, $disper_{i,ij} = \frac{(varsal_{i,ij})^{0.5}}{avesal_{i,ij}}$, where $varsal_{i,ij} = \frac{\sum (sal_{ki} - avesal_{i,ij})^2 \cdot mp_{ki,ij}}{\sum mp_{ki,ij}}$. This measure is adjusted for the number of minutes played by each player in each game. Note that the $disper_{i,ij}$ varies across each game; so does the ratio of salary dispersion between two teams. Since team quality and coaching turnover will also affect the performance (e.g. Katayama and Nuch 2011; Roach

2013) , I construct two variables, $record_{ij}$ and exp_{ij} to control the team characteristics. The coaches' records variable is measured by the ratio of the coaches' losses to his total previous games, while the coaches' experiences variable is measured as total number of games in which the coach had previously taken part as a head coach.

Taylor (2002) notes that NBA teams respond to tournament incentives by changes in performance. Therefore, I create four dummy variables to control this characteristic of team i and team j. I set $clinch_{i,ij}$ equal to 1 if team i has already clinched a playoff spot when playing at home against j, and set it equal to 0 if not. Similarly, $Oclinch_{i,ij}$ equal to 1 if team i's opponent, namely team j, has already clinched a playoff spot when i playing at home against j, and it equal to 0 if team j has not clinched a playoff spot yet. I set $elim_{i,ij}$ equal to 1 if team i has been eliminated from playoff, and set it equal to 0 if not. Similarly, $Oelim_{i,ij}$ equal to 1 if team i's opponent, namely team j has been eliminate from playoff and it equals 0 if not.

IV. Data

This study constructs a dataset, which focuses on only one regular NBA season 2015-2016. I choose the 2015-2016 season as my sample because there were more frequent trades between teams during that season compared to any other season. Hence, I believe that the results based on this sample set will be representative for my topic. The dataset includes information on players who participated in games for this season. The variables used in this study are calculated according to the formulas we presented in last section and the game-level panel consists of 1,316 unique games in total. The salary data is taken from basketball-reference.com. In the dataset, all players had at least one salary figure quoted for each season. When a player moved or was traded from one team to another, his salary figures in the respective teams are sometimes not available. In such a case, his last known salary for season 2015-2016 is used in my study.

The game-level statistics used in this study are taken from the box scores of the regular NBA season 2015-2016, sourced from basketball-reference.com. They include individual performance statistics such as points scored and minutes played for all players who participated in the game. Table 1 shows a sample of my data set. I use the salary data and game minutes played data collected to calculating the average salary measure and salary dispersion measure for each game and each team according to the formula I constructed in section 3.

Table 2-7 presents summary statistics of the variables used for estimation which includes game level data of all 30 teams, 6 high potential ranked teams, 6 low potential ranked teams, 15 teams trade more than 5 times, and 15 teams trade less than 5 times respectively. The mean of each variable is around one, which is expected, as the variables are the ratio of competing teams' statistics. When the ratio is greater than one, it means that the value of that variable of team *i* is greater than the value of that variable of team *j*. According the Table 2, the mean of ratio of average salary is 1.322, which is reasonable since some teams have higher total team payrolls. This shows that despite the existence of salary caps, which aim to establish some level of equity between teams, large discrepancies between teams at the game level are still possible when it comes to salaries of actively participating players. There is a good deal of variation in each of the variables, including those relating to salaries. In a single game, the participating members of one team may have up to four times the level of salary dispersion compared to its opponent. Note that the mean of average salary measure in Table 3 is larger than that of average salary measure in Table 4. This evidence indicates that strong teams are likely to pay more salaries than weak teams. The means of salary dispersion measure in Table 5 are higher than that of salary dispersion measure in Table 6, which suggests that trade might decrease the amount of variations in salaries. The ratios of coaches' experiences in all summary statistics are very high, which suggest that the difference in coaches' experiences is significant in the league.

