Tournament Incentives, Individual Outcomes and Team Performance: Evidence from the NBA

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ABSTRACT

Corporate researchers use compensation-based proxies for promotion-based tournament prizes and find that firm performance and risk relate positively to tournament prizes in firm and industry tournaments. However, the inability to observe individual outcomes and access to data only at the executive levels in organizational hierarchies limit inferences from corporate data. We use granular and transparent data from the NBA to examine the influence of tournament prizes associated with greater playing time on individual team outcomes. NBA data allow us to examine players in lower tiers of the hierarchy as well as in the upper tiers, and also allow us to examine how outcomes for players in different positions vary with the size of the tournament prize. Individual and team performance and individual aggressiveness relate positively to tournament prizes linked to greater playing time. Better performance stems from more aggressive play. We find no evidence that tournament incentives encourage players to improve their skills. Overall, our analysis informs on the relation between outcomes and tournament incentives when individuals can to exert effort between multiple activities.

JEL classification: G30; G34; J33

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1. Introduction

Tournament theory suggests that differences in remuneration across the hierarchical levels in organizations create promotion-based incentives that encourage workers to exert effort in order to win the "tournament prize" of higher pay at the next level (Lazear and Rosen, 1981). The key insight from tournament theory is that the total benefit of compensation is not just the marginal contribution of the individual worker in exchange for a wage, but the incentive effect created by the tournament prize associated with promotion that induces greater effort from all workers. To examine the influence of tournament incentives in corporations, researchers use the pay gap between CEOs and lower-tier executives as a proxy for the tournament prize. The empirical findings from corporate studies are generally consistent with outcomes one would expect under tournament theory. At the firm level, Bognanno (2001) finds that pay rises with hierarchical level and that the tournament prize increases with the number of competitors. Kale, Reis, and Venkateswaran (2009) find that firm performance relates positively to the pay gap, and Kini and Williams (2012) find a positive relation between firm risk and the pay gap. At the industry level, Coles, Li, and Wang (2018) find that both firm performance and risk relate positivity to the pay gap between the CEO at one firm and the second highest paid CEO in the industry or in a size-industry group.

Since tournament theory suggests that competing for the tournament prize encourages greater effort among all workers, it would be informative to examine outcomes at the individual worker level. Unfortunately, individual outcomes are generally unobservable in corporate data. An analysis that informs at the individual level would be particularly useful to understand the behavior of individuals when they can choose to exert effort across various activities. In Lazear and Rosen's (1981) model, effort is one-dimensional. However, as noted by Prendergast (1999) workers more generally carry out multiple activities. For example, a marketing executive might make choose to exert effort differently than a finance executive. Alternatively, a corporate executive could exert effort to analyze her company or acquire new skills, or she could compete more aggressively and implement policies that increase firm risk. These various activities are not mutually exclusive, but corporate data allow researchers to examine only firm-level outcomes associated with the various activities of multiple executives. To overcome these data limitations in corporate data, we use more granular data from the National Basketball Association (NBA) to examine the influence of tournament prizes on both individual player and team outcomes.

The use of NBA data provides several advantages for analyzing tournament incentives. Detailed and publicly available statistics provide data at the player level that allow specific tests of the influence of tournament incentives on individual outcomes. Moreover, the NBA data allow us to shed light on tournament incentives when the individual can choose to exert effort across multiple activities. For instance, guards might choose to exert more effort toward scoring points, while centers might choose to exert more effort to rebound. The NBA data facilitate an examination of outcomes by position (guard, center, or forward), which allows us to inform on outcomes when players exert effort based on their different roles. Additionally, we use the NBA data to construct metrics that allow us to discern between outcomes that result from effort to improve skill and outcomes that reflect aggressiveness and risk taking. For instance, we can observe if a player is more aggressive and shoots more, improves his shooting ability, or is both more aggressive and improves his skill. Another advantage to using NBA data is that the compensation gap between players in different salary levels is immune to criticisms related to CEO power. Bebchuk, Cremers, and Peyer (2011) and Masulis and Zhang (2014) argue that the pay gap in corporations may reflect the influence of CEO power or be endogenously determined with CEO power and therefore the pay gap may not be a good proxy for the tournament prize.

Similar to corporations, the NBA salary structure exhibits significant pay disparity, which makes it suitable for examining tournament theory. Reports in the popular press indicate the average CEO in the S&P 500 earned 373 times the pay of the average pay of production and non-supervisory employees in 2014.[1] The maximum salary of players in the NBA development league in 2014 is about $30,000 per year compared to the average salary in the main league of $4,935,593. The highest-paid player in 2014 (Kobe Bryant) earned nearly 696 times higher than the maximum pay of the highest paid development league player. The compensation disparity continues in the main NBA league as well. The thirty highest-paid players represent only 7.7% of the players in the NBA but earn $528.46 million, about 27.6% of the total player remuneration. In contrast, the bottom 100 lowest-paid players represent 25.8% of NBA players and earn $100.32 million, about 5.24% of the total.[2] Additionally, the NBA is a substantial economic entity. *Forbes* values the average NBA team at $1.9 billion in 2019, which would be near the top of the market capitalization range for small-cap stocks. The aggregate revenue generated by the NBA is about $8 billion, which would rank the NBA around 380 in the *Fortune 500* if it were a standalone corporation.[3]

To assemble a sample for our study, we collect NBA statistics and compensation data from 2001 to 2014. A disadvantage of NBA data compared to corporate data is that there are no established organizational hierarchies among players. However, just as employees compete for promotions in firm, players compete for playing time in the NBA. Thus, we rank players in a

[1] See Melanie Trottman, "Top CEOs make 373 times the Average US Worker", in blogs.wsj.com.

[2] http://freedompresspectives.com/2014/09/24/income-differential-in-the-nba/

[3] https://www.forbes.com/sites/forbespr/2019/02/06/forbes-releases-21st-annual-nba-team-valuations/#477c92911a70

season by playing time and use the one-dimensional statistical clustering technique proposed by Hartigan (1975) as modified by Cox (2007) to identify hierarchies of five levels based on natural breaks in the data. Since playing-time can change each year and players likely compete for playing time by position (e.g., guards compete with other guards) for playing time, we estimate hierarchies by position for each year. Our method uses playing time and compensation data for players throughout the league so our analysis mimics a corporate industry tournament similar to Coles, Li, and Wang (2018) who use corporate data to examine industry tournaments.[4]

In the spirit of Bognanno (2001), Kale et al. (2009), Kini and Williams (2012), and Coles, Li, and Wang (2016) we use the salary gap between the average salary in the player's salary level and the average salary in the next level (or between the average salary in the level and the maximum salary if the player is in the top salary level) as a proxy for the expected tournament prize. We then estimate fixed effects regressions that control for player-team fixed effects, coach fixed effects, and year fixed effects to examine the relation between outcomes and the compensation gap. Specifically, we examine the influence of the compensation gap on (i) player performance, (ii) player aggressiveness and risk taking, (iii) player skill, and (iv) team outcomes.

As predicted by tournament theory, our analysis provides strong evidence that player performance is associated with the pay gap between the player's playing-time level and the next level. At the player level, we find that points per game, assists per game, and rebounds per game, are all positively related to the compensation gap for all players. Parsing the data reveals that certain performance improvements are correlated with the roles served by players in different positions. For instance, the relation between defensive rebounds and the compensation gap

[4] Other studies of tournament incentives at the industry level include Knoeber (1992), Knoeber and Thurman (1995), Brown, Harlow, and Starks (1996, and Agrawal, Knoeber, and Tsoulouhas (2006).

appears to be driven primarily by centers and forwards. At the firm level, we find that winning percentage and the likelihood of making the playoffs are positively related to the average team salary gap. We do not document any relation between measures of attendance and the pay gap.

The results of our analysis suggest that outcomes derive primarily from more aggressive play and risk taking. We find no evidence to suggest that players improve their skill. For instance, the number of scoring attempts taken by a player is positively related to the pay gap for field goals and three point field goals, but field goal percentage and three-point field goal percentage are not related to the pay gap. The evidence for free throws is particularly telling. Aggressive play would presumably result in players drawing more fouls and therefore taking more free throws, but the ability to make a free throw depends solely on the player's skill. Consistent with aggressive play, we find that the number of free throws is positively related to the compensation gap. In contrast, we find that free throw percentage is unrelated to the compensation gap overall, and is actually negatively related with the pay gap for guards. In addition, steals and turnovers, both of which are associated with aggressive play, positively relate to the pay gap.

Altogether, our analysis of NBA compensation and performance data provides support for the predictions of tournament theory at the both the player level and the team level. The limited availability and opacity of corporate data restricts studies of tournament theory based on corporations to drawing inferences based on firm outcomes. Based on firm outcomes, however, Coles et al. (2018) show performance and risk at the firm level are related to industry tournament prizes. Using more granular NBA data, we show the influence of industry tournament incentives at both the team and player levels. A major contribution of our study is that the use of NBA data allows us to examine directly outcomes associated with players and therefore draw inferences about the influence of tournament incentives based on the performance of the player who competes in the tournament instead of limiting inferences to the performance of the organization. Moreover, our data allow us to capture the effects of incentives on individuals at lower tiers in the hierarchy. Most corporate data provide information only on executives in the highest tiers of the organization. Of particular note, we show multiple outcomes related differently to the pay gap depending on the position of the player, which suggests that tournament incentives motivate individuals with multiple activities but different responsibilities in different ways.

