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Show Me The Money:

Examining the Validity of the Contract Year Phenomenon in the NBA

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Abstract

The media narrative of the 'contract year effect' is espoused across all major professional American sports leagues, particularly the MLB and NBA. In line with basic incentive theory, this hypothesis has been shown to be true in baseball, but the analysis in basketball to this point has been flawed. In estimating the contract year effect in the NBA, this paper is the first to define rigorously the various states of contract incentives, the ignorance of which has been a source of bias in the literature thus far. It further expands on previous analyses by measuring individual performance more broadly across a range of advanced metrics. Lastly, it attempts to account for the intrinsic endogeneity of playing in a contract year, as better players get longer contracts and are thus less likely to be in a contract year, by using exogenous variations in the NBA's contract structure to form an instrument, and by comparing performance to a priori expectations. In this manner, this paper produces the first rigorous finding of a positive contract year phenomenon. The estimated effect is about half that found in baseball, equivalent to a 3-5 percentile boost in performance for the median player in the NBA.

Acknowledgments

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I. INTRODUCTION

At the core of any economic discipline is the notion that people respond to incentives, and this foundational assumption has been baked into all fields of economic thought. The National Basketball Association (NBA), and specifically the league's contract structure, allow us to examine the impact of extremely high-powered incentives on players' performance. This paper examines the impact on players with increased incentives to perform at an even higher level than their usual high pressure work environment, when they are facing what is colloquially known as a 'contract year'. It is the first to demonstrate rigorously a positive effect on performance.

These highly leveraged incentive situations arise because of the NBA's contract structure. At any one time, each player is under contract with one of the league's 30 franchises. Unlike a classical labor market, with numerous widely heterogeneous companies among which an individual laborer can move with relative freedom, the NBA labor market has strict contract lengths for every player, and only a finite number of destinations for each player once that contract is over. Players are very rarely 'fired' as in a traditional labor market. In the place of firing, quitting, and hiring as found in traditional labor markets, the NBA has free agency. When a player's contract is up, every team in the league has the right to offer that player a contract. These contracts vary primarily in their compensation and length and are standardized across the league by the Collective Bargaining Agreement (CBA), signed between the players' union and the league. The result is analogous to a first-price auction system[1] for the rights to players by the 30 teams, whereby 'price' increases with both compensation and length of contract. The auction 'game' is complicated by multiple factors,

[1] It is somewhere between a first-price sealed bid auction and an English auction, as when teams offer players contracts, the player may or may not divulge the other offers he has received to that point

including complexities within contracts such as option years, or the ability of a player's current team to offer an extra year as under the current CBA. The crucial element of this contract system is that the majority of NBA contracts involve guaranteed money. Once a contract is signed for, the player receives that sum over that timeframe.[2] Even in the case of injury, the player is paid, though the team may receive some insurance payments.

The so-called contract year, borne from this system, allows a player the foresight that he will enter free agency at the end of the season.[3] NBA teams overvalue a player's most recent performance, relative to previous years, when making decisions on how much to offer (Stiroh, 2007). As a result, players correctly infer that the final year of their contract is the most highly leveraged regarding future payment and are absolutely incentivized to perform at a higher level. Expectancy type theories of motivation predict increases in performance during the contract year because it is the period in which external factors are most salient for the player (Behling and Starke, 1973). These incentives are compounded by the salary cap for each team, which creates a finite pool of available dollars in the league.[4] Thus, to some degree, every extra dollar earned by a player comes at the expense of the rest of the league and the motivation to outperform one's peers is enhanced. While in a perfectly competitive marketplace one will be largely correctly compensated for performance, in the auction system you are paid what the best bidder offers.[5] To demonstrate the magnitude of the incentives at stake for these players, consider the recent plight of Wesley Matthews.

[2] There are extremely rare possible exceptions such as the case of gross misconduct by the player

[3] As outlined in Section II, there are actually two types of free agency, unrestricted and restricted, with different incentives attached

[4] Each team can spend $63.065 million dollars on its roster for the 2014-2015 season. This number changes slightly from year to year, and is known as a 'soft cap', as teams are able to exceed the cap to re-sign their own players (Coon, 2012)

[5] This first-price auction mechanism may further compound incentives for the contract year player. The winner's curse amplifies as value increases (Thaler, 1992), and so the returns to the player of increasing his valuation may compound

Matthews, playing in a contract year this season, was slated to receive something close to a maximum contract[6] at the end of the season worth approximately $100 million over five years. But after tearing his Achilles tendon in early March, an injury from which some players do not return to the same level of play, he is now being predicted to receive only around $50 million over four years (Cato, 2015).

In accordance with the powerful incentive to raise performance in a contract year, there is some anecdotal evidence that NBA players do indeed experience performance boosts. The media has embraced this hypothesis, and perhaps the most infamous case is Erick Dampier. During his eighth season in the league in 2003-2004, the 6’ 11’’ center had a career year, posting career highs in points, rebounds and assists per game. Known previously for being a solid defensive big with little or no offensive prowess,[7] Dampier miraculously transformed into a borderline all-star as he became an efficient post-up threat and supremely capable rebounder. His reward at the end of the season was a seven-year $73 million contract from the Dallas Mavericks. After signing, Dampier swiftly returned to his perfectly ordinary self, worth roughly a tenth of what he was being paid, and the opportunity cost of having Dampier take up significant cap space was crippling to the Mavericks for the next seven seasons.[8] It is frequently described as one of the worst contracts ever offered by a team (Brown, 2013). Dampier’s one season of excellence as nothing more than the contract year phenomenon is frequently brought up by the media as proof of its existence (Simmons, 2006).

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[6] No player can earn more than a maximum contract, set at 25% of the cap for players who have played six or fewer seasons, 30% of the cap for players in their seventh through ninth seasons, and 35% of the cap thereafter. For various exceptions to this rule whereby players can be paid slightly more, please see Coon (2012)

[7] Statistical plus-minus (SPM) rated him before 2003-2004 as approximately a replacement level player (see Section 3 for explanation of SPM)

[8] Perhaps it is no coincidence that Dallas won the NBA title in 2012, a year after Dampier’s contract finally came off the books

In similarly structured labor markets, the contract year effect has been shown to exist and exert a positive influence on performance. Major League Baseball players also sign guaranteed contracts of a predetermined length. For the contract year phenomenon, as with many topics in basketball analytics, baseball was there first. Baseball is a static rather than continuous sport and can be boiled down to a Markov chain, making any mathematical analysis simpler.[9] Dayn Perry of *Baseball Prospectus* produced the defining research on baseball's 'walk years', the sport's colloquialism for contract years (Perry, 2006). Major League Baseball's contract system, with draft picks under team control for significantly longer than in the NBA due to arbitration, means that top players tend to hit free agency around the same point, with an average age of 31.0 in Perry's study. Although studies by Bill James amongst others show that a player most often hits his peak between ages twenty-five and twenty-nine, players saw a considerable uptick in performance for top players in their walk year, showing that "age doesn't explain away the walk years' performance discrepancy" (Perry, 2006, 201). On average, players' performance increased by 9% in their walk year, while posting the same performance as a group in the years before and after the walk year. The increase was partly due to volume as pitchers, for example, played more games in the walk year relative to surrounding years, indicating an increased desire to play through discomfort or injury. While "the bump in playing time explains away part of the walk year [performance] advantage … it's not enough to nullify the trend completely" (Perry, 2006, 202).

[9] From an initial state, there are a finite number of next states: a batter's value is defined as his ability to get to states with subsequently higher expected values, while a pitcher's value is to stop the batter from reaching those states. By examining the probability distribution over states for batters and pitchers, we can assign them a value. In addition, because baseball has such a developed farm system, we can ascertain the expected value of a replacement player for each team called up from the minor leagues. Hence, the fairly accurate all-in-one statistic of Wins Above Replacement (WAR) can be calculated and used to compare performance extremely well, accurately accounting for a baseball player's contributions in a season

The performance of high level CEOs has also been shown to exhibit this pattern. CEOs at large corporations often sign guaranteed contracts for set lengths of time, and it has been found that "job uncertainty created by expiring employment contracts induces changes in managerial behaviors that have significant positive impacts on firm financial activities and outcomes" (Liu and Xuan, 2012, 23). The empirical evidence for the contract year phenomenon in other similar disciplines with highly leveraged incentives suggests the existence of a similar effect existing in basketball.

