

**Gambling for resurrection:  
Value and risk taking in the National Basketball Association\***

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**ABSTRACT**

We study how NBA players' gambling incentives vary with their contract cycle. A player's salary is certain when signed to a contract but is highly uncertain as he enters into free-agency. Accordingly, as he nears the end of his contract his risk-taking incentives increase. We show that in the final three-months of his contract, his propensity to play injured increases. In particular, the likelihood of missing a game due to injury falls by 75%, and should time out due to injury be unavoidable, recovery time decreases by 17 days. In the cross-section of player value, we find that, unlike the average player, highly-valued players actually reduce risk-taking. These findings are consistent with the view that a player will adopt 'bang-bang' strategies of minimal or maximal risk depending on his inherent value. Finally, we show that for every additional player on a team who is in the last three-months of their contract, the likelihood of the team winning falls by approximately 5%. Our findings are consistent with the 'gambling for resurrection' hypothesis propagated in the economics literature.

JEL Classification: D81, D86, G21, L83

Key Words: gambling for resurrection, risk taking, injury, contracts, NBA.

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\* We thank Joe Price for helpful discussions and providing us with data used in earlier analysis. We also thank Brent Ambrose, Mike Mao, Gen Nowak, David Yermack and Xiaoyun Yu for helpful comments and discussions. Finally, thanks to Chandler Phelps for his excellent research assistance in collecting the data. This draft: 28 August 2014.

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## 1. Introduction

To economists, the term ‘gambling for resurrection’ usually references the lending behaviour of Savings and Loans (S&L) institutions and other banks during the S&L Crisis in the 1980s. Put simply, when a bank’s franchise value is falling such that it is heading towards insolvency, the bank has incentives to increase risk taking, i.e., gamble. If the gamble pays off, the bank becomes solvent, and if not, the bank is no worse off. Any losses from the bank’s gambling are typically borne by the tax payer—heads I win, tails you lose.

The seemingly clear theoretical prediction of gambling for resurrection turns out to be empirically elusive. A typical empirical study amounts to regressing a proxy for bank risk taking, for example, non-performing-loans or equity volatility, on a proxy for bank value such as return-on-assets or the market-to-book ratio. The empirical evidence for a negative relation between bank value and bank risk taking is mixed and plagued with identification issues.

In this paper, we study incentives to gamble for resurrection using unique data from the National Basketball Association (NBA). A distinctive feature of the NBA is the way player contracts are designed. Once signed, a player’s salary (“value”) is guaranteed and fixed for the length of the contract. However, with few exceptions, a player’s future *expected* salary is lower heading toward the end of his contract.<sup>1</sup> The reason for this is that an out of contract player’s salary is highly uncertain (e.g., due to competition for a small number of contracts), and so there is a distinct possibility that future earnings are zero. For example, in 2013, there were a total of 204 “free agents” looking for a new team, however, only 149 (73%) signed new deals.<sup>2</sup> The NBA careers for the remaining 55 players were over, at least temporarily. The remaining Fifty-

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<sup>1</sup> Superstars like Kevin Durant, Michael Jordan, and LeBron James are the exception.

<sup>2</sup> An out of contract player is known as a “free agent” and is able to negotiate a new contract with any team.

five players represent over 12% of all the players in the NBA and this proportion is not particularly unique to 2013. Each year, 60 new players are drafted into the NBA from college and elsewhere, necessitating a turnover of talent.<sup>3</sup> A recent article by USA Today reported that the average career length in the NBA is 4.8 years and data from Basketball-Reference.com suggests that approximately 50% of NBA players have careers that last only one or two seasons.<sup>4</sup>

Accordingly, for many players in our dataset, we have repeated events where we observe reductions in expected salary or value as he approaches the end of his current contract. The contract end dates which are negotiated ex-ante, largely coincide with the end of the regular playing season and differ across players. The NBA therefore provides an ideal setting to study incentives to gamble for resurrection.

In this paper we use frequency and/or duration (i.e., recovery time) of injury as a proxy for the risk taking behaviour of NBA players. Playing injured or returning to play before having fully recovered from injury is inherently risky behaviour. Playing injured or returning to play with insufficient recovery time increases the risk of exacerbating the injury or turning a minor injury into a chronic condition (Greene et al, 2001; Hootman et al, 2007). A player is willing to take this risk if he believes the rewards (e.g., the signing of a new contract or an increase in his future “value”) outweigh the risks (e.g., exacerbating the injury). In the literature, the propensity for athletes to play through injury or return early from injury for possible financial gains is well documented (Bauman, 2005; Lehn, 1982; O’Connell, 2012). Further, Bauman (2005) states that as the financial rewards and scrutiny of professional athletes both increase, so will the likelihood of athletes being prepared to return more quickly from injury. Heuristically, playing through

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<sup>3</sup> The NBA currently allows each team a maximum of 15 players on their playing roster, so with 30 teams this makes a total of 450 players.

<sup>4</sup> See <http://ftw.usatoday.com/2013/10/average-career-earnings-nfl-nba-mlb-nhl-mls>

injury and/or returning early from injury are sensible strategies for an NBA player who believes he needs to showcase his skills to be offered a new contract. The guaranteed nature of NBA contracts adds to the appeal of this strategy.

Little known Australian, Patty Mills, provides an interesting example.<sup>5</sup> Drafted and signed by the Portland Trail Blazers in 2009, Mills spent his time at Portland in and out of the team. He was eventually dumped by Portland in 2011 when his contract ended. The 2011 NBA lockout almost ended Mills' NBA career however he was a late signing to the San Antonio Spurs on a short contract in late March 2012. He then resigned with the Spurs in July 2012 to fill the role as the team's second string point guard for two seasons. His last contracted season, 2013-2014, turned out to be his breakout season as he entered into free agency.<sup>6</sup> Interestingly, he admitted to playing with a torn rotator cuff for most of the season which required immediate surgery post-season.<sup>7</sup> Despite this, he eventually signed a three-year \$12 million contract with the San Antonio Spurs once the surgery was deemed a success.<sup>8</sup>

We collect data on player contract signing dates, salary, contract length, game 'box score' information, player characteristics and injuries. The data cover 23 seasons and over 1,800 games for the years 1991 to 2013. Over this period, we observe 7220 contract signings and 8454 player injuries of various types. Using this information, we are able to determine when a player misses

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<sup>5</sup> Gambling does not always pay off. In 2005, Abdur-Rahim, had a new 6-year deal with the New York Nets cancelled when a medical examination discovered scar tissue in his knee. In a press conference following the cancellation of the deal Abdur-Rahim was quoted as saying: "Look at my history, I've never missed a game because of my knees." See "Abdur-Rahim wants to move on past the Nets." By ESPN.com news services, August 7, 2005. <http://sports.espn.go.com/nba/news/story?id=2127979>

<sup>6</sup> "Popovich has a simple explanation for Mills' breakout." By Dan McCarney, Spurs Nation, March 27, 2014. <http://blog.mysanantonio.com/spursnation/2014/03/27/popovich-has-simple-explanation-for-mills-breakout/>

<sup>7</sup> "Patty Mills admits he played with shoulder injury since the start of 2013-14 regular season." By Jeff Garcia, Project Spurs, July 23, 2014. <http://projectspurs.com/2014-articles/patty-mills-admits-he-played-with-shoulder-injury-since-start-of-2013-14-regular-season.html>

<sup>8</sup> "Surgery on Mills' shoulder successful." By Mike Monroe, San Antonio Express News, July 3, 2014. <http://www.expressnews.com/sports/spurs/article/Surgery-on-Mills-shoulder-successful-5599281.php#/0>

a game due to injury and the recovery time taken once an injury occurs relative to his contract cycle.

We begin by estimating the cost of missing a game due to injury for a player in the final months of his contract. A logistic regression analysis shows that for every additional game missed in the final three-months of his contract, a player is 10% less likely to sign a new contract. Further, conditional on signing a new contract, missing a game in the last three-months of his contract does not appear to significantly impact the length of his new contract, however it does reduce the negotiated salary. On average, missing an additional game in the last three-months of his contract leads to a reduction in his future salary of about \$17,500 per season. These numbers highlight the significant potential gains from gambling by avoiding time out due to injury near contract end.

We next examine the propensity for players to play injured. We find a striking result: in the last three-months of his contract, a player is almost 75% less likely to miss a game due to injury. This finding is consistent with the notion of a player gambling for resurrection (i.e., being more likely to play injured) in the last months of his contract. This result is robust to multiple specifications and sub-sample analyses. Further, in a placebo analysis we examine the propensity to miss a game due to injury just prior to other types of NBA transactions (i.e., around trades, waivers, and extensions) where typically the player does not know ex-ante the date the transaction will occur. Importantly, as expected, we find no evidence of player gambling around these other transactions types.

If time out due to injury is unavoidable, a player can gamble by minimising his recovery time. To this end, we study whether the time taken to recover from an injury varies with a player's contract cycle. We find that given an injury is observed, a player takes about 17 fewer

days to recover if injured in the last three-months of his contract. The most common injury in the NBA is one to the knee, requiring an average of 20 days recovery time. A reduction in recovery time of 17 days therefore amounts to an 85% reduction in recovery time if the injury occurs in the last three-months of a player's contract.