A recent paper by Benson, Li, and Shue (2019) uses microdata on the performance of sales workers to examine the Peter Principle, which suggests that promotions based on performance leads to inefficient promotion decisions that provide a mismatch between the attributes of the worker and the position at the next higher level. Our evidence suggest that tournament incentives encourage NBA players to play more aggressively, but that they do not encourage players to invest in improving their skills. If promotion-based incentives for sales workers have a similar effect, then a possible explanation for the results in Benson et al. (2019) is that sales workers are promoted because they compete more aggressively, but that the incentives fail to encourage additional investment in human capital that might be useful at the next level.

Our paper also contributes to a genre of the literature that uses sports data to examine outcomes within a tournament theory framework. In a study of promotions of NFL assistant coaches, Fee, Hadlock, and Pierce (2006) find the likelihood of external promotion is strongly related to individual performance and weakly related to team performance. Ehrenberg and Bognanno (1990) and Brown (2011) show that the size of the purse in the Professional Golfers' Association (PGA) tournaments affects the performance of professional golfers. Becker and Huselid (1992) find that both the performance and the safety of race car drivers relates to the prize differential in the National Association for Stock Car Auto Racing (NASCAR) games. We add to these studies by showing that the performance of NBA players and their teams is positively related to higher expected remuneration associated with more playing time. In addition, we show that player performance stems from more aggressive play and not improved skill. To our knowledge, our study is the first to show that the size of the tournament prize influences the performance and aggressiveness of players, as well as the performance of the team, in a team sport.

2. Hypotheses

Combining tournament theory with the detailed data on various performance metrics by position and for teams allows use to impose restrictions on the data to produce hypotheses for the influence of tournament incentives on multiple outcomes. Specifically, we propose testable hypotheses for the influence of tournament incentives on (i) individual performance, (ii) aggressiveness and risk taking, (iii) skill development, and (iv) team performance.

2.1 Individual Performance

Tournament theory (Lazear and Rosen, 1981) suggests that the larger the tournament prize, the greater the incentive to exert effort and thus the greater the influence on performance. Bognano (2001) proposes that the compensation gap between the CEO and lower-tier executives serves as a proxy for the tournament prize in corporations. Corporate finance researchers use measures of the internal pay gap to examine the influence of tournament incentives on firm performance (Kale et al., 2009) and firm risk (Kini and Williams, 2012). Coles, Li, and Wang (2018) use industry-level salary gaps to examine both performance and risk in industry-wide tournaments. In the spirit of these studies, we use the pay gap between different player pay levels based on playing time as our measure of the tournament prize. This approach leads us to propose the following hypothesis, henceforth known as the *individual performance hypothesis*.

H1: Performance of NBA players will be positively related to the pay gap.

We use four different measures of individual performance: (i) points per game, (ii) assists per game, (iii) offensive rebounds per game, and (iv) defensive rebounds per game. For sure, the success of the team would benefit if all players improved performance in all these areas. However, players in specific positions (center, forward, or guard) are likely to be rewarded differently for outcomes related to specific roles associated with their position and therefore may choose to exert effort to improve different outcomes. Thus, we argue that outcomes will be more strongly related to the pay gap for performance metrics that are more closely aligned with the role of the player position. For instance, we expect that the influence of tournament incentives on rebounds is greater for centers and forwards than for guards, and that the influence on assists is greater for guards than for centers and for forwards. This argument, based on the premise that players in different roles would choose to allocate effort differently among multiple activities, leads us to propose the following hypothesis.

H1a: The positive relation between performance and the compensation gap will be greater for performance metrics that are primarily associated with the roles of a specific position.

2.2 Aggressiveness and Risk-taking

Increased effort in response to tournament incentives could be reflected in more aggressive play and greater risk taking on the part of players. Although such behavior by players could result in higher personal performance along certain metrics, it could also result in outcomes that are not necessarily in the best interest of overall team success. Thus, we propose the following hypothesis, henceforth known as the *aggressive play hypothesis*.

H2: Risk-taking and aggressive play of NBA players will be positively related to the compensation gap.

We use five metrics to measure individual risk taking and more aggressive play: (i) field goal attempts per game, (ii) three-point field goal attempts per game, (iii) free throws per game, (iv) steals per game, and (v) turnovers per game.

2.3 Skill Development

Increased effort in response to tournament incentives could also focused on improving skills. For instance, players could devote more time to personal practice to improve shooting efficiency. Such effort should improve personal performance and contribute positively to team objectives with no negative externalities. This argument results in the following hypothesis, henceforth known as the *skill efficiency hypothesis*.

H3: Skill efficiency of NBA players will be positively related to the compensation gap.

We use three metrics to measure improvement in individual skill efficiency: (i) field goal shooting percentage, (ii) three-point field goal shooting percentage and (iii) free throw shooting percentage.

2.4 Team Performance

As contracts expire, the NBA labor market allows for relatively easy free movement across teams. In addition, skills are readily transferrable and performance is easily observable, which suggests that the NBA is a homogeneous labor market. Parrino (1997) argues that managers can more easily transfer skills across firms in a homogeneous industry. This increased homogeneity can make incentives related to industry tournament prizes to be more effective to induce individual player effort, but it suggests that individual firm tournaments will be less prevalent and less effective in homogeneous industries (Kale et al., 2009). Thus, since rank-order tournament among players in the NBA is similar to an industry tournament, it remains an open question as to whether the player pay gap will influence tem performance. To explore this question, we propose the following hypothesis, henceforth known as the *team performance* hypothesis.

H4: Team performance will be positively related to the players' compensation gap.

We use four measures of team performance: (i) winning percentage, (ii) the chance of making the playoffs, (iii) attendance, and (iv) attendance relative to arena capacity.

3. Data and Empirical Method

3.1 Sample and Data Sources

To obtain a sample for our study, we collect player compensation data, player performance data, player age, and team performance data for all teams in the NBA from the 2001 season to the 2014 season. We obtain individual compensation data, individual performance data, and team performance data from the basketball reference website, www.basketball-reference.com. To obtain data on player contracts, specifically the last year of the contract, we rely on USA Today websites for 2001 and 2002,[5] Jazzhoops.net for 2003 and 2004,[6] and the storytellerscotracts.info website for 2005 through 2014.[7]

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[5] http://usatoday30.usatoday.com/sports/nba/stories/2001-02-salaries.htm, http://usatoday30.usatoday.com/sports/basketball/nba/2002-2003-nba-salaries-eastern-conference.htm, http://usatoday30.usatoday.com/sports/basketball/nba/2002-2003-nba-salaries-western-conference.htm.

[6] http://www.jazzhoops.net/archive/salary2004.htm, http://www.jazzhoops.net/archive/salary05.htm

[7] http://www.storytellerscontracts.info/resources/05-06salaries.htm, http://www.storytellerscontracts.info/resources/11-12salaries.htm

We exclude players with missing information on performance data, salary data, or contract data, which leaves us with an initial sample of 1,134 players and 5,258 player-year observations. We require that players play in at least 25% of the games (21 games) in a given season to be included in the sample. We impose this requirement to ensure that compensation, and hence the compensation gap, reflects a true tournament prize based on competitive players in the tournament. Since players who earn the maximum salary for their position have already achieved the maximum tournament prize and would not face tournament incentives, we also exclude the player by each position who earns the maximum salary for his position in a given year. The final sample used in the fixed effects analysis comprises 1,093 players and 5,062 player-year observations.

Since players in different positions possess different skills and contribute to the success of their teams in different ways, it stands to reason that tournament prizes would vary by position and that players would compete in a tournament with other players from their positions. For instance, a guard who is adept at creating assists would likely compete in a tournament with other guards along this metric, while a center who is adept at rebounding would likely compete with other centers. Thus, we categorize all players by position – guard, forward, or center – according to player profiles provided by USA Today and www.basketball-reference.com.[8] We classify power forwards as centers because their responsibilities and incentives are arguably similar to centers but are different from small forwards. Some players are listed as hybrid players, for instance guard/forward or forward/center. For these players, we classify the player according to the first position listed. Player performance is also likely to be influenced by the team on which he is playing, which makes it desirable to control for team fixed effects as well as player fixed effects.

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[8] http://www.usatoday.com/sports/nba/

However, players are sometimes traded during the season. When a player is traded during the season, we read news articles and other online sources such as Wikipedia to ascertain the duration of time on each team and use the team for which he played the most games. For example, Chris Webber was traded from the Philadelphia 76ers to the Detroit Pistons on January 16, 2007. Since the season began on October 31, 2006, he spent the majority of his time during the 2006-2007 season with Detroit. Thus, we consider Chris Webber to be a Detroit Piston for the 2006-2007 season.

3.2 Playing-time Hierarchies

In corporations, workers compete for promotions to the next level in the organizational hierarchy. The NBA data do not provide pre-defined hierarchies such as lower-tier executives, CEO, etc. However, just as workers in corporations compete to win the promotion to the next level in the organizational hierarchy, NBA players compete for playing time. To estimate hierarchies by playing time, we first rank players in a season by playing time use the one-dimensional statistical clustering technique proposed by Hartigan (1975) as modified by Cox (2007) to identify hierarchies of five levels based on natural breaks in the playing-time data. Since playing-time can change each year and players likely compete for playing time by position (e.g., guards compete with other guards) for playing time, we estimate hierarchies by position for each year. The approach determines boundaries between playing-time levels within a hierarchy that minimize the sum of within-cluster summed squared deviation from cluster means over the possible combination of k-1 possible clusters from the sample of n-1 players, where k=5 and n is the number of players in a given position in a given year. By season, we then assign each player to one of the five playing-time levels for his position according to his playing time during that particular season and the boundaries determined by the natural-break cluster method.

