Pump-faking the effort? Evidence from NBA players' contracts

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Abstract

We examine the effect of contract-based incentives on the performance of NBA players using data from the 2004–05 to 2014–15 seasons. We find support for a contract year effect, meaning that players in the last season of their current contract improve their performance in order to secure better conditions in their next contract. In addition, having secured a big contract, players have an immediate incentive to shirk, resulting in significantly lower performance in their first year of the new contract. Higher ability players are generally less responsive to the contract year effect, while still exhibiting a big contract effect. Furthermore, these incentive effects are impacted in the intuitive directions by contract timing factors - contract year effects weaken with the number of years remaining in the contract, while the length of a new contract enhances the disincentive effect from a big contract. Overall, these findings provide robust evidence for dynamic incentive considerations in players' performances in a high stakes setting.

Keywords: contract effect; incentive effect, effort, shirking, sports

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1 Introduction

The National Basketball Association (NBA), as one of the world's most popular professional sports leagues, is a large and active industry, achieving a gross revenue of 5.18 billion dollars in the 2014-15 season. As revenues have continued to increase, the salary cap under which teams are allowed to sign players has also increased over time. As a result, players face increasingly high stakes in the incentives provided by their contracts, which may naturally lead to dynamic allocations in the effort domain.

Anecdotally, opportunistic behaviors are thought to occur after players secure a long-term guaranteed contract, due to the incentive effect on player effort levels. From an intertemporal perspective, in order to maximize personal utility, players may have incentive to increase their effort immediately prior to signing another contract in order to obtain a better paying contract, while reducing effort after a new contract has been signed.

The former phenomenon is often referred to as a "contract year effect", where the contract year refers to the last season in a player's contract. Players in the contract year are perceived as more likely to have above-average performance, in order to gain the attention of team managements. For example, the 2014-15 season was the last year of the existing contract of Jimmy Butler, a point guard on the Chicago Bulls. That year, he was having a career-high season, averaging 20.0 points, 5.8 rebounds and 3.3 assists. His other statistics also increased more generally including his comprehensive player efficiency rating (PER) which jumped from 13.5 in the 2013-2014 season to 21.3 in the 2014-2015 season.

On the other hand, the so-called "big contract effect" describes a drop in performance shortly after signing a lucrative contract, due to the reduced immediacy of their performance incentive. An example is Chandler Parsons, who signed a 4-year contract worth over 94 million dollars with Memphis Grizzlies in July of 2016. However, his performance in the subsequent season turned out to be disappointing, averaging 6.2 points, 2.5 rebounds and 1.6 assists, which along with other statistics are far from his career average level. His player efficiency rating (PER) even declined from 16.2 to 7.7. In later seasons, his performance rebounded from the big contract effect.[1]

The implications of contract effects in labor markets extend broadly, including application to employee bonus schemes, election of politicians, and tenure of professors. In this paper, we empirically investigate the above-mentioned "contract year effect" and "big contract effect" by using NBA players' performance data. Compared to most labor contract settings, such dynamic incentive effects are thought to be mitigated in the domain of professional

[1] In the 2017-2018 season for example, he averaged 7.9 points, 2.5 rebounds and 1.9 assists, with a PER of 13.6.

sports. One reason is that a wide range of statistics covering all players' performances are simultaneously available, allowing for effective real-time evaluation and supervision by the coach and management. Another factor is that NBA players' performances are highly tracked and paid attention to by the general public. Players have an additional constant incentive to maintain high performance for the purpose of building their celebrity status and long-term reputation.

The literature has not pointed to an obvious result regarding the detection of dynamic effort allocation of NBA players based on contract effects. One caveat is that the statistics only include those on-court performances which can be quantified, such as points scored, assists, rebounds, steals and turnovers, and so on. Even if the comprehensive use of tracking data is enabled, the statistics may still not provide all the answers. For example, Fort (2003) questions whether a player has direct control over his performance based purely on effort. Also, players are not very likely to exhibit very obvious shirking during a game because of the high level of competition in the moment, and they may shirk by other means off the court, for example, devoting less effort to their training sessions, deviating from their recommended dietary plan, or devoting more time to appearances in commercial activities compared to improving their game performance. These shirking behaviors may affect players' on-court performance but might not be directly inferred from the performance statistics.

Furthermore, as Stiroh (2007) points out, dynamic incentive effects in contracts may be obscured by two factors– selection effects and career concerns. In terms of selection effects, teams will anticipate the strategic behavior of players, thus preferring to offer guaranteed long-term big contracts primarily to those outstanding players who are more self-motivated, disciplined and high performing. As for career concerns, players are typically motivated to focus on their professional development in the long-run. This is because although shirking behaviors timed strategically may not affect their current contract, they can still leave players with a bad reputation, which could lead to reduced pay and length of contracts in later years.[2]

To summarize, given the various specific features of the NBA as a labor contract setting, if the data still demonstrate the dynamic pattern of worsened performance after players sign big contracts and improved performance when contracts are ending, this provides convincing support for the idea that these two effects are indeed dominant phenomena in high stakes labor contract settings. Our analysis suggests that a "big contract" can have incentive and signaling effects when players are seeking to secure a new contract (the "contract year effect"), and it also allows for the possibility of and opportunity for shirking when players already have such a contract in hand (the "big contract effect").

[2]Career concerns are less important for players nearing retirement, whose performance decline is expected to be the most substantial.

We implement a quasi-experimental econometric design to empirically test whether the "contract year" phenomenon is present, and whether "big contracts" lead to shirking, based on detailed NBA data over 11 seasons. Specifically, we not only empirically evaluate these two contract-related effects, but also examine how these two effects are influenced by players' ability, level of salary increase, and the timing of contracts. Our findings confirm both the "contract year effect" and the "big contract effect" for NBA players, contributing to the literature by being the first to our knowledge to provide significant evidence for the co-existence of such two effects in the domain of professional sports.

The rest of the paper is organized as follows. section 2 reviews the related literature. section 3 proposes the hypotheses on contract status and player performance. In section 4, we describe the data. In section 5, we conduct empirical analysis and deliver our main results. section 6 concludes.

2 Literature Review

Agency theory generally focuses on incentive concerns of relevant parties in different contexts. On the one hand, employees must be compensated for their costly effort and contributions. On the other hand, the employer's future success is determined by employees' levels of devotion. Many related studies such as Alchian and Demsetz (1972), Holmström (1979), Sappington (1991), Prendergast (1999), have contributed theoretically to solving the moral hazard problem inherent in this relationship.

There have been quite a few studies addressing the incentive mechanisms embedded in labor contracts. Asch (1990) studied how U.S. Navy recruiters react to a multi-period incentive plan from April to August in 1986, finding that recruiters strategically adjust their behaviors due to the plan. In particular, those who had just won a prize recruited significantly less in subsequent period. Oyer (1998) found a non-linear relationship between the revenue of companies and the compensation of salesman, which allows intentional manipulation of efforts to influence the timing and price of purchases. Miklós-Thal and Ullrich (2016) find that being selected to national team in Euro Cup has positive effects on the performances of players with intermediate chances of being selected, but negative effects on the performances of players whose selection is very probable.

Under varying methods, models or measurements chosen, previous studies on the "contract year" phenomenon in professional sports domains did not reach consistent conclusions. In a theoretical study of the dynamics of incentives in a multi-period contract, Iossa and Rey (2014) show that incentives are stronger and performance is higher when the contract approaches its expiry date. Sen and Rice (2011) used NBA data from 1999 to 2010, and identified significantly higher performance in the "contract year" than in other seasons. O'Neill (2013) selected 256 free agents in Major League Baseball, and found by fixed effect panel data regression, that offensive statistics were enhanced in the last season of a contract after controlling for retirement possibilities. On the other hand, White II and Sheldon (2013) found no change in the non-scoring statistics (e.g. blocked shots, field goal percentage) in the contract year group of NBA. From a different perspective, Taylor and Trogdon (2002) found that NBA teams with no play-off hopes would exert even less effort which are incentivized by the potential lottery draft. Price et al. (2010) found stronger results after controlling for unobservable team and season heterogeneity in a fixed effects model.

Studies on shirking behavior after a guaranteed contract have also had mixed results. Berri and Krautmann (2006), Krautmann and Solow (2009) both had varied outcomes if two alternative indexes are used to measure player performance. Krautmann (1990) pointed out that the decline in performance could be due to its random nature, considering the complexity of a contract. In addition, Maxcy et al. (2002) and Stankiewicz (2009) also rejected the null hypothesis of opportunistic behavior. From a different perspective, Sanders and Walia (2012) propose a behavioral model to explain why it is possible that under greater incentive less effort may be induced due to pressure, resulting in the shirking and "choking" phenomenon in performance evaluation. Nevertheless, some researchers did find evidence of shirking, including Lehn (1982), Scoggins (1993), Woolway (1997).[3]

3 Hypotheses on Contract Status and Performance

In order to investigate how a player's contract status impacts his on-court performance and further infer the incentive mechanisms of the labor contracts, we select the contract-related variables as the main explanatory variables. Other variables serve as the control variables in the analysis. We can model a player's performance as a function of the contract, player and team factors:

$$Performance = f(Contract, Player, Team) \tag{1}$$

We choose the Player Efficiency Rating (PER) as the response variable. The PER is a per-minute rating developed by ESPN.com columnist John Hollinger, which is widely used as a comprehensive measure of concurrent player performance (see for example, Stiroh (2007); Hoffer and Freidel (2004); Deshpande and Jensen (2016). The average PER of the league is

[3]Another related type of shirking behavior, which is not associated with "a big contract" but due to housing wealth gains, is investigated in Gu et al. (2020).

set at 15, which allows comparisons of different player performances across seasons.

Contract-related variables include: dummy variable for "contract Year" (D_l), dummy variable for "big Contract" (D_b), annual salary ($Salary$), percentage increase of salary ($Jump_{pct}$), contract length ($Years$) and years remaining in contract ($Remain$).

Contract Year (D_l) and Big Contract (D_b) are the key variables of our analysis: D_l equals 1 when the player is in the last season of his current contract, (ie. he is expecting a new contract in the next season) and equals 0 otherwise. D_b equals 1 when a player receives a "big contract" (to be defined more specifically in Section 4.2) in the current season, and equals 0 otherwise. We test whether a player's contract status as determined by these variables, has an impact on his subsequent performance.