We also study how the propensity to miss a game due to injury varies in the cross-section of player value or quality. Some players, the superstars of the game, like Michael Jordan and LeBron James have much more certainty about their future earnings at contract end. Other things equal, these players have no downside risk. Accordingly, we do not expect them to behave in a similar fashion to the average NBA player. Their value is well known and net worth is high and so they have strong incentives *not* to gamble in order to protect this value. Each year, a panel of experts determine a list of "*all-NBA*" players. The *all-NBA* list constitutes the 15 players who make up the three best hypothetical basketball teams based on performance in the previous season. We perform a subsample analyses split on whether a player has been selected for one of the *all-NBA* teams or not and find a striking difference. The likelihood of missing a game due to injury actually increases in the last three-months on contract for *all-NBA* players, compared to a decrease for all other players. Our coefficient estimates suggest that *all-NBA* players are twice as likely to miss a game due to injury in the last three-months on contract. A highly publicised example of a high value player being overly cautious is Derrick Rose. A former Most Valuable Player (MVP), and the Chicago Bulls' franchise player, Rose injured his knee in 2012 which required surgery. After months of recovery, Rose was cleared to play by team doctors but opted to take additional recovery time. He was quoted as saying that he would

not return until “in his mind” he was confident enough to dunk off his left foot.<sup>9</sup> We find consistent results when performing sub-sample analyses on high-low value players based on other well know metrics, namely, a player’s Berri Win Score, Win Shares, and Player Efficiency Rating.

In the same way regulators are concerned that banks’ gambling can lead to system wide financial instability, a natural question to ask is whether gambling behaviour by players has a broader impact on team outcomes. To address this question, we use the proportion of players in a team who are in the final three-months of their contract to predict the likelihood of victory and victory margin. Our analysis reveals that this proportion is negatively associated with both the probability of winning and the victory margin. Our point estimates imply that increasing the number of players on the team who are in the last three-months of their contract by one will reduce the likelihood of victory by almost 5% (assuming a 10 man playing team). Similarly, the same change leads to a fall in the victory margin by about 0.3 points. Since we normalise the victory margin to be zero (by counting loses as a negative margin), this reduction corresponds to a shift from a drawn game to a loss.

Our paper is closely related to the literature studying the risk taking incentives of economic agents. Risk taking incentives has been a key focus of the banking literature. One of the keystone ideas is that banks with higher franchise value and more to lose in the event of failure will take less risk. On the other hand, banks with low to zero value will gamble for resurrection. For example, there are a many studies examining the link between bank capital requirements and bank risk taking. In their influential paper, Hellmann, Murdock and Stiglitz

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<sup>9</sup> “Source: Derrick Rose cleared to play.” By Melissa Isaacson, ESPNChicago.com, March 9, 2013. [http://espn.go.com/chicago/nba/story/\\_/id/9031045/derrick-rose-chicago-bulls-cleared-play-waiting-dunk-confidently-left-foot-source-says](http://espn.go.com/chicago/nba/story/_/id/9031045/derrick-rose-chicago-bulls-cleared-play-waiting-dunk-confidently-left-foot-source-says)

(2000) argue that capital requirements reduce gambling incentives by putting equity at risk. However, capital regulation also reduces bank franchise value thus encouraging gambling. International evidence of this positive link between regulation and risk-taking is documented in Laeven and Levine, (2009). In this paper the authors argue that stricter regulations reduce bank franchise value which then encourages banks to take more on more risk.

Similarly, the literature bank on competition and bank risk taking also relies on the existence of a negative relation between value and risk taking (for example, Keeley, 1990; Gan, 2004; Boyd and De Nicolo, 2005; Martinez-Miera and Repullo, 2010). The typical argument suggests that higher competition leads banks to bid up deposit rates and drive down franchise value. Lower franchise value in turn exacerbates risk taking incentives. The conclusion then is higher competition leads to financial instability. Keeley (1990) provides evidence consistent with this conclusion for banks in the United States (US) between 1970 and 1986. More recently, Gan (2004), who studies the behaviour of thrifts during the Texas real estate crisis, shows that competition reduces value, and when faced with a negative shock, thrifts adopt ‘bang-bang’ strategies of minimal and maximal risk—high value thrifts reduce risk, low value thrifts gamble. Our findings are in line with Gan (2004). We show players on average increase risk taking in the final months of their contract, and when we look at the difference between elite (high-value) players and regular (low-value) players we find that elite players minimise risk whereas low value players increase risk—the ‘bank-bang’ strategy Gan (2004) refers to.

Of course, the study of risk taking incentives is not confined to the banking literature. The term gambling for resurrection has been used in political science to describe the behaviour of incumbent politicians who prolong war because cessation would, given the state of domestic affairs, cause the incumbent to be removed from office (Downs and Rocke, 1994). In a

corporate finance setting, many authors have studied the relation between CEO compensation and CEO risk taking behaviour (for example, Carpenter, 2000; Coles et al, 2006). Options are usually granted out-of-the-money (i.e., zero or negative value upon exercise), further, stock options are more valuable when the underlying stock is more volatile. It is therefore possible that a compensation package with a large stock option component will encourage CEOs to take on riskier projects to increase stock volatility.

Our paper is also related to a vast number of papers using sports data to answer important economic questions. For example, a recent controversial paper by Price and Wolfers (2010) documents racial bias in the NBA. The authors show that players are awarded more fouls when being officiated by an opposite-race refereeing crew than when being officiated by an own-race crew. Similar findings of racial bias have also been documented in Major League Baseball (MLB) by Parsons et al (2011). More closely related to us, there have been a handful of papers studying player performance (effort) around the contract cycle in differing sports, with mixed findings. Maxcy et al (2002) reject the notion of strategic performance around the contract cycle for MLB whereas Stiroh (2007) finds evidence of players increasing performance (in terms of game statistics like points scored, rebounds, assists etc.) in their final contract year using data from the NBA. In contrast, we are the first to study player risk taking behaviour around the contract cycle using injury data as our risk taking metric.

The rest of the paper is structured as follows. Section 2 provides a brief background into NBA contracts. Section 3 describes our data and empirical approach. Section 4 presents the results. Section 5 concludes.

## **2. NBA Contracts**

This section provides a brief outline of the key features of NBA player contracts. Player contracting in the NBA is governed by the collective bargaining agreement (CBA). The current CBA was negotiated in 2011 and runs through to the 2020-21 season (see NBA CBA101, 2012). The CBA imposes restrictions on virtually every labour practice such as contract length, salary, trade rules, draft rules, and team salary caps.

The 2011 CBA begins by defining the minimum and maximum team salaries. That is, minimum (floor) and maximum (cap) combined salary for the 15 man roster. For the 2013-14 season, the cap was \$58.044 million and the floor was \$49.337 million. In the past, the cap was a soft cap in the sense that teams going over the cap simply paid a “luxury” tax to the NBA. The 2011 CBA limits the amount over which teams can go over the cap without having additional penalties (other than the luxury tax) being imposed. Under the new CBA, teams whose payroll exceed the “apron” (about \$75 million) are restricted in their ability to acquire new talent (e.g. the team cannot engage in sign-and-trade deals).

The CBA also imposes restrictions on maximum contract lengths. For the standard signing, the maximum contract length is four years. Exceptions to this standard include a maximum of five years for ‘Bird’ free agents—named after Larry Bird—who qualify once they have played a minimum of three seasons with the same team without signing as a free agent or being waived. Another exception is for players on minimum salaries who have a maximum term of two years.

Salaries in the NBA are also governed by the CBA. Both minimum and maximum salaries depend on the player’s years of service in the NBA. For 2013-14, the minimum wage

ranges from \$490,180 for a player who has no experience in the NBA to \$1.399 million for a player with 10 or more years of experience. Maximum player salaries differ depending on whether a player has seven or less, between seven and 10, or more than 10 years' experience. In each case, a player's maximum salary is the greater of either 105% of his previous year's salary or 25%, 30% or 35% of the salary cap respectively.

Finally, unlike other sports, for example the National Football League (NFL), NBA contracts are guaranteed. A player will be paid his contract amount if he cannot fulfil his playing obligations due to injury or sickness—whether basketball related or not. Even if the player underperforms and is released or waived by the team, his contract salary is guaranteed. This feature of NBA contract implies that once signed, a player's salary is safe for the life of the contract. Inside this incredibly restricted framework, players and teams negotiate contracts.

### **3. Data and empirical approach**

Our data come from two key sources. Injury and contract dates were scrapped from the website Pro Sports Transactions (<http://www.prosportstransactions.com/>). This website is an archive of every transaction in the four major sports in the US. The transactions include trades, contract signings, waivings, injuries, disciplinary action and so on. The site has over 90,000 transaction records for the NBA, searchable by date, player, team or team executive. All other data, including salary, game data and box score information are scrapped from the website Basletball-Reference.com (<http://www.basketball-reference.com/>). Our final sample covers 23 seasons and more than 1,800 regular season games for the years 1991 to 2013, resulting in about

460,000 player-date observations.<sup>10</sup> Over this period, we observe 7220 contract signings and 8454 player injuries of various types for 1978 unique players.

Our dependent variable is an indicator equal to one if player  $i$  misses a game due to injury on date  $t$  and zero otherwise. The independent variable of interest is an indicator variable  $3M\ LEFT_{it}$  which is equal to one if player  $i$  has three-months or less remaining on his contract at date  $t$  and zero otherwise. We test whether a player's propensity to miss a game due to injury does not vary with his contract cycle using the following logistic regression

$$\text{logit}(E[y_{it} | \mathbf{X}_{it}]) = \alpha + \beta 3M\ LEFT_{it} + \boldsymbol{\delta}'\mathbf{Z}_{it} + \theta_t + \theta_j + \varepsilon_{it}. \quad (1)$$

Here  $\mathbf{Z}_{it}$  is a vector of player characteristics including:  $AGE_{it}$  which is the player  $i$ 's age in years at time  $t$ ,  $WEIGHT_{it}$  which is player  $i$ 's weight at time  $t$  in pounds and  $HEIGHT_{it}$  which is player  $i$ 's height at time  $t$  in feet.  $\theta_t$  is a year fixed-effect to control for common time effects and  $\theta_j$  is a team fixed-effect. An increase in player risk taking in the last three-months on contract, as measured by the likelihood of playing injured, implies that the coefficient on  $3M\ LEFT_{it}$  should be negative and significant.