3.3 The Tournament Prize

Tournament theory suggests that the tournament prize provides players with the incentives to exert effort in order to improve performance and win the tournament prize. In the spirit of Bognano (2001), Kale, Reis, and Venkateswaran (2009), Kini and Williams (2012) and Coles et al. (2018), we use an estimate of the potential increase in salary for a player if he is promoted as our measure of the tournament prize. One could view the tournament as a competition among all players to win the tournament prize equal to the difference between his current salary and the highest salary in the league for his position. We reject this approach since it seems unlikely that most players at lower levels of playing time would view moving from their current level to the playing-time level associated maximum salary by position as unrealistic. However, it is likely that players within a specific playing-time level would realistically have an incentive to exert effort to earn the *expected* salary differential associated with playing time at the next higher level and the remuneration at their current level. Thus, for the first four levels in a playing-time hierarchy, we estimate the tournament prize as expected salary differential associated with moving from one playing-time level to the next level that is, the average salary in the next higher level of playing time less the average salary in the player's current playing-time level. For the highest level of playing time, we estimate the tournament prize as the maximum salary in the top level less the average salary. To avoid negative pay gaps, we add the absolute value of the minimum pay gap to our estimate. Figure 1 shows the outcome associated with our method.

[Figure 1 here]

As can be seen in Figure 1, playing-time increases monotonically across the five levels for each position, and the pay gap increases monotonically starting with the second playing-time level. For illustration, consider a center who is in the second playing-time level, which is about 925 minutes per season on average across all seasons. If the center effectively competes for playing time and moves to the next level, he would expect to earn the expected pay differential of about $2.85 million in additional salary, on average across all seasons. Thus, under tournament theory, the expected pay differential associated with moving from his current playing-time level to the next level provides the player with the incentive to exert effort to gain more playing time.

3.4 Summary statistics

Table 1 presents summary statistics for player compensation, contract information, and player age. On average, players receive about $4.4 million in salary and have a tournament prize in the form of a compensation gap of $4.9 million. Hence, the tournament incentives are nontrivial and can make a substantial impact on a player's salary. Notably, there is considerable variation in compensation across players as indicated by a standard deviation of $4.25 million. The player who earns the maximum salary is Kevin Garnett for the Minnesota Timberwolves in 2003 while Cartier Martin receives the minimum salary for playing in 33 games for the Charlotte Hornets in 2008.[9] The mean (median) time remaining on a player's contract is 2.42 years (2 years). The average (median) player age is 27 (26) with a minimum age of 18 and a maximum age of 42.

[Table 1 Here]

For teams, the mean (median) average salary is $4.39 million ($4.28 million), with a minimum of about $1.366 million (Charlotte in 2004) and a maximum of nearly $7.766 million (Orlando in 2010). On average, teams have 12.61 players in a given year; the median is 13. The

[9] In 2008-2009 season, Cartier Martin signed two short-term contracts in Jan. and Feb. 2009 and signed for the rest of the season in late Feb. The salary of 26,007 is not the contract-salary but the amount he received for playing.

minimum number of players is 6 and the maximum is 16.[10] The typical team, as measured by the median, had 31% of its players in the last year of their respective contracts. At least one team has no player in the last year of his contract, and the maximum percentage of players in the last year of this contract is 92%.[11] The mean average ages is 26.74 (26.58). Berri and Schmidt (2010) present evidence that the performance of NBA players peaks around the age of 27 and declines by over 150% per year beginning with the age of 34. The data suggest that teams manage their rosters such that the average and median player age is near the age of peak performance. The majority of the teams has no player above the age of 34 in a given year. In untabulated results, we document that the maximum percentage of players above the age of 34 for a given team in a particular year is 36%. On average, about 31% of the players on a team are in the last year of their contract.

A perusal of the data by player position reveals that forwards and centers tend to be the highest compensated players and also tend to face the largest tournament price in the form of a compensation gap, followed by guards. For instance the mean (median) salary for forwards is \$4.39 million (\$2.96 million) compared to \$4.80 million (\$3.20 million) for centers and \$4.00 million (\$2.53 million) for guards. From a tournament incentive standpoint, players in each position have the potential to increase their salaries significantly by reaching the next playing-time level. Centers have a mean (median) compensation gap of \$5.00 million (\$3.73 million), while the mean (median) compensation gap for guards is \$5.01 million (\$3.38 million). The mean (median) compensation gap for forwards is \$4.47 million (\$3.42 million).

[10] For the Denver Nuggets in 2001, contract information is available for only six players who played in at least 20% of the games.

[11] All the players but one for both Miami and Brooklyn are in the last year of their contracts in 2014.

Table 2 presents summary statistics for player and team performance variables. Players average playing 1,476.42 minutes per season (about 18 minutes per game for an 82-game season) with a maximum playing time of 3,485 minutes (about 42.5 minutes per game). On average, players score 9.21 points per game during our time period, with a maximum of 35.40 points per game (Kobe Bryant of the Los Angeles Lakers in 2005) and a minimum of 0.30 points per game. The mean (median) number of rebounds is 1.09 (0.83) offensive rebounds per game and 2.90 (2.52) defensive rebounds. The maximum average number of rebounds for a player is 5.52 offensive rebounds and 11.42 defensive rebounds. The mean (median) number of assists per game is 2.01 (1.40) and the mean (median) number of steals is 0.71 (0.63). On average, guards make the most assists (3.09) and the most steals (0.86), but also commit the most turnovers (1.49). There is considerable dispersion in the data. For instance, the maximum number of assists per game is 11.7 and the minimum is zero. On average, players shoot 73% from the free throw line, make 24% of the three-point attempts, and 45% of all field goal attempts. A review of the performance metrics by position again underscores the differential performance contributions across the various positions. For instance, guards average 3.09 assists per game compared to 1.50 assists per game for forwards and 1.10 assists per game for centers. In contrast, centers average 3.70 defensive rebounds per game, compared to 3.09 defensive rebounds for forwards and 2.10 defensive rebounds for guards.

[Table 2 Here]

3.5 Empirical Method

3.5.1 *Fixed Effects Regression Specifications*

Our primary test of tournament theory is the relation between player outcomes and the log of the compensation gap. Since the match between an individual player and a specific team could influence both player compensation and player performance, we use a specification that controls for player-team fixed effects. We also recognize that the coach could also influence player performance, and that events throughout the league in a given year could influence contract and player performance. Thus, we also control for coach and year fixed effects in our regressions. To control for peak age and the rapid decline in performance after the age of 34 (Berri and Schmidt, 2010) we include age, age^2, an indicator variable for age greater than 34, and an interaction term between the log of the compensation gap and the indicator variable. Jean (2010) finds that performance peaks in the last year of a contract, consistent with the notion that players are being more carefully scrutinized, which minimizes agency conflicts. To control for this influence, we include an indicator variable for the last year of a contract and interact this indicator variable with the log of the compensation gap. As controls for the skill level of the player and the skill levels of his teammates, we control for the player's salary and also for the salaries of the other players on the team that could also affect an individual player's performance. We also recognize that the outcomes associated with a player could be influenced by the number of minutes he plays as well as the number of minutes that the other players play, so we include controls for minutes played by the focal player and by his teammates. Specifically, we estimate fixed effect regressions of the following form:

$$Outcome_{PT} = \beta_0 + \beta_1 \log(gap) + \beta_2 \log(age) + \beta_3 \log(age)^2 + \beta_4 D_{Over\ 34} + \beta_5 \ \log(\text{salary}) + \beta_6 \log(salary_{Others}) + \beta_7 log(minutes\ plauyed) + \beta_8 \log(minutes\ played\ by\ others) + \beta_9 D_{Last\ year} + \beta_{10} D_{Last\ year} X log(gap) + \delta_{PT} + \delta_\tau + \delta_C \quad (1)$$

where $Outcome_{P\tau}$ is the outcome of player P in year τ, δ_{PT} is the player-team fixed effect, δ_C is the coach fixed effect, and δ_τ is the year fixed effect.

All players can improve their value to a team on the margin and potentially earn increased playing time by improving outcomes in all facets of the game, e.g., scoring more, getting more rebounds, and so forth. However since players can choose to exert effort along multiple dimensions, a key premise in our study is that they will choose to allocate their effort along those dimensions that are most valued for the role of their position, and therefore be more likely to result in increased playing time. Thus, we estimate our regressions for all players and then separately by position.