Generally speaking, a player's performance is jointly determined by his ability and effort, of which teams have full knowledge in a complete information world. In this case, every player will be correctly priced in the contract. However, in reality, teams cannot perfectly distinguish between a player's ability and effort due to information asymmetry. As a practicality, they use a player's past performances as a weighted estimate, and make the appraisal of a player's worth. It is reasonable for teams to place more weight on performance in recent years since they are more relevant to future performance. Thus, from a rational player's perspective, he has incentive to purposely improve performance in the "contract year" in order to increase his appraisal, so that he obtains a better contract.[4] Therefore, we propose Conjecture 1a as the Contract Year Effect:

Conjecture 1a (Contract Year Effect): All else equal, players exert greater effort, resulting in higher performance in their "contract year".

However, once a "big contract" is signed, most of the player's salary over the next few years are guaranteed and unconditional on concurrent performance. Since the level of future income is largely independent from the concurrent performance, a player has a dynamic disincentive to exert increased effort immediately following the contract signing. Moreover, if the contract amount is fairly large, he may incur psychological satisfaction, and easily become lazy or complacent. From another angle, a player may try to avoid injuries in order to earn a stable income since the career length for an average NBA player is just 4 to 5 years. A strategic player may think it is too risky to sprint for every ball possession. With these influencing factors in mind, we propose Conjecture 1b as the "big Contract Effect":

Conjecture 1b (Big Contract Effect): All else equal, after signing a "big

[4]While managers may anticipate such behavior, the standard structure of the contracts makes it difficult for them to sub-contract specifically upon final contract year performance apart from other years. Therefore the best that teams can do is to positively incentivize efforts made by the players, including in the final contract year.

contract", players tend to shirk, thus decreasing their performance.

Next, we use $Salary$ (annual salary) or lag_PER (PER in the previous season) as potential measures of the ability of the players, given that higher ability is usually accompanied with high salary and higher previous PER. An important reason for the variation among players' performances is individual differences. Players with different innate abilities can behave distinctly when responding to the change of their contract status. Star players are likely to care more about personal and team achievements beyond immediate salary factors, and hence are likely to be less impacted by these contract-related incentives. Thus, we obtain the following Conjectures 2a and 2b regarding the interaction effects with ability measures:

Conjecture 2a (Contract Year Effect by Ability): All else equal, higher ability players exhibit a weaker "contract year" effect.

Conjecture 2b (Big Contract Effect by Ability): All else equal, higher ability players exhibit a weaker "big contract" effect.

We then compute the salary percentage change $Jump\_pct = \frac{currentsalary}{previoussalary} - 1$ to find the influence of income changes on player performance. The percentage change in salary is likely to alter players' return-risk expectation. Take players in the "contract year" as an example: such players could obtain more potential satisfaction from the anticipated higher salary increase compared to the existing contract, and thus be more likely to be motivated. On the other hand, once a "big contract" is locked in, the obtained salary increase may induce a reduction in effort. Thus we put forth Conjectures 3a and 3b about the interaction effects of salary increases.

Conjecture 3a (Salary Increase and Contract Year Effect): All else equal, the subsequent salary increase enhances the performance boost in the "contract year".

Conjecture 3b (Salary Increase and Big Contract Effect): All else equal, the salary increase enhances the performance decline after signing a "big contract".

Finally, we use the variables $Remain$ (remaining years in a contract) and $Years$ (contract length) to characterize the influence of timing-related factors of the contract. It is reasonable to suppose players adjust their efforts during the process of the contract duration. The driving force becomes strongest in anticipation of a new contract in the upcoming year. At the same time, once a big contract is signed, the length of the new contract should increase the shirking tendency in the first year, since players have relatively more time until their next contract year. Thus, we propose the following conjectures 4a and 4b regarding the interaction effect of contract timing:

Conjecture 4a (Years Remaining and Contract Year Effect): All else equal,

the Contract Year effect is declining in the number of years remaining in the contract.

Conjecture 4b (Contract Length and Big Contract Effect): All else equal, the Big Contract effect is increasing in the total contract length.

In order to obtain a better estimate of the true effect, we add several factors concerning individual players and teams as the control variables in the empirical model specification. The first one is *Age*, which is a critical factor for professional players. Players usually make improvements by training their skills and accumulating experiences during the early stage of their careers (Fair, 2008). However, after reaching their peak, their performance gradually declines as a result of aging and injuries, until retirement.

We expect the "contract year" effects to be more evident for younger players than for older players, since older players would be more susceptible to a retirement effect. Furthermore, age is a good indicator of remaining career concerns (Gibbons and Murphy, 1992). Younger players are facing more uncertainty about the future, as well as more upside potential. Based on this perception, they are less likely to shirk after obtaining a "big contract". However, they may also play "smarter" as they age. Veteran players in anticipation of their retirement have the largest incentives to reduce effort, under both situations.

By introducing the variable GP (number of games played in a season) into the model, we are able to partially measure the influence of player injury on performance. This is because GP is a good inverse representative of injury, given the difficulties in collecting the relevant data. It is reasonable to predict that player participation in games is negatively affected by the occurrence of injury. Furthermore, GS_pct (percentage of games played as starting players) could also make a difference. Players who are put into starting lineups are usually more experienced, with higher ability, and of more tactical importance or better recognized by coaches. So these players are generally more likely to perform better, and this feature is also controlled for in the regression.

With regard to team-related factors, Win_pct (the team's winning percentage) and Pop (the team's market size) are considered. Berri and Krautmann (2007) mention that excellent players can have positive influences on the teammates, boosting their performances. However, diminishing marginal returns suggest that a player's individual performance could be restrained if better players occupy more opportunities in a game. Meanwhile, the team market size may also have a subtle effect. Players may have more motivation to become high-performing players in big cities like Los Angeles, but could be more easily distracted by non-game commercial opportunities as well. We use the population of the metropolitan area that a team is located in to represent the team's market size. The data from the 2010 U.S. Census and the 2011 Canadian Census are utilized, assuming no significant change in population shares during the sample period.

4 Data

4.1 Data Sources and Descriptions

We collect NBA data on contract details, player statistics and team characteristics from the 2004-05 season to the 2014-15 season. The 2011-12 season was reduced to 66 games because of the lockout imposed by the league during renegotiation on the Collective Bargaining Agreement (CBA). So we recover data from the 2011-12 season to 82 games on a pro-rata basis. Through preliminary screening, our panel data consists of 5415 observations of 809 players over 11 seasons, averaging 492 observations each season (including in-season transfers).

The data used in this paper are collected from various sports statistics websites and databases. Player and team related data are from the website www.basketballreference.com. Contract related data are from website www.spotrac.com. Metropolitan population data are from the U.S. 2010 census and Canada 2011 censuses.

4.2 Matching

To infer the effects that contract-related incentives have on players' efforts, we focus on the difference in performances between two consecutive seasons. For each season in the time range 2005-2006 through 2014-2015, we denote as period T, the season that player enters his "contract year" or obtains a "big contract". The previous season is then denoted as period $T-1$. The distribution of different contract statuses in the data is shown in Table 1.

The data show that the distribution of salaries is relatively stable over time. Most players earn an annual salary between 1 million to 5 million dollars, whereas players whose salaries are above 10 million dollars account for nearly 15 percent on average. Since the Collective Bargaining Agreement (CBA) applies specific limitations on players' salary increases during a contract, the percentage of salary increase of the majority of players is less than 10%. About 16 percent of the players obtain salary increases over 50%, which is achieved by either transfer or contract renewal.

During the sample period, the proportion of "contract year" players gradually rises, reflecting the tendency of teams to shift from long-term contracts to short-term ones. Nearly 40 percent of players sign new contracts in each season, of which 70 percent and 50 percent are longer than 1 year and 2 years, respectively. As for guaranteed pay, 100% guaranteed contracts are very common. However the number of contracts for which the guaranteed percentage is under 80% has been increasing since the 12-13 season.

The term "big contract" in the NBA usually refers to long-term contracts with an annual salary above 10 million dollars. Since we hypothesize that the change in salary may also have an influence on players' strategic behavior, we incorporate two more conditions to our definition of "big contract" in the analysis: a large salary percentage increase and a high percentage of guaranteed pay. Specifically, we define a "big contract" as one with an annual salary exceeding 10 million dollars or a salary increase of over 50%, where under both circumstances more than 80% of the salary is guaranteed for contract length of at least 2 years.[5]

Table 1: Distribution of Different Contract Statuses

Contract Status	05-06	06-07	07-08	08-09	09-10	10-11	11-12	12-13	13-14	14-15
Contract Year	34	59	67	84	137	148	185	142	161	188
Big Contract	28	14	25	26	20	23	26	29	31	37
Others	221	253	279	312	278	284	262	303	262	241
Observations	283	326	371	422	435	455	473	474	454	466

In our data set, we remove those player-observations who do not have enough playing time (less than 41 games played total, and minutes per game played less than a quarter of the game, or 12 minutes) in the two consecutive seasons (Berri and Krautmann, 2006). The reason is that these players' performances are more easily affected by other factors because of their limited on-court time. As a result, their statistics tend to be more volatile, which could bias the estimate.

In the subsequent analyses, we regard "contract year" and "big contract" as treatment variables. Thus, the observations in the data are categorized into treatment groups and control groups according to each of these variables. However, this is purely an observational study since we clearly do not manipulate whether a player in a given year gets the treatment beforehand. The players who receive the treatment are not randomly chosen. For example, signing a "big contract" may partly due to self-selection, that is, outstanding players are more likely to receive favorable contracts from teams. Therefore, the results will be biased if we simply compare the performances of players who receive the treatment with those who do not.