V. Estimation results

Table 8 presents the estimation results when including every team in the NBA. I estimate the model using the standard fixed-effects method. The coefficient on $disper_{ijt}$ is found to be negative and significant at the 5% level. An increase in the ratio of salary dispersion by 10% will cause the ratio of score to decrease by 0.28%. This indicates that better team performance is associated with lower salary dispersion, which is in sharp contrast with evidence provided by Frick et al. (2003) and Berri and Jewell (2004) but consistent with the results from the fixed effects model in Katayama and Nuch (2011). The coefficient on $avesal_{i,ij}$ is positive and significant at the 5% level. 10% increase in ratio of average salary will increase the ratio of team score by 0.55%. Not surprisingly, teams with higher average salaries appear to have better game outcomes. $Oelim_{j,ijt}$ is positively related to the ratio of score. As O$elim_{j,ijt}$ changes from 0 to 1, the ratio of score increase by 5.7%, which confirm the results from Taylor and Trogdon (2002) that non-playoff teams have incentives to lose in order to gain higher draft positions in the next season. Both coefficients on the $Clinch_{i,ijt}$ and $Oclinch_{j,ijt}$ are negative and significant. Note that the effects of clinching a playoff invitation are confounding. For those teams which have already clinched the playoff, some of them may still have the incentive to win in order to move up their rankings and capture more home court advantage the further they advance in the playoffs. On the other hand, other teams may choose to rest key players to make better preparation for the playoff games. As $Clinch_{j,ijt}$ changes from 0 to 1, the ratio of score decreases by 4.3%. This is reasonable since top players will be rested to prepare for the competition in the playoffs. As $Oclinch_{j,ijt}$ changes from 0 to 1, the ratio of score decreases by 3%. The negative relationship between $Oclinch_{i,ijt}$ and ratio of final points may be explained by the intense competition in rankings. Since the gap between teams' rankings is small, teams which have already clinched a spot in the playoffs tend to make more efforts to move up their rankings, so that they will be able to play against relatively weaker opponents and have more home advantages during the playoffs. Ratio of coaches' records is negatively associated with the ratio of scores and significant at the 1% level. 10% increase in ratio of coaches' records will decrease the ratio of score by 0.59%, which implies that coaches with better winning records are able to lead the team with better performance. The coefficient of coaches' experience is not significant, suggesting that the effect of coaches' experience on team performance is unclear.

The first column in Table 9 presents the estimation result of the 6 teams with high odds to get into the playoffs. $Both\,Clinch_{i,ijt}$ and $Oclinch_{j,ijt}$ are negatively related to team performance, which are consistent with the results from my original model. However, the coefficient of the ratio of salary dispersion is positive and insignificant, which is in contrast with results I obtained from the first model. The coefficient of ratio of coaches' records is negative and significant and the coefficient of ratio of coaches' experience is positive but insignificant. Both these two estimation results are consistent with the results in the first model.

The second column in Table 9 shows the estimation result of the 6 teams with low odds to get into playoff. Among the four dummy variables, only $Elim_{i,ijt}$ is significant and its coefficient is negative. This evidence supports the conclusions from Taylor and Oughton (2002) that eliminate effect will affect the team performance, since teams that have been eliminate will make less winning efforts. The coefficient of ratio of salary dispersion is positive but not significant in this group.

I use the two sample t-test to test the difference of coefficients among these two groups. The p-value is 0.009 which shows that there is significant difference between two coefficients of salary dispersion. This two-group fixed effect model based on playoff likelihoods suggests that the effect of salary dispersion on team performance remains unclear. One potential explanation for the insignificance of results is that the dataset I tested only includes 246 observations in total. Further study can re-examine the model based on a bigger data set.

The first column in Table 10 shows the estimation results of 15 teams with more than five transactions during that season. Results show that $Oelim_{j,ijt}$ is negatively related to team performance. Average salary is positively and significantly related to team performance at 1% level, while the salary dispersion is negatively and significantly related to team performance at 5% level. These results are consistent with the results in the first model.

The second column in Table 10 shows the estimation results of remaining 15 teams made less than five transactions during that season. Results shows that average salary is positively related to team performance and salary dispersion is negatively related to team performance. However, none of these two coefficients is significant. The effects of these two variables for teams that trade less than 5 times is unclear.