If missing games due to injury is unavoidable, then a player in the last three-months of his contract can gamble by minimising time out of the game and returning to play before full recovery. Accordingly, we calculate the number of days taken by a player to recover from injury, given an injury has occurred and been recorded. In a secondary test for gambling behaviour, we regress this variable on the variable  $3M\ LEFT_{it}$  and the same player characteristics as in equation (1). We again include year and team fixed-effects. Since different injuries

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<sup>10</sup> Since a large fraction of player contracts end on the last game of the season, we consider only regular season games to rule out the possibility that players are probably also less likely to miss a game if the game is more important (i.e., play-off and finals games).

inherently require different recovery times, where data are available, we classify each injury into categories based on the body part that was injured, e.g. knee, ankle and include injury-type fixed effects into the regression. Again, gambling behaviour implies a negative coefficient on the variable  $3M\ LEFT_{it}$ .

#### **4. Results**

This section presents the results of our main research question along with robustness and additional tests. Before doing so, we briefly discuss summary statistics and present analysis estimating the financial incentives to play injured. Table 1A presents summary statistics for our injury data. We categorise each injury into categories based on the body part that was injured and present the data by injury type. We see that of the 8454 recorded injuries, we are able to classify 7148 of the injuries and are able to calculate the recovery times (in days) for 8255 of the recorded injuries. The most common injuries are knee injuries, with 1496 recorded cases and an average recovery time of just over 20 days. The next most common injuries are ankle injuries with 1245 cases and an average recovery time of about 12 days. Notice that there is substantial variation in recovery times, even within injury type. This is because our classification is still rather coarse, for example, ‘twisted ankle’ is classified in the same category (ankle) as ‘broken ankle’. Of course, the latter involves a much longer recovery time.

Table 1B presents summary statistics for player transactions. The focus of this study is on new signing events, i.e., when a player signs a new contract with either his current team or a new team. In our sample, there are 7220 recorded new contract signings. The average contract length for the full sample is about 1.5 years at an average annual salary of about \$1.5 million.

We also collect information on the other types of player transactions, namely: waivers, trades, drafts, extensions and expansions. We use this information in placebo tests discussed below. Finally, Table 1C presents the summary statistics for player characteristics and box score information. The average player is 27.5 years old, weighs 217 pounds, and is 6.6 feet (6f 7in) tall. He plays an average of 23.8 minutes a game, scoring 9.7 points, with 4.1 rebounds, 2.1 assists, 0.8 steals, 0.5 a block, 1.5 turnovers and 2 fouls.

Before moving onto our main analysis, we estimate the financial incentives to gamble. We study the implication of missing games due to injury in the final months of a player's contract on three financial outcomes for the player: (1) the player's likelihood of signing a new contract (i.e. an indicator equal one if the player signs a new contract, and zero otherwise); (2) the change in contract length (in years), given a player has signed a contract; and (3) the change in annual salary (in dollars), given a player has signed a contract. Our independent variable of interest is the number of games a player misses due to injury in the final three-months of his contract. We control for the player's age, weight, height and past performance using the *PER*.<sup>11</sup> We also include year and team fixed-effects. The results are presented in Table 2. We find that a player is less likely to sign a new contract if he misses games due to injury in the final three-months of his contract. The coefficient estimate in Model 1 is -0.102 and is significant, implying that for each additional game a player misses due to injury in his last three-months on contract, the likelihood of him signing a new contract falls by about 10%. Moving on to the contract terms, we find that there is no significant impact of missing games due to injury on the change in

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<sup>11</sup> The *PER* is a per-minute rating, calculated on an annual basis, developed by ESPN.com columnist John Hollinger. In simple terms, the *PER* sums up all a player's positive accomplishments, subtracts the negative accomplishments, and returns a per-minute rating of a player's performance. The measure is standardised such that for any given year, the league-average *PER* is always 15. Scores above 15 indicate an above average player. We obtain *PER*s from the website Basketball-Reference.com.

contract length once signed (Model 2). However, missing games due to injury does impact on the negotiated salary, for every additional game missed due to injury in the final three-months on contract, the change in a player's salary is about -\$17,500 (Model 3). Compared to the average salary for signings, this number corresponds to approximately -1.2%. As a robustness check, we also redo the analysis using alternative pre-contract date windows to calculate the number of games missed due to injury. In particular, we use the number of games missed in the last 6, 9 and 12 months on contract as our independent variable of interest and find similar results, save that the magnitude of the impact falls as the pre-contract date window increases. These results are not reported to conserve space.

#### 4.1. Playing injured

To detect whether a player is more likely to play injured in the final months of his contract, we study how the likelihood of missing a game due to injury varies with his contract cycle. We begin with simple a univariate analysis presented in Table 3, Panel A. For each player-game observation, we determine whether the observation falls into one of five sub-periods: greater than 12 months left on his contract, and less than 12, 9, 6, and 3 months left on his contract. We also know for each player-game observation whether the player missed the game due to injury or not. Using this information, we can calculate the frequency or proportion of games missed due to injury in each of the five sub-samples. We can see that the likelihood of missing a game due to injury is about 5.8% for a player with more than 12 months left on his contract. This proportion falls as the player moves closer to the end of his contract. With 12 to 6 months left on his contract, a player only misses a game due to injury about 4.5% of the time. However, in the last three-months on his contract, the proportion falls to only 2.7%, less than

half of the value compared to when the player has more than 12 months remaining on his contract. This result is consistent with the idea that a player is likely to gamble and play injured as he nears the end of his contract.

We next study the propensity to miss a game due to injury in a logistic regression setting. We estimate equation (1) and report the findings in Table 4 Model 4. The results show that our indicator  $3M\ LEFT_{it}$  is negative and significant, implying that in the last three-months of his contract, a player is less likely to miss a game due to injury. The coefficient estimate is -1.4 which implies that in the last three-months, a player is approximately 75% less likely to miss a game due to injury. This finding is in line with our expectations and consistent with gambling behaviour by NBA players. We also rerun the analysis using alternative pre-contract date windows. In particular, we use indicators for the last 6, 9 and 12 months on contract as our independent variable of interest and find similar results. For each of these indicators, the magnitudes are smaller than for the three-month indicator and imply a reduction in the likelihood of missing a game due to injury of between 40% and 45%.

Since many contracts tend to end when the NBA season ends, it is possible that our result is driven by peculiar behaviour towards the end of the season. We have already restricted our sample to regular season games only, to ameliorate the problem that players may also play injured and miss fewer games in the last part of the season because it is play-off time. To rule out the possibility that our results are spurious, we conduct our experiment around alternative player transactions where the player either has no (or very little) knowledge that the transaction will occur before it does or when the player knows ex-ante that he is more than likely to be signed to a new contract. First consider, player trades and waivers. Players routinely get traded from one team to another, and at times with no knowledge that the trade is going to occur until it

has already happened. Waivings are a situation where a player gets released from his current contract by his current team. In the 48 hours after the waiving, players are able to be traded to another team. However after the initial 48 hour period, the waived player become a free-agent and is free to negotiate with any team. His original contract is honoured by his original team. Like trades, in most cases, a player has much less knowledge (if any) of the date that he is to be waived. We regress our indicator for whether player  $i$  misses a game due to injury on date  $t$  on a redefined  $3M\ LEFT_{it}$  indicator, now equal one for all dates in the three-months prior to player  $i$  being traded or waived. The results in Table 5 (Model 1) show that the coefficient is insignificant, and in fact, positive.

In some cases, teams have an option to extend a player's contract for an extra season at the player's current wage. Contracts with an option for extension are usually reserved for better players or players with more potential, and typically, teams will only exercise this option if the option is in the money (i.e., the player is worth at least his current salary). A player whose contract is to be extended is usually in discussions with team management long before his contract expires and knows long before the transaction date whether his contract will be extended or not. Accordingly, we expect that player risk taking to not change just before the extension of a player's contract. Table 5 Model 2 presents the results of estimating equation (1) redefining  $3M\ LEFT_{it}$  to equal one for all dates in the three-months prior to player  $i$ 's contract being extended. As expected, we find no evidence of gambling behaviour in the months leading up to an extension.

In further robustness, Table 5 (Model 3) includes player position fixed effects to account for the possibility that playing in particular positions may expose the player to a higher likelihood of injury. Additionally in Model 4 we include opposition fixed effects in case a player

is more willing to play injured against a team he feels may be interested in signing him in the future. In both cases, our main finding does not change.