We employ the Mahalanobis Metric Matching to pair the observations based on observable features (see Appendix for further details). By taking other variables into consideration that

[5]The percentage salary guaranteed in the contract is indicative of the bargaining power of the players. Typically, prime-age starting players have fully guaranteed contracts, while veteran non-star players or players not drafted in the first round have partially guaranteed contracts.

may affect the dependent variable, we are able to reduce the bias caused by confounding variables in such a non-experimental setting. Confounding variables are correlated with independent and dependent variables at the same time, for example, age in this study. They have to be identified and controlled so as to derive the correct causal inference. It is reasonable that a player performs at a relatively stable level especially during a short period of time, in the absence of unexpected incidences, such as contract and injury. So we propose to match based on Age and PER, both of which are important characteristics of an individual player. If two matched players are close in age as well as performance at period $T-1$, which indicates similar development potential and capability traits, then our approach supposes that the change in their performances at period T would be approximately equal.

$$E(\Delta PER_{it}^{treatment}) \approx E(\Delta PER_{it}^{control}) \tag{2}$$

where i denotes the paired observations, t denotes the time period, and ΔPER is the difference in PER over time. If Equation (2) holds, the study can now be considered a quasi-experiment, and any significant deviation in values on either side of the equation can be attributed to the treatment effect.

The matching procedure is conducted using the following steps:

(1) For each observation in the treatment group at period $T-1$, construct the two-dimensional coordinate (Age_{T-1}, PER_{T-1}).

(2) Compute the Mahalanobis Distances (see Appendix) of all observations in the same season and not in the treatment group with the above coordinate.

(3) Take the observation that minimizes the distance as the paired observation, which is then put in the control group.

To increase the sample size, so as to alleviate the influence of abnormal fluctuations, we repeat the above steps to have two paired control observations for every observation in the treatment group.

5 Empirical Results

5.1 Contract Year Effect

We first examine "contract year" as the treatment variable. The treatment group includes observations who are in the "contract year" at period T, while the control group is determined according to the aforementioned matching procedure. We aim to find evidence about whether the "contract year" effect exists by comparing the difference in performances across the two consecutive seasons (T and $T-1$) between the two groups.

We have 266 observations in the treatment group and 532 observations in the control group. Table 2 reports the descriptive statistics of the main variables in the analysis.

Table 2: Descriptive Statistics, Panel A ("Contract Year Effect")

Variable	Previous Season ($T-1$)				Current Season (T)			
	Treatment Group		Control Group		Treatment Group		Control Group	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Response Variable								
PER	15.25	(3.916)	15.25	(3.910)	15.98	(3.978)	15.41	(3.987)
Independent Variable								
D_l	0	(0)	0	(0)	1	(0)	0	(0)
$Salary$	4717230	(4711237)	6252050	(4663861)	5203605	(4897111)	6699281	(4975719)
$Remain$	2.000	(0.000)	3.714	(0.855)	1.000	(0.000)	2.714	(0.855)
Age	25.51	(3.648)	25.34	(3.439)	26.51	(3.648)	26.34	(3.439)
GP	71.01	(10.76)	72.31	(9.853)	70.90	(10.82)	70.73	(10.78)
GS_pct	58.4%	(40.1%)	66.4%	(36.9%)	64.8%	(37.9%)	68.6%	(37.2%)
Win_pct	51.8%	(15.5%)	50.6%	(15.6%)	51.5%	(15.1%)	51.3%	(15.6%)
Pop	4.607	(4.030)	5.128	(4.852)	4.510	(3.724)	5.183	(4.950)

For both groups, the mean values of PER are slightly larger than 15, the league average level, indicating good sample representativeness among the selection of players eligible for new contracts. The average annual salary is around 6 million dollars, comparable to a mid-level contract in the NBA. Meanwhile, the observations in the control group usually have 2 to 3 years remaining in the current contracts. At these times, players are likely to perform consistently, which provides a reasonable benchmark for performance. Other control variables are very similar between the treatment and control groups.

To first obtain a basic understanding, we plot PER_{T-1} and PER_T in the two consecutive seasons for all players in both groups and fit a linear relationship for each group. Theoretically, a player's performance in the previous season is predictive of his performance in the next season, which means the fitted lines should be close to the 45° line, as shown in Figure 1. In addition, we note that the fitted line of the treatment group is above that of the control group, which means that given the same PER_{T-1} value, players in the "contract year" tend to have a higher PER_T compared to their counterparts.

Another set of graphs also illustrates the difference well. Figure 2 shows using box plots that the 25th to 75th percentile (indicated by the boxed area) of the treatment group shifts upward at period T, with the median (horizontal solid line) exceeding 15 from below. Outliers are plotted using dots. By contrast, the features of PER shown by the control

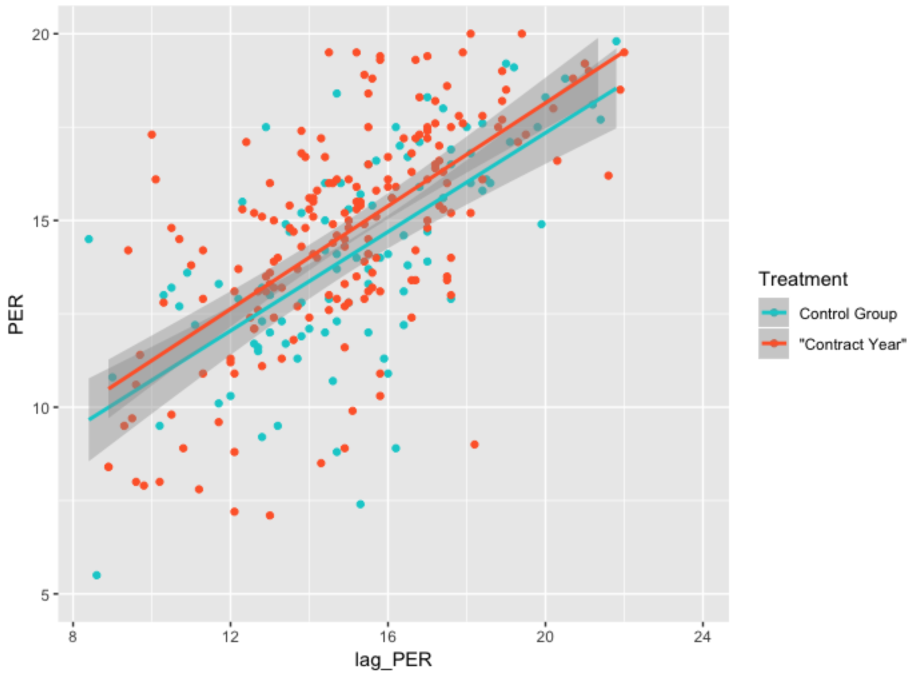

Figure 1: Scatterplot of PER Comparison between “Contract Year” and Control Groups

group box plots are nearly constant across the current and previous seasons.

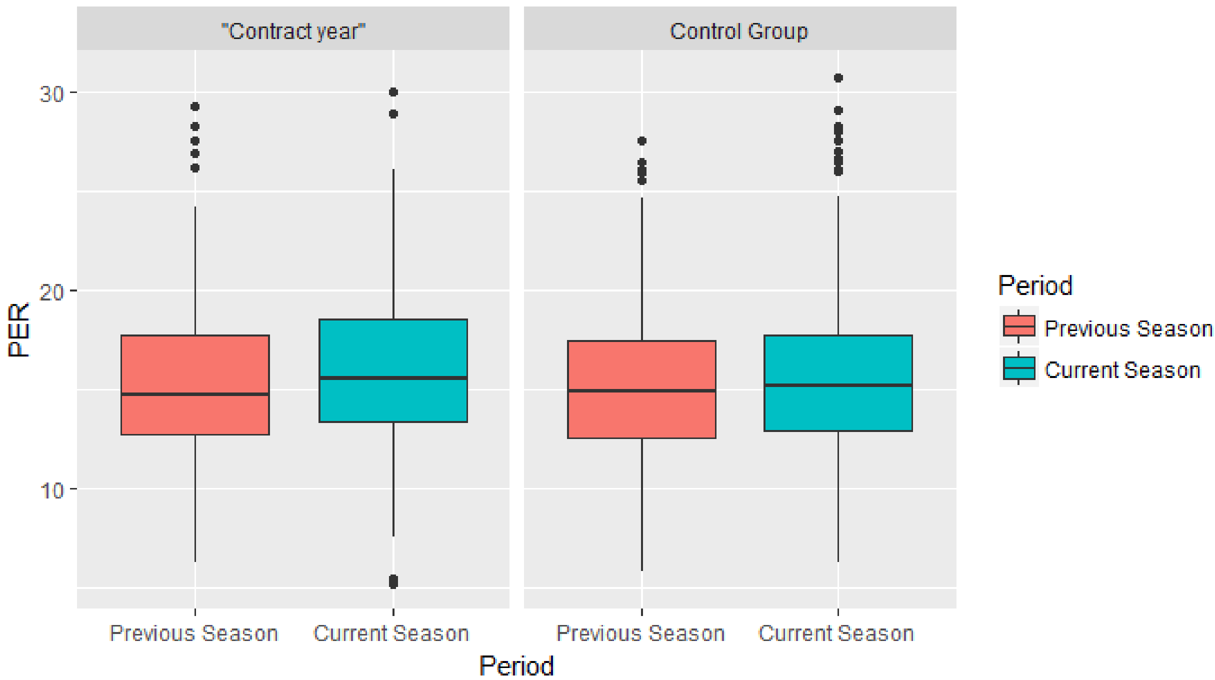

Figure 2: Boxplot of PER Comparison for “Contract Year” and Control Groups

We are then able to use a twice-differenced statistic as a basic estimate of the treatment effect. Table 3 displays the results measured in terms of both the mean and median. In the previous season, the two groups have the same average PER, which shows that the matching procedure has achieved its objective. When the players in the treatment group enter the "contract year", their average PER jumps to 15.98, which is much larger than that of the control group. By twice differencing, the estimated treatment effect is 0.568 in terms of the mean and 0.600 in terms of the median. Furthermore, a two sample t-test is implemented on the differenced PER. The test results show the change in PER of the treatment group is significantly higher than that of the control group, with $p - value$ of 8.385×10^{-4} and one-sided confidence interval of $[0.264, \infty)$.

Table 3: Comparison of Differenced PER, Panel A ("Contract Year Effect")

	PER	Previous Season	Current Season	First Differencing	Twice Differencing
Mean	Treatment Group	15.25	15.98	0.728	0.568
	Control Group	15.25	15.41	0.160	
Median	Treatment Group	14.75	15.60	0.850	0.600
	Control Group	14.95	15.20	0.250	

Based on the results, we have identified a positive treatment effect of the "contract year". However, this result is obtained without controlling for other variables. Thus, further analysis is required to obtain a causal effect that conditions upon the other observable variables. For the subsequent empirical specifications, the detailed derivations are provided in the Appendix.