Although there is theoretical motivation and anecdotal evidence of the contract year effect in basketball, and empirical evidence in other similar disciplines, empirical approaches in basketball up to this point have been severely lacking in rigor. The major paper on the topic by White and Sheldon (2013) used a similar technique to that of Perry, comparing contract year performance to baseline performance, which they defined as pre- and post-contract year performance. They observed boosts in scoring statistics and no decline in non-scoring statistics, resulting in the main finding of an overall increase of +0.75 (p-value < 0.001) in Player Efficiency Rating (PER), an all-in-one measure of a player's per-possession efficiency, derived from the events counted in the box score[10] of each game. However, beyond the inability to draw conclusions from looking solely at PER,[11] White and Sheldon's method induces biased estimates, as basketball players (unlike in baseball where players almost always sign a new contract) frequently do not get another contract. Considering only players who played during, before and after a contract year limits your sample only to players who

[10] The box score is the tabulated results of a basketball game, historically reported in the newspaper the morning after a game. It typically contains the points, rebounds, assists, steals, blocks and turnovers for each player. It records all the major observed events in a game for each player, but certainly does not contain all the information about a player's performance

[11] PER has come under heavy criticism for Dave Berri, among others, and the various methods of evaluating individual performance will be delved into in Section III

were able to get another contract after their contract year. Conditional upon that fact, they must have played well enough in that contract year to merit another season of play, while those who played poorly were cut from the sample, upwardly biasing the results.

Jean (2010) also comes to similar conclusions within an ordinary least squares framework that scoring statistics increase, while also corroborating the conclusion of Berri and Krautmann (2006) that players do not “shirk” defensive responsibilities in pursuit of offensive output. The magnitude of his estimated contract year effect is extremely high in comparison to Sheldon and White’s, an anomaly Jean ascribes to his model’s “weak predictive power” given his negative adjusted R-squared values (Jean, 2010, 42). Gaffaney (2013) tries to control for quality of teammate and analyzes smaller groups divided by age, position, and quality, with similar findings to White and Sheldon, though with some variation in magnitude across groups. The extremely low number of observations[12] Gaffaney uses is a potential cause of the observed variation in effect.

All methods up to this point have been largely invalid for failing to address three major concerns. The first is that none have attempted to consider the intricacies of NBA contracts and thus have not correctly identified a player’s contract state. Dampier’s infamous story is the battle cry of the media whenever the contract year phenomenon is discussed, but there is a deep irony to its usage: by my definition, Dampier was not even in a contract year during the 2003-2004 season. Dampier declined his player option and opted out of his contract with the Golden State Warriors after his extremely successful season precisely because he wanted to secure a lucrative new contract (Navalta, 2004). However, had he played poorly during the season, he most surely would have opted in and played another season in the bay area.

[12] As low as 70 observations in some cases, as he only uses player data from the 2012-2013 season and compares it to career averages

Hence, 2003-2004 was neither a contract year nor what I term a non-contract year for Dampier. There are many different nuances to NBA contracts, but if we are to estimate the contract year effect, it must be between two well-defined contract incentive states, which are broadly constant across players. White and Sheldon abruptly acknowledge that "while all of these nuances [of contracts] have their own unique characteristics, we did not attempt to deal with these differences" (White and Sheldon, 2013, 4), failing to distinguish even between unrestricted and restricted free agency. Furthermore, their dataset straddles both side of the 2005 CBA which altered the incentive state for non-contract years as it made it much harder for teams to waive players in its aftermath. These inaccuracies in contract analysis also hold for the other two pieces of literature from Jean (2010) and Gaffaney (2013). Section II goes into detail on NBA contract situations and my definition of contract states.

Secondly, all previous papers have only measured performance from events observed in the box score. Whereas baseball boils down to a series of static individual interactions between pitcher and hitter, with occasional teamwork as a result of those interactions, basketball is a continuous sport with constant and various interactions across the court. As a result, attributing individual credit is significantly more difficult. For instance, if a player hits a three from the corner, the box score gives him three points, but to what extent was he aided by the point guard who drove into the lane and collapsed the defense before passing the ball, or by the defender that gave him too much slack? Of those three points, it is difficult to know exactly how to accredit points between the shooter, the passer, the primary defender, and indeed everyone else on the court at the time. Players have significant contributions outside of the observed outcomes recorded in the box score, such as defensive pressure that does not result in a shot being taken, or setting an excellent screen such that a teammate has a higher chance of scoring. By expanding measures of performance to plus-minus based metrics, and indeed the more accurate box score metric of win shares, this paper evaluates a more complete measurement of performance in measuring the contract year effect (see Section III for details).

Thirdly and most importantly, the literature thus far has neglected to consider the intrinsic endogeneity of being in a contract year. Less impressive players get shorter contracts and are thus more likely to be in a contract year, creating a negative correlation between performance and the probability of being in a contract year. Jean (2010) and Gaffaney (2013) ignore this endogeneity by operating within an ordinary least squares framework while White and Sheldon's method induces biased estimates for reasons outlined above. I instead use an instrumental variables framework with a seasonal instrument which takes advantage of exogenous variation in the NBA's contract structure, which impacts the likelihood of a player being in a contract year but not his performance (see Section IV for details). In addition, Paine's projection system[13] is utilized to compare a player against his expected performance, further reducing the endogeneity issue.

After correcting for these three major concerns with the literature, this paper finds the first clean evidence of a positive contract year effect. The effect is estimated to be approximately a 3-5 percentile boost in performance for the median NBA player, and equivalent to an increased output of 0.009 wins per 48 minutes.[14] This is about half of what is observed in the baseball literature, and roughly two-thirds the estimate from White and Sheldon (2013). In further contrast to White and Sheldon, the contract year effect is seen primarily in rebounding and steals in the box score rather than in offensive statistics.

[13] See Appendix 4 for details of how this projection is calculated
[14] Using the win shares per 48 estimate from column (5) of Table X

As methods of measuring individual performance in the NBA become more precise and less noisy, and if a more accurate projection system is developed, the framework outlined in this paper could be used in future research to further refine the contract year estimate. At this point in time, however, we readily conclude that there is indeed an effect, but that the media at large overstates this effect.

II. CONTRACT SITUATIONS

At the beginning of each NBA season, a player may find himself in a variety of distinct contract situations. We want to examine the precise effect of heading into a guaranteed contract year at the beginning of the season versus the alternative guaranteed situation of playing under the same current contract at the beginning of next season. It is possible that the player may change teams in this second scenario – for example, if he is traded – but the player will nonetheless be certain that he will not enter free agency in the offseason. Outside of these two possibilities, there are numerous other contract situations that offer differing incentives.[15]

The first category is any form of contract with unguaranteed or partially guaranteed portions. Players with such clauses have increased incentives to perform, and stay healthy to receive the financial benefits explicitly outlined in their contracts. This creates a fundamentally different scenario from a player whose financial remuneration is guaranteed independent of his current play.

The second category is any contract for which the next season involves an option. There are three types of options in the NBA: team options, player options, and early termination options. The team option gives the team the right to opt into another year of the contract, which alters the player's incentives: if he performs extremely well, and his team opts into the next year of his contract, he will be locked into a potentially below-market deal. If he performs poorly, however, the team will likely opt out, and his price in free agency will take a hit. The incentives are also influenced by a player's satisfaction playing for his current team. If his satisfaction is low, the player might deliberately diminish his value so that the team

[15] The majority of information in this section comes from Larry Coon's invaluable guide to the nuances of the CBA (Coon, 2012)

option is not exercised. Team option contracts thus create different sets of incentives from definitively being in a contract year or not.