We measure team performance along four dimensions: (i) winning percentage, (ii) making the playoffs, (iii) attendance, and (iv) attendance as a percentage of arena capacity. For our analysis of team performance, we estimate a similar fixed effects regression except that we use team-coach fixed effects and year fixed effects. In the team performance regressions, the logarithm of the average salary gap for the team is our measure of the tournament prize. Similar reasons stated for player-level regressions, we control for average player age of the team, the percentage of players older than 34, and the percentage of players on the team in the last year of their contracts. Teams sometimes struggle to find the right mix of players to create a winning formula or they experience injuries that impede team performance. Both these challenges result in lower average playing time for plyers, so we include the average of the minutes played by the players of the team as a control variable. Attendance depends on team characteristics, but also depends on the available population in the market area to attend games. Thus, we include an indicator variable that equals 1 if the team is located in a top-10 MSA according to the census in 2000 and 2010 that predates the season and 0 if not. At the team level, we estimate fixed effect regressions as presented below in equation (2).

$$Outcome_{Win} = \beta_0 + \beta_1 \log(team\ gap) + \beta_2 \log(team\ age) + \beta_3 \log(team\ age)^2 + \beta_4 Percent_{Over\ 34} + \beta_5 \log(team\ avg.salary) + \beta_6 \log(team\ avg.minutes\ played) + \beta_7 Percent_{last_{year}} + \delta_{TC} + \delta_{\tau} \quad (2)$$

where $Outcome_{Win}$ equals winning percentage or indicator variable for making the playoffs, δ_{TC} is team-coach fixed effects, and δ_{τ} is time fixed effects. For outcome measures based on attendance, we add an indicator variable for presence in a top-1o MSA as indicated in equation (3), below.

$$Outcome_{Win} = \beta_0 + \beta_1 \log(team\ gap) + \beta_2 \log(team\ age) + \beta_3 \log(team\ age)^2 + \beta_4 Percent_{Over\ 34} + \beta_5 \log(team\ avg.salary) + \beta_6 \log(team\ avg.minutes\ played) + \beta_7 Percent_{last_{year}} + D_{Top-10\ MSA} + \delta_{TC} + \delta_{\tau} \quad (3)$$

4. Influence of Tournament Incentives on Player Performance

4.1 Scoring: Points per Game and Assists per Game

The first performance metric that we examine are related to scoring: points per game and assists per game. Table 3 presents the results of our fixed effects regressions. Consistent with our perdition of a positive influence of tournament incentives, we find a positive relation, significant at the 1% level, between points per game and the log of the compensation gap and between assists per game. We document this relation for all players and for players in each position. The relation with age is as expected. Coefficients are positive and significant on age and negative and significant on age^2, both coefficients significant at the 1% level.

[Table 3 Here]

4.2 Rebounds per Game

We next examine the influence of the compensation gap on rebounds per game. The results of our analysis are presented in Table 4. Overall, there is a positive relation between offensive rebounds and the compensation gap (coefficient equals 0.012), significant at the 1% level, and a strong positive relation between defensive rebounds per game (coefficient equals 0.49), significant at the 1% level. As would be expected if players in different positions exert effort differently when they can choose between multiple activities, we find that the relation between offensive rebounds and the compensation gap is driven strictly centers (coefficient equals 0.098), significantly positive at the 1% level. Defensive rebounds relate positively to the compensation gap for all positions, but the result is stronger for centers (coefficient equals 0.219) and forwards (coefficient equals 0.037) with *t*-statistics that are significant at the 1% level. The coefficient for guards is 0.049, but it is only significant at the 10% level (*t*-statistics equals 1.65). Taken together, the evidence for rebounds suggests that payers in different positions will allocate effort differently among multiple activities consistent with the roles of their positions.

[Table 4 Here]

5. Tournament Incentives: Effort to Improve Skill or Effort that Reflects Aggressiveness?

The evidence thus far suggests that tournament incentives have a positive influence on a variety of performance metrics consistent with the premise that the player exerts greater effort. Moreover, the data are consistent with the premise that players in different positions that serve different roles choose how they allocate their effort among multiple activities differently. Players can also direct their effort directed toward playing more aggressively and taking more risks, or they can focus their effort on improving their skill. If effort is directed only toward the skill development, teams should be strictly better off ceteris paribus. However, if effort induces more aggressive play and greater risk taking, teams face a tradeoff between the positive impact on performance of aggressive play and the potential negative implications of aggressive and risky play. In this section, we compare and contrast the influence of tournament incentives on three proxies for aggressive and risky play – field goal attempts per game, three-point field goals per game, and turnovers per game – with three corresponding proxies for skill improvement – field goal percentage, three-point field goal percentage and free throw percentage.

5.1 Field Goal Attempts per Game

If players exert effort to exhibit a more aggressive style of play, we expect to observe more field goal attempts per game, both two-point field goal attempts and three-point field goal attempts. In addition, as our hypothesis H1a and evidence in table 4 suggest that the influence of tournament incentives on field goal attempts, particularly three-point attempts, will be greater for guards than for centers and forwards. Table 5 present our analysis of field goal attempts per game. Consistent with the premise that larger tournament incentives result in more aggressive play, the coefficient on the compensation gap is positive and significant at the 1% level for all players. The results holds for all field goals (coefficient equals 0.170, significant at the 1% level) and for three-point field goals (coefficient equals 0.034, significant at the 1% level. Guards, who are generally called upon to shoot more and score more points have the highest coefficient (0.535) and t-statistic (5.01) for total field goal attempts.

[Table 5 Here]

The results for three-point field goals stem solely from shots attempted by players in the guard position. Although the coefficient on the compensation gap is positive for all positions, it is only statistically significant for guards (coefficient equals 0.186, *t*-value equals 3.73). The coefficient on the compensation gap for forwards 0.0087 and for centers is 0.037. These coefficients are insignificant with t-values equal to 0.45 and 1.31 for forwards and centers, respectively.

5.2 Field goal Percentage

Players can also focus their effort on improving their skill as a hooter, so we analyze field goal percentage and three-point field goal percentage to assess outcomes associated with effort targeted to improve shooting skill. We note that being more aggressive by taking more shots and devoting effort to improving shooting skill are not mutually exclusive. It is feasible that a player could choose to exert effort to be more aggressive and also to improve his skills. We present the results of our analysis of field goal percentage in Table 6. With regard to the skill efficiency hypothesis, we find no evidence that field goal percentage, either total field goal percentage of three-point field goal percentage, is positively related to the compensation gap. Coefficients, regardless or position, are consistently near zero with *t*-statistics that range from -0.11 to -1.28. Thus, we find no evidence to support the skill efficiency hypothesis based on our analysis of field goal percentage.

[Table 6 Here]

5.3 Free Throws and Free Throw Percentage

Table 7 presents our analysis of free throws and free throw percentage. If a player engages in more aggressive play, he is likely to draw more fouls and therefore shoot more free throws. On the other hand, free throws are an uncontested shot, so the likelihood of making a free throw relates almost exclusively to the player's skill at shooting free throws. Thus, comparing the number of free throws taken by a player to the percentage of free throws made provides a relatively clean test of the aggressive play hypothesis and the skill efficiency hypothesis.

[Table 7 Here]

As predicted by the aggressive play hypothesis, the number of free throws attempted increases with the compensation gap for all players, significant at the 1% level (coefficient equals 0.060, *t*-value equals 4.18). The relation is consistent positive across positions with coefficients on the compensation gap of 0.031 for forwards (*t*-statistic equals 2.40), 0.156 for centers (*t*-statistic equals 2.90), and 0.215 for guards (*t*-statistic equals 3.31). With regard to improving skill, however, the coefficient on the compensation gap for all players is 0.00 (*t*-statistic equals 0.22). Dividing the sample by position, we estimate a coefficient on the compensation gap of -0.001 for centers (*t*-

statistic equals -0.11) and 0.01 for forwards ((*t*-statistic equals .30). For guards, the coefficient on the compensation gap is -0.008 (*t*-statistic equals -2.07, significant at the 5% level), which is opposite the predicted sign for the skill efficiency hypothesis. Thus, our evidence from free throws lends support to the aggressive play hypothesis and rejects the skill efficiency hypothesis. Overall, the results of our free throw analysis suggest that tournament incentives motivate players to devote effort to aggressive play and not to improving their skills.

5.4 Steals and Turnovers

In our final player-level test, we compare the relation between steals, which may reflect both aggressive play and skill, and the compensation gap to the relation between turnovers, which are a negative outcome associated with aggressive play, and the compensation gap. Table 8 presents the results of our analysis. Steals positively relate to the compensation gap for all players (coefficient equals 0.009 with a *t*-value of 2.53), guards (coefficient equals 0.042 with a *t*-value of 3.04) and centers (coefficient equals 0.019 with a *t*-value of 1.71). The coefficient on the compensation gap for forward is also positive (coefficient equals 0.003), but is insignificant with a *t*-statistic of 0.75. Turning our attention to turnovers, we document a positive coefficient on the compensation gap of 0.018 for all players, significant at the 1% level (*t*-value equals 3.22). The positive association with turnovers is strongest for centers (coefficient equals 0.0062 with a *t*-value of 2.66) and guards (coefficient equals 0.053 with a *t*-value of 2.42). Although the coefficient on the compensation gap is positive for forwards, it is insignificant at the 10% level (coefficient equals 0.010 with a *t*-value of 1.33).

[Table 8 Here]

5.5 Discussion: Aggressive Play or Skill Improvement?

When players have the opportunity to choose between multiple activities, one choice is to exert effort in a way that results in more aggressive play (the aggressive play hypothesis) and another choice is to exert effort to improve one's skill (the skill efficiency hypothesis. Although the choices are not mutually exclusive, the data strongly support the aggressive play hypothesis and offer no support for the skill efficiency hypothesis. Aggressive play, for instance shooting more, can clearly have positive benefits to the team. Indeed, our results in table three suggest that a larger tournament prize as measured by the compensation gap does result in the player scoring more points. On the other hand, as illustrated by our analysis of turnovers, aggressive play can results in negative results as well. To weigh the aggregate effect of the positive and negative benefits of more aggressive play, we next analyze team performance.

6. Influence of Tournament Incentives on Team Performance

The free agent model in pro sports creates an industry-wide tournament where winning the tournament prize can often involve leaving one team to join another team. Thus, the NBA provides a good setting to analyze industry-wide tournament incentives in a homogeneous industry with relatively high labor mobility. In addition, play on the court, including effort during the game, is transparent and observable to decision makers. We use this setting to examine whether individual teams benefit from the incentives created by the industry compensation gap. We use four metrics to examine the influence of industry-wide tournament incentives on team performance. Two of these measures relate to the team's performance on the court: (i) the team's winning percentage in a given season and (ii) the likelihood that a team makes the playoffs. The other two measures relate to the team's success at attracting fans to attend the game (i) the log of the annual attendance for the season and (ii) attendance as a percentage of arena capacity. Table 9 presents the results of the team performance analysis.