Suppose there is a linear relationship between the random variable PER and the dummy variable D_l. Then for observation i at period t, the difference-in-difference (DID) model is defined as follows:

$$PER_{it} = \alpha + \gamma D_l + \lambda d_t + \delta(D_{lt}) + Z'_{it}\beta + \varepsilon_{it} \tag{3}$$

where Z_{it} is a vector of control variables:

$$Z_{it} = (Salary_{it}, Remain_{it}, Age_{it}, GP_{it}, GS\_pct_{it}, Win\_pct_{it}, Pop_{it}, D_t)'$$

D_l is the dummy variable for last year in the contract (the treatment), D_t is the year dummy, such that $D_t = 1$ if the observation is in year t. d_t is the dummy variable for treated individual and post treatment observations. The coefficient δ on the interaction term $D_{lt} = D_l \cdot d_t$ is the treatment effect estimation that we are interested in. If δ is significantly larger than 0, the performance boost (in other words the positive incentive in the "contract year") is empirically validated.

In the NBA there are different types of contracts that fall under the Collective Bargaining Agreement (CBA). The NBA Collective Bargaining Agreement is a contract between the National Basketball Association (the commissioner and the 30 team owners) and the National Basketball Players Association (the players' union), that dictates the rules of player contracts, trades, revenue distribution, the NBA Draft, salaries, and so on.

As mentioned earlier, a new version of the CBA was put in place after the renegotiation between the league and the union in 2011. Compared to the 2005 CBA, the 2011 CBA made several modifications, including those concerning contract-related incentives as listed in Table 4.[6] It can be easily seen that the 2011 CBA caters more to the league's interests in a way that weakens players' benefits. The relevant changes in the 2011 CBA may therefore affect players' expectations, thus influencing the incentives imposed on them. To account for this policy change, we divide the full sample into two sub-samples to reflect the change in CBA: before 2011 and after 2011, and then model the sub-samples respectively.

Table 4: Main Incentive Differences between the 2011 and 2005 CBA

2011 CBA	corresponding rule of 2005 CBA
Except for Bird or Early Bird contracts or extensions, players can receive **4.5%** raises in other contracts.	**8%**
Except for Bird free agents, all other free agent contracts can be up to **4 years**.	**5 years**
Unlikely bonuses may not exceed **15%** of regular salary.	**25%**
The maximum signing bonus is **15%**.	**20%**

The results of the DID model are shown in Table 5. The DID statistic δ, the coefficient on $D_l \cdot d_t$, is estimated to be 0.133 in the full sample regression, and is statistically significant. Since $\hat{\delta}$ is significantly larger than 0, the treatment effect of "contract year" on player performance is positive, which is consistent with our conjecture. This relationship is also confirmed by tests on the sub-samples by years. Under both the 2005 CBA and the 2011 CBA, the "contract year" effect is statistically significant and of similar magnitudes. Across the samples, the coefficients retain their signs, significance levels and orders of magnitude. The coefficients on the control variables are also in intuitive directions. The performance improvement is significantly increasing in player salary, percentage of games as starting player, and team's winning rate, while decreasing in age.

[6]Referring to Table 4, the Bird exception (named after Larry Bird) allows teams to exceed the salary cap in order to re-sign their own current players. An Unlikely bonus refers to a player-specific achievement incentive, typically rewarding players for exceeding their own past performance.

Table 5: Results of DID Estimation for Conjecture 1a and Sub-samples

Variables	Full Sample	Sub-sample	
	Conjecture 1a	2011 CBA	2005 CBA
(Intercept)	0.032	0.045	0.036
	(0.027)	(0.033)	(0.029)
Dummy Variables			
D_l	0.315**	0.301**	0.327**
	(0.128)	(0.125)	(0.130)
d_t	0.057	0.064	0.038
	(0.046)	(0.041)	(0.053)
$\boldsymbol{D_l \cdot d_t}$	0.133***	0.140***	0.126***
	(0.042)	(0.048)	(0.031)
Control Variables			
Salary	0.417***	0.493***	0.430***
	(0.052)	(0.083)	(0.055)
Remain	0.038	0.047	0.026
	(0.042)	(0.052)	(0.034)
Age	−0.271***	−0.262***	−0.291***
	(0.029)	(0.046)	(0.057)
GP	0.006	0.024	0.017
	(0.015)	(0.018)	(0.021)
GS_pct	0.159***	0.171***	0.186***
	(0.040)	(0.049)	(0.053)
Win_pct	0.146***	0.153***	0.140***
	(0.034)	(0.039)	(0.033)
Pop	−0.005	0.035	−0.020
	(0.017)	(0.026)	(0.019)
Obs.	1088	976	946
Adj. R^2	0.417	0.412	0.401

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; The values in the parentheses are heteroskedasiticity-autocorrelation robust standard errors.

This result constitutes our main finding for the Contract Year Effect. To check the robustness of the Contract Year Effect to our matching procedure, as well as to test the interaction effects proposed in Conjectures 2a to 4a, we further propose a standard differenced regression to model the dynamic change between the two consecutive seasons, and estimate their relationship as:

$$\Delta PER = \beta_0 + \beta_1 Age + \beta_2 \Delta GP + \beta_3 \Delta GS\_pct + \beta_4 \Delta Win\_pct + \beta_5 \Delta Pop + \gamma X + \varepsilon$$

where X is the interaction term between the dummy variable D_l and other variables of interest. Thus, we empirically test Conjectures 1a (Contract Year Effect), 2a (Contract Year Effect by Ability), 3a (Salary Increase and Contract Year Effect) and 4a (Years Remaining) as stated earlier, by examining the coefficients on the interaction terms.

Table 6 displays the regression results. Firstly, for Conjecture 1a in the first column, the dummy variable D_l has a positive effect on ΔPER (significance level $\alpha = 0.01$), which is consistent with the results of the previous DID estimation. While holding other variables constant, players' PER increases by 0.202 on average when entering the "contract year". This is the main "contract year" effect in the data.

The other columns test the interactions between the contract year effect and the other relevant variables. In our test of Conjecture 2a regarding differing contract year effects by player ability, the coefficient on $D_l \cdot lag\_PER$ however, is significantly negative, confirming that players with higher ability as proxied by lagged performance, are less affected by the contract year effect. By contrast, for Conjecture 2a, the use of players' salary as a proxy for ability does not yield statistically significant support, which perhaps is due to the heterogeneity in treatment effect and variance in outcomes across players' salary levels. As the column for Conjecture 3a indicates, the relationship between the contract year performance boost and subsequent salary increase is also not statistically significant in either direction, again potentially due to the heterogeneity in effect across salary-related measures. Conjecture 4a is validated by the negative sign on the coefficient for $D_l \cdot Remain$. That is, as the "contract year" approaches, players choose to increase their effort.

In terms of the control variables, the coefficients on Age, ΔGP and ΔGS_pct are statistically significant in all five models. As expected, the performance boost is lowest for older players. On one hand, their true ability has been demonstrated by past performance over the years. However, on the other hand, one would anticipate smaller room for their future growth. ΔGP and ΔGS_pct are both positively correlated with ΔPER, meaning that more appearances in the starting lineup and less frequent injuries contribute to better performance. Team strength and market size as control variables are generally less robust as predictors of individual performance, although team performance is positively associated with performance increase in three of the five regressions at a marginal significance level.

For the differenced regression model, we also implement a robustness check using a logistic regression with an indicator variable for PER increase greater than 2 as the dependent variable. The details are provided in the Appendix, and the results are similar to those in Table 6.

Table 6: Regression Results for Conjectures 1a, 2a, 3a, 4a

Variables	Conjecture 1a	Conjecture 2a	Conjecture 2a	Conjecture 3a	Conjecture 4a
(Intercept)	-0.067	-0.004	0.000	-0.005	-0.067
	(0.042)	(0.034)	(0.033)	(0.035)	(0.042)
Control Variables					
Age	-0.204^{***}	-0.190^{***}	-0.195^{***}	-0.194^{***}	-0.204^{***}
	(0.032)	(0.035)	(0.032)	(0.034)	(0.032)
ΔGP	0.173^{***}	0.180^{***}	0.175^{***}	0.179^{***}	0.173^{***}
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
ΔGS_pct	0.092^{***}	0.097^{***}	0.099^{***}	0.098^{***}	0.092^{***}
	(0.032)	(0.032)	(0.031)	(0.032)	(0.032)
ΔWin_pct	0.058^{*}	0.056	0.062^{*}	0.055	0.058^{*}
	(0.035)	(0.035)	(0.034)	(0.035)	(0.035)
ΔPop	-0.024	-0.028	-0.025	-0.027	-0.024
	(0.043)	(0.043)	(0.043)	(0.044)	(0.043)
Contract-related Variables					
D_l	0.202^{***}				
	(0.069)				
$D_l \cdot Salary$		-0.062			
		(0.067)			
$D_l \cdot lag\_PER$			-0.252^{***}		
			(0.059)		
$D_l \cdot Jump\_pct$				0.045	
				(0.051)	
$D_l \cdot Remain$					-0.189^{***}
					(0.064)
Obs.	798	798	798	798	798
Adj. R^2	0.107	0.099	0.119	0.098	0.107

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; The values in the parentheses are White heteroskedasitisity robust standard errors.

5.2 Big Contract Effect

We continue by investigating whether obtaining a "big contract" encourages shirking. Similar to the previous analyses, the players who sign a "big contract" at period T are included in the treatment group. As described earlier, the matched players of the control group are then selected accordingly. Our overall methodology to establish inference regarding "big contract" effects is analogous to our previous analyses for the "contract year" effect.

Following the previously described matching procedure, we have 160 and 320 observations in the treatment and control groups, respectively. The descriptive statistics are provided in Table 7.