Finally, we study whether gambling behaviour differs for in-season versus out-of-season signings. The results are presented in Table 5 (Models 5 and 6). Both in-season and out-of-season signings display gambling behaviour by players in the months before the signing. The magnitude of coefficient on  $3M\ LEFT_{it}$  for the in-season signings is similar to that of the full sample, whereas the coefficient for out-of-season signings is slightly smaller implying a reduction in the likelihood of missing a game due to injury by about 67%. As a final test, we check whether, for out-of-season signings, there is a difference in gambling behaviour for a player who signs immediately after the season ends versus one who sign towards the end of the free agency market (i.e., just before the next season starts). Teams have a fixed number of slots on the roster to fill and salary caps which determine the amount of money available for any given season. Accordingly, players signed late are more likely to earn lower wages, and are at the most risk of missing out altogether.<sup>12</sup> To the extent that a late signing is indicative of the player being a fringe player, who has a higher chance of poor contract outcome, we expect this type of player to have stronger gambling incentives. We calculate the number of days a player spends as a free agent before signing a new contract (i.e. the number of days between his last game on contract and the date of his contract signing) and perform subsample analysis for the top (Q4) and bottom quartile (Q1) of days spent as a free agent. The results are presented in Table 5 (Models 7 and 8). In both models, there is evidence that a player is significantly less likely to miss a game due to injury in the final three-months of his contract. We see that for players signed quickly after entering into free-agency (Model 7), the coefficient estimate on  $3M\ LEFT_{it}$  is similar to out-of-

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<sup>12</sup> See discussion in “NBA AM: Free Agents Headed for the Minimum.” By Lange Greene, Basketball Insiders, July 23 2014. <http://www.basketballinsiders.com/nba-am-free-agents-headed-for-the-minimum/>

season signings and for the full sample. Interestingly, as expected, players who spend the most time as free agents but are eventually signed display the greatest propensity to gamble. The coefficient estimate on  $3M\ LEFT_{it}$  is -2.5 implying a reduction in the likelihood of missing a game due to injury by over 90% for these players. We will investigate the cross-sectional difference in gambling behaviour of high value (superstars) and low value (fringe) players more directly in subsequent sections.

#### 4.2. Returning from injury early

If playing through injury is not an option for a player because the injury is sufficiently severe, then an alternative way players can gamble is to return to play before the injury has fully healed. Gambling therefore implies that in the last months on his contract, a player's recovery time given an injury has occurred and recorded is lower than other periods. From our data, we calculate the number of days between when a player injury is recorded to when he returns to play (i.e., recovery time). In Table 3 (Panel B), we present the summary statistics for a player's recovery time by five sub-periods according to when the injury occurred: with more than 12 months left on his contract, and less than 12, 9, 6, and 3 months left on his contract. We can see that the mean recovery time is 13.8 days when a player has more than 12 months left on his contract. As expected, this average recovery time falls to 12.4 days with 12 months left, 11.1 days with 9 months left and 10.1 days with only 6 months left. However, the mean recovery time for a player injuring himself in the last three-months of his contract is 14.5 days, higher than all other subsamples. This result at first seems counterintuitive, however, recall that from Panel A of Table 3 the likelihood of a player missing a game due to injury in the last three-months of his contract is less than half the likelihood when the player has 12 months or more on his

contract remaining. This reduction in the likelihood of observing injury is a classic selection issue and biases the average recovery time upward since players are tending to play through injury and only take time out for very severe or chronic injuries. We come back to this issue in our regression analysis.

We regress the recovery time for player  $i$  given an injury occurred on date  $t$  on our  $3M$   $LEFT_{it}$  indicator and the same list of controls as in equation (1). In a similar fashion to Table 5, we also use alternative time to contract end windows as robustness, namely 12, 9 and 6 months. The results are reported in Table 6 and echo the summary statistics reported in Table 3 Panel B. From Models 1 to 4, we see that, on average, a player takes 1.4 fewer days to recover from injury in the last 12 months of his contract. This number increases to 1.5 in the last nine months and 2.0 in the last six months. However in the last three-months, a player takes about 4.1 extra days to recover, though this result is insignificant. As mentioned previously, this counterintuitive finding is likely due to selection bias and the fact that a player is not going to miss a game due to injury unless the injury is particularly severe or chronic.

As a first attempt to adjust for the severity of injury, we include injury type fixed effects using our previously defined categories of injury, categorised by the body part that was injured. We re-estimate Models 1 to 4 (of Table 6) including injury fixed-effects and report the results in Models 5 to 8. We find similar results to previously, save that the magnitude of the coefficients are more pronounced, a player with 12, 9, and 6 months left on his contract will return to play with 0.9, 2.7 and 4.0 days less recovery time. Again, the coefficient on  $3M$   $LEFT_{it}$  remains positive and insignificant, though the magnitude drops to 2.2, implying a player in his last three-months on contract takes an extra 2.2 days to recover if an injury occurs. As discussed previously, the problem with categorising injuries by body part is that there is still a lot of

variation in recover time within injury category so injury fixed-effects may not adequately control for the severity of the injury.

In addition to including injury fixed-effects, we consider the influence of chronic injuries. We create a variable  $CHRONIC\ SCALE_{it}$  which is a count, for player  $i$  who injures himself at time  $t$ , of the number of times the player has injured the same body part. In our sample, the maximum value of  $CHRONIC\ SCALE_{it}$  is 15 and belongs to Kenyon Martin, a former No. 1 draft pick who had chronic knee problems throughout his career. The second highest score is Tracy Mcgrady, a 7-time *all-NBA* player, at 12 with back spasms. We include  $CHRONIC\ SCALE_{it}$  into the regression along with its interaction with  $3M\ LEFT_{it}$  and re-estimate the main model. The results are presented in Table 7 Model 4. The inclusion of this variable makes a drastic difference to the coefficient estimate on  $3M\ LEFT_{it}$  which is now negative and significant as expected. We find that on average, a player takes about 17 fewer days to recover from injury in the last three-months of his contract. If we compare this estimate to an average recovery time for knee injuries (the most common injury in the NBA) of 20 days, it corresponds to an 85% reduction in recovery time in the last three-months of a player's contract. As an alternative, we also create an indicator,  $CHRONIC_{it}$  which is an indicator equal to one if player  $i$  who is injured on date  $t$  has previously injured the same body part and redo the analysis. The results are similar to those using  $CHRONIC\ SCALE_{it}$  however the coefficient estimate on  $3M\ LEFT_{it}$  while being negative as expected, is insignificant. These findings indicate that players need to injure the same body part more than twice for the injury to be severe enough to explain the counterintuitive rise in the average recovery time just before contract end.

### 4.3. Player value and incentives to gamble

In this section, we investigate how gambling incentives differ in the cross-section of player value or quality. While our results show on average players tend to play injured in the final months on contract, this need not be the case for all players. In particular, high-value players, the superstars of the game like Michael Jordan or LeBron James have very different incentives. Injury aside, as a player of this quality nears contract end, he has no downside risk about his future expected earnings. However, a bad injury just before his contract end can potentially lead to a negative contract outcome. Accordingly, to protect this inherent value, a high quality player may actually reduce risk taking heading toward the end of his contract, that is, he is more likely to miss games due to injury. This may be because he misses games even for minor ailments or takes a longer than needed recovery time. At the very least, we might expect that the gambling behaviour to be ameliorated.

Objective measures of player value or quality are hard to come by so we use four different measures here. Our first proxy is whether a player has been selected as an *all-NBA* player in the past. Each year, a group of experts choose the “top” 15 players in the league which make up the list of *all-NBA* players. These players represent the top 3% of players, so are considered to be elite. We estimate equation (1) separately for players who have previously been selected as an *all-NBA* player and for players who have not. The results are presented in Table 8 Models 1 and 2. For players who have previously been selected as *all-NBA*, the coefficient on  $3M\ LEFT_{it}$  is in fact positive and significant. The point estimate implies that in the last three-months of his contract, the likelihood of missing a game due to injury for an *all-NBA* player doubles. This striking difference suggests that NBA players adopt what Gan (2004) refers to as a ‘bang-bang’ strategy of either minimal or maximal risk taking.

We next use three alternative measures of player quality based on past performance. All three measures are indices which increase with a player's positive accomplishments (e.g. points scored), and fall with the negative accomplishments (e.g. personal fouls). The most common performance metric cited in the NBA is the Player Efficiency Rating or *PER*. This measure is calculated annually and standardised such that the league average for any given year is 15, players with a *PER* higher than 15 are considered above average. Two alternative measures, can be calculated on a game-by-game basis using box-score information, these are the Berri Win Score and Win Shares (*WS*). For these two measures, we calculate the 48 min equivalent for each player-game observation and take the average across the entire season to be comparable to the *PER*. For each performance metric, we divide the sample into terciles and re-estimate equation (1) for the bottom (lowest value players) and top (highest value player) separately.<sup>13</sup> The results are presented in Table 8 Models 3 to 8. Across all models the coefficient on  $3M LEFT_{it}$  is negative and significant. There is, however, a significant difference between the magnitude of the coefficients across the low and high player-value terciles. The point estimate on  $3M LEFT_{it}$  is similar to that obtained for the full sample for low value players but is much higher (less negative) for high value players. For example, using *PER* as the player-value metric, the coefficient estimate for high-value players is -0.45 implying a reduction in the likelihood of missing a game due to injury by about 36%. This is about half the magnitude of the reduction for low-valued players. These findings are consistent with the view that a higher quality player has reduced incentives to gamble by playing injured in the last three-months of his contract.

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<sup>13</sup> Results for the middle tercile are similar to the lowest tercile. We also perform the analysis by splitting the sample by the median value and find similar results. The difference in high and low in that instance is less pronounced.

#### 4.4. The implications of gambling behaviour

It is typical to ask what the broader implications of this individual gambling behaviour are. In this final section we study how individual player performance changes in final months of a player's contract and then investigate the implications of individual gambling behaviour on team performance.