[Table 9 Here]

Supporting the premise that the incentive created by the industry-wide tournament translates into better performance on the court, we document a positive relation between the team's winning percentage and the average compensation gap on the team, significant at the 1% level (coefficient equals 0.125 with a *t*-statistic of 3.50). In addition, the results of our linear probability model with fixed effects provides evidence that teams with a larger average compensate gap are more likely to make the playoffs. The coefficient on the compensation gap is 0.295 with a *t*-statistics of 1.93. Thus, the evidence suggests that industry tournament incentives not only induce players to exert more effort, the evidence also suggests that this effort translates into better team performance on the court.

On the other hand, we do not find any significant relation between the attendance measures and the compensation gap. The evidence for attendance suggests that attendance depends primarily on being located in a large MSA, which provides a large fan base to attend. In addition, attendance appears to have a concave relation with team age, which suggests that having a seasoned tem that is not "too old" helps attract fans as well.

7. Conclusion

We use NBA compensation and performance data to examine external tournament incentives for players in the NBA. Our data allow us to observe individual player performance metrics, aggressive play metrics, and skill efficiency metrics. The granularity and transparency of the data allow us to more sharply distinguish individual effort and whether this effort is devoted to more aggressive play or invested in improving the efficacy of player skills. In addition, we are able to examine outcomes based on different positions, which helps to inform on how players choose to exert effort when they engage in multiple activities. We also observe team performance metrics, which enable our analysis to inform on the benefits of industry-wide tournaments for individuals to the organizations within the industry.

Our results provide convincing support for the predictions of tournament theory and the presence of an external industry-wide tournament in the NBA. Moreover, incentive effects appear to be stronger for roles associated with specific positions, which suggests that players that engage in multiple activities choose to exert effort differently. A major conclusion from our analysis is that aggressive play provide the primary channel through which tournament incentives influence performance and that players do not exert effort to improve skill efficiency in response to tournament incentives. We also find that the tournament incentives relate positively to better performance on the court, but that they do not translate into better attendance. For researchers, our results underscore the advantages of having more granular and transparent data that allow the examination of outcomes at the individual level as well as at the organizational date. More research based on more granular and transparent corporate data is needed.

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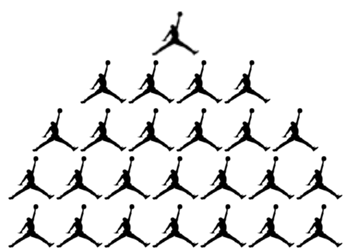
Figure 1. Illustration of hierarchies by postion

This figure provides an illustration of hierararchies by position over our sample period of 2001-2014 and presents data on the number of observations, the average minutes played, and the average pay gap in each hierarchy.

Centers

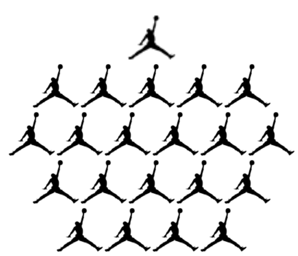
Level	Obs.	Salary ($1000)	Minutes Played	Pay Gap ($1000)
5	235	9,815.42	2,679.73	14,194.59
4	331	6,271.03	2,106.44	5,643.33
3	389	4,625.00	1,517.06	3,388.12
2	420	3,566.61	924.83	2,850.17
1	431	2,273.39	384.13	3,042.47

Forwards



Level	Obs.	Salary ($1000)	Minutes Played	Pay Gap ($1000)
5	157	7,365.81	2,827.83	13,053.77
4	242	6,179.43	2,237.13	3,475.27
3	268	4,244.68	1,631.92	3,321.19
2	267	3,330.92	987.70	2,803.11
1	264	2,195.55	440.52	3,110.99

Guards



Level	Obs.	Salary ($1000)	Minutes Played	Pay Gap ($1000)
5	351	7,186.25	2,780.05	14,176.83
4	450	5,181.07	2,129.07	4,055.53
3	440	3,628.29	1,547.67	3,336.41
2	440	2,792.08	992.23	2,642.34
1	377	1,593.95	437.73	2,927.69

Table 1. Summary statistics for compensation, contract information and player age

This table provides summary statistics for compensation, contract horizon and player age. Salary is the annual salary for players and total annual salary for teams, respectively. Avg. salary_other is the average salary of other players on the same team as the focal player. Gap is the difference between the average salary in the player's salary bracket and the average salary in the next salary bracket or the difference between the average salary and the maximum salary for players in the top bracket. We calculate the gap by position and add the absolute value of the minimum gap across all positions to avoid negative values. The 5 levels are based on natural breaks of minutes played. Contract year left is the number of years that remain on the player's contract.

	Obs.	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
All Players								
Salary ($1,000)	5,062	4,377.85	4,249.63	26.01	1,200	2,900.97	5,900	26,517.86
Avg. salary_other ($1,000)	5,062	4,377.85	1,125.94	1,150.16	3,619.36	4,285.40	5,084.15	8,401.88
Gap ($1,000)	5,062	4,914.06	4,203.31	0	2,601.42	3,475.92	4,841.43	21,941.00
Contract year left	5,062	1.44	1.38	0	0	1	2	12
Age	5,062	26.71	4.27	18	23	26	30	42
Centers								
Salary ($1,000)	1,806	4,796.74	4,513	64.58	1,352.18	3,203	6,500	26,517.86
Avg. salary_other ($1,000)	1,806	4,349.32	1,130.72	1,150.16	3,575.69	4,275.53	5,093.77	8,401.88
Gap ($1,000)	1,806	5,000.10	4,073.53	651.49	2,696.33	3,727.46	5,275.67	21,474.92
Contract year left	1,806	1.44	1.40	0	0	1	2	12
Age	1,806	26.75	4.26	18	24	26	30	41
Forwards								
Salary ($1,000)	1,198	4,390.27	4,210.38	26.01	1,191.24	2,963.75	6,200	23,016
Avg. salary_other ($1,000)	1,198	4,362.97	1,116.18	1,339.91	3,628.46	4,259.26	5,031.03	8,352.91
Gap ($1,000)	1,198	4,465.74	3,846.73	0	2,131.29	3,419.88	4,972.76	17,768.54
Contract year left	1,198	1.50	1.39	0	0	1	2	7
Age	1,198	26.67	4.28	18	23	26	30	42
Guards								
Salary ($1,000)	2,058	4,003.01	3,993.77	89.67	1,106.94	2,534.11	5,350	23,181
Avg. salary_other ($1,000)	2,058	4,411.54	1,127.05	1,362.86	3,648.64	4,305.82	5,115.23	8,316.29
Gap ($1,000)	2,058	5,099.52	4,487.77	750.16	2,660.74	3,375.94	4,477.72	21,941
Contract year left	2,058	1.41	1.36	0	0	1	2	7
Age	2,058	26.71	4.27	18	23	26	30	40
Team								
Average Salary ($1,000)	417	4,392.24	1,078.49	1,365.96	3,664.67	4,277.01	5,104.53	7,766.17
Average gap ($1,000)	417	4,951.34	1,144.43	2,404.50	4,112.65	4,762.47	5,665.07	9,100.53
Total players	417	12.61	1.37	6	12	13	13	16
Avg. age	417	26.74	1.60	22.67	25.50	26.58	27.77	31.73
Last contract yr%	417	0.31	0.17	0	0.18	0.31	0.40	1

Table 2. Summary statistics for player and team performance variables

This table provides summary statistics for player performance variables. Filed Goal Att./Game is field goal attempts per game. Free Throw % is free throws made per game over free throws attempted per game. 3 Points % is 3 points made per game over 3 points attempted per game. Field Goal% is field goal made per game over field goal attempted per game. Wins % is the total wins over total games in the regular season. Attendance is the total attendance in the season. Attendance % is attendance per game (attendance/82) over arena capacity for the respective season.

	Obs.	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
All Players								
Minutes played	5,062	1,476.42	828.44	72	760	1,423	2,135	3,485
Points/Game	5,062	9.21	5.81	0.30	4.57	7.94	12.62	35.40
Offensive Rebounds/Game	5,062	1.09	0.84	0	0.44	0.83	1.54	5.52
Defensive Rebounds/Game	5,062	2.90	1.74	0.17	1.64	2.52	3.70	11.41
Assists/Game	5,062	2.01	1.86	0	0.70	1.40	2.67	11.70
Filed Goal Att./Game	5,062	7.65	4.51	0.40	4.03	6.73	10.49	27.82
Three Point Att./Game	5,062	1.65	1.75	0	0.05	1.11	2.85	8.69
Free Throw Att./Game	5,062	2.29	1.82	0	0.99	1.77	3.05	11.74
Field Goal %	5,062	0.45	0.06	0.16	0.41	0.44	0.48	0.74
3 Points %	5,062	0.24	0.17	0	0	0.31	0.37	1
Free Throw %	5,062	0.73	0.12	0	0.67	0.76	0.82	1
Steals/Game	5,062	0.71	0.43	0	0.38	0.63	0.95	2.89
Turnovers/Game	5,062	1.31	0.77	0.03	0.73	1.14	1.75	4.59
Centers								
Minutes played	1,806	1,369.20	811.58	73	678	1,301.50	2,024	3,406
Points/Game	1,806	8.32	5.52	0.45	4	6.93	11.54	28.66
Offensive Rebounds/Game	1,806	1.68	0.88	0.14	0.97	1.59	2.23	5.52
Defensive Rebounds/Game	1,806	3.70	2.04	0.33	2.12	3.26	4.95	10.83
Assists/Game	1,806	1.10	0.97	0	0.42	0.80	1.44	7.25
Filed Goal Att./Game	1,806	6.75	4.28	0.40	3.36	5.71	9.29	22.22
Three Point Att./Game	1,806	0.62	1.24	0	0	0.04	0.39	7.96
Free Throw Att./Game	1,806	2.29	1.77	0	1.01	1.81	3.04	11.74
Field Goal %	1,806	0.48	0.07	0.23	0.44	0.48	0.52	0.74
3 Points %	1,806	0.14	0.20	0	0	0	0.31	1
Free Throw %	1,806	0.68	0.14	0	0.61	0.70	0.77	1
Steals/Game	1,806	0.55	0.33	0	0.29	0.48	0.74	2.11
Turnovers/Game	1,806	1.18	0.67	0.09	0.66	1.04	1.54	4.31