Player options are for one year only, whilst early termination options can last up to two years. In both cases, the player may opt into the contract at a set price. These too create different incentives, as the player is protected from poor performance: if he plays badly, he can opt in and have a 'second attempt' at a contract year. In this respect, not accounting for player option contracts can engender significant bias in results. Those who opt out are likely to have outperformed their contracts, receiving a bigger haul in free agency compared to those who opt into their contracts. Hence, considering players who opt out after just playing in a contract year biases performance upwards; it does not consider players who would have played in a contract year had they opted in, an action highly correlated with worse performance. This was the key bias in the literature's definition of ex-post contract year status, as player options are relatively common in the NBA.[16] In producing my dataset, all player-seasons followed by an option year of any variety were excluded as they were neither 'pure' non-contract nor contract years. If an option was exercised, however, then that year is included as a guaranteed contract year in my dataset.[17]

The third category consists of players on rookie contracts. For first-round picks, contracts are four years in length, with two guaranteed years and two team option years. Approximately 72% of teams opt into these option years because rookie deals tend to be cheap relative to the free agent auction price for talent (Silver, 2014). The value of the contract for the first four seasons is determined solely by the player's pick number as per the

[16] Particularly after the 2011 CBA (Lowe, 2014(a))

[17] Unless it was the first of two early termination option years. In that case only the second exercised option would be considered a contract year

Collective Bargaining Agreement (CBA).[18] In the first two seasons, incentives are obstructed: players want to stay in the league, avoid time in the NBA Development league (as is common for young players), and receive the latter two team option years. In the offseason after the third season, elite players often receive five-year extensions before the player can hit free agency, meaning that the third year of a rookie contract is a quasi-contract year.[19] Extensions cannot be signed until this time. If no extension is signed and a player plays under the fourth year of his rookie deal, then the player enters restricted rather than unrestricted free agency. In this relatively common scenario, the player's team has 72 hours to match any offer sheet the player signs with any other franchise. The player must then sign this matched offer sheet if his team extends it. Other than signing a deal with his own team or signing an offer sheet with another team (which can be matched by his current team), the only other option a player has is to sign a qualifying offer, also predetermined by his draft pick number, for a fifth season. This alternative often offers remuneration significantly below market value as players approach their prime.

The fifth season of a rookie contract while under a qualifying offer is categorized as a contract year, as the player is without question going into unrestricted free agency at the end of the year. In addition, if a player signs an extension after his third season which comes into effect after his fourth year when his rookie deal is completed, then the fourth year of a rookie deal may be considered a bona fide non-contract year. However, under all other circumstances of a rookie contract, a player faces differing incentives than he would face in a

[18] There is some wiggle room as teams can technically offer between 80% and 120% of the number the CBA mandates, but almost all contracts are signed at 120%

[19] Extensions cannot be signed until after a player has been in the league for three years.

guaranteed contract or non-contract year.[20] Outside of these two specific exceptions, all player-seasons on rookie contracts are hence excluded from my dataset.

Second-round picks do not have specific set lengths or prices, as first-rounders do, but the league-wide standard has come to be four-year deals which are never fully guaranteed, for amounts varying with player quality (Lowe, 2014(b)). Usually, the first two seasons will carry either a full or partial guarantee, with the latter two fully unguaranteed. To some degree, these latter two years act as de facto team options with the team able to dump the player for no cost at any point up until January 10th of any league year; at that date, all contracts become guaranteed for the rest of the season, mimicking the situation of first-round rookie contracts. Regardless of the specifics of the contracts, second-round picks will always enter restricted free agency at the end of their rookie deals, with the same choices as first-rounders.[21] As a result, they are not in the same incentive state as those who will be entering unrestricted free agency at the end of their contract and thus are excluded from my dataset.[22]

While under contract, a player's situation can be modified in three main ways other than entering free agency. Extensions are commonly offered to elite third-year players as described previously, such that the player cannot test the waters of restricted free agency after his fourth year. Aside from that instance, however, only a contract for four or more seasons can be extended – and then only after three years. Additionally, an extension can only be used to offer a salary increase to a player, and is only an option for teams under the

[20] Coon (2013) provides substantial empirical evidence for differences between restricted and unrestricted free agency; while Lowe (2013) shows anecdotal evidence of the same result. Together, we can readily conclude that players facing restricted free agency are in a different incentive state to those facing unrestricted free agency

[21] They can choose to sign a qualifying offer then enter unrestricted free agency after a year; sign with their current team; or sign an offer sheet with another team which their current team has the right to match. However, unlike first round picks who have their qualifying offer set by the CBA, second round picks can only sign at the league minimum if they choose this option and so this is exceedingly rare

[22] With the same caveat that qualifying offer years do count as guaranteed contract years

cap.[23] Not including option years at the end, as of the 2011 CBA, four years is the current maximum contract length a team can offer a player in free agency, though a team re-signing their own player is allowed the luxury of offering five years. Under the 2005 CBA, those maximum lengths were five and six years respectively and prior to 2005, there was no formal limit on contract length.[24] These factors combine to make extensions extremely rare. One could argue that players with four- or five-year contracts have an increased incentive to play for an extension from the third year of their contract onward, before the final 'true' contract year. This quasi-contract year exists only to impress their current team rather than the auction mechanism of thirty franchises bidding for services, but this could still be considered distinct from the non-contract year state. However, a very small sample of players receive contracts of four or more years; and the athletes that do will invariably have player option years attached,[25] reducing the incentive to seek an extension. Regardless, extremely few players are now extended in the NBA, in stark contrast to years before the 2005 CBA. Hence, I have not designated these players as under a different incentive state.

The second way by which contract situations can change is by waiving or buyout. These terms respectively describe when a player, despite holding guaranteed salary, is voluntarily or involuntarily cut from a team's roster (unguaranteed contracts cut are also described as waiving by the media, but are not relevant to my discussion, as I have eliminated these contracts.) When a guaranteed player is cut, his contract is still paid by the team, but

[23] Most of the top teams operate over the cap, having spent extra money re-signing their own good players, which is why they are now top teams

[24] This is the case in all other American sports leagues. The NBA is the only league with maximum contract lengths

[25] Because the CBA limits the maximum value of a contract as a percentage of the cap (see footnote 3), the very best players in the league provide a large amount of excess value to their franchises. These are the players who get longer term deals and because the contract is already slanted in the team's favor by the price ceiling, they are also almost always given the luxury of player options attached at the end

he is eligible to join other franchises on a new contract.[26] That guaranteed money paid out by the original team, still counts against their salary cap as 'dead money' as of the 2005 CBA.[27] Before the 2005-2006 season, NBA players could be cut and still paid their money, but that salary would not count against the cap. Post-2005, this new approach fundamentally changed team's attitudes towards cutting players, as waiving a player now had the added opportunity cost of not being able to spend that money on other players. For this reason, my sample only goes back to the 2005-2006 season; prior to that time, players were generally more likely to be cut, and therefore operated under a markedly different incentive state.[28] All other literature on the NBA contract year effect sidesteps this matter, using a dataset that straddles the 2005 CBA without mentioning this significant issue.[29]

The difference between waiving and buyout is based on whether the player consents or not. A buyout is a mutual agreement between the player and the team, wherein in exchange for gaining his freedom to sign elsewhere, the player agrees to receive a reduction on the remaining salary he is owed. This option is understandably rarely taken, especially prior to the last season of a contract. It is usually exercised in situations where the player either wants more playing time, or hopes to play for a contending team to try to win a title. Both waiving and buyouts are extremely rare, primarily exercised on albatross contracts – previously good players who have since become dead weight for a franchise.[30] Nonetheless,

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[26] This process is needlessly complicated and irrelevant to our discussion (see Coon (2012) for details). The new contract signed by the player is considered separately from the old one in my analysis, when determining whether seasons are contract years or non-contract years.