Again, I use the two sample t-test to test the difference of coefficients among these two groups. The p-value is less than 0.01, which implies that there is a significant difference between the two coefficients of salary dispersion. Comparing the coefficients of each variable in these two groups, I find that trade might increase the effects of salary dispersion and average salary on team performance. However, more studies are needed to explore the effect of trade on payrolls and team performance.

Are the regular season results consistent with those in the playoffs?

Playoff teams always work on updating their team roster in March and early April before the playoffs by signing free agents. These transaction behaviors are considered as a way to increase team performance since elimination effects no longer exist in the playoffs. This fact motivates me to re-examine the effect of trade in the playoffs. A data set was constructed by using data from 172 playoff games in 2015-2016 season. The following model for season-level data is considered:

$$Y_{ijt} = \beta_1 avesal_{ijt} + \beta_2 disper_{ijt} + \beta_3 record_{ijt} + \beta_4 exp_{ijt} + \mu_{ij} + \varepsilon_{it}$$

Note that this equation is the same as equation 2, except for four dummy variables which are used to control tournament incentive characteristics are no longer included in the model. There is no more losing prize for the teams in the playoffs, therefore, teams will try their best to win each game. Although players do not get paid in the playoffs, they will try their best in order to win the title or get a bigger contract for the future season. Therefore, it is reasonable to use regular season salary to measures the salary dispersion and test its effect on performance in the playoffs. The estimation results are presented in Table 7. The fixed effects results indicate that the relationship between salary dispersion and team performance is negative but insignificant, while the relationship between average salary and team performance is positive and significant. Comparing the coefficient of average salary in regular season to the coefficient of average salary in the playoffs, I find that the impact of average salary on performance actually becomes bigger in the playoffs. This evidence implies that teams that invest more money are more likely to win the title. If I had a bigger dataset, the effect of salary dispersion might turn out to be significant. This research question is potentially worth exploring,

VI. Implications

My results from the previous section have several implications. Since salary may have a positive impact on team performance, it seems reasonable to increase the salary caps in the leagues. Higher salaries will encourage the players to have better performance, and players need to play better in order to obtain higher paying contracts in the future. However, by comparing the coefficients of average salaries and salary dispersion from estimation results, I find that salary dispersion has more impacts on team performance than average salary. Therefore, it might be necessary to regulate the salary structures in order to increase the competitiveness and performance of the league. One potential method is to redesign and improve the individual cap policy, since individual cap does not improve the competitive balance in the NBA as efficiently as payroll cap (Kesenne 2000). The 'Derrick Rose Rule' issued after 2011 is a great example of improvement on individual cap policy. According to the rule, each team in the NBA can nominate a player on his rookie contract to receive a "Designated Player" contract extension. A Designated Player coming off his rookie contract may be eligible to earn 30% of the salary cap (rather than the standard 25%) if he passes certain criteria. Through the 2017–18 season, in order to be eligible, the player must be voted to start in two All-Star Games, or be named to an All-NBA Team twice (at any level), or be named MVP. On the one hand, this rule limits the ability of rookie players to require bigger contracts. On the other hand, this rule encourages rookie players to improve their performance so that they will have higher chance to be nominated as the 'designated player'. My study suggests that more improvement needs to be done on individual cap policy in order to stimulate the growth of team performance for the whole league.

I note that for one specific season, not all the teams aim to win the championship. Teams with less possibilities to get into playoff tend to make less winning efforts so that they can move down their standings and get higher possibilities to receive higher draft picks for the next season. These teams sometimes are also willing to trade their star players for young and developing players. Note that these teams will have lower payrolls which lead to worse team performance. Consequently, the league will become competitively unbalanced. Hence, the league needs to set the amount of the salary floor close to that of the salary cap so that teams will tend to have nearly equal performance. Whenever the salary cap increases, an increase in salary floor must be enforced. Although the NBA and NHL have instituted lottery systems in which teams with the worst records have the best chance of securing the top draft pick but not sure to get it, the incentive-to-lose behaviors are still very common in the NBA. Therefore, improvement needs to be made on the lottery system. This is a tough problem for the league because it reduces the possibility of the weaker team getting the top draft pick, which will also hurt the weaker teams.