Table 7: Descriptive Statistics, Panel B ("Big Contract Effect")

Variable	Previous Season				Current Season			
	Treatment Group		Control Group		Treatment Group		Control Group	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Response Variable								
PER	17.23	-4.12	16.89	-4.003	16.17	-4.279	16.63	-4.294
Independent Variable								
D_b	0	0	0	0	1	0	0	0
$Salary$	4758998	-5651388	7344614	-4941381	8750033	-4752909	7883825	-5269545
$Remain$	1.106	-0.414	3.872	-0.953	3.919	-1.197	2.872	-0.953
Age	25.58	-3.121	25.45	-2.963	26.58	-3.121	26.45	-2.963
GP	72.39	-10.23	71.89	-9.724	71.18	-10.26	70.73	-10.76
GS_pct	71.00%	-35.60%	73.10%	-35.20%	72.50%	-37.10%	74.00%	-36.10%
Win_pct	54.80%	-13.90%	51.50%	-15.20%	52.40%	-15.50%	51.70%	-15.90%
Pop	5.313	-4.49	5.449	-4.98	4.985	-4.216	5.529	-5.089

Both groups have an average PER greater than 16, which results from players who are qualified for a "big contract" being more likely to have above average performance, and thus so is the control group via the matching procedure. In addition, the annual salary of the treatment group increases substantially due to the "big contract". There are on average around 3 years remaining in the current contract for observations in the control group, which provides a preferable condition for comparison by avoiding possible end of contract effects. There are only minor differences in the other control variables.

Once again, by plotting PER_{T-1} and PER_T of the observations from both groups and fitting a linear line for each group in Figure 3, we can gain insight into the "big contract" effect. Similar to in the "contract year" effect, the player's performances are largely consistent between the two consecutive seasons. However, this time we can identify a bigger difference in the performance changes of the two groups. The players who signed a "big contract" under-perform compared to the players who did not, on average, given the same PER value in the previous season. Examining the equivalent plot for the subsample of high performing players, ie., the ones with high PER (top 25%, with star players), as shown in Figure 4, or the high PER players excluding star players, as in Figure 5, the effect is even stronger.

This difference is confirmed by the boxplot in Figure 6. The PER of the treatment group, as a whole, has a distinguishable drop between previous and current seasons, along with

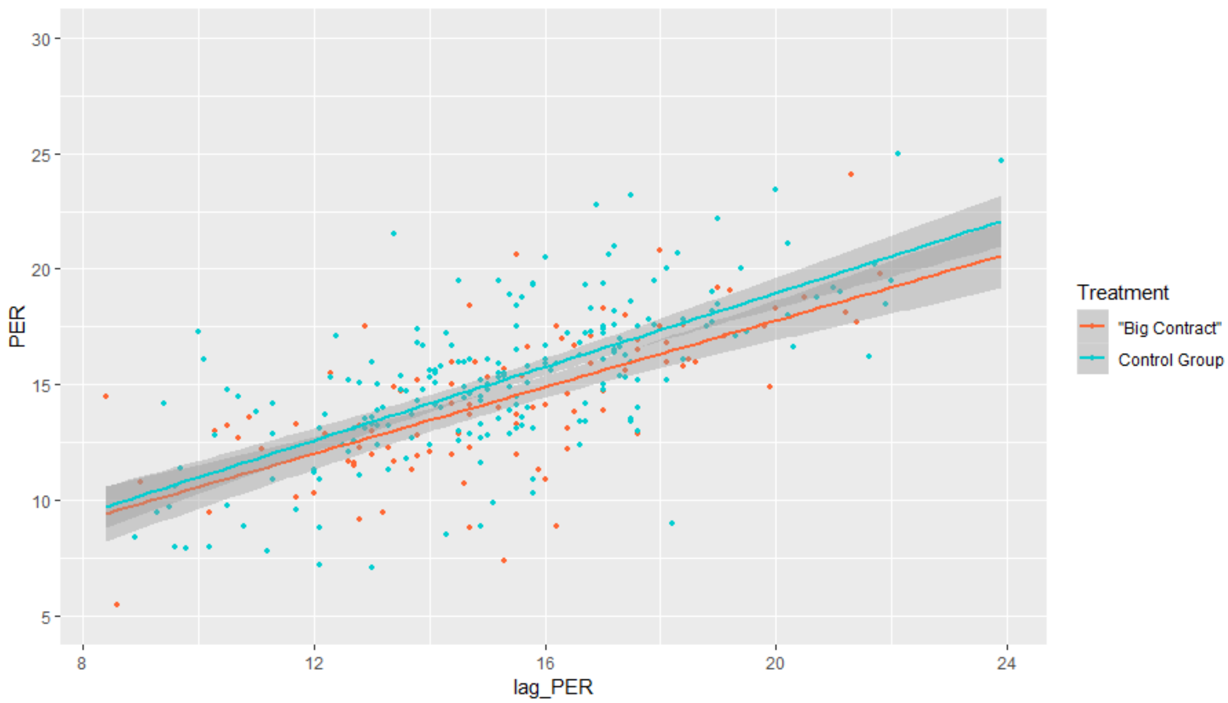

Figure 3: Scatterplot of PER Comparisons between "Big Contract" and Control Groups

increased dispersion, whereas the control group does not. Figure 7 additionally illustrates the relationship between the change in PER and contract length for the treatment group, which shows a inverse-U shaped pattern of rising from 2 to 4 years and declining from 4 to 6 years, but remaining primarily in the domain of negative change in PER across contract lengths.

Table 8 presents the results of the twice-differenced statistics. Measured by the mean and median, the approximate treatment effects are a drop in PER of -0.793 and -0.550, respectively. While the average performances of the two groups in the previous season are quite similar, the drop in PER value is much larger for those who obtained "big contracts" in the current season. The two sample t-test gives a $p-value$ of 2.27×10^{-8} and the one-sided confidence interval is $(-\infty, -0.874]$, indicating a significant decline in the performance of the treatment group.

Table 8: Comparison of Differenced PER, Panel B ("Big Contract Effect")

	PER	Previous Season	Current Season	First Differencing	Twice Differencing
Mean	Treatment Group	17.23	16.17	-1.058	-0.793
	Control Group	16.89	16.63	-0.265	
Median	Treatment Group	16.80	15.95	-0.850	-0.550
	Control Group	16.55	16.25	-0.300	

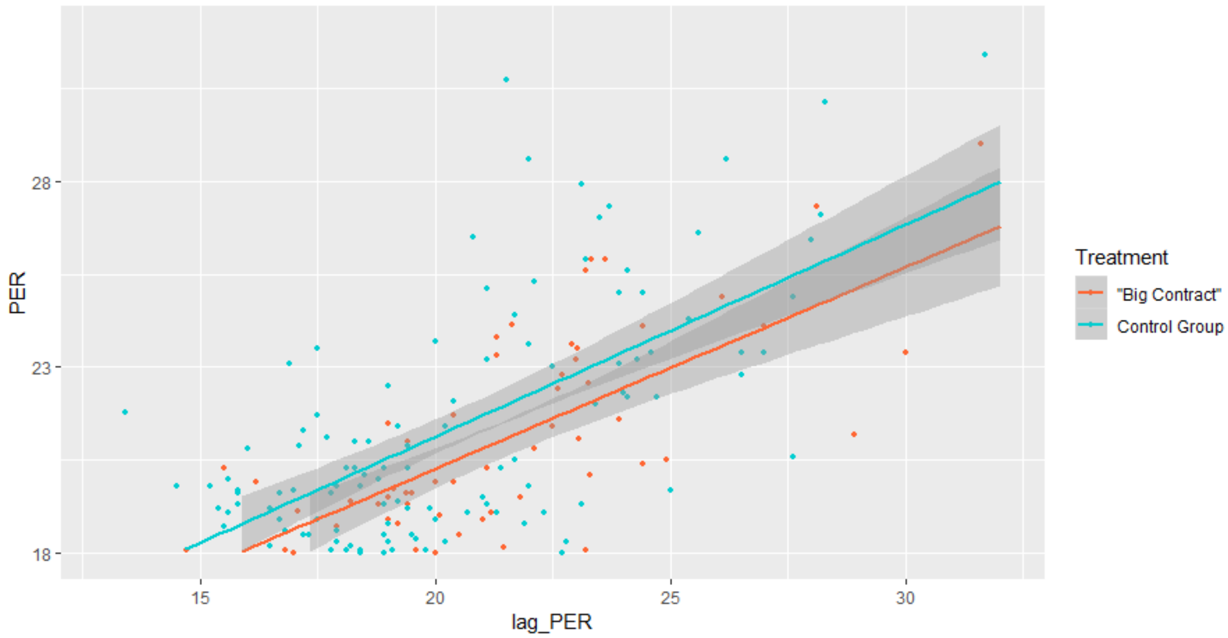

Figure 4: Scatterplot of PER Comparisons between "Big Contract" and Control Groups (for High Performing Players)

Having detected a significant overall negative impact of the "big contract" effect, we use the DID model to further control for the influence of other variables. Supposing a linear relationship between PER and D_b, the model is specified similarly as in the previous section:

$$PER_{it} = \alpha + \gamma D_b + \lambda d_t + \delta(D_b \cdot d_t) + Z'_{it}\beta + \varepsilon_{bt} \tag{4}$$

where

$$Z_{it} = (Salary_{it}, Remain_{it}, Age_{it}, GP_{it}, GS\_pct_{it}, Win\_pct_{it}, Pop_{it}, D_t)'$$

The treatment effect is estimated by the DID statistic, the coefficient δ of $D_b \cdot d_t$. If δ is significantly negative, we can find support for the "big contract" effect.

Recall that the definition of "big contract" here is comprised of two categories of players: those whose annual salary exceeds 10 million dollars, and those whose annual salary is lower than this amount but with a salary increase over 50%. The higher salary a player has, the more likely that he is among the star players. We are interested in whether these two subgroups of players behave differently. So we again divide the full sample into sub-samples based on these criteria, and also run regressions under the 2011 CBA and the 2005 CBA.