[27] A situation congruous to the current state of the NFL

[28] There is substantial anecdotal evidence that this is the case (Jackson, 2005)

[29] White and Sheldon (2013) use a sample from 2003-2004 to 2009-2010. Jean uses a sample from 2001-2002 to 2008-2009. Gaffaney's sample is peculiar in solely focusing on the 2012-2013 season, and comparing performance in that season to career averages

[30] For more information about the minutiae of these processes and in particular the stretch provision, please see Coon (2012)

waiving or a buyout is a constant possibility for players in any contract state, and should be factored in as part of their incentive situation: playing well enough to maintain a roster spot.

The third way in which players can be cut is the amnesty provision. The amnesty provision allows each franchise to designate one guaranteed player, signed under the previous CBA, to be cut without their contract counting against the cap.[31] This provision was written to allow teams one 'get out of jail free' card for a contract signed under the old CBA that is no longer effective under the new league rules. Each team may only use the provision once ever, and thus some players are more likely to be amnestied than others. In addition to the quality of the player and size of his contract, this probability depends on whether a player's contract was signed under the current CBA or the old one, and also which team they are playing for, as some franchises have already designated their one player and others have not. This slightly varying possibility of being amnestied could alter the incentive state, as those with higher probability of being amnestied would have higher incentive to keep their job. Ultimately, however, this probability is realistically unlikely to make any meaningful difference to a player's incentives – even for eligible players, the probability of this happening is extremely low as only 30 total players can be amnestied over six years.[32] Hence, my dataset is not corrected for this discrepancy.

Finally, to form my dataset, I only included player-seasons which were either a guaranteed contract year – in which the player knew at the end of the season that he would enter unrestricted free agency – or a guaranteed non-contract year, in which the player knew that he would continue playing under his contract, whatever its wrinkles might be, for this season and the next. All others, including any first contract in the league,[33] any contract

[31] Though the salary is still paid and the 'set-off' mechanism still applies (see Coon (2012) for details)
[32] The length of each CBA before it is renegotiated
[33] Qualifying offers and fourth years after extensions notwithstanding

containing unguaranteed money or incentives, or any year going into an option year, were excluded. Any of these other variations ultimately change incentives and could pick up different effects than the causal nature on performance of being in a contract year. This is particularly important with regard to the previously detailed bias toward player option contracts.

This information was not readily available. I collected three large databases of contract information, from *Basketball-Reference.com*, from Mark Deeks at S*hamSports.com*, and from S*potrac.com*. Across these three sources of information, I ascertained the contract states of each season for every player who has played in the NBA in some capacity since 2005-06. This date cut-off was chosen because of the aforementioned change in teams' penchant for cutting players after the 2005 CBA, and was also the point when contract information started to become less detailed.[34] Some player-seasons were in all three sources, while some were only in one. Not infrequently, the sources disagreed, resulting in a manual internet search for media coverage at the time the contract was signed to retrieve contract details.[35] Only by such arduous measures was I able to produce the first dataset of its kind, which rigorously considers players' contract situations.

Overall, a plurality of athletes sign only one contract with an NBA team; most never make it back to the NBA, playing overseas or retiring instead. These players never made it into my sample, which is comprised only of players who signed second contracts.[36] Beyond that, a small number were only able to secure unguaranteed contracts and were also excluded, with the rest of the exclusions resulting from option scenarios. Of the 4,133 player-

[34] In particular, the distinction between guaranteed and unguaranteed contracts was often left out, and option years were not as clearly demarcated.
[35] I required at least two independent media sources to agree on the specifics of a contract to verify a player-season's contract state
[36] Footnote 33 still applies

seasons from 2005-2006 to 2013-2014 across 1,038 players, 1,870 player-seasons across 439 players were included in my dataset as either contract or non-contract years as per my definition. Despite this attrition from only including contract and non-contract years, compared to other studies, this sample is still the largest.[37] More importantly, it is the first to be appropriate for analyzing the contract year phenomenon, summarily defined as the change in performance between these two discrete and now well-defined states.

[37] White and Sheldon (2013) used 510 player-seasons across 170 NBA players; Jean (2010) used 1864 player-seasons across 231 players; and Gaffaney used 230 player-seasons from the 2012-2013 season.

III. EVALUATING INDIVIDUAL PERFORMANCE

No current all-in-one basketball statistic can capture a player's contribution to the extent that wins above replacement (WAR)[38] can in baseball. Basketball is a continuous sport while baseball is static; as such, it is far more difficult to determine how to apportion credit between players.[39] As grandfather of basketball analytics Dean Oliver put it: "Because teamwork is not a big part of baseball and because baseball measures progress toward scoring through bases, analysis of baseball player contributions is easier than analysis of basketball player contributions" (Oliver, 2004, 81).

This difficulty has not stopped people from trying to produce so-called 'holy grail' statistics in an attempt to summarize a player's overall contribution to his team. The most common approach is to use linear weights on box score statistics to estimate overall performance. By seeing what box score outcomes are associated with overall team performance,[40] we can infer that players producing such outcomes more often are better players. However, all these formulas are just approximate ways of representing someone's opinion about the quality of players. They are limited to only the information recorded in the box score, and can only partially take into account team environment by incorporating team statistics as well. Despite being written in 2004, Oliver's work summarizes most of the linear weight valuation systems in the public domain today. It is clear that some box score outcomes demonstrate positive value provided by the player while others demonstrate negative value, but the weights differ dramatically, indicative of the difficulty in determining one clear, objective value. Table I is reproduced from Dean Oliver's 2004 research.

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[38] Replacement level is an important concept in player evaluation. It refers, in basketball, to the expected quality of the fictitious best available player not currently on a NBA roster

[39] See introduction for some more color on this topic

[40] This is usually defined as offensive and defensive efficiency – points scored and points allowed respectively – per 100 possessions

Table I: Weights Assigned to Different Statistics, Relative to Points

Statistic	Manley Credits	Hoopstat Grade	Steele Value	Bellotti Points Created[b]	Claerbaut Quality Points[a]	Mays Magic Metric[a]	Schaller TPR[c]	Player Efficiency Rating[a]	Berri Individual Wins[a]
Points	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Assists	1.00	1.39	1.25	1.08	0.63	0.98	0.90	0.79	0.92
Offensive Rebounds	1.00	1.18	1.00	0.92	0.63	0.71	0.75	0.85	3.82
Defensive Rebounds	1.00	0.69	1.00	0.92	0.63	0.71	0.75	0.35	1.71
Steals	1.00	1.39	1.25	0.92	0.63	1.09	1.80	1.20	2.44
Blocks	1.00	1.94	1.00	0.92	0.63	0.87	1.10	0.85	0.86
Missed Field Goals	-1.00	-0.83	-1.00	-0.92	-0.63	-0.71	-1.00	-0.85	-1.38
Missed Free Throws	-1.00	-0.50	-0.50	-0.92	-0.24	-0.55	-0.90	-0.45	-0.79
Turnovers	-1.00	-1.25	-1.25	-0.92	0.63	-1.09	-1.80	-1.20	-2.77
Personal Fouls	0.00	0.00	-0.50	-0.46	0.00	0.00	-0.60	-0.41	-0.46

Table is reproduced from p.83 of *Basketball on Paper* (2004) by Dean Oliver, current head of basketball analytics for the Sacramento Kings

Table is a rough guide only to weights, as many of these use additional team statistics to further refine estimates, particularly for defense

[a]Requires assumption about the average number of free throws made, 2-point field goals made, and 3-point field goals made. Uses approximate averages

[b]Assumes value of ball possession = 0.92, based off Bellotti's own estimates

[c]Adds additional 0.5 points for each 3-point shot made

There are two broad categories of these systems: weights stemming from empirical regression-based formulations and weights stemming from theoretical frameworks. Of the regression-based metrics, the public is most familiar with Hollinger's Player Efficiency Rating (PER), widely popularized by ESPN, which is likely the best of this category. Its fairly complex calculation[41] incorporates team pace and statistics into evaluation of an individual player's box score statistics, with the league average minute set to 15 PER.