According to Frick et al. (2003) and Berri and Jewell (2004), greater salary disparity leads to better team performance in NBA. This is reasonable since teams with more star players tend to have better performance, while star players earn higher salaries and cause the inequality of wage distribution in the team. However, based on the results from both my study and Katayama and Nuch (2011), teams with compressed salary structures tend to have better performance in the current NBA. One potential explanation for this phenomenon is that in recent years, more and more players value championship above their salaries. These players are willing to give up money to make the team better. For example, when LeBron James and Chris Bosh joined Miami Heats in 2010, both of them came at a cut rate. Miami Heats' star player, Dwayne Wade took an even bigger discount in order for the Heats to recruit LeBron James and Chris Bosh with limited salary cap space. This phenomenon has become more and more common in recent years.

The negative relationship between salary dispersion and performance is found in my study. Assume players' salaries reflect their productivity, it is important to build a team consisting of all players with equal skills rather than make the team out of a few star players and other mediocre players. However, in reality, teams in the NBA always spend heavily on star players. For example, on July 14, 2016, NBA star guard, Michael Conley re-signed with the Grizzlies for a five-year, $153 million deal, which is the greatest contract by total value in NBA history. Why do teams spend so much money on buying a star player when they could use a strategy of building a team out of equally skilled players to improve performance? One explanation is provided by Berri and Jewell (2004), which studies the impact of star power in NBA. They indicate that fans have a high preference of stars than on-court productivity. Star players can attract more fans and a larger audience, thereby generating more revenue for the owners, whose ultimate objective is to maximize profit. Moreover, teams can not only use star players as signs of prominence to recruit more talented players, but also use them as attractive transaction chips to trade for other players or picks.

My results of all six datasets show that ratio of coaches' records is negative and significant related to team performance. None of the estimation results show there is a significant relationship between coaching experience and team performance. Therefore, one suggestion for team owners in order to increase team performance is hiring coaches with better win records. It is not clear whether coach experience is an important factor that affects team performance, since

I only use the number of games coached as head coach to measure coaching experience. Further study can re-examine this relationship by developing the measures. For instance, number of games coached as an assistant coach also needs to be taken into account.

VII. Conclusion

This paper examines the relationship between within-team salary disparity on team performance at the game level, using a salary dispersion measure based on actual players in the game. My analysis reveals that salary dispersion has a significant negative effect on team performance. The findings in this study appear to support the theories emphasizing the importance of harmony among group members (Akerlof and Yellen, 1988). As such, a compressed salary structure leads to harmony among group members and thereby increases productivity. However, the theory emphasizing the importance of harmony cannot be applied to every team in the NBA or other sports leagues. Different teams may have different salary structures for different purposes. I also found that team average salaries are an important determinant of team performance. If the average salary among active players is high, the team is more likely to actualize a win. A coaches' losing record always affects team performance negatively, which suggests teams should hire coaches with winning records in order to improve performance. I analyze the same regression model again by categorizing teams into two groups and test whether different team situations affect the effect of salary dispersion. First, I categorize the teams based on likelihoods of getting into playoff. One group includes 6 teams with high odds of getting into the playoffs, while the other group includes 6 teams with low odds of getting into the playoffs. The results show that the effect of salary dispersion on team peformance remains unclear. Then, I also categorize the teams based on number of transactions each of them made. One group includes 15 teams trade more than 5 times and the other group includes 15 teams trade less than 5 times. Result from the first group shows that salary dispersion negatively affects team performance, which is consistent with the results I found for my original model. Note that my results do not generalize to other professional sports, as the number of players on the field is larger in other sports such as baseball and football. However, the generalized model can be applied to similar studies in other sports.