The regression results are shown in Table 9. The estimated coefficient $\hat{\delta}$ of $D_b \cdot d_t$ is negative and statistically significant in the full sample regression. Meanwhile, the value of $\hat{\delta}$

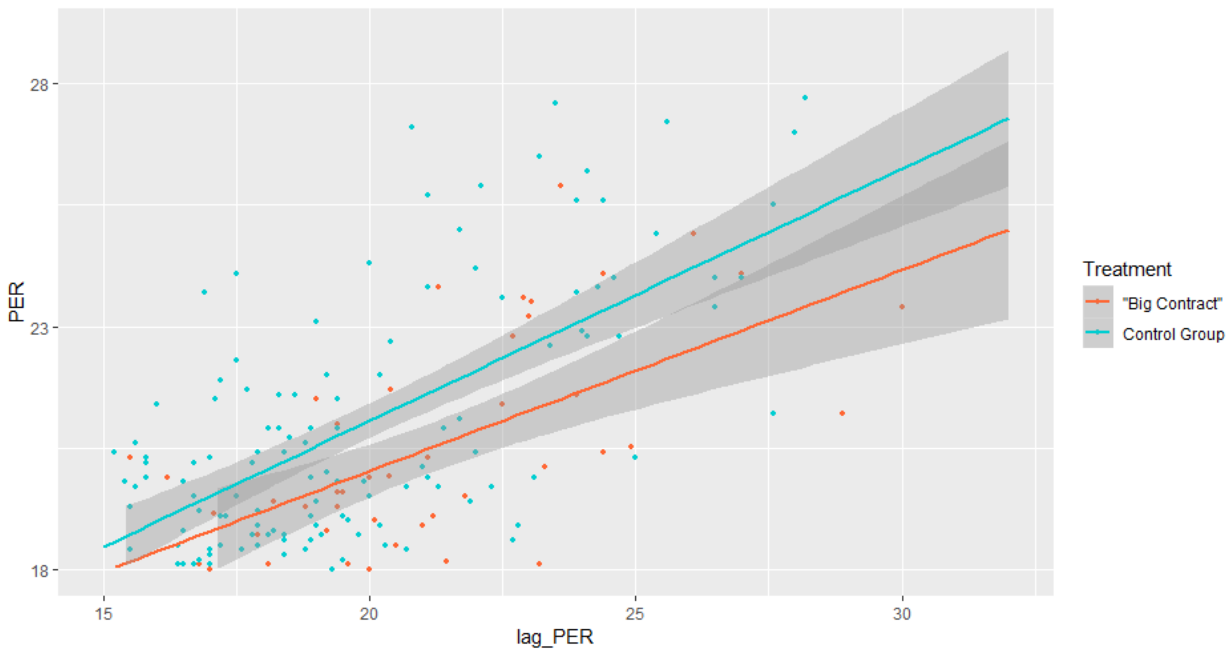

Figure 5: Scatterplot of PER Comparisons between "Big Contract" and Control Groups (for High Performing Players Excluding Star Players)

is close to the twice-differenced statistic. This provides support for Conjecture 1b. We also notice that the players in the sub-sample whose annual salary is below 10 million dollars are more adversely affected by a "big contract", which could be due to the star players being more self-motivated and tending to shirk less. In addition, the "big contract" effect is significant after 2011 but insignificant before that time, meaning that the 2011 CBA seemed to increase shirking to some extent because of the reduction in bonuses. The other variables are almost consistent across all five models, indicating a general robustness of the model.

As a robustness check on the DID result for Conjecture 1b, as well as to test the conjectures involving interaction effects with the Big Contract Effect, we again use a differenced regression model to test the influence of other factors on player performance changes.

$$\Delta PER = \beta_0 + \beta_1 Age + \beta_2 \Delta GP + \beta_3 \Delta GS\_pct + \beta_4 \Delta Win\_pct + \beta_5 \Delta Pop + \gamma X + \varepsilon \quad (5)$$

where X is the interaction term of the dummy variable D_b and other contract-related variables. We check the direction and significance of coefficients to verify Conjectures 1b (Big Contract Effect), 2b (Big Contract Effect by Ability), 3b (Salary Increase and Big Contract Effect), 4b (Contract Length).

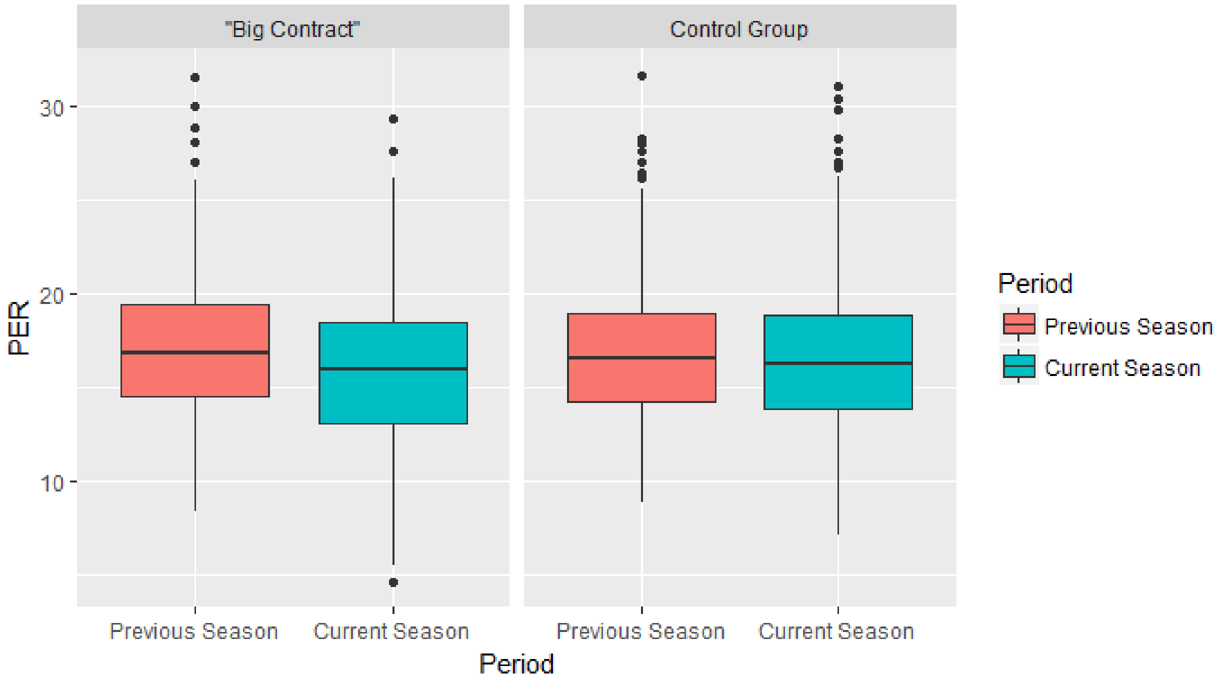

Figure 6: Boxplot of PER Comparison for “Big Contract” and Control Groups

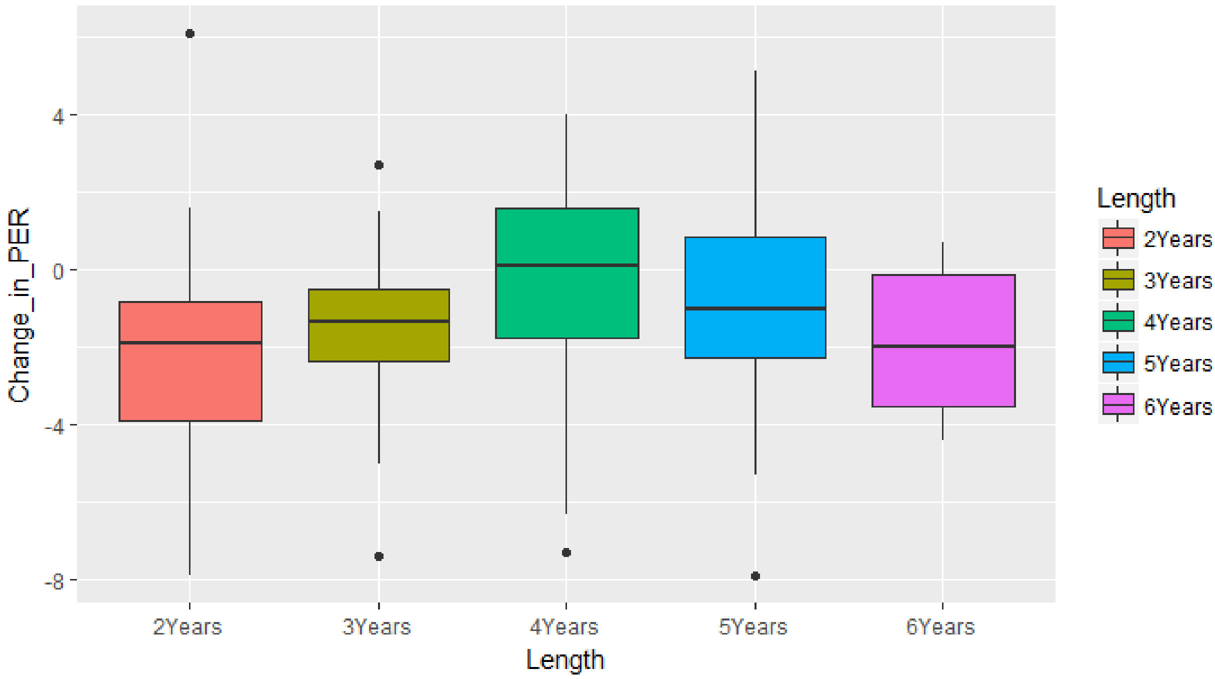

Figure 7: Boxplot of Change in PER by Contract Length

Table 9: Results of DID Estimation for Conjecture 1b and Sub-samples

Variables	Full Sample	Sub-sample		Sub-sample	
	Conjecture 1b	Over 10 million ($)	under 10 million ($)	2011 CBA	2005 CBA
(Intercept)	0.007	0.043	-0.052	-0.032	0.030
	(0.048)	(0.068)	(0.067)	(0.075)	(0.059)
Dummy Variables					
D_b	0.331^{***}	0.295	0.446^{***}	0.495^{***}	0.206
	(0.111)	(0.204)	(0.151)	(0.174)	(0.146)
d_t	-0.059	-0.095	0.033	-0.046	-0.096
	(0.070)	(0.102)	(0.101)	(0.107)	(0.085)
$\boldsymbol{D_b \cdot d_t}$	-0.527^{***}	-0.565^{*}	-0.677^{***}	-0.662^{**}	-0.306
	(0.159)	(0.292)	(0.218)	(0.259)	(0.195)
Control Variables					
$Salary$	0.577^{***}	0.450^{***}	0.379^{***}	0.515^{***}	0.652^{***}
	(0.038)	(0.061)	(0.056)	(0.053)	(0.049)
$Remain$	-0.009	0.090	0.014	0.083	-0.096^{*}
	(0.043)	(0.078)	(0.061)	(0.064)	(0.052)
Age	-0.224^{***}	-0.369^{***}	-0.214^{***}	-0.165^{***}	-0.277^{***}
	(0.030)	(0.049)	(0.040)	(0.046)	(0.038)
GP	0.008	-0.015	0.031	0.036	0.015
	(0.030)	(0.049)	(0.044)	(0.041)	(0.037)
GS_pct	0.143^{***}	0.110^{**}	0.137^{***}	0.136^{***}	0.182^{***}
	(0.028)	(0.043)	(0.040)	(0.041)	(0.035)
Win_pct	0.138^{***}	0.216^{***}	0.081^{**}	0.143^{***}	0.121^{***}
	(0.026)	(0.046)	(0.038)	(0.041)	(0.032)
Pop	-0.067^{**}	-0.054	-0.032	-0.066^{*}	-0.054
	(0.026)	(0.040)	(0.039)	(0.039)	(0.034)
$Obs.$	960	372	372	462	594
Adj. R^2	0.403	0.295	0.318	0.389	0.434

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; The values in parentheses are heteroskedasiticity-autocorrelation robust standard errors.