The "major weakness in the original PER concept is lack of consideration for defense" (Lawhorn, 2014) and in addition, its inability to correctly punish inefficient high volume shooting. In terms of defense, on an individual level, the box score only keeps track of blocks and steals. PER does not use play-by-play data, so determining defensive contributions is truly limited, especially when one considers that "a player can actually have a large number of steals and blocked shots, even though he is a lousy defender in the team concept" (Ellis, 2013). Noted sports economist Dave Berri has a very harsh critique of Hollinger, calculating that:

> "A player will 'break even' on two point field goals attempts if he hits on 30.4% of these shots. On three pointers the break-even point is 21.4%. If a player exceeds these thresholds, and virtually every NBA player does so with respect to two-point shots, the more he shoots the higher his value in PER. So a player can be an inefficient scorer and simply inflate his value by taking a large number of shots" (Berri, 2006).

In this way, PER overvalues high usage players and to some extent punishes low volume, but high efficiency, offensive contributors. Hollinger responded directly to this claim, arguing that since the PER is calibrated to a league average of 15.0 each season, the 'break-even' points calculated by Berri are invalid. So while PER is the best of a relatively poor group of regression-based linear approaches and the furthest previous studies have gone in analyzing the contract

[41] See Appendix 1 for details

year phenomenon,[42] it still leaves much to be desired regarding accurate evaluation. Ultimately, in Berri's opinion, "one can show … that metrics like [PER] are capturing people's perceptions of performance," despite "evidence that perceptions of performance in basketball do not match the player's actual impact on wins" (Berri, 2006), with particularly an overemphasis on scoring points over other attributes.

Berri's own system of 'Wins Produced' (WP)[43] was the first leader in theoretical formulations of the linear weights, which started with *a priori* assumptions about how to assign weights – and then used regression from the data to assign values (Berri, 2006). This is in contrast to Hollinger's approach, in which it is assumed little is known, begin with regressions, and make adjustments based on sensible intuition from there. Oliver produced his own all-in-one statistic from a theoretical framework, creating individual offensive and defensive ratings, which estimate how many points a player scores and allows per 100 possessions, respectively. Oliver's insight was to use interactive weighting, which fluctuates based on a team's characteristics. For example, he argues that "an assist on a good shooting team tends to be more valuable than one on a poor shooting team" (Oliver, 2004, 147), and thus the weight on assists should vary accordingly. This concept "allows unique assignment of team success to the teammates who cooperated to create that success" (Oliver, 2004, 149). His formulas were updated by Justin Kubatko to produce an all-in-one 'win shares' metric (Kubatko, 2009). This metric can be split into offensive and defensive contributions, correcting for league environment to estimate the number of wins produced by each player.[44]

Paine's 2011 study 'Is WP a Legitimate Stat?' compares these major box score systems. Ultimately, he found that "the more time that goes by, the worse and worse WP gets relative

[42] White and Sheldon (2013) drew primary conclusions from PER
[43] Jean (2010) used a simplified version of this metric
[44] See Appendix 2 for details of calculating win shares

to the competition" (Paine, 2011) and is arguably no better than PER, but win shares consistently outperforms the others in his study and is likely the best linear weights system. Rosenbaum (2012) upheld the study's conclusion, and win shares are now considered to be the industry standard linear weights performance metric by the APBRmetric[45] community, significantly improving upon Hollinger and Berri's approaches.

Nonetheless, as with all rating systems based on box score data, win shares cannot account for contributions not tracked in the box score, notably on defense (Pelton, 2012). The stat sheet ignores screens, boxing out, the spacing provided by an elite shooter, and countless other tangible and intangible contributions a basketball player provides to his team. Hence, all of these box score derived metrics can belie the truth of an observed contract year effect. If we want to test if players play better in a contract year, then our metric for performance should be better at taking defensive contributions into account, and less beholden to offensive output. It is very possible that players, knowing they are in a contract year, will try to take more shots and put up points – but in doing so, they may hurt their team if they shoot when they should pass. A statistic better able to evaluate a player's actual overall contribution to a team, including what is not recorded in the box score, will allow us more insight as to whether or not there is truly a contract year effect.

In order to create a static analogue to baseball within basketball, possessions can be considered as their own discrete events. By evaluating a player's contributions to offensive and defensive possessions on average, we can estimate an overall contribution by the player on a per-possession basis. These metrics are adjusted plus-minus statistics, which as a

[45] APBRmetrics stands for Association for Professional Basketball Research Metrics and is a term used to refer to the statistical analysis of basketball. It is basketball's corollary for the better known term Sabermetrics, derived from the acronym SABR (Society for American Baseball Research), coined by pioneer Bill James

baseline take a player's plus-minus[46] on each end, but then crucially adjusts for all other players on the court. This adjustment is vital, as good players will face other good players more often than they face bad players, so their raw plus-minus will belie their true contributions. The underlying framework is that each possession has a known value, which is the points scored, and ten variables that are the contributions of each player. Most systems additionally adjust for the average per possession home court advantage in the NBA,[47] and then plug in every possession in an NBA season in an ordinary least squares framework to find the values for all the unknown variables – the players' offensive and defensive contributions. This method attempts to consider all of a player's entire contributions on the offensive and defensive end in one number, without relying on what humans have chosen to record and assigning weights to those observations. The result is two numbers for each players, usually expressed as the number of points above or below the average a player contributes to each 100 offensive and defensive possessions. The sum of these two is an all-in-one metric summarizing a player's quality over the course of a season.

Major issues exist with this framework. The first is the assumption that a player applies a constant amount of defensive and offensive impact over the course of the season, and that each possession is played in the same environment.[48] Player quality is not allowed to fluctuate over the course of a season, despite times when a player may be slightly injured or other exogenous factors. Most notably, though it controls for the quality of teammates, it does not control for the changing role of a player if he is traded or if the coach institutes a new system.

[46] Plus-minus refers to a player's team's point differential while he is on the court. It has recently become a part of the box score, but is almost meaningless by itself unless you adjust for the other players on the court

[47] In basketball, home teams win about 60% of the time in the NBA. This home court advantage is likely almost entirely due to refereeing bias (Dubner, 2011)

[48] In contrast, Goldman and Rao (2013) have found evidence of an 'elastic effect' that players play better when behind than when ahead, with all other things equal

Some players will thrive in one system but falter in another, independent of the quality of their teammates. In addition, 'garbage time' minutes – the final minutes of a game which has a clear winner – are likely different from the possessions at the end of a game in which the win is determined by the final possession or last shot. Yet in this system, all contributions on each possession are weighted evenly.[49]

The second issue is that collinearity occurs in this data because of the way coaches use rotations. Some players may only be subbed in or out of the game together. In the extreme, consider if two players play every possession together in a season except one, in which the team scores two points (efficiency = 200 points per 100 possessions), so the player on court at the time would be rated +200 over the other player on offense. Assuming that after accounting for all the other possessions and contributions from other players their offensive contributions must sum to zero, then one player gets +100 points over average and the other gets -100 points below average, despite having markedly similar seasons. A second case is when two players are only substituted for each other. When this is the case, we only really can detect how they relate to each other, not how the two of them relate to their teammates. If a team is overall +8, we cannot tell if the center (the position occupied solely by two players) is +10 and the team is -2, or vice-versa, without any possessions during which the center is not on the court. Furthermore, the numbers that are returned are subject to the vagaries and wild noise of the few minutes when neither center is playing (Myers, 2011).