continued

Table 2. Continued

	Obs.	Mean	Std. Dev.	Min.	Q1	Median	Q3	Max.
Forwards								
Minutes played	1,198	1,505.23	841.72	72	740	1,474	2,181	3,388
Points/Game	1,198	9.29	6.09	0.30	4.58	7.88	12.67	32.09
Offensive Rebounds/Game	1,198	1.15	0.75	0	0.61	0.98	1.54	4.36
Defensive Rebounds/Game	1,198	3.09	1.65	0.30	1.82	2.87	4.05	11.41
Assists/Game	1,198	1.50	1.19	0	0.65	1.21	1.97	8.57
Filed Goal Att./Game	1,198	7.62	4.63	0.64	3.97	6.53	10.36	24.17
Three Point Att./Game	1,198	1.73	1.71	0	0.09	1.32	3	7.11
Free Throw Att./Game	1,198	2.35	1.94	0	0.99	1.75	3.10	10.30
Turnovers/Game	1,198	1.22	0.74	0.03	0.67	1.06	1.62	4
Steals/Game	1,198	0.70	0.41	0	0.38	0.64	0.93	2.51
Free Throw %	1,198	0.72	0.12	0	0.67	0.75	0.81	1
3 Points %	1,198	0.25	0.16	0	0.11	0.32	0.37	1
Field Goal %	1,198	0.45	0.06	0.20	0.41	0.45	0.48	0.66
Guards								
Minutes played	2,058	1,553.75	825.70	90	865	1,511.5	2,204	3,485
Points/Game	2,058	9.95	5.79	0.50	5.29	9.01	13.47	35.40
Offensive Rebounds/Game	2,058	0.53	0.35	0	0.28	0.45	0.69	2.73
Defensive Rebounds/Game	2,058	2.10	1.00	0.17	1.34	2	2.72	6.50
Assists/Game	2,058	3.09	2.18	0.14	1.42	2.50	4.36	11.70
Filed Goal Att./Game	2,058	8.45	4.49	0.46	4.82	7.76	11.36	27.82
Three Point Att./Game	2,058	2.52	1.67	0	1.16	2.31	3.69	8.69
Free Throw Att./Game	2,058	2.26	1.79	0.05	0.96	1.72	3.02	11.51
Turnovers/Game	2,058	1.49	0.83	0.13	0.85	1.32	2	4.59
Steals/Game	2,058	0.86	0.46	0	0.52	0.78	1.12	2.89
Free Throw %	2,058	0.78	0.09	0	0.74	0.80	0.84	1
3 Points %	2,058	0.33	0.09	0	0.30	0.35	0.38	1
Field Goal %	2,058	0.42	0.04	0.16	0.40	0.42	0.45	0.59
Team								
Wins %	417	0.49	0.15	0.09	0.39	0.50	0.61	0.82
Makes playoffs	417	0.55	0.50	0	0	0.5	1	1
Attendance	417	702,538	93,769	460,719	636,268	704,702	776,311	908,600
Attendance/capacity	417	0.45	0.05	0.23	0.41	0.46	0.49	0.56

Table 3. Relation between scoring and the compensation gap

This table shows the fixed effects regression results of points per game and assists per game. Log(gap) is the logarithm of gap salary plus 1. Log(Age) and Log(Age)2 denote the logarithm of players' age and its squared term, respectively. Over_34 is a dummy variable which equals 1 when the player is older than 34 and 0 otherwise. Log(Avg. Sal_other) is the logarithm of average salary of other players on the team. Log(Minutes played other) is the logarithm of average minutes played of other players on the team. Last year equals 1 when the contract has only 1 year or less left and 0 otherwise. The specification includes player-team, coach, and year fixed effects. T-*values* are reported in the parenthesis. Standard errors are clustered at the player-team level. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Points per Game				Assists per Game			
	All Players	Centers	Forwards	Guards	All Players	Centers	Forwards	Guards
Log(Gap)	0.226***	0.636***	0.128***	0.774***	0.048***	0.077***	0.023**	0.250***
	(5.13)	(4.27)	(3.02)	(5.03)	(3.97)	(2.86)	(2.08)	(4.73)
Log(Age)	151.629***	118.091***	182.994***	167.428**	19.382***	9.458***	27.985**	23.516
	(4.94)	(4.39)	(2.78)	(2.21)	(3.32)	(3.13)	(2.30)	(1.13)
Log(Age)^2	-19.903***	-11.495**	-20.391*	-24.215**	-2.331**	-0.961*	-3.263	-3.110
	(-3.77)	(-2.30)	(-1.67)	(-1.99)	(-2.41)	(-1.94)	(-1.43)	(-0.94)
Over_34 (0/1)	7.061*	21.918**	4.230	4.490	-1.190	0.172	1.671	-5.566
	(1.89)	(2.50)	(0.90)	(0.62)	(-0.66)	(0.08)	(1.55)	(-1.37)
Log(Gap) X Over_34	-0.487**	-1.485**	-0.261	-0.299	0.076	-0.018	-0.112	0.381
	(-2.02)	(-2.57)	(-0.83)	(-0.65)	(0.63)	(-0.13)	(-1.49)	(1.42)
Log(Salary)	0.745***	0.474**	0.272	1.064***	0.199***	0.091**	0.101	0.320***
	(5.22)	(2.39)	(0.90)	(4.43)	(4.65)	(2.23)	(1.40)	(3.59)
Log(Avg. Sal_other)	-1.257***	-0.717	-1.411**	-1.269***	-0.287***	-0.136	-0.461***	-0.400**
	(-4.40)	(-1.64)	(-2.33)	(-2.85)	(-3.21)	(-1.56)	(-3.29)	(-2.23)
Log(Minutes played)	2.848***	2.291***	2.647***	2.747***	0.522***	0.270***	0.470***	0.743***
	(26.12)	(14.34)	(12.88)	(14.91)	(16.30)	(9.82)	(9.08)	(9.45)
Log(Minutes played other)	-2.664***	-2.060***	-3.479***	-2.248**	-0.585***	-0.331**	-0.141	-0.677**
	(-4.97)	(-2.69)	(-2.80)	(-2.54)	(-3.72)	(-2.02)	(-0.52)	(-2.14)
Last year (0/1)	-0.913	-2.004	0.856	-5.814	0.312	1.459**	0.490	0.819
	(-0.64)	(-0.67)	(0.47)	(-1.59)	(0.78)	(2.53)	(1.01)	(0.59)
Log(Gap) X Last year	0.080	0.139	-0.021	0.405*	-0.019	-0.096**	-0.029	-0.047
	(0.85)	(0.71)	(-0.17)	(1.70)	(-0.71)	(-2.53)	(-0.88)	(-0.51)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Player-team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coach Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,062	1,806	1,198	2,058	5,062	1,806	1,198	2,058
R^2	0.50	0.59	0.59	0.58	0.33	0.43	0.56	0.43

Table 4. Relation between rebounds and the compensation gap

This table shows the fixed effects regression results of points per game and assists per game. Log(gap) is the logarithm of gap salary plus 1. Log(Age) and Log(Age)2 denote the logarithm of players' age and its squared term, respectively. Over_34 is a dummy variable which equals 1 when the player is older than 34 and 0 otherwise. Log(Avg. Sal_other) is the logarithm of average salary of other players on the team. Log(Minutes played other) is the logarithm of average minutes played of other players on the team. Last year equals 1 when the contract has only 1 year or less left and 0 otherwise. The specification includes player-team, coach, and year fixed effects. T-*values* are reported in the parenthesis. Standard errors are clustered at the player-team level. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Offensive Rebounds per Game				Defensive Rebounds per Game			
	All Players	Centers	Forwards	Guards	All Players	Centers	Forwards	Guards
Log(Gap)	0.012*	0.098***	0.008	0.010	0.049***	0.219***	0.037***	0.049*
	(1.81)	(3.71)	(0.79)	(0.98)	(4.26)	(3.80)	(2.74)	(1.65)
Log(Age)	9.562***	17.796***	2.073	0.259	35.289***	36.289***	37.145***	18.611**
	(2.70)	(4.38)	(0.53)	(0.09)	(4.48)	(4.03)	(2.71)	(2.01)
$Log(Age)^2$	-1.159**	-1.882***	0.299	0.137	-4.683***	-3.015*	-3.587	-2.612*
	(-2.03)	(-2.61)	(0.44)	(0.28)	(-3.51)	(-1.86)	(-1.41)	(-1.76)
Over_34 (0/1)	0.745	4.139**	-0.672	0.311	1.535	5.362	2.776	-0.652
	(0.82)	(2.39)	(-0.46)	(0.57)	(0.74)	(1.59)	(0.85)	(-0.65)
Log(Gap) X Over_34	-0.050	-0.270**	0.029	-0.021	-0.115	-0.376*	-0.211	0.043
	(-0.85)	(-2.37)	(0.31)	(-0.57)	(-0.86)	(-1.68)	(-1.01)	(0.67)
Log(Salary)	0.003	-0.025	0.071*	-0.009	0.152***	0.024	0.269***	0.068
	(0.17)	(-0.68)	(1.73)	(-0.54)	(3.52)	(0.35)	(2.61)	(1.58)
Log(Avg. Sal_other)	-0.134***	-0.241***	-0.120	-0.007	-0.401***	-0.379**	-0.638***	-0.227***
	(-3.17)	(-2.71)	(-1.29)	(-0.22)	(-4.74)	(-2.26)	(-3.29)	(-2.71)
Log(Minutes played)	0.376***	0.526***	0.342***	0.172***	0.908***	1.163***	0.821***	0.577***
	(19.17)	(14.24)	(10.62)	(12.67)	(23.74)	(16.34)	(12.33)	(14.13)
Log(Minutes played other)	-0.200**	-0.149	-0.342**	-0.115*	-0.460***	-0.364	-0.692*	-0.311
	(-2.48)	(-0.92)	(-2.14)	(-1.79)	(-2.67)	(-1.06)	(-1.83)	(-1.63)
Last year (0/1)	0.431**	0.416	0.628***	-0.002	0.501	1.201	0.568	-0.220
	(2.51)	(0.61)	(2.78)	(-0.01)	(1.21)	(0.88)	(0.87)	(-0.29)
Log(Gap) X Last year	-0.025**	-0.021	-0.038**	0.002	-0.028	-0.072	-0.029	0.017
	(-2.21)	(-0.47)	(-2.56)	(0.11)	(-1.03)	(-0.80)	(-0.66)	(0.33)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Player-team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coach Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,062	1,806	1,198	2,058	5,062	1,806	1,198	2,058
R^2	0.35	0.52	0.48	0.37	0.44	0.58	0.56	0.45