My study has several limitations. First, the conclusions above are all based on the fixed effects estimator. Recall that Katayama and Nuch (2011) argue the average salary measure and salary dispersion measure are endogenous variables; they depend on the number of game-minutes played by players and therefore are determined jointly with the game outcome. Therefore, the results generated from the fixed effects model may be inconsistent. One potential method for further study is to eliminate the fixed effects by differencing my Equation 2 and then estimate the coefficient in the GMM framework, which provides the most efficient estimates on the basis of moment conditions available. Second, my estimation model fails to take the sunk-costs effect into account. Staw and Hoang (1995) argue that draft order is an important predictor of the game minutes played by each player. Therefore, further study needs to take draft order as a control variable when using game-minute-adjusted formula to measure salary dispersion. Another limitation of my study is that I am not able to interpret the effect of trade efficiently based on the results I have. One potential methodology for future study is to analyze the causality between trade and salary dispersion by using causal inference techniques. Note that my study looks at the effects of trade and salary dispersion on team performance on average through the season, using the causal inference techniques such as difference-in-difference to analyze the causality between trade and salary dispersion will allow me to have a closer look at the immediate effect of trade.

VIII. Tables and Graphs

Table 1. Sample data (The first two games for Cleveland Cavaliers)

Game	Starters	Salary	salary2	MP	MP2	MP4	MP3	Salary*MP4		avesal	(sal-avesal)^2			varsal	disper	avesal	disper
1	Mo Williams	2100000	2.1	37:09:00	0:37:09	37.150	0.619	78.015	2365.219	9.85508	60.14127	2234.248	16614.67	69.22781	0.844268	9.85508	0.844268
1	LeBron James	22971000	22.971	36:04:00	0:36:04	36.067	0.601	828.4874	2365.219	9.85508	172.0273	6204.453	16614.67	69.22781	0.844268	8.682192	0.936599
1	Kevin Love	19500000	19.5	34:49:00	0:34:49	34.817	0.580	678.925	2365.219	9.85508	93.02447	3238.802	16614.67	69.22781	0.844268	9.525357	0.875989
1	J.R. Smith	5000000	5	30:27:00	0:30:27	30.450	0.508	152.25	2365.219	9.85508	23.57181	717.7615	16614.67	69.22781	0.844268	8.517552	1.008088
1	Timofey Mozgov	4950000	4.95	20:54	0:20:54	20.900	0.348	103.455	2365.219	9.85508	24.05981	502.8501	16614.67	69.22781	0.844268	8.93978	0.972722
1	Tristan Thompson	14260870	14.26087	24:55:00	0:24:55	24.917	0.415	355.333344	2365.219	9.85508	19.41098	483.657	16614.67	69.22781	0.844268	9.005838	0.978596
1	Matthew Dellavec	1147280	1.14728	20:12	0:20:12	20.200	0.337	23.175056	2365.219	9.85508	75.82579	1531.681	16614.67	69.22781	0.844268	9.537679	0.92157
1	Richard Jefferson	1499000	1.499	16:57	0:16:57	16.950	0.283	25.40805	2365.219	9.85508	69.82408	1183.518	16614.67	69.22781	0.844268	10.18965	0.841508
1	Anderson Varejao	9638554	9.638554	11:33	0:11:33	11.550	0.193	111.325299	2365.219	9.85508	0.046884	0.541506	16614.67	69.22781	0.844268	9.605805	0.893724