[49] There is significant philosophical debate in the APBRmetrics community as to whether to weight possessions differently depending on their importance. It is currently argued that we cannot infer the average player's effort level if their team has a 50% chance of winning relative to a 95% chance relative to a 5% chance, and so we should just treat effort as constant and weight all possessions equally. In contrast to this, Michael Beuoy of inpredictable.com has created a performance metric called Win Probability Added (WPA) which weights possessions by their probability of altering the final result (Beuoy, 2014). However, it has come under heavy criticism as performance is largely being determined by a few plays in close games late in the fourth quarter and thus is ultimately unrepresentative of a player's true seasonal performance

This occurrence is fairly common at the center position, which relatively few humans can play owing to a shortage of seven-foot tall people in the world. Consider, for example, the 2009-2010 Orlando Magic team, with Dwight Howard and Marcin Gortat both 6'11" and both playing center. Any Magic lineup which played for more than 13 minutes all season contained exactly one of Gortat, a solid back-up who may have started for some teams, and Howard, an MVP candidate and likely the best center in the game that season. Pure adjusted plus-minus[50] considered Gortat to be 13.73 points above average per two hundred possessions, which would be a runaway MVP performance if true most years, with Howard also overvalued at +24.97 (Myers, 2011). In reality, Gortat was likely around league average or slightly below and Howard was 11 points better than him, right around a typical MVP performance, but collinearity conspired to paint the two as gods surrounded by a team of significantly below replacement level ne'er-do-wells.

The final and most significant issue is that "the sample size within one season is not enough for stability" (Myers, 2011). Thus, it is an incredibly noisy statistic with large standard errors on individuals, even within an 82 game season and roughly 200 possessions per game. Ken Pomeroy's simple simulation demonstrates this effect. He created a hypothetical player who has absolutely no impact on the game, with defined probabilities of scoring on each possession as the same for both teams with these probabilities unchanged whether the player is in the game or on the bench (Pomeroy, 2011). He then simulated a shortened season of twenty games and tallied his non-impactful player's plus-minus. On average, and in a situation where one does not need to account for teammates as they are constants, the player's average per game plus-minus was 4.8 points[51] away from zero, despite there being "very few

[50] Not containing any of the adjustments later described in xRAPM

[51] This overstates the effect, as some of the noise would reduce over a 82-game season

players in the country who, if they got hurt, would move the Vegas line for their team by more than a couple of points" (Pomeroy, 2011).

Though various stabilization techniques can be used to correct for this excessive noise, it is ultimately very difficult to use adjusted plus-minus alone to draw meaningful conclusions about an individual player's performance in a single season. However, in estimating the contract year effect, we are concerned with evaluating performance in aggregate. If we assume that errors in measuring performance are independent of being in a contract year, then we can potentially still draw conclusions. Pure adjusted plus-minus is still far too noisy, given the size of my dataset, but I will use two stabilized versions in my analysis.

The first is again derived from the box score. Known as 'statistical plus-minus' (SPM), this approach places linear weights on observed outcomes to estimate adjusted plus-minus as the dependent variable. This estimate is much more consistent than the underlying variable from year to year, and improves identifying performance over other box score derived metrics described above (Paine, 2011). Daniel Myers' recently created 'box plus-minus' (BPM) is the best of this category of metrics for three reasons. Firstly, he was extremely careful in how he set up his model, which though it "leans toward the empirical side", is grounded in theory and goes further than its competitors as a couple of nonlinear interactions are modelled, which are highly statistically significant and make sense (Myers, 2015). Secondly, the sample draws on 'advanced box score' measures rather than, for example, simple points scored and field goals attempted, which are more accurate and less skewed by context. Finally, his underlying sample is both better stabilized and covers a longer period of time than any other statistical plus-minus approach.[52] The results[53] are likely the best single season estimate of a player's performance, and in particular solve the collinearity issue.

The second version I will use in my analysis is Engelmann's xRAPM. His basic approach to stabilization is to produce a prior estimate of performance for each player, and then subsequently update that number given the observed adjusted plus-minus into a posterior estimate of a player's contribution for the season. This Bayesian technique could be as easy as assuming as a prior that every player has an average rating of 0.0, and then regressing each player to this mean by a certain number of minutes. Engelmann's more complex approach to forming a prior is threefold: his formula considers this season's statistical plus-minus, using some variant of Myers' number; a player's age; and the previous year's xRAPM. The weighting on these numbers is a function of both age itself and the minutes played this season and last. By using last year's xRAPM, he is implicitly using xRAPM from the year before, and so on and so forth. Engelmann recursively solves his system of equations over multiple previous seasons to determine his final results, and his method of posterior estimation takes advantage of a mathematical method known as Tikhonov Regularization. Usually, the extent of regression towards the prior is based off how many minutes were played this season and how that compares to the last few seasons, informing the confidence of the prior. Tikhonov Regularization adds a penalty factor for observed outcomes which are very dissimilar to the prior, adding more weight to the prior if the observed number is very far away, with the optimal penalty factor chosen by k-fold cross validation.

[52] Myers uses an unweighted 14-year sample from 2001-2014 of Jeremias' Engelmann's 'Expected Regularized Adjusted Plus-Minus' (xRAPM), as will be described in the following paragraph, as the basis of the regression
[53] Appendix 3 contains the framework of Myers' approximation to plus-minus and shows his estimated coefficients

Engelmann's method is the best publicly available method of stabilizing the pure adjusted plus-minus data, and thus probably the best estimation of an individual's pure performance in an individual season, but there are two major concerns. It is still significantly noisier than statistical plus-minus and the linear systems, and secondly, it is arguable that it is ill-suited to estimate the contract year effect. Contract years are more likely to occur on the downslope of the aging curve,[54] and given that a large part of a player's prior is his previous season xRAPM adjusted for age, he is expected to perform worse than last year in most contract years. Because of the penalty factor, xRAPM is more skeptical of increases over expected performance – as one would see in a contract year – than of decreases as some level of diminished performance is expected. Hence, in this manner, estimates could be biased downwards.

This section serves to formalize that there is no 'holy grail,' all-in-one statistic to measure overall player performance as there is in baseball. Acknowledging this limitation, it is best to proceed consider a variety of all possible approaches. This paper will analyze the best regression-based linear weights system, Hollinger's PER; the best theoretical-based linear weights system, Kubatko and Oliver's win shares (WS);[55] the best statistical plus-minus, Myers' box plus-minus (BPM); and the best stabilized adjusted plus-minus, Engelmann's xRAPM. All of these metrics are relative to league average and have both an efficiency (value produced per minute on average in a season) and volume (total value produced in a season) component. Estimated Wins Added (EWA), Statistical Wins Above Replacement (SWAR) and Wins Above Replacement (WAR) are the volume corollaries to PER, BPM and xRAPM

[54] Players are more likely to receive shorter contracts when past their prime and hence are more likely to be in contract years (see Table V)
[55] Win shares per 48 minutes is the efficiency corollary

respectively.[56] All efficiency metrics except PER have offensive and defensive components. All volume metrics are measured in wins, with EWA and WS purporting to be the overall wins contributed by a player, and SWAR and WAR the wins contributed by a player above replacement level.[57] Only win shares has offensive and defensive volume components, as it is not reasonable to consider separate offensive and defensive replacement levels for the plus-minus statistic and PER has no separate defensive component.[58] BPM and xRAPM are measured in points above or below average per 200 possessions, while their offensive and defensive components are measured over 100 possessions on that end of the court. For all these metrics, Tables II and III contains summary statistics for the NBA from 2005-2014 for all player-seasons in that timeframe, not just those in my sample. Take note that performance can be considered to be negative, if the performance of a player is such that he takes away from a team's ability to win, relative to a replacement level player (which is defined at different levels by the metrics).

All data on PER, win shares and statistical plus-minus was taken from the databases at B*asketball-Reference.com*, as was any other box score information and background information used in Section IV.[59] All xRAPM-related info was taken from Engelmann's website at *stats-for-the-nba.appspot.com*.

None of these measures of performance in isolation provide a wholly accurate description of a player's overall contributions to his team, or anything akin to WAR in baseball.

[56] Appendices 1-3 contain the formula for converting the efficiency metrics into volume metrics

[57] Replacement level, as outlined in footnote 32, has come to be defined after much debate as -2.0 points below average per 200 possessions (100 offensive and 100 defensive) in the NBA (Tango, 2014)

[58] In basketball, some players are primarily offensive in nature and some are primarily defensive and this varies with position. For example, almost all point guards would be below 'defensive replacement level' and almost all centers would be below 'offensive replacement level'. One could conceivably alter replacement level based with position as is done in baseball analysis, but positions in the NBA are nowhere near as well defined as in baseball. The upshot is that it is currently thought to be of little value to consider offensive and defensive replacement levels separately (Tango, 2014)

[59] For example, a player's height, weight, age and so forth

However, when taken together as a group, performance is measured more broadly from various different angles, and we start to get closer to an objective view of performance. Basketball analytics is still very much in its infancy and as the field progresses and new and more precise performance metrics are produced, the methodology outlined in the next section will only produce more precise results.