##### 4.4.1. Individual performance

Table 9 presents results from regressions of various player performance metrics on  $3M LEFT_{it}$  and the same list of controls as equation (1). If a player is playing injured in the last months of his contract, then other things equal, his overall performance should fall. This effect may be countered by a possible positive effort effect in the last three-months on contract as documented by Stiroh (2007). The net effect of the contract cycle on player performance is therefore an empirical issue.

We begin by examining overall player performance using 48 minute equivalent Berri Scores and Win Shares.<sup>14</sup> For both measures, the coefficient on  $3M LEFT_{it}$  is negative and significant implying a reduction in overall performance in the last three-months on contract. The reduction in overall performance is large, for example, the estimate on  $3M LEFT_{it}$  using the Berri Score as the metric for overall performance is -1.9. Compared to a mean Berri Score of 6.8, a reduction in performance of this magnitude corresponds to a 28% fall in overall performance. Other aggregate measures of performance calculated by the NBA include a player's offensive and defensive rating, these variables estimate the number of points produced and allowed by a player per 100 possessions respectively. We can see that for both measures the coefficient on

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<sup>14</sup> We cannot use the *PER* as it is an annual measure and we require game-by-game measures for this analysis.

$3M LEFT_{it}$  is negative and significant implying a fall in performance. A final aggregate measure of performance is a player's usage percentage ( $USG\%$ ). This metric is an estimate of the percentage of team plays which use a given player while he was on the floor. Interestingly, we find that the coefficient on  $3M LEFT_{it}$  is insignificant which means a player is used no more in set plays in his final months on contract. This is not surprising since set plays are to a large extent determined by the coaching staff.

If we look at what happens to individual box score statistics (i.e. shooting percentage, rebounds etc.) in the last three-months of a player's contract, a very interesting picture emerges: players become more selfish, play more aggressively and make more mistakes. Two results indicative of a player becoming more selfish in his last three-months on contract are the negative coefficient estimates on  $3M LEFT_{it}$  for assist percentage ( $AST\%$ ) and defensive rebound percentage ( $DRB\%$ ). Assist percentage is an estimate of the percentage of teammate field goals a player assisted with while on the floor, a fall in this metric in the last three-months on contract suggests a player tends to hang onto the ball more and pass to his teammates less. Defensive rebound percentage is an estimate of the percentage of available defensive rebounds a player grabbed while on the floor. A fall in  $DRB\%$  before contract end is indicative of a player being more interested in showcasing his offensive prowess and less in team-benefiting defence.

There is also evidence players tends to play more aggressively in his last three-months on contract, with an increase in his offensive rebound percentage ( $ORB\%$ ), steals percentage ( $STL\%$ ), blocks percentage ( $BLK\%$ ) and personal fouls per 48 minutes played ( $PF48$ ). These results are consistent with the increased effort Stiroh (2007) documents. It appears however, that a player also tends to make more mistakes in the last three-months on contract, possibly because he is playing through injury. In the last three-months on contract, a players true shooting

percentage (*TS\_RATE*), a measure of shooting efficiency accounting for 2-point field goals, 3-point field goals and free-throws falls. This fall in shooting accuracy results in a fall in the average number of points scored per 48 minutes of play by 2.4 points. Finally, one of the biggest mistakes a player can make in a game is to turn the ball over to the opposition. Our results indicate that a player in the last three-months of his contract increases his turnover percentage (*TOV%*), calculated as turnovers per 100 plays, significantly.

#### 4.4.2. Team consequences

Finally, we investigate the team level implications of player gambling. If players are playing injured resulting in a drop in performance, then we expect player gambling to negatively impact on team outcomes. For each date  $t$ , we calculate the proportion of players in a team who are in the last three-months of their contracts (*%PLAYERS 3M LEFT*). We then regress proxies for team success on *%PLAYERS 3M LEFT* and control variables *HOME*, an indicator equal to one if the team is playing at home; *AVE. TEAM AGE*, the average age of the paying team; *AVE. TEAM HEIGHT*, the average height of the team; *AVE. TEAM WEIGHT*, the average weight of the team and *TEAM BERRI*, the Berri Win Score calculated using team level box score statistics. We also include year, team and opposition-team fixed-effects. The results are presented in Table 10. In Model 1, our measure of team success is an indicator equal to one if the team  $j$  wins a game on date  $t$  and zero otherwise. The results from a logistic regression show that the proportion of players who are in the last three-months of their contract negatively predicts team performance. Our point estimates imply that increasing the number of players on the team who are in the last three-months of their contract by one will reduce the likelihood of victory by almost 5% (assuming a 10 man team). Our second measure of team success is the victory margin. We calculate the victory margin as the difference in points scored by a team and the

points scored by its opposition. Positive values of imply a victory whereas negative values indicate a loss. Since for each game, the positive victory margin for the winning team perfectly cancels out with the victory margin of the losing team, the expected victory margin is zero (i.e. a draw). Using least squares, we regress victory margin on %*PLAYERS 3M LEFT* and the same previously defined controls. The results presented in Model 2 show that increasing the number of players on a team who are in the last three-months of their contract by one will reduce the victory margin by about 0.3 points. Since we normalise the victory margin to be zero, 0.3 points corresponds to a shift from a drawn game to a loss. Compared to a team with no players in the last three-months of their contract, if all players in the team are in the last three-months of their contract, then the team is expected to lose by about 3 points.

## **5. Conclusion**

Gambling for resurrection is the term used to describe the increase in risk taking behaviour of economic agents who have everything to gain but nothing to lose from gambling. The academic literature has, to a large extent focused on the behaviour of low value (failing) banks to identify gambling. However, this literature is plagued with identification problems and has found mixed results.

In this paper, we study the gambling incentives of players in the NBA around their contract cycle. A typical player heading toward the end of his contract has lower expected earnings given the distinct possibility of his contract not being renewed or renewed at unfavourable terms. We show that in response to this shock to expected earnings (value), players increase risk taking. Our measure for risk taking is the likelihood a player is playing

injured or the recovery time given an injury has occurred and time out is unavoidable. Our results indicate that in the last three-months of his contract a player is 75% less likely to miss a game due to injury. Further, if time out of the game is unavoidable when injury occurs, the average recovery time for a player injured in the last three-months of his contract is about 17 days shorter. Compared to a recover time of 20 days for the most common injury in the NBA (knee injuries), 17 days corresponds to an 85% reduction in recovery time.

We also show that the gambling incentives differ in the cross-section of player quality. Unlike the typical player, an elite, high-value, *all-NBA* player actually reduces his risk taking in the last months of his contract. That is, he is twice as likely to miss a game due to injury. This result is consistent with the view that a player adopts ‘bang-bang’ strategies of minimal or maximal risk depending on his inherent quality or value.

Finally, we show that player gambling has implications for team outcomes. Since gambling in our context implies playing injured, we expect player risk taking to negatively predict team success. Indeed, we find for every additional player on the team who is in his final three-months of his contract, the probability of winning falls by approximately 5%. Our findings highlight the possible need for team management to stagger player contract dates to avoid negative repercussions for the team.

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## Appendix

### Variable Definitions

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<i>12M LEFT</i>	Player has 12 months left on his contract
<i>9M LEFT</i>	Player has 9 months left on his contract
<i>6M LEFT</i>	Player has 6 months left on his contract
<i>3M LEFT</i>	Player has 3 months left on his contract
<i>GAMES INJURED IN LAST 12M</i>	Games missed by a player in the last 12 months of his current contract
<i>GAMES INJURED IN LAST 9M</i>	Games missed by a player in the last 9 months of his current contract
<i>GAMES INJURED IN LAST 6M</i>	Games missed by a player in the last 6 months of his current contract
<i>GAMES INJURED IN LAST 3M</i>	Games missed by a player in the last 3 months of his current contract
<i>%PLAYERS 3M LEFT</i>	% of players in a given team for a given game who are in the last 3 months of their current contract
<i>AGE</i>	Player age (years)
<i>WEIGHT</i>	Player weight (pounds)
<i>HEIGHT</i>	Player height (feet)
<i>CHRONIC</i>	Indicator equal 1 if a player has injured the same body part more than once
<i>CHRONIC SCALE</i>	Count variable for the number of times a player has injured a given body part
<i>MIN PLAYED</i>	Minutes played
<i>FG</i>	Field goals made
<i>FGA</i>	Field goal attempts
<i>3PM</i>	3 pointers made
<i>3PA</i>	3 pointer attempts
<i>FT</i>	Free throws made
<i>FTA</i>	Free throw attempts
<i>ORB</i>	Offensive rebounds
<i>DRB</i>	Defensive rebounds
<i>TRB</i>	Total rebounds
<i>AST</i>	Assists
<i>STL</i>	Steals
<i>BLK</i>	Blocks
<i>TOV</i>	Turnovers
<i>PF</i>	Personal fouls
<i>PTS</i>	Points scored