Table 5. Relation between field goal attempts per game and the compensation gap

This table shows the fixed effects regression results of filed goal attempts per game. Log(gap) is the logarithm of gap salary plus 1. Log(Age) and Log(Age)2 denote the logarithm of players' age and its squared term, respectively. Over_34 is a dummy variable which equals 1 when the player is older than 34 and 0 otherwise. Log(Avg. Sal_other) is the logarithm of average salary of other players on the team. Log(Minutes played other) is the logarithm of average minutes played of other players on the team. Last year equals 1 when the contract has only 1 year or less left and 0 otherwise. The specification includes player-team, coach, and year fixed effects. T-*values* are reported in the parenthesis. Standard errors are clustered at the player-team level. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Field goal attempts per Game				Three-point field goal attempts per Game			
	All Players	Centers	Forwards	Guards	All Players	Centers	Forwards	Guards
Log(Gap)	0.170***	0.458***	0.104***	0.535***	0.034***	0.037	0.008	0.186***
	(4.92)	(4.02)	(2.73)	(5.01)	(2.93)	(1.31)	(0.45)	(3.73)
Log(Age)	106.036***	86.300***	124.809***	116.404**	14.832***	1.141	29.631**	22.651*
	(5.06)	(4.65)	(2.82)	(2.21)	(2.69)	(0.34)	(2.11)	(1.80)
Log(Age)^2	-13.977***	-8.570**	-14.441*	-16.778**	-1.865**	0.250	-3.414	-3.230*
	(-3.88)	(-2.40)	(-1.78)	(-1.98)	(-2.08)	(0.47)	(-1.42)	(-1.65)
Over_34 (0/1)	3.904	11.517	1.972	3.167	1.035	-1.642	1.013	2.493
	(1.41)	(1.64)	(0.42)	(0.58)	(0.90)	(-0.69)	(0.66)	(1.33)
Log(Gap) X Over_34	-0.274	-0.780*	-0.133	-0.205	-0.084	0.111	-0.069	-0.180
	(-1.54)	(-1.69)	(-0.44)	(-0.58)	(-1.10)	(0.70)	(-0.65)	(-1.51)
Log(Salary)	0.666***	0.429***	0.357	0.949***	0.090**	-0.012	-0.149	0.304***
	(5.91)	(2.67)	(1.47)	(4.71)	(2.06)	(-0.32)	(-1.46)	(3.49)
Log(Avg. Sal_other)	-1.172***	-0.852**	-1.264**	-1.228***	-0.143*	-0.036	-0.467**	-0.130
	(-5.17)	(-2.43)	(-2.49)	(-3.60)	(-1.71)	(-0.43)	(-2.41)	(-0.92)
Log(Minutes played)	2.133***	1.660***	1.909***	2.174***	0.444***	0.102***	0.538***	0.653***
	(25.18)	(13.02)	(11.78)	(15.20)	(12.26)	(2.93)	(7.15)	(9.45)
Log(Minutes played other)	-2.291***	-1.799***	-3.105***	-1.609**	-0.246	-0.438**	-0.209	0.137
	(-5.44)	(-2.87)	(-3.44)	(-2.30)	(-1.45)	(-2.31)	(-0.48)	(0.46)
Last year (0/1)	-0.378	0.288	1.245	-4.416	-0.362	0.058	0.022	-0.244
	(-0.35)	(0.13)	(1.01)	(-1.62)	(-0.97)	(0.09)	(0.03)	(-0.22)
Log(Gap) X Last year	0.038	-0.017	-0.057	0.308*	0.024	-0.005	0.002	0.017
	(0.53)	(-0.11)	(-0.69)	(1.73)	(0.97)	(-0.12)	(0.05)	(0.23)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Player-team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coach Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,062	1,806	1,198	2,058	5,062	1,806	1,198	2,058
R^2	0.50	0.59	0.59	0.58	0.26	0.31	0.43	0.45

Table 6. Relation between field goal percentage and the compensation gap

This table shows the fixed effects regression results of field goal percentage. Log(gap) is the logarithm of gap salary plus 1. Log(Age) and Log(Age)2 denote the logarithm of players' age and its squared term, respectively. Over_34 is a dummy variable which equals 1 when the player is older than 34 and 0 otherwise. Log(Avg. Sal_other) is the logarithm of average salary of other players on the team. Log(Minutes played other) is the logarithm of average minutes played of other players on the team. Last year equals 1 when the contract has only 1 year or less left and 0 otherwise. The specification includes player-team, coach, and year fixed effects. T-*values* are reported in the parenthesis. Standard errors are clustered at the player-team level. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Total Field Goal Percentage				Three-point Field Goal Percentage			
	All Players	Centers	Forwards	Guards	All Players	Centers	Forwards	Guards
Log(Gap)	-0.000	-0.001	0.000	-0.001	0.001	0.010	-0.000	-0.005
	(-0.11)	(-0.47)	(0.18)	(-0.49)	(0.79)	(0.91)	(-0.16)	(-1.28)
Log(Age)	0.650**	0.689	0.312	0.991***	0.642	-0.506	0.439	1.637**
	(2.39)	(1.40)	(0.72)	(2.64)	(1.48)	(-0.60)	(0.56)	(2.51)
Log(Age)^2	-0.091**	-0.089	-0.050	-0.149**	-0.077	0.195	-0.022	-0.243**
	(-2.10)	(-1.10)	(-0.80)	(-2.53)	(-1.12)	(1.62)	(-0.18)	(-2.31)
Over_34 (0/1)	0.022	0.273	-0.168**	0.081	-0.359	-0.276	0.117	-0.455***
	(0.34)	(1.40)	(-2.17)	(0.94)	(-0.95)	(-0.43)	(0.33)	(-2.76)
Log(Gap) X Over_34	-0.001	-0.018	0.010*	-0.004	0.022	0.009	-0.002	0.029***
	(-0.25)	(-1.47)	(1.91)	(-0.77)	(0.90)	(0.22)	(-0.10)	(2.74)
Log(Salary)	-0.004**	-0.005	-0.006	-0.005*	-0.001	0.004	-0.014	-0.011**
	(-2.51)	(-1.64)	(-1.47)	(-1.85)	(-0.22)	(0.31)	(-1.41)	(-2.23)
Log(Avg. Sal_other)	0.010**	0.011	0.011	0.007	0.021*	0.077**	0.026	-0.002
	(2.52)	(1.55)	(1.15)	(1.18)	(1.65)	(2.54)	(1.01)	(-0.19)
Log(Minutes played)	0.026***	0.030***	0.026***	0.022***	0.019***	0.014	0.025**	0.022**
	(11.59)	(8.37)	(5.10)	(4.65)	(3.39)	(1.05)	(2.40)	(2.42)
Log(Minutes played other)	0.001	0.008	0.007	-0.009	0.002	-0.053	0.017	0.022
	(0.12)	(0.58)	(0.38)	(-0.65)	(0.06)	(-0.89)	(0.36)	(0.85)
Last year (0/1)	-0.022	-0.097	-0.003	-0.045	-0.053	0.056	-0.149	0.076
	(-1.07)	(-1.64)	(-0.09)	(-0.93)	(-0.74)	(0.25)	(-1.23)	(0.81)
Log(Gap) X Last year	0.001	0.006*	0.000	0.003	0.004	-0.004	0.010	-0.005
	(1.10)	(1.65)	(0.14)	(0.90)	(0.78)	(-0.26)	(1.29)	(-0.82)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Player-team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coach Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,062	1,806	1,198	2,058	5,062	1,806	1,198	2,058
R^2	0.19	0.29	0.27	0.23	0.05	0.12	0.17	0.14