1	James Jones	1499000	1.499	3:49	0:03:49	3.817	0.064	5.72118333	2365.219	9.85508	69.82408	266.4952	16614.67	69.22781	0.844268	9.648051	0.883767
1	Jared Cunninghan	981348	0.981348	3:11	0:03:11	3.183	0.053	3.1239578	2365.219	9.85508	78.74313	250.6656	16614.67	69.22781	0.844268	9.671327	0.882298
1	Sasha Kaun	1300000	1.3	0	0:00:00	0.000	0.000	0	2365.219	9.85508	73.1894	0	16614.67	69.22781	0.844268	9.59085	0.879938
1	Joe Harris	845059	0.845059	0	0:00:00	0.000	0.000	0	2365.219	9.85508	81.18049	0	16614.67	69.22781	0.844268	10.07394	0.813534
2	J.R. Smith	5000000	5	33:51:00	0:33:51	33.850	0.564	169.25	2083.726	8.682192	13.55854	458.9566	15870	66.12502	0.936599	9.88036	0.855881
2	LeBron James	22971000	22.971	30:48:00	0:30:48	30.800	0.513	707.5068	2083.726	8.682192	204.17	6288.437	15870	66.12502	0.936599	10.51276	0.808006
2	Kevin Love	19500000	19.5	28:51:00	0:28:51	28.850	0.481	562.575	2083.726	8.682192	117.025	3376.17	15870	66.12502	0.936599	9.484309	0.901988
2	Timofey Mozgov	4950000	4.95	25:04:00	0:25:04	25.067	0.418	124.08	2083.726	8.682192	13.92926	349.1601	15870	66.12502	0.936599	9.916756	0.838814
2	Mo Williams	2100000	2.1	22:38	0:22:38	22.633	0.377	47.53	2083.726	8.682192	43.32525	980.5949	15870	66.12502	0.936599	9.75028	0.866485
2	Tristan Thompson	14260870	14.26087	19:59	0:19:59	19.983	0.333	284.979719	2083.726	8.682192	31.12165	621.9142	15870	66.12502	0.936599	10.01719	0.858935
2	Richard Jefferson	1499000	1.499	18:20	0:18:20	18.333	0.306	27.4816667	2083.726	8.682192	51.59825	945.9679	15870	66.12502	0.936599	5.442898	1.10314
2	Matthew Dellavec	1147280	1.14728	17:59	0:17:59	17.983	0.300	20.6319187	2083.726	8.682192	56.7749	1021.002	15870	66.12502	0.936599	8.971915	0.987322
2	Jared Cunninghan	981348	0.981348	15:09	0:15:09	15.150	0.253	14.8674222	2083.726	8.682192	59.303	898.4405	15870	66.12502	0.936599	8.640522	0.941387
2	Anderson Varejao	9638554	9.638554	10:52	0:10:52	10.867	0.181	104.738953	2083.726	8.682192	0.914628	9.938957	15870	66.12502	0.936599	9.978462	0.814512
2	Sasha Kaun	1300000	1.3	5:59	0:05:59	5.983	0.100	7.77833333	2083.726	8.682192	54.49676	326.0723	15870	66.12502	0.936599	10.02946	0.858649
2	James Jones	1499000	1.499	5:15	0:05:15	5.250	0.088	7.86975	2083.726	8.682192	51.59825	270.8908	15870	66.12502	0.936599	9.005361	0.847368
2	Joe Harris	845059	0.845059	5:15	0:05:15	5.250	0.088	4.43655975	2083.726	8.682192	61.42066	322.4584	15870	66.12502	0.936599	11.4259	0.6893
3	LeBron James	22971000	22.971	33:56:00	0:33:56	33.933	0.566	779.4826	2286.086	9.525357	180.7853	6134.648	16709.79	69.62414	0.875989	12.27791	0.616953
3	Kevin Love	19500000	19.5	33:07:00	0:33:07	33.117	0.552	645.775	2286.086	9.525357	99.4935	3294.893	16709.79	69.62414	0.875989	8.236881	0.928849
3	Mo Williams	2100000	2.1	25:48:00	0:25:48	25.800	0.430	54.18	2286.086	9.525357	55.13593	1422.507	16709.79	69.62414	0.875989	10.87026	0.715918
3	J.R. Smith	5000000	5	22:15	0:22:15	22.250	0.371	111.25	2286.086	9.525357	20.47886	455.6545	16709.79	69.62414	0.875989	10.70753	0.742569
3	Timofey Mozgov	4950000	4.95	18:04	0:18:04	18.067	0.301	89.43	2286.086	9.525357	20.93389	378.2056	16709.79	69.62414	0.875989	10.35371	0.75206