The results are shown in Table 10. For all Xs in the five models, only the coefficient on $D_b \cdot Salary$ is not statistically significant. Firstly, following Conjecture 1b, and consistent with the DID results, D_b negatively affects ΔPER (significance level $\alpha = 0.01$), averaging -0.276 while holding other variables constant. Inconsistent with Conjecture 2b, the coefficient estimated for $D_b \cdot lag\_PER$ is negative, meaning that higher ability players as indicated by lagged performance, are still significantly influenced by the big contract effect. The coefficient on $D_b \cdot Jump\_pct$ is negative, which shows that the rising income in the new contract reduces performance, supportive of Conjecture 3b. Finally, the extent of the performance drop increases the longer the new contract is, which is consistent with Conjecture 4b.

The results also show that the coefficients on Age, ΔGS_pct and ΔWin_pct are significant across all models, while the coefficients of ΔGP and ΔPop are not significant. As players age, they tend to adjust their efforts (reducing injuries or planning on retirement) in response to a "big contract", leading to performance decline. Finally, ΔGS_pct and ΔWin_pct both have a positive correlation with ΔPER. More games as starting players and being part of a strong team, along with the "big contract" effect, help to improve performance.

As a further robustness check, we implement a logistic regression for the differenced regression model using an indicator variable as the dependent variable. Performance decline is defined as having at least a 2 point drop in PER, and the results are provided in the Appendix. The results are similar to those discussed above, with the exception that the coefficient on the interaction between Big Contract and contract length is not significant in this alternative specification. This suggests that the contract length effect is not well-captured by the threshold of 2 for the magnitude of PER decline, and is likely occurring at a smaller margin of PER.

Table 10: Regression Results for Conjecture 1b, 2b, 3b, 4b

Variables	Conjecture 1b	Conjecture 2b	Conjecture 2b	Conjecture 3a	Conjecture 4b
(Intercept)	0.092^{*}	-0.001	0.004	0.029	0.062
	(0.055)	(0.044)	(0.044)	(0.047)	(0.053)
Control Variables					
Age	-0.131^{***}	-0.136^{***}	-0.128^{***}	-0.151^{***}	-0.142^{***}
	(0.041)	(0.043)	(0.043)	(0.044)	(0.042)
ΔGP	-0.008	-0.010	-0.009	-0.007	-0.009
	(0.056)	(0.056)	(0.055)	(0.055)	(0.056)
ΔGS_pct	0.126^{***}	0.126^{***}	0.121^{***}	0.125^{***}	0.126^{***}
	(0.040)	(0.041)	(0.041)	(0.041)	(0.041)
ΔWin_pct	0.159^{***}	0.170^{***}	0.165^{***}	0.165^{***}	0.163^{***}
	(0.055)	(0.055)	(0.054)	(0.055)	(0.055)
ΔPop	-0.038	-0.029	-0.027	-0.037	-0.036
	(0.051)	(0.052)	(0.051)	(0.050)	(0.051)
Contract-related Variables					
D_b	-0.276^{***}				
	(0.091)				
$D_b \cdot Salary$		0.026			
		(0.078)			
$D_b \cdot lag\_PER$			-0.205^{***}		
			(0.079)		
$D_b \cdot Jump\_pct$				-0.100^{*}	
				(0.060)	
$D_b \cdot Years$					-0.142^{**}
					(0.059)
$Obs.$	480	480	480	480	480
Adj. R^2	0.067	0.050	0.064	0.057	0.060

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; The values in the parentheses are White heteroskedastisity robust standard errors.

6 Conclusions

In this paper, we have examined the effects of contract-related incentives on player performance using NBA data over the recent decade. We focus on two types of contract-related incentive effects: The Contract Year Effect, which describes players' increased effort and performance in the year leading up to their contract renewal; and the Big Contract Effect, which describes players' decreased effort and performance immediately after signing an advantageous contract. NBA players have high-stakes material incentives attached to their contracts, while at the same time being in the public eye, which might arguably serve to weaken the dynamic incentive effects compared to the incentive for overall performance. However, we find that in fact Contract Year and Big Contract effects feature prominently in the data under a variety of empirical tests, which indicates that contract-based incentives prevail in shaping player's dynamic effort allocation over their contract stages.

We further test the interaction effects between these two main types of contract effects, and observable features such as player ability, level of salary increase, and timing effects of the contracts. For interactions with the Contract Year Effect, we find significant additional effects of ability and contract timing in the predicted directions. Players of higher ability are less prone to the Contract Year Effect, while the time remaining in the contract negatively predicts performance improvements. In terms of interactions with Big Contract Effects, we find significant additional effects as conjectured, for salary increases and total contract length. In particular, a higher salary increase combined with a big contract tends to reduce performance, as does the total length of the contract awarded. In terms of ability-based interaction effects, contrary to the conjecture, we find that high performing players seem further prone to Big Contract effects.

Regarding the interaction effects of player ability, a notable finding is that higher ability players are less prone to Contract Year Effects, while still being significantly affected by Big Contract Effects. This suggests that higher ability players may take a somewhat longer-term horizon on their incentives, while lower ability players could be forced to respond to short-term considerations. This is consistent with the intuition that higher ability players can "afford" to have longer-term outlooks on their career and performance measures, while lower ability players may face persistent short-term pressure.

The contract timing interaction effects also show that, while the years immediately preceding and following a new contract are dominant forces towards changes in player performance, longer-term considerations also have intuitive effects on player performances: the incentive effect is weakened in the years before the contract year, while a longer new contract tends to strengthen the disincentive effect. This indicates that the Contract Year and Big Contract effects are not limited to the immediate years prior and subsequent to contract signing, but are more generalized phenomena across the entire contract periods.

We note that while our analysis controls for many personal characteristics of players and teams within the game, this study has not examined the potential effects of individual characteristics outside of the game on players' effort responses to contract effects. Further collection of data on players' personal background characteristics, which could be incorporated into a similar analysis as the one we have conducted here, could shed light on related interaction effects between personal features and sensitivity to contract effects. We leave this as a direction for future research.

7 Appendix

7.1 Mahalanobis Distance

Mahalanobis Distance was first introduced by P. C. Mahalanobis in 1936. It measures the distance of two random vectors, $\boldsymbol{x}$ and $\boldsymbol{y}$, following the same distribution with covariance matrix $\boldsymbol{\Sigma}$. Mahalanobis Distance is unitless and scale-invariant, and takes into account the correlations of the data set:

$$d(\boldsymbol{x}, \boldsymbol{y}) = \sqrt{(\boldsymbol{x} - \boldsymbol{y})^T \boldsymbol{\Sigma}^{-1} (\boldsymbol{x} - \boldsymbol{y})} \tag{6}$$

7.2 Difference-in-Differences Estimation

Commonly used in experimental study and causal inference, Difference-in-Differences estimation aims to explain the treatment effect by comparing the average changes in the response variable before and after the treatment of the experiment group and the control group. It also deals with biases brought by missing variables through unobserved fixed effects on the group level. A key assumption of the DID estimation is that the response variables of both groups have the same trend during the two periods. In this study, the assumption is basically satisfied by matching important characteristics (Age and PER).

Define i as individuals, s as groups (exp and con), t as periods (bef and aft), then PER_{ist} is the PER value of player i in group s at period t. Equation 1 can be extended to get the treatment effect as the difference of differences in PER of each group during two consecutive seasons:

$$\begin{aligned} Treatment\ effect =& E(\Delta PER_{it}^{experiment}) - E(\Delta PER_{it}^{control}) \\ =& E(\Delta PER_{ist} | s = exp) - E(\Delta PER_{ist} | s = con) \\ =& [E(PER_{ist} | s = exp, t = aft) - E(PER_{ist} | s = exp, t = bef)] - \\ & [E(PER_{ist} | s = con, t = aft) - E(PER_{ist} | s = con, t = bef)] \end{aligned} \tag{7}$$

which can be estimated using sample averages:

$$\begin{aligned} Treatm\hat{e}nt\ effect = & \left[\frac{1}{n} \sum_{i=1}^{n} PER_{ist,s=exp,t=aft} - \frac{1}{n} \sum_{i=1}^{n} PER_{ist,s=exp,t=bef} \right] - \\ & \left[\frac{1}{2n} \sum_{i=1}^{2n} PER_{ist,s=con,t=aft} - \frac{1}{2n} \sum_{i=1}^{2n} PER_{ist,s=con,t=bef} \right] \end{aligned} \tag{8}$$

Negative value of the estimation would indicate a negative impact on player performances, vice versa.