<i>TS_RATE</i>	True Shooting Percentage; a measure of shooting efficiency that takes into account 2-point field goals, 3-point field goals, and free throws.
<i>EFG_RATE</i>	Effective Field Goal Percentage; this statistic adjusts for the fact that a 3-point field goal is worth one more point than a 2-point field goal.
<i>FT_RATE</i>	Free Throw Attempt Rate, Number of FT Attempts Per FG Attempt
<i>3PA_RATE</i>	3-Point Attempt Rate, Percentage of FG Attempts from 3-Point Range
<i>ORB%</i>	Offensive Rebound Percentage; an estimate of the percentage of available offensive rebounds a player grabbed while he was on the floor.
<i>DRB%</i>	Defensive Rebound Percentage; an estimate of the percentage of available defensive rebounds a player grabbed while he was on the floor.
<i>TRB%</i>	Total Rebound Percentage; an estimate of the percentage of available rebounds a player grabbed while he was on the floor.
<i>AST%</i>	Assist Percentage; an estimate of the percentage of teammate field goals a player assisted while he was on the floor.
<i>STL%</i>	Steal Percentage; an estimate of the percentage of opponent possessions that end with a steal by the player while he was on the floor.
<i>BLK%</i>	Block Percentage; an estimate of the percentage of opponent two-point field goal attempts blocked by the player while he was on the floor.
<i>TOV%</i>	Turnover Percentage; an estimate of turnovers per 100 plays.
<i>USG%</i>	Usage Percentage; an estimate of the percentage of team plays used by a player while he was on the floor.
<i>OFF_SCORE</i>	Offensive Rating: An estimate of points produced (players) or scored (teams) per 100 possessions
<i>DEF_SCORE</i>	Defensive Rating: An estimate of points allowed per 100 possessions
<i>PER</i>	Player Efficiency Rating; a measure of per-minute production standardized such that the league average is 15.
<i>OWS</i>	Offensive Win Shares; an estimate of the number of wins contributed by a player due to his offense.
<i>DWS</i>	Defensive Win Shares; an estimate of the number of wins contributed by a player due to his defence.
<i>WS</i>	Win Shares; an estimate of the number of wins contributed by a player.
<i>BERRI</i>	Berri Win Score = $PTS+ORB+DRB+STL+0.5*BLK+0.5*AST-FGA-0.5*FTA-TOV-0.5*PF$

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**Table 1A****Injury count by type**

This table presents the frequency of injury types categorised by the body part injured. We also report the average recovery time for each injury type calculated as the number of days between when a player's injury is recorded to when he returns to play. The data are obtained from the website Pro Sports Transactions (<http://www.prosportstransactions.com/>).

	Injury count by type		Obs.	Recovery time given injury	
	Freq.	Percent		Mean	Std. Dev.
Achilles	154	2.15	148	21.06	35.54
Abdomen	68	0.95	68	14.51	22.94
Anaemia	5	0.07	5	7.00	4.18
Ankle	1245	17.42	1228	12.42	25.14
Arm	12	0.17	10	26.80	34.11
Back	760	10.63	748	10.45	24.45
Calf	176	2.46	171	7.97	15.97
Cheekbone	9	0.13	7	8.57	18.33
Elbow	122	1.71	119	10.32	18.19
Eye	53	0.74	50	8.52	13.54
Fibula	12	0.17	11	43.27	34.32
Finger	140	1.96	132	19.95	25.80
Foot	508	7.11	490	18.60	28.78
Groin	253	3.54	248	10.25	19.32
Hamstring	270	3.78	264	9.36	19.68
Hand	113	1.58	103	23.37	26.15
Heel	59	0.83	59	11.00	19.74
Hip	219	3.06	216	11.75	23.46
Jaw	9	0.13	9	38.89	47.67
Knee	1496	20.93	1462	20.26	31.76
Leg	91	1.27	85	12.14	21.81
Neck	80	1.12	78	8.78	23.75
Nose	39	0.55	35	12.09	21.69
Quadriceps	119	1.66	116	12.23	31.12
Rib	55	0.77	55	3.80	7.08
Rotator cuff	11	0.15	11	11.18	19.30
Shin	30	0.42	29	9.48	15.91
Shoulder	320	4.48	313	18.12	31.83
Sternum	4	0.06	4	15.25	23.24
Stomach	164	2.29	163	1.48	1.60
Tailbone	9	0.13	8	4.38	8.05
Thigh	92	1.29	89	4.60	10.27
Thumb	136	1.90	133	24.33	29.51
Toe	122	1.71	122	9.20	18.32
Wrist	193	2.70	188	23.43	34.27
Unknown	1306	.	1278	6.59	17.15
Total	8454		8255	13.45	25.90

**Table 1B****Contract information**

This table presents the frequencies of various contract transactions along with summary statistics for the average contract length and salary. The focus in this study is on signings, however, other contract transactions are included here for completeness. Contract transaction dates and contract lengths are collected from the website Pro Sports Transactions (<http://www.prosportstransactions.com/>), whereas salary information is collected from Basleball-Reference.com (<http://www.basketball-reference.com/>).

	Freq.	Percent	Contract Length (years)			Salary (annual)		
			Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Sign	7220	43.27	7111	1.44	1.55	5929	\$ 1,425,779.00	\$ 2,318,098.00
Waive	5064	30.35	4933	0.74	0.96	3333	\$ 1,422,603.00	\$ 2,381,946.00
Trade	2409	14.44	2315	1.82	1.33	2267	\$ 3,022,468.00	\$ 3,510,306.00
Draft	1299	7.78	1207	2.47	1.46	1268	\$ 1,069,501.00	\$ 925,700.00
Extend	623	3.73	606	1.08	0.81	593	\$ 2,575,618.00	\$ 2,858,038.00
Expansion	71	0.43	66	1.52	1.43	59	\$ 1,031,059.00	\$ 1,026,089.00
Total	16686	100.00	16238	1.35	1.42	13449	\$ 1,715,793.00	\$ 2,596,917.00

**Table 1C**

## Summary Statistics

This table presents summary statistics for the variables used in our study. Variable definitions can be found in Appendix A.

	Obs.	Mean	Std. Dev.	p25	p50	p75
<i>AGE</i>	798340	27.52	4.21	24.18	26.92	30.44
<i>WEIGHT</i>	808876	216.99	27.97	195	218	235
<i>HEIGHT</i>	808876	6.59	0.32	6.33	6.58	6.83
<i>MIN PLAYED</i>	540031	23.82	11.97	14.60	24	33.83
<i>FG</i>	540031	3.66	3.10	1	3	6
<i>FGA</i>	540031	8.04	5.81	3	7	12
<i>3PM</i>	540031	0.52	1.01	0	0	1
<i>3PA</i>	540031	1.46	2.13	0	0	2
<i>FT</i>	540031	1.88	2.44	0	1	3
<i>FTA</i>	540031	2.50	3.02	0	2	4
<i>ORB</i>	540031	1.20	1.52	0	1	2
<i>DRB</i>	540031	2.94	2.69	1	2	4
<i>TRB</i>	540031	4.14	3.62	1	3	6
<i>AST</i>	540031	2.18	2.59	0	1	3
<i>STL</i>	540031	0.78	1.03	0	0	1
<i>BLK</i>	540031	0.50	0.94	0	0	1
<i>TOV</i>	540031	1.42	1.44	0	1	2
<i>PF</i>	540031	2.16	1.55	1	2	3
<i>PTS</i>	540031	9.72	8.08	3	8	15
<i>TS_RATE</i>	753665	0.51	0.09	0.48	0.52	0.55
<i>EFG_RATE</i>	753261	0.47	0.09	0.44	0.48	0.51
<i>FT_RATE</i>	755910	0.35	1.35	0.20	0.29	0.40
<i>3PA_RATE</i>	756314	0.23	1.77	0.01	0.10	0.31
<i>ORB%</i>	756314	6.25	4.82	2.60	5.30	9.10
<i>DRB%</i>	756314	13.93	6.27	9.20	13	18.10
<i>TRB%</i>	756314	10.05	4.87	6.10	9.30	13.50
<i>AST%</i>	756620	13.02	9.65	6.10	10.20	17.60
<i>STL%</i>	754632	1.74	3.07	1.10	1.50	2.10
<i>BLK%</i>	756620	1.57	2	0.40	1	2.10
<i>TOV%</i>	754927	14.77	8.24	11.20	13.80	17.10
<i>USG%</i>	756314	19.35	8.15	15.50	18.70	22.20
<i>OFF_SCORE</i>	756314	101.78	16.59	97	104	110
<i>DEF_SCORE</i>	756314	105.92	8.18	103	107	110
<i>PER</i>	756314	12.74	6.08	10	12.90	15.80
<i>OWS</i>	756314	1.41	2.15	0	0.60	2.20
<i>DWS</i>	756314	1.29	1.29	0.30	0.90	1.90
<i>WS48</i>	753665	0.07	0.10	0.04	0.08	0.12
<i>BERRI48</i>	540031	6.83	16.43	0.00	7.20	13.71

**Table 2**

## Financial incentives to gamble

This table presents the results of regression analysis of financial incentives for players to gamble. The dependent variables are (1) an indicator equal one if player  $i$  signs a new contract at date  $t$  and zero otherwise (Model 1); (2) the change in contract length, given player  $i$  signs a new contract (Model 2); and (3) the change in annual salary, given player  $i$  signs a new contract (Model 3). Our independent variable of interest is *GAMES INJURED IN LAST 3M* which is the number of games a player misses due to injury in the last three-months of his contract. Detailed descriptions of other variables are provided in Appendix A. The regressions include year and team fixed-effects. We report t-statistics in parentheses, which are robust to heteroskedasticity and clustered at the player level. Significance levels of 10, 5, and 1 percent are represented by \*, \*\*, and \*\*\*, respectively.