Table 7. Relation between free throws and the compensation gap

This table shows the fixed effects regression results of free throws. Log(gap) is the logarithm of gap salary plus 1. Log(Age) and Log(Age)2 denote the logarithm of players' age and its squared term, respectively. Over_34 is a dummy variable which equals 1 when the player is older than 34 and 0 otherwise. Log(Avg. Sal_other) is the logarithm of average salary of other players on the team. Log(Minutes played other) is the logarithm of average minutes played of other players on the team. Last year equals 1 when the contract has only 1 year or less left and 0 otherwise. The specification includes player-team, coach, and year fixed effects. T-*values* are reported in the parenthesis. Standard errors are clustered at the player-team level. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Free Throw Attempts				Free Throw Percentage			
	All Players	Centers	Forwards	Guards	All Players	Centers	Forwards	Guards
Log(Gap)	0.060***	0.156***	0.031**	0.215***	0.000	-0.001	0.001	-0.008**
	(4.18)	(2.90)	(2.40)	(3.31)	(0.22)	(-0.11)	(0.30)	(-2.07)
Log(Age)	47.890***	35.661***	58.566**	51.929**	0.280	0.475	0.851	0.465
	(4.53)	(3.95)	(2.53)	(2.02)	(0.37)	(0.33)	(1.19)	(0.56)
$Log(Age)^2$	-6.187***	-2.955*	-6.100	-7.543*	-0.026	-0.111	-0.146	-0.050
	(-3.40)	(-1.94)	(-1.41)	(-1.82)	(-0.22)	(-0.47)	(-1.26)	(-0.38)
Over_34 (0/1)	2.004	6.007*	2.156	1.469	0.128	0.114	0.084	0.092
	(1.30)	(1.69)	(1.45)	(0.50)	(0.94)	(0.28)	(0.45)	(0.37)
Log(Gap) X Over_34	-0.136	-0.413*	-0.121	-0.100	-0.008	-0.006	-0.007	-0.006
	(-1.35)	(-1.77)	(-1.11)	(-0.54)	(-0.95)	(-0.22)	(-0.57)	(-0.42)
Log(Salary)	0.228***	0.152**	0.110	0.305***	0.003	0.009	-0.001	-0.003
	(4.49)	(2.34)	(0.96)	(3.59)	(0.69)	(1.22)	(-0.14)	(-0.71)
Log(Avg. Sal_other)	-0.426***	-0.211	-0.541***	-0.404***	0.008	0.030*	0.010	-0.001
	(-4.38)	(-1.35)	(-2.76)	(-2.60)	(1.04)	(1.65)	(0.65)	(-0.08)
Log(Minutes played)	0.640***	0.557***	0.604***	0.551***	0.034***	0.041***	0.031***	0.035***
	(17.87)	(10.78)	(8.08)	(8.61)	(7.41)	(4.36)	(3.49)	(4.20)
Log(Minutes played other)	-0.623***	-0.253	-0.727*	-0.838***	-0.020	-0.055	-0.026	-0.010
	(-3.36)	(-0.96)	(-1.80)	(-2.71)	(-1.18)	(-1.48)	(-0.86)	(-0.46)
Last year (0/1)	-0.199	-1.814*	-0.250	-0.961	-0.072	0.146	-0.160**	-0.168*
	(-0.40)	(-1.69)	(-0.40)	(-0.78)	(-1.13)	(0.82)	(-2.10)	(-1.81)
Log(Gap) X Last year	0.022	0.126*	0.030	0.073	0.005	-0.009	0.011**	0.010*
	(0.66)	(1.79)	(0.70)	(0.90)	(1.12)	(-0.81)	(2.09)	(1.79)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Player-team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coach Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,062	1,806	1,198	2,058	5,062	1,806	1,198	2,058
R^2	0.36	0.48	0.51	0.45	0.11	0.17	0.30	0.17

Table 8. Relation between steals/turnovers and the compensation gap

This table shows the fixed effects regression results of steals and turnovers. Log(gap) is the logarithm of gap salary plus 1. Log(Age) and Log(Age)2 denote the logarithm of players' age and its squared term, respectively. Over_34 is a dummy variable which equals 1 when the player is older than 34 and 0 otherwise. Log(Avg. Sal_other) is the logarithm of average salary of other players on the team. Log(Minutes played other) is the logarithm of average minutes played of other players on the team. Last year equals 1 when the contract has only 1 year or less left and 0 otherwise. The specification includes player-team, coach, and year fixed effects. T-*values* are reported in the parenthesis. Standard errors are clustered at the player-team level. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Steals per Game				Turnovers per Game			
	All Players	Centers	Forwards	Guards	All Players	Centers	Forwards	Guards
Log(Gap)	0.009**	0.019*	0.003	0.042***	0.018***	0.062***	0.010	0.053**
	(2.53)	(1.71)	(0.75)	(3.04)	(3.22)	(2.66)	(1.33)	(2.42)
Log(Age)	5.992***	3.400***	5.660*	7.937**	13.314***	10.226***	15.419***	11.699*
	(3.95)	(2.71)	(1.84)	(2.00)	(5.05)	(3.90)	(2.74)	(1.79)
Log(Age)^2	-0.672**	0.117	-0.522	-1.069*	-1.660***	-0.880*	-1.627	-1.588
	(-2.55)	(0.55)	(-0.96)	(-1.71)	(-3.71)	(-1.75)	(-1.62)	(-1.52)
Over_34 (0/1)	0.468	2.959***	-0.399	0.734	0.477	2.125	0.363	-0.521
	(1.20)	(4.02)	(-1.00)	(1.34)	(0.73)	(1.27)	(0.53)	(-0.42)
Log(Gap) X Over_34	-0.029	-0.194***	0.028	-0.040	-0.029	-0.144	-0.020	0.044
	(-1.14)	(-4.07)	(1.07)	(-1.13)	(-0.66)	(-1.33)	(-0.43)	(0.54)
Log(Salary)	0.023*	-0.032**	-0.002	0.068**	0.101***	0.047	0.029	0.160***
	(1.72)	(-2.51)	(-0.07)	(2.55)	(5.30)	(1.58)	(0.58)	(4.78)
Log(Avg. Sal_other)	-0.012	-0.061*	0.015	0.015	-0.237***	-0.122**	-0.322***	-0.290***
	(-0.55)	(-1.87)	(0.32)	(0.39)	(-5.48)	(-1.97)	(-3.30)	(-3.92)
Log(Minutes played)	0.208***	0.156***	0.194***	0.243***	0.321***	0.307***	0.292***	0.326***
	(23.43)	(13.10)	(11.39)	(12.98)	(20.39)	(12.56)	(9.01)	(11.42)
Log(Minutes played other)	-0.208***	-0.174***	-0.256***	-0.156*	-0.398***	-0.251**	-0.353**	-0.430***
	(-4.84)	(-2.87)	(-3.00)	(-1.91)	(-5.13)	(-2.16)	(-2.31)	(-3.12)
Last year (0/1)	-0.195*	0.189	-0.340**	-0.137	0.152	0.175	0.476*	-0.491
	(-1.92)	(0.69)	(-2.16)	(-0.43)	(0.81)	(0.40)	(1.95)	(-0.84)
Log(Gap) X Last year	0.014**	-0.013	0.025**	0.011	-0.009	-0.013	-0.028*	0.035
	(2.11)	(-0.72)	(2.36)	(0.53)	(-0.73)	(-0.44)	(-1.74)	(0.91)
Constant	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Player-team Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Coach Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,062	1,806	1,198	2,058	5,062	1,806	1,198	2,058
R^2	0.38	0.49	0.51	0.47	0.40	0.50	0.53	0.45

Table 9. Influence of compensation gap on team performance-team level

This table shows the fixed effects regression results of team performance, including winning %, playoff round and the log of yearly attendance. Log(Team gap) is the logarithm of average gap in a given team-year. Log(Team age) and Log(Team age)2 denote the logarithm of average age in a given team-year and its squared term, respectively. Log(Team avg. salary) is the logarithm of average salary in a given team-year. Log(Team avg. minutes played) is the logarithm of average minutes played by players on the team in given team-year. Team>34 % is the percentage of players on the team who are older than 34. Team last year % is the percentage of players whose contract has only 1 year or less left in a given team-year. The specification includes player-team, year, and coach, fixed effects. Team Last year % is the percentage of players on the team whose contract has only 1 year or less left. *T-values* are reported in the parenthesis. Standard errors are clustered at the team-coach level. ***, **, and * represent significance at the 0.01, 0.05, and 0.10 levels, respectively.

	Win %	Playoff	Log(Attendance)	Attend./Capacity
Log(Team gap)	0.125***	0.295*	0.006	0.003
	(3.50)	(1.93)	(0.27)	(0.29)
Log(Avg. team age)	15.534	50.801	14.632***	6.304***
	(1.29)	(1.30)	(2.75)	(2.83)
Log(Avg. team age^2)	-2.240	-7.538	-2.183***	-0.941***
	(-1.22)	(-1.26)	(-2.69)	(-2.77)
Team>34 %	-0.074	1.054*	0.152	0.071*
	(-0.50)	(1.67)	(1.62)	(1.76)
Log(Team avg. salary)	0.059	0.198	0.015	0.011
	(1.24)	(0.96)	(0.51)	(0.77)
Log(Team avg. minutes played)	0.189**	0.453	0.076	0.027
	(2.38)	(1.15)	(1.28)	(1.02)
Last year of contract team %	-0.045	0.115	-0.002	0.004
	(-0.93)	(0.57)	(-0.05)	(0.23)
			0.150***	0.063***
			(5.80)	(5.85)
Constant	Yes	Yes	Yes	Yes
Team-Coach Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	417	417	417	417
R^2	0.32	0.13	0.45	0.46