Using the same notation, DID estimation assume the latent PER outcome of the players in the control group is the sum two part, group effect γ_s and year effect λ_t:

$$E(PER_{0ist}|s,t) = \gamma_s + \lambda_t \tag{9}$$

Let D_{st} be a dummy variable. $D_{st} = 1$ if the group receives treatment at period t. Further assume $E(PER_{1ist} - PER_{0ist}|s,t)$ is a constant, expressed as δ:

$$E(PER_{1ist} - PER_{0ist}|s,t) = \delta \tag{10}$$

Hence, the observable player performance PER_{ist} can be written as:

$$PER_{ist} = \gamma_s + \lambda_t + \delta D_{st} + \varepsilon_{ist} \tag{11}$$

where $E(\varepsilon_{ist}|s,t) = 0$. Based on Equation (4), we have:

$$\begin{aligned} &E(PER_{ist}|s = con, t = aft) - E(PER_{ist}|s = con, t = bef) \\ =&\lambda_{aft} - \lambda_{bef} \end{aligned} \tag{12}$$

as well as:

$$\begin{aligned} &E(PER_{ist}|s = exp, t = aft) - E(PER_{ist}|s = exp, t = bef) \\ =&\lambda_{aft} - \lambda_{bef} + \delta \end{aligned} \tag{13}$$

Combining equation (7) and equation (4) gives us the total difference:

$$\begin{aligned} &[E(PER_{ist}|s = exp, t = aft) - E(PER_{ist}|s = exp, t = bef)] \\ &- [E(PER_{ist}|s = con, t = aft) - E(PER_{ist}|s = con, t = bef)] \\ =&\delta \end{aligned} \tag{14}$$

which is the desired treatment effect. We can estimate the treatment effect by constructing the DID model. In this paper, PER is the response variable we are interested in. D_s and D_t are dummy variables. D_s equals 1 if the player is in the "contract year" or getting a "big contract", and 0 otherwise. D_t[7] equals 1 the player is in the current season T and 0 in the previous season $T-1$. Hence, the PER of player i in group s at period t is given by:

$$PER_{it} = \alpha + \gamma D_s + \lambda d_t + \delta(D_s \cdot d_t) + \varepsilon_{it} \tag{15}$$

[7]Please note that this D_t is different from the previously defined year dummy D_t.

which is identical to Equation (5) where $D_s \cdot d_t = D_{st}$. Equation (10) can be modified by taking more covariates into account, which follows:

$$E(PER_{0it}|s, t, Z_{it}) = \gamma_s + \lambda_t + Z'_{it}\beta \tag{16}$$

where Z_{it} is a vector of covariates contingent on individual, group and period, like Age, GP, etc. which describe a player's personal traits. Thus, the DID model that the empirical analysis builds upon is in the following manner:

$$PER_{it} = \alpha + \gamma D_s + \lambda d_t + \delta(D_s \cdot d_t) + Z'_{it}\beta + \varepsilon_{it} \tag{17}$$

7.3 Robustness Test for Contract Year Effect

This section investigates the robustness of the results in Section 6 by adopting a generalized linear regression, logistic regression. We introduce a new dummy variable D_{up} as the dependent variable. For each observation, D_{up} is equal to 1 if PER increases by over 2 in the season, and is equal to 0 otherwise. This robustness check helps distinguish whether a player has an obvious performance boost in the "contract year". Table 11 displays the results of the logistic regression. The signs and significance of the coefficients of the main variables are consistent with the OLS estimates, thus our conclusions are unchanged.

Table 11: Logistic Regression Results, Panel a

Variables	Conjecture 1a	Conjecture 2a	Conjecture 2a	Conjecture 3a	Conjecture 4a
(Intercept)	-1.197^{***}	-1.099^{***}	-1.129^{***}	-1.097^{***}	-1.197^{***}
	(0.107)	(0.088)	(0.089)	(0.088)	(0.107)
Control Variables					
Age	-0.456^{***}	-0.442^{***}	-0.448^{***}	-0.448^{***}	-0.456^{***}
	(0.094)	(0.096)	(0.098)	(0.097)	(0.094)
ΔGP	0.252^{***}	0.259^{***}	0.248^{***}	0.257^{***}	0.252^{***}
	(0.091)	(0.091)	(0.092)	(0.091)	(0.091)
ΔGS_pct	0.125	0.130	0.130^{*}	0.131^{*}	0.125
	(0.080)	(0.080)	(0.079)	(0.080)	(0.080)
ΔWin_pct	0.175^{**}	0.172^{**}	0.190^{**}	0.171^{**}	0.175^{**}
	(0.087)	(0.087)	(0.086)	(0.087)	(0.087)
ΔPop	0.033	0.031	0.039	0.031	0.033
	(0.106)	(0.105)	(0.106)	(0.105)	(0.106)
Contract-related Variables					
D_l	0.291^{*}				
	(0.172)				
$D_l \cdot Salary$		-0.052			
		(0.187)			
$D_l \cdot lag\_PER$			-0.713^{***}		
			(0.171)		
$D_l \cdot Jump\_pct$				0.015	
				(0.138)	
$D_l \cdot Remain$					-0.272^{*}
					(0.161)
$Obs.$	798	798	798	798	798

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; The values in the parentheses are White heteroskedasitisity robust standard errors.

7.4 Robustness Test for Big Contract Effect

We apply the logistic regression to check the robustness of the results in Section 7. A new dummy variable D_{down} is incorporated as the dependent variable. D_{down} is equal to 1 if a player's PER decreases by more than 2, and is equal to 0 otherwise. It is noted here that the expected sign of the coefficients should be opposite to the OLS estimates due to the dependent variable definition. The regression results are provided in Table 12, leading to largely similar conclusions as previously discussed.

Table 12: Logistic Regression Results, Panel b

Variables	Conjecture 1b	Conjecture 2b	Conjecture 2b	Conjecture 3b	Conjecture 4b
(Intercept)	-1.132^{***}	-1.005^{***}	-1.025^{***}	-1.015^{***}	-1.106^{***}
	(0.133)	(0.106)	(0.107)	(0.110)	(0.127)
Control Variables					
Age	0.133	0.123	0.120	0.146	0.151
	(0.102)	(0.103)	(0.103)	(0.106)	(0.104)
ΔGP	-0.018	-0.013	-0.017	-0.016	-0.017
	(0.116)	(0.117)	(0.116)	(0.115)	(0.117)
ΔGS_pct	-0.251^{**}	-0.249^{**}	-0.256^{**}	-0.250^{**}	-0.254^{**}
	(0.098)	(0.102)	(0.105)	(0.100)	(0.100)
ΔWin_pct	-0.197^{*}	-0.212^{*}	-0.201^{*}	-0.209^{*}	-0.202^{*}
	(0.113)	(0.113)	(0.114)	(0.113)	(0.114)
ΔPop	0.001	-0.016	-0.023	-0.008	-0.002
	(0.120)	(0.123)	(0.121)	(0.120)	(0.120)
Contract-related Variables					
D_b	0.385^{*}				
	(0.215)				
$D_b \cdot Salary$		0.168			
		(0.188)			
$D_b \cdot lag\_PER$			0.518^{***}		
			(0.172)		
$D_b \cdot Jump\_pct$				0.059	
				(0.116)	
$D_b \cdot Years$					0.232
					(0.142)
$Obs.$	480	480	480	480	480

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$; The values in the parentheses are White heteroskedasitisity robust standard errors.

7.5 Difference-in-Differences (DID) Estimation

Define i as individuals, s as groups (exp and con), t as periods (bef and aft), then PER_{ist} is the PER value of player i in group s at period t. Equation (2) can be extended to get the treatment effect as the difference of differences in PER of each group during two consecutive seasons:

$$
\begin{aligned}
Treatment\ effect =& E(\Delta PER_{it}^{experiment}) - E(\Delta PER_{it}^{control}) \\
=& E(\Delta PER_{ist}|s = exp) - E(\Delta PER_{ist}|s = con) \\
=& [E(PER_{ist}|s = exp, t = aft) - E(PER_{ist}|s = exp, t = bef)] - \\
& [E(PER_{ist}|s = con, t = aft) - E(PER_{ist}|s = con, t = bef)]
\end{aligned}
\tag{18}
$$

Again, we estimate the treatment effect by constructing the DID model. As defined earlier, D_s is a dummy variable for the player is in the "contract year" or getting a "big contract". D_t is a dummy variable for the current season T. Z_{it} is a vector of covariates contingent on individual, group and period, like Age, GP, etc. which describe a player's personal traits. Hence, the PER of player i in group s at period t is given by:

$$
PER_{it} = \alpha + \gamma D_s + \lambda d_t + \delta(D_s \cdot d_t) + Z_{it}'\beta + \varepsilon_{it} \tag{19}
$$

The Mahalanobis Metric Matching deals with the selection bias of sampling based on the observable factors. At the same time, the selection bias can also originate from unobservable factors, which could be eliminated by DID estimation as long as these factors do not change significantly (Lei and Lin, 2009).

7.6 Differenced Regression Model

The performance of professional players is influenced by numerous factors such as ability, effort, age and injury. It will fluctuate around the mean across seasons. Nevertheless, the performance would be relatively stable in the short term (in 2 or 3 years), while holding others constant. It is very likely a player's performance converges to that of his previous season, which allows us to predict that:

$$
E(PER_T) = PER_{T-1} \tag{20}
$$

Krautmann and Solow (2009) defines the level of shirking as the deviation of actual performance from expected performance:

$$
Shirk_T = E(PER_T) - PER_T \tag{21}
$$

Combining the two equations gives us:

$$
Shirk_T = PER_{T-1} - PER_T = -\Delta PER_T \tag{22}
$$

Thus we can model shirking as the change in performances of two consecutive seasons.

We also want to know whether other contract-related variables have an impact on player performance. To this end, we propose a differenced model:

$$\Delta PER = \boldsymbol{X\beta} + \varepsilon \tag{23}$$

where $\boldsymbol{X}$ is a vector of variables, β is a vector of coefficients. Specifically, we use the following linear model to investigate these relations:

$$\begin{aligned}\Delta PER = &\beta_0 + \beta_1 Age + \beta_2 \Delta GP + \beta_3 \Delta GS\_pct + \\ &\beta_4 \Delta Win\_pct + \beta_5 \Delta Pop + \gamma X + \varepsilon\end{aligned} \tag{24}$$

where X are the contract-related variables of interest. We replace X by different variables to check the sign and significance of the coefficients.

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