	(1) <i>PROBABILITY OF NEW CONTRACT</i>	(2) $\Delta$ <i>CONTRACT LENGTH</i>	(3) $\Delta$ <i>SALARY</i>
<i>GAMES INJURED IN LAST 3M</i>	-0.102*** (-3.12)	-0.002 (-1.17)	-17,452.793*** (-18.47)
<i>AGE</i>	-0.103*** (-12.10)	-0.046*** (-46.12)	-13,640.790*** (-23.98)
<i>WEIGHT</i>	-0.007*** (-3.23)	0.001*** (3.95)	1,194.192*** (8.39)
<i>HEIGHT</i>	-0.006 (-0.04)	-0.023 (-1.08)	-83,338.548*** (-6.82)
<i>PER</i>	-0.052*** (-14.88)	0.034*** (55.26)	9,164.374*** (25.32)
Constant	-0.621 (-0.75)	2.354*** (21.43)	1017091.220*** (16.53)
Observations	263,087	248,131	256,808
R-squared	.	0.0604	0.0525
Year FE	Y	Y	Y
Team FE	Y	Y	Y

**Table 3****Probability of missing a game due to injury and recovery time**

This table presents univariate analysis of the probability of missing a game due to injury and average recovery time given an injury has occurred in the months leading up to a contract ending.

Panel A	Probability of missing a game due to injury		
	Obs.	Mean	Std. Dev.
Greater than 12 months left in contract	590946	0.058	0.234
12 months or less left on contract	217968	0.044	0.205
9 months or less left on contract	169127	0.047	0.211
6 months or less left on contract	80675	0.044	0.205
3 months or less left on contract	15128	0.027	0.161

  

Panel B	Recovery time given injury (days)		
	Obs.	Mean	Std. Dev.
Greater than 12 months left in contract	6315	13.78	26.33
12 months or less left on contract	1940	12.42	24.47
9 months or less left on contract	1546	11.06	23.03
6 months or less left on contract	723	10.09	22.13
3 months or less left on contract	99	14.50	26.28

**Table 4**

## The propensity to miss a game due to injury

This table presents the results from estimating equation (1). The dependent variable is an indicator equal to one if player  $i$  misses a game due to injury on date  $t$  and zero otherwise. Our independent variable of interest is  $3M\ LEFT$  which is an indicator equal to one for player  $i$  if he is in the last three-months of his contract at date  $t$ . Detailed descriptions of other variables are provided in Appendix A. The regressions include year and team fixed-effects. We report t-statistics in parentheses, which are robust to heteroskedasticity and clustered at the player level. Significance levels of 10, 5, and 1 percent are represented by \*, \*\*, and \*\*\*, respectively.

	(1)	(2)	(3)	(4)
<i>12M LEFT</i>	-0.596*** (-36.54)			
<i>9M LEFT</i>		-0.513*** (-28.77)		
<i>6M LEFT</i>			-0.613*** (-23.41)	
<i>3M LEFT</i>				-1.339*** (-15.78)
<i>AGE</i>	0.042*** (27.74)	0.038*** (25.47)	0.036*** (23.72)	0.033*** (22.30)
<i>WEIGHT</i>	0.000 (0.04)	-0.000 (-0.37)	-0.000 (-0.72)	-0.000 (-0.97)
<i>HEIGHT</i>	0.183*** (5.05)	0.205*** (5.67)	0.219*** (6.07)	0.234*** (6.48)
Constant	-6.184*** (-32.30)	-6.249*** (-32.70)	-6.283*** (-32.90)	-6.334*** (-33.17)
Observations	458,170	458,170	458,170	458,170
Year FE	Y	Y	Y	Y
Team FE	Y	Y	Y	Y

**Table 5**

The propensity to miss a game due to injury: Robustness and sub-sample analyses

This table presents the results from estimating equation (1). The dependent variable is an indicator equal to one if player  $i$  misses a game due to injury on date  $t$  and zero otherwise. Our independent variable of interest is  $3M\ LEFT$  which is an indicator equal to one for player  $i$  if he is in the last three-months of his contract at date  $t$ . *Trades & Waivings* refer to player trades and waivings, *Extensions* refer to player contract extensions, *Position FE* refers to the inclusion of position fixed-effects, *Opposition FE* refers to the inclusion of opposition-team fixed-effects, *In-season* refers to in-season signings, *Out-of-season* refers to out of season signings, *Time as free-agent* refers to the number of days a player spends a free-agent (for out-of-season signings) where  $Q1$  and  $Q4$  refer to the bottom and top quartiles. Detailed descriptions of other variables are provided in Appendix A. The regressions include year and team fixed-effects. We report t-statistics in parentheses, which are robust to heteroskedasticity and clustered at the player level. Significance levels of 10, 5, and 1 percent are represented by \*, \*\*, and \*\*\*, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>Trades &amp; Waivings</i>	<i>Extensions</i>	<i>Position FE</i>	<i>Opposition FE</i>	<i>In season</i>	<i>Out of season</i>	<i>Time as free-agent Q1</i>	<i>Time as free-agent Q4</i>
<i>3M LEFT</i>	0.091 (1.29)	0.147 (0.79)	-1.198*** (-16.02)	-1.120*** (-14.96)	-1.370*** (-10.77)	-1.105*** (-11.12)	-1.125*** (-5.05)	-2.458*** (-6.92)
<i>AGE</i>	0.054*** (23.35)	-0.020*** (-2.66)	0.028*** (18.83)	0.031*** (21.29)	0.017*** (5.64)	0.031*** (17.23)	0.035*** (9.66)	0.029*** (7.17)
<i>WEIGHT</i>	0.005*** (9.38)	-0.002 (-1.38)	0.003*** (6.94)	0.001*** (3.54)	-0.002** (-2.01)	0.002*** (5.05)	0.003*** (2.87)	0.000 (0.36)
<i>HEIGHT</i>	-0.448*** (-9.05)	0.805*** (6.93)	0.270*** (5.66)	0.177*** (5.09)	0.603*** (8.32)	0.043 (0.99)	0.130 (1.62)	0.076 (0.80)
Constant	-5.145*** (-16.23)	-23.020 (-0.02)	-5.700*** (-17.50)	-4.661*** (-26.13)	-6.772*** (-18.38)	-3.897*** (-17.81)	-4.372*** (-10.44)	-4.086*** (-8.45)
Observations	234,546	50,953	468,285	463,623	120,393	293,651	75,660	67,466
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Team FE	Y	Y	Y	Y	Y	Y	Y	Y

**Table 6**

## Recovery time given injury has occurred

This table presents the results from regression analysis of player recovery time given injury has occurred. The dependent variable is equal to the number of days player  $i$  takes to recover from an injury occurring on date  $t$ . Our independent variable of interest is  $3M\ LEFT$  which is an indicator equal to one for player  $i$  if he is in the last three-months of his contract at date  $t$ . Detailed descriptions of other variables are provided in Appendix A. The regressions include year and team fixed-effects. We report t-statistics in parentheses, which are robust to heteroskedasticity and clustered at the player level. Significance levels of 10, 5, and 1 percent are represented by \*, \*\*, and \*\*\*, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>12M LEFT</i>	-1.442* (-1.74)				-0.915 (-0.86)			
<i>9M LEFT</i>		-1.490* (-1.66)				-2.670** (-2.26)		
<i>6M LEFT</i>			-2.019 (-1.58)				-3.961** (-2.39)	
<i>3M LEFT</i>				4.106 (1.10)				2.145 (0.49)
<i>AGE</i>	0.104 (1.21)	0.097 (1.14)	0.089 (1.05)	0.079 (0.93)	-0.051 (-0.47)	-0.037 (-0.35)	-0.046 (-0.43)	-0.065 (-0.61)
<i>WEIGHT</i>	0.008 (0.38)	0.008 (0.38)	0.007 (0.32)	0.007 (0.32)	0.020 (0.77)	0.020 (0.76)	0.019 (0.73)	0.020 (0.77)
<i>HEIGHT</i>	-0.746 (-0.40)	-0.752 (-0.40)	-0.655 (-0.35)	-0.614 (-0.33)	-0.399 (-0.17)	-0.444 (-0.19)	-0.338 (-0.14)	-0.344 (-0.15)
Constant	52.973*** (3.91)	53.206*** (3.93)	53.056*** (3.92)	52.906*** (3.91)	49.353 (1.64)	49.224 (1.63)	49.329 (1.64)	49.499 (1.64)
Observations	4,067	4,067	4,067	4,067	4,156	4,156	4,156	4,156
R-squared	0.0337	0.0337	0.0336	0.0333	0.0817	0.0827	0.0829	0.0816
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Team FE	Y	Y	Y	Y	Y	Y	Y	Y
Injury FE	N	N	N	N	Y	Y	Y	Y

**Table 7****Chronic injuries and recovery time**

This table presents the results from regression analysis of player recovery time given injury has occurred. The dependent variable is equal to the number of days player  $i$  takes to recover from an injury occurring on date  $t$ . Our independent variables of interest are: (1)  $3M\ LEFT$  which is an indicator equal to one for player  $i$  if he is in the last three-months of his contract at date  $t$ ; (2)  $CHRONIC\ SCALE_{it}$  which is a count, for player  $i$  who injures himself at time  $t$ , of the number of times the player has injured the same body part; and (3)  $CHRONIC_{it}$  which is an indicator equal to one if player  $i$  who is injured on date  $t$  has previously injured the same body part. Detailed descriptions of other variables are provided in Appendix A. The regressions include year and team fixed-effects. We report t-statistics in parentheses, which are robust to heteroskedasticity and clustered at the player level. Significance levels of 10, 5, and 1 percent are represented by \*, \*\*, and \*\*\*, respectively.