Table 2. Summary statistics (all 30 teams)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Ratio of scores (*y*)	1,230	0.983	0.131	0.580	1.750
Ratio of average salaries(*avesal*)	1,230	1.322	1.486	0.0778	13.94
Ratio of dispersion (*disper*)	1,230	1.062	0.361	0.354	4.115
Ratio of coaches' experience (*exp*)	1,230	9.844	76.91	0.00217	1,777
Ratio of coaches' records (*records*)	1,230	1.097	0.546	0	5.321
Number of teams	30				

Notes: These statistics are calculated using 1230 unique games. *avesal* refers to the ratio between opposing teams of their minute-adjusted average salaries. *disper* refer to the ratio between opposing teams of their minute-adjusted coefficient of variation of salaries. The ratio of caoches' records refers to the ratio between opposing teams of their coaches' previous losing records, where a losing record is the ratio of losses to total games. The ration of coaches' experience is the ratio between opposing teams of their coaches' experience measured in game coached.

Table 3. Summary statistics (6 teams with more than 90% possibilities to get into playoff)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Ratio of scores (*y*)	246	1.052	.143	.724	1.750
Ratio of average salaries(*avesal*)	246	1.840	1.962	.290	13.942
Ratio of dispersion (*disper*)	246	.972	.290	.414	2.090
Ratio of coaches' experience (*exp*)	246	21.745	160.538	.002	1777
Ratio of coaches' records (*records*)	246	.789	.454	0	3.490
Number of teams	6				

Notes: These statistics are calculated using 246 unique games. For the description of each variable, please see the notes below Table 2.

Table 4. Summary statistics (6 teams with less than 5% possibilities to get into playoff)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Ratio of scores (*y*)	246	.935	.106	.610	1.320
Ratio of average salaries(*avesal*)	246	1.131	.165	.165	11.630
Ratio of dispersion (*disper*)	246	1.171	.435	.354	4.115
Ratio of coaches' experience (*exp*)	246	1.460	17.124	.008	201
Ratio of coaches' records (*records*)	246	5.064	.585	0	5.259
Number of teams	6				

Notes: These statistics are calculated using 246 unique games. For the description of each variable, please see the notes below Table 2.

Table 5. Summary statistics (15 teams trade more than 5 times during that season)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Ratio of scores (*y*)	615	0.967	0.125	0.580	1.461
Ratio of average salaries(*avesal*)	615	1.191	1.468	0.078	13.94
Ratio of dispersion (*disper*)	615	1.057	0.366	0.354	4.115
Ratio of coaches' experience (*exp*)	615	6.517	28.14	0.005	563
Ratio of coaches' records (*records*)	615	1.141	0.565	0	5.321
Number of teams	15				

Notes: These statistics are calculated using 615 unique games. For the description of each variable, please see the notes below Table 2.

Table 6. Summary statistics (15 teams trade less than 5 times during that season)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Ratio of scores (*y*)	615	0.999	0.136	0.610	1.750
Ratio of average salaries(*avesal*)	615	1.453	1.492	0.290	12.61
Ratio of dispersion (*disper*)	615	1.067	0.355	0.432	2.569
Ratio of coaches' experience (*exp*)	615	13.17	105	0.002	1,777
Ratio of coaches' records (*records*)	615	1.052	0.524	0	4.670
Number of teams	15				

Notes: These statistics are calculated using 615 unique games. For the description of each variable, please see the notes below Table 2.

Table 7. Summary statistics (16 teams in playoff)

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Ratio of scores (*y*)	86	0.931	0.149	0.648	1.299
Ratio of average salaries(*avesal*)	86	1.268	1.417	0.096	9.816
Ratio of dispersion (*disper*)	86	1.078	0.386	0.451	2.145
Ratio of coaches' experience (*exp*)	86	4.200	6.413	0.053	19.786
Ratio of coaches' records (*records*)	86	1.199	0.524	.308	3.32
Number of teams	16				

Notes: These statistics are calculated using 86 unique games. For the description of each variable, please see the notes below Table 2 and 3.