Table II: Summary Statistics for Efficiency Metrics

Metrics	Mean	Standard Deviation	5th Percentile	25th Percentile	50th Percentile	75th Percentile	95th Percentile
Player Efficiency Rating	3.85	6.14	4.1	9.8	12.8	15.9	21.3
Win Shares per 48 Minutes	0.073	0.096	-0.049	0.037	0.080	0.121	0.179
Statistical Plus-Minus (SPM)	-1.75	3.89	-7.7	-3.5	-1.4	0.5	3.4
xRAPM	-0.96	2.54	-4.3	-2.6	-1.5	0.3	3.9
Offensive Win Shares per 48 Minutes	0.025	0.085	-0.085	0.000	0.033	0.067	0.118
Defensive Win Shares per 48 Minutes	0.046	0.026	0.000	0.030	0.046	0.064	0.090
Offensive SPM	-1.42	3.29	-6.3	-3.0	-1.3	0.5	3.0
Defensive SPM	-0.33	1.88	-3.1	-1.5	-0.3	0.8	2.6
Offensive xRAPM	-0.61	1.92	-3.4	-1.8	-0.9	0.3	2.9
Defensive xRAPM	-0.34	1.82	-2.8	-1.5	-0.7	0.6	3.2

Source: Basketball-Reference.com & stats-for-the-nba.appspot.com. Sample includes all player-seasons from 2005-2014

Table III: Summary Statistics for Volume Metrics

Metrics	Mean	Standard Deviation	5th Percentile	25th Percentile	50th Percentile	75th Percentile	95th Percentile
Estimated Wins Added	2.69	4.59	-1.2	-0.1	0.9	4.0	12.2
Win Shares	2.75	3.08	-0.2	0.3	1.8	4.3	9.0
Statistical Wins Above Replacement	1.76	3.55	-1.4	-0.3	0.3	3.0	8.6
Wins Above Replacement	1.82	3.82	-1.5	-0.2	0.2	2.8	10.1
Offensive Win Shares	1.43	2.15	-0.5	0.0	0.7	2.3	5.7
Defensive Win Shares	1.32	1.24	0.0	0.3	1.0	2.0	3.8

Source: Basketball-Reference.com & stats-for-the-nba.appspot.com. Sample includes all player-seasons from 2005-2014. Volume metrics for the 2011-12 season are prorated to 82 games.

IV. METHODOLOGY & RESULTS

My baseline attempt to estimate the true effect of being in a contract year, relative to being in a non-contract year as now rigorously defined, was to use a player fixed-effects model within a two-stage least squares instrumental variables framework, as follows (see footnote for details of variables).[60]

$$CY_{it} = \theta_i + \pi \cdot X_{it} + \tau \cdot I + \mu_{it} \quad (1)$$

$$Y_{it} = \alpha_i + \beta \cdot X_{it} + \delta CY_{it} + \epsilon_{it} \quad (2)$$

Including player fixed effects in this manner led me to duplicate my analysis for both the full dataset and a reduced sample, which only includes players who had both contract and non-contract years from 2005-2014. For those not meeting this criterion, the constant player fixed effects (θ_i,α_i) account for their permanent contract state during the sample. The reduced sample contains only 1,458 player-seasons across 276 players of the 1,870 player-seasons across 439 players in the full sample. Analyzing the reduced sample allows me to perform an important sensitivity check by modifying my first stage to a probit model as in equation (3), with $\vec{X}_{it}$ as all the independent variables in equation (1) including my instrument.

$$\hat{p} = \Pr\left(CY_{it} = 1 \middle| \vec{X}_{it}\right) = \Phi(\vec{X}'_{it} \cdot \gamma) \quad (3)$$

Subsequently, I use the predicted $\hat{p}$ values as my instrument in equation (1), such that my first stage residuals are uncorrelated with covariates and fitted values (Wooldridge, 2002, 623-625). Table III suggests that the shift between the full and reduced samples is not a drastic change in composition. I calculate each player's average win shares per 48 minutes from 2005-2014 for all seasons, not just those in my sample. I then categorize the player and his

[60] θ_i and α_i are my fixed effects for player *i*; X_{it} are the background covariates, as outlined later, for player *i* in season t; CY_{it} is a dummy for whether player *i* is in a contract year in season *t*; Y_{it} is a performance metric for player *i* in season *t*; and I is my instrument described below.

player-seasons by his quartile relative to the entire league during this period, not just the players in my dataset. Under this lens, more player-seasons and players do drop out from the top and bottom quartiles, but not that much more than from the middle two quartiles. It also shows that the players in my dataset, composed of veterans who were able to secure guaranteed contracts, are above average. Table VI provides further insight into the difference between the full and reduced samples.

Table IV: Comparison of Full and Reduced Samples

Performance Quartile	Number of Player-Seasons			
	Full Sample	Reduced Sample	Change	Percent Change
First Quartile	213	166	47	22%
Second Quartile	524	426	98	19%
Third Quartile	735	576	159	22%
Fourth Quartile	398	290	108	27%
Total	1870	1458	412	22%
Performance Quartile	**Number of Players**			
	Full Sample	Reduced Sample	Change	Percent Change
First Quartile	60	37	23	38%
Second Quartile	138	92	46	33%
Third Quartile	159	102	57	36%
Fourth Quartile	82	45	37	45%
Total	439	276	163	37%

Source: Basketball-Reference.com, Spotrac.com & ShamSports.com
Full sample consists of all player-seasons from 2005-2014 which were either contract years or non-contract years. Reduced sample only kept player-seasons for which player had both a contract and non-contract year from 2005-2014. Refer to text for definitions of contract states and for definition of performance quartile, which is measured relative to the NBA as a whole, not just my dataset

My background covariates in equations (1) and (2) are a player's age and age squared in that season to allow for convexity, centered around the sample mean to reduce collinearity;

his height and weight, treated as constants over his career as there is no annual measuring in the NBA; dummies for position, as defined by *Basketball-Reference.com* for each player-season; and finally team quality.[61]

This framework vastly improves over an ordinary least squares approach, as it can identify the causal effect of being in a contract year, taking into account the inherent endogeneity of being in a contract year. Worse players get shorter contracts and hence have a higher probability of being in a contract year. Table V clearly demonstrates this endogeneity (results are very similar for the reduced sample), and ignoring it and simply comparing means as in Table VI would lead us to incorrectly conclude in a negative contract year effect.

The constant player fixed effects attempt to be a proxy for unobserved player quality, assumed within the model to be constant over the course of the timeframe of the dataset after controlling for age, position, height, and weight. Given this approach, I require an instrument that affects a player's probability of being in a contract year without being correlated with performance. Fortunately, I can take advantage of exogenous shifts in the league structure, such that the former is affected independent of player quality. As shown in Figure I, the percentage of the total proportion of NBA players in a contract year varies substantially over the timeframe.