	(1)	(2)	(3)	(4)
	Chronic		Chronic Scale	
<i>3M LEFT</i>	-3.141 (-0.59)	-3.658 (-0.67)	-16.389** (-2.34)	-16.710** (-2.40)
<i>CHRONIC</i>	5.557*** (7.07)	18.243** (2.04)		
<i>3M LEFT</i> × <i>CHRONIC</i>	10.684 (1.42)	9.236*** (9.83)		
<i>CHRONIC SCALE</i>			1.134*** (3.55)	11.866*** (3.27)
<i>3M LEFT</i> × <i>CHRONIC SCALE</i>			11.780*** (3.22)	0.840** (2.49)
<i>AGE</i>	-0.137 (-1.43)	-0.309*** (-2.85)	-0.062 (-0.62)	-0.042 (-0.42)
<i>WEIGHT</i>	0.026 (1.13)	0.016 (0.63)	0.009 (0.37)	-0.001 (-0.05)
<i>HEIGHT</i>	-1.434 (-0.69)	-0.964 (-0.41)	0.680 (0.32)	0.999 (0.47)
Constant	85.200*** (5.82)	60.698** (2.04)	71.993*** (4.34)	73.941*** (4.44)
Observations	4,928	4,156	3,929	3,929
R-squared	0.0550	0.0891	0.0434	0.0504
Year FE	Y	Y	Y	Y
Team FE	Y	Y	Y	Y
Injury FE	N	Y	N	Y

**Table 8**

## Player value and gambling incentives

This table presents the results from estimating equation (1) in subsamples split by measures of player quality or value. The dependent variable is an indicator equal one if player  $i$  misses a due to injury on date  $t$  and zero otherwise. Our independent variable of interest is  $3M\ LEFT$  which is an indicator equal to one for player  $i$  if he is in the last three-months of his contract at date  $t$ .  $all-NBA$  is an indicator for if a player has even been selected for one of the  $all-NBA$  teams,  $BERRI48$  is the 48 minute equivalent Berri Score for player  $i$ ,  $WS48$  is the 48 minute equivalent Win Shares for player  $i$ , and  $PER$  is the annual Player Efficiency Rating for player  $i$ . Low and High refer to the bottom and top tercile for each player value measure. Detailed descriptions of other variables are provided in Appendix A. The regressions include year and team fixed-effects. We report t-statistics in parentheses, which are robust to heteroskedasticity and clustered at the player level. Significance levels of 10, 5, and 1 percent are represented by \*, \*\*, and \*\*\*, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	<i>all-NBA</i>		<i>BERRI48</i>		<i>WS48</i>		<i>PER</i>	
	No	Yes	Low	High	Low	High	Low	High
<i>3M LEFT</i>	-1.263*** (-16.48)	0.745* (1.92)	-1.362*** (-11.43)	-0.728*** (-6.17)	-1.452*** (-13.42)	-1.041*** (-6.61)	-1.216*** (-10.52)	-0.449*** (-3.61)
<i>AGE</i>	0.032*** (21.73)	-0.023 (-1.54)	0.050*** (19.48)	0.018*** (6.96)	0.053*** (22.17)	0.018*** (6.54)	0.029*** (11.87)	0.024*** (9.21)
<i>WEIGHT</i>	0.001** (1.96)	0.012*** (5.22)	-0.001 (-0.73)	0.005*** (7.80)	0.006*** (9.03)	0.003*** (4.80)	0.004*** (4.65)	0.002*** (3.39)
<i>HEIGHT</i>	0.224*** (6.33)	-0.978*** (-3.25)	0.336*** (4.76)	-0.054 (-0.94)	-0.142** (-2.18)	0.110* (1.94)	-0.201*** (-2.85)	0.265*** (4.90)
Constant	-4.868*** (-27.46)	1.869 (1.16)	-5.696*** (-16.69)	-3.582*** (-11.21)	-4.007*** (-12.41)	-4.210*** (-14.16)	-3.151*** (-9.05)	-4.973*** (-17.61)
Observations	448,477	16,687	141,185	166,447	141,119	165,387	130,857	152,394
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Team FE	Y	Y	Y	Y	Y	Y	Y	Y

**Table 9**

## Individual performance around the contract cycle

This table presents regression analysis of various player performance statistics around their contract cycle. Our independent variable of interest is *3M LEFT* which is an indicator equal to one for player *i* if he is in the last three-months of his contract at date *t*. Detailed descriptions of other variables are provided in Appendix A. The regressions include year and team fixed-effects. We report t-statistics in parentheses, which are robust to heteroskedasticity and clustered at the player level. Significance levels of 10, 5, and 1 percent are represented by \*, \*\*, and \*\*\*, respectively.

	(1)	(2)	(3)	(4)	(5)	(8)	(9)
	<i>BERRI48</i>	<i>WS48</i>	<i>OFF_SCORE</i>	<i>DEF_SCORE</i>	<i>USG%</i>	<i>AST%</i>	<i>DRB%</i>
<i>3M LEFT</i>	-1.938*** (-8.50)	-0.036*** (-40.95)	-5.803*** (-37.84)	-0.591*** (-8.37)	0.066 (0.80)	-1.986*** (-25.81)	-0.279*** (-5.65)
<i>AGE</i>	0.126*** (17.52)	0.002*** (85.63)	0.367*** (73.82)	-0.073*** (-31.99)	-0.221*** (-82.41)	0.087*** (34.77)	0.056*** (34.87)
<i>WEIGHT</i>	0.025*** (13.13)	0.000*** (9.39)	-0.005*** (-3.51)	-0.015*** (-24.09)	-0.007*** (-9.67)	-0.057*** (-86.37)	0.066*** (154.33)
<i>HEIGHT</i>	3.546*** (21.62)	0.011*** (17.10)	-0.948*** (-8.22)	-3.669*** (-69.14)	-0.770*** (-12.41)	-16.282*** (-281.21)	7.986*** (215.03)
Constant	-25.137*** (-30.74)	-0.084*** (-25.26)	95.265*** (163.81)	131.135*** (490.10)	33.427*** (106.77)	130.417*** (446.46)	-54.904*** (-293.15)
Observations	339,566	439,091	440,125	440,125	440,125	440,143	440,125
R-squared	0.0128	0.0536	0.0512	0.1602	0.0288	0.4804	0.4762
Year FE	Y	Y	Y	Y	Y	Y	Y
Team FE	Y	Y	Y	Y	Y	Y	Y

	(10)	(11)	(12)	(13)	(6)	(7)	(14)
	<i>ORB%</i>	<i>STL%</i>	<i>BLK%</i>	<i>PF48</i>	<i>TS_RATE</i>	<i>PTS48</i>	<i>TOV%</i>
<i>3M LEFT</i>	0.698*** (18.35)	0.178*** (5.96)	0.079*** (5.02)	1.174*** (5.16)	-0.027*** (-31.43)	-2.442*** (-13.92)	1.277*** (17.46)
<i>AGE</i>	-0.071*** (-57.90)	-0.001 (-1.38)	-0.019*** (-37.99)	-0.051*** (-7.06)	0.001*** (37.24)	-0.154*** (-27.65)	-0.003 (-1.34)
<i>WEIGHT</i>	0.057*** (173.48)	-0.001** (-2.02)	0.002*** (13.08)	0.027*** (14.11)	0.000*** (11.79)	-0.008*** (-5.22)	0.030*** (47.94)
<i>HEIGHT</i>	4.397*** (153.67)	-0.921*** (-40.97)	3.133*** (265.87)	0.758*** (4.63)	0.001** (2.20)	-0.026 (-0.21)	-3.081*** (-56.11)
Constant	-31.858*** (-220.82)	8.456*** (74.63)	-19.215*** (-323.24)	-3.816*** (-4.67)	0.430*** (131.46)	23.881*** (37.93)	28.264*** (102.04)
Observations	440,125	439,555	440,143	339,566	339,566	439,091	439,708
R-squared	0.4242	0.0221	0.3604	0.0039	0.0103	0.0503	0.0269
Year FE	Y	Y	Y	Y	Y	Y	Y
Team FE	Y	Y	Y	Y	Y	Y	Y

**Table 10**

## The implications of gambling on team performance

This table presents regression analysis of team performance. Our dependent variables of interest are: (1) an indicator equal one if team  $j$  wins on date  $t$  and zero otherwise (Model 1); and (2) team  $j$ 's victory margin, calculated as the difference between team  $j$ 's score and its opponents score on date  $t$ , negative values indicate a loss (Model 2). Our independent variable of interest is *%PLAYERS 3M LEFT* which is the proportion of players in team  $j$  who are in the last three-months of their contract at date  $t$ . Detailed descriptions of other variables are provided in Appendix A. The regressions include year and team fixed-effects. We report t-statistics in parentheses, which are robust to heteroskedasticity and clustered at the player level. Significance levels of 10, 5, and 1 percent are represented by \*, \*\*, and \*\*\*, respectively.

	(1) <i>PROBABILITY OF VICTORY</i>	(2) <i>VICTORY MARGIN</i>
<i>%PLAYERS 3M LEFT</i>	-0.492*** (-3.69)	-2.662*** (-5.01)
<i>HOME</i>	0.305*** (40.86)	1.529*** (50.76)
<i>AVE. TEAM AGE</i>	0.002*** (12.30)	0.007*** (11.68)
<i>AVE. TEAM HEIGHT</i>	0.018*** (7.50)	0.024** (2.52)
<i>AVE. TEAM WEIGHT</i>	-0.000*** (-7.41)	-0.001** (-2.28)
<i>TEAM BERRI</i>	0.110*** (292.50)	0.577*** (520.79)
Constant	-5.201*** (-90.13)	-27.589*** (-125.57)
Observations	469,269	469,269
R-squared	.	0.4194
Year FE	Y	Y
Team FE	Y	Y
Opposition FE	Y	Y