Table 8. Estimation results (all 30 teams)

VARIABLES	(1) Fixed Effects
Clinch	-0.043***
	(0.012)
Oclinch	-0.030**
	(0.014)
Elim	-0.019
	(0.013)
Oelim	0.057***
	(0.014)
avesal	0.005**
	(0.002)
disper	-0.028**
	(0.011)
records	-0.059***
	(0.010)
exp	-2.83e-05*
	(1.40e-05)
Constant	1.072***
	(0.019)
Observations	1,230
Number of teams	30
R-squared	0.103

Notes: *Clinch* refers to the dummy variable that determines whether the team has clinched playoff spot. *Oclinch* refers to the dummy variable that determines whether the opponents team has clinched playoff spot. *Elim* refers to the dummy variable that determines whether the team has eliminated from playoff. *Oelim* refers to the dummy variable that determines whether the opponent team has eliminated from playoff. Standard errors are presented in parentheses. ***, ** and * indicate significance at the 1, 5, and 10% levels, respectively.

Table 9. Estimation results (Categorizing teams into two groups based on odds of getting into playoffs)

VARIABLES	(1) Fixed Effects (high playoff likelihoods)	(2) Fixed Effects (low playoff likelihoods)
Clinch	-0.046**	-
	(0.013)	
Oclinch	-0.059*	0.0001
	(0.026)	(0.029)
Elim	-	-0.032**
		(0.009)
Oelim	0.051	0.028
	(0.029)	(0.030)
avesal	0.0002	0.011
	(0.003)	(0.007)
disper	0.008	0.002
	(0.024)	(0.027)
records	-0.095**	-0.037*
	(0.034)	(0.015)
exp	-2.85e-05**	-0.0004
	(1.06e-05)	(0.0004)
Constant	1.128***	0.980***
	(0.0395)	(0.037)
Observations	246	246
R-squared	0.106	0.092
Number of teams	6	6

Notes: Column 1 presents the results for 6 teams with high possibilities to get into playoff and column 2 presents the results for the rest 6 teams with low possibilities to get into playoff. For the descriptions of each variable, please see the notes below Table 2 and 8. Robust standard errors are presented in parentheses. ***, ** and * indicate significance at the 1, 5, and 10% levels, respectively.

Table 10. Estimation results (Categorizing into two groups based on numbers of transactions the team made)

VARIABLES	(1) Fixed Effects (High number of trades)	(2) Fixed Effects (Low number of trades)
Clinch	-0.027	-0.049***
	(0.022)	(0.015)
Oclinch	-0.030	-0.033
	(0.018)	(0.021)
Elim	-0.014	-0.024
	(0.015)	(0.023)
Oelim	0.059***	0.052**
	(0.020)	(0.018)
avesal	0.009**	0.002
	(0.004)	(0.003)
disper	-0.031*	-0.022
	(0.014)	(0.018)
records	-0.045***	-0.078***
	(0.012)	(0.013)
exp	-0.0001	-2.72e-05***
	(8.21e-05)	(7.34e-06)
Constant	1.040***	1.104***
	(0.029)	(0.022)
Observations	615	615
R-squared	0.094	0.121
Numbers of teams	15	15

Notes: Column 1 presents the results for 15 teams trade more than 5 times during that season and column 2 presents the results for the rest 15 teams trade less than 5 times during that season. For the descriptions of each variable, please see the notes below Table 2 and 8. Robust standard errors are presented in parentheses. ***, ** and * indicate significance at the 1, 5, and 10% levels, respectively.

Table 11. Estimation results (16 teams in the playoffs)

VARIABLES	(1) Fixed Effects (Playoffs)
avesal	0.019***
	(0.004)
disper	-0.106
	(0.071)
records	-0.027
	(0.038)
exp	-0.009***
	(0.003)
Constant	1.091***
	(0.065)
Observations	86
Number of teams	16
R-squared	0.199

Notes: For the descriptions of each variable, please see the notes below Table 2 and 8. Robust standard errors are presented in parentheses. ***, ** and * indicate significance at the 1, 5, and 10% levels, respectively.

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