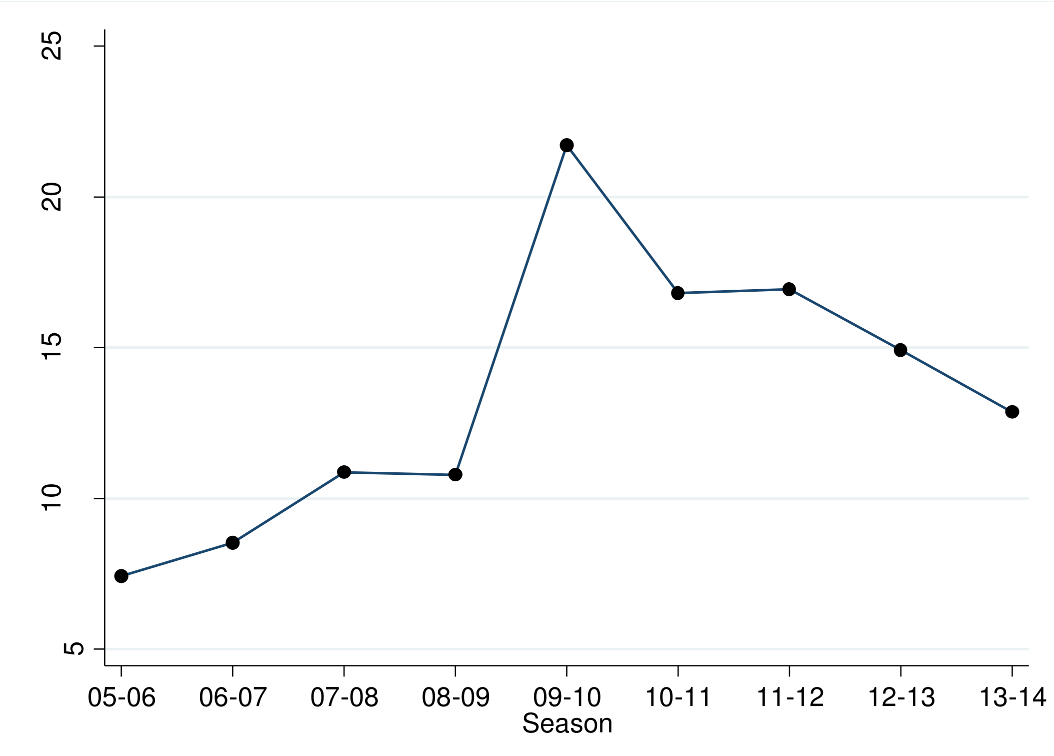
[61] Team quality was calculated thusly: Improving on Gaffaney's crude use of team wins as a measure of quality, a team's simple rating (SRS) was used instead. SRS is a team's average point differential on a neutral floor over the course of a season. Crucially, unlike pure wins, it is adjusted for strength of schedule. If a player played three quarters of his minutes for one team and a quarter for another, then he was given the average of those two teams for that season, weighted by the minutes played, with this process repeated for any player who played for greater than one team in a given season. In addition using team dummies for each of the 30 franchises, to potentially pick up a team's 'good culture' beyond just quality in that given season, failed to pass an extra-sum-of-squares F-test for either the first or second stage in equations (1) and (2), with p-values returned in excess of 0.4. Hence they were excluded from the specification. All upcoming results, including team dummies are reported in Appendix 5 as a sensitivity check.

Table V: Correlation with Contract Year Dummy

PER	-0.2485
WS/48	-0.1784
SPM	-0.2186
xRAPM	-0.2461
Team Quality	-0.0526
Age	0.2197
Height	-0.0216
Weight	-0.0135
Point Guard	0.0243
Shooting Guard	-0.0197
Small Forward	0.0091
Power Forward	0.0088
Center	-0.023

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com
Results shown are for full sample of 1870 player-seasons from 2005-2014 which were either contract years or non-contract years. Refer to text for definitions of these, and for description of performance metrics. Team quality is measured by a team's SRS, as outlined in footnote 61. Positional designations for players are from Basketball-Reference.com

Figure I: Percentage of NBA Players in a Contract Year from 2005-2014



Source: Basketball-Reference.com, ShamSports.com & Spotrac.com
Note: Shows the proportion of players in the NBA in a contract year, as defined in the text, for all seasons from 2005-2006 to 2013-2014

Table VI: Summary Statistics

Comparison of Means by Contract Year Status

Efficiency Metrics	Full		Reduced	
	Non-CY	CY	Non-CY	CY
Player Efficiency Rating	14.8	12.1	14.4	12.3
	(0.133)	(0.196)	(0.145)	(0.216)
Win Shares/48 (WS/48)	0.102	0.0768	0.0994	0.0791
	(0.00182)	(0.00257)	(0.00183)	(0.0028)
Statistical Plus-Minus (SPM)	-0.0892	-1.56	-0.198	-1.43
	(0.0827)	(0.129)	(0.0902)	(0.142)
xRAPM	0.335	-1.176	0.189	-0.999
	(0.0782)	(0.0103)	(0.0885)	(0.115)
Offensive WS/48	0.0508	0.0262	0.0486	0.0286
	(0.0262)	(0.00269)	(0.00162)	(0.00295)
Defensive WS/48	0.0512	0.0492	0.0507	0.0493
	(0.000687)	(0.000973)	(0.000787)	(0.00106)
Offensive SPM	-0.173	-1.431	-0.254	-1.34
	(0.0712)	(0.111)	(0.0775)	(0.123)
Defensive SPM	0.0833	-0.135	0.0549	-0.0946
	(0.0485)	(0.0704)	(0.0548)	(0.0764)
Offensive xRAPM	0.0869	-0.960	-0.0328	-0.861
	(0.0626)	(0.0794)	(0.0698)	(0.088)
Defensive xRAPM	0.248	-0.214	0.222	-0.136
	(0.0583)	(0.0795)	(0.0674)	(0.0876)

Volume Metrics	Full		Reduced	
	Non-CY	CY	Non-CY	CY
Estimated Wins Added	4.70	1.90	4.34	2.13
	(0.153)	(0.158)	(0.166)	(0.179)
Win Shares (WS)	4.37	2.46	4.23	2.65
	(0.0943)	(0.110)	(0.103)	(0.122)
Statistical Wins Above Replacement	3.41	1.36	3.20	1.57
	(0.117)	(0.120)	(0.123)	(0.135)
Wins Above Replacement	3.70	1.37	3.48	1.62
	(0.130)	(0.141)	(0.145)	(0.159)
Offensive WS	2.41	1.20	2.30	1.33
	(0.0686)	(0.0783)	(0.0738)	(0.0880)
Defensive WS	1.96	1.26	1.93	1.32
	(0.0383)	(0.0440)	(0.0436)	(0.0492)

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com

Results for both full and reduced samples, as defined in text, from 2005-2014. Refer to text for definitions of contract year, and for descriptions of performance metrics. All volume metrics from 2011-12 season are prorated to an 82-game season.

The 2005 Collective Bargaining Agreement (CBA) had a drastic impact on the contract landscape of the NBA. Because the penalty for cutting players became much harsher in the aftermath, substantially increasing the opportunity cost, the length of new contracts was reduced, as the cost of an overpriced, long contract was greater. Extensions became exceedingly rare, resulting in more players completing their contracts and thereby entering contract years, as well as a reduction in the maximum length of contracts as outlined earlier, also producing more contract years. This rise coincided with the introduction of 'moneyball' into basketball as analytics began to take hold in front offices (Lewis, 2009).[62] Relative to the more traditional approach, analytics has tended to preach caution with handing out long contracts, given the associated increased risk of injury or reduced performance with long contracts.

These effects explain the steady increase in the number of contract years from 2005-2006 to 2008-2009. But the jump in 2009-2010 springs from the institution of standardized first round rookie contracts. By making these contracts four years in length until restricted free agency – five years until unrestricted free agency, with nuances as described earlier – we see a lagged effect from the 2005 CBA, with a huge jump after the 2005 NBA draftees begin to enter unrestricted free agency from their second contracts. The market also quickly adjusted to provide second round contracts of similar length, leading to the situation described earlier. This was compounded by a greater number of shorter contracts signed from 2005-2009 than previously, but that too came in steadily with a lag. This lag was the result of formerly optimistic very long contracts, signed under the 1999 CBA, which were deadweight on NBA rosters post-2005, and those toxic contracts took time to clear as only a few could be

[62] A landmark moment was the Houston Rockets' hiring of Daryl Morey as the first pure statistician to be a general manager in May 2007

amnestied. These lagged effects explain some of the leap, but to explain the boom of 2009-2010 we need to consider the 'LeBron effect'.

A generational talent, LeBron James signposted his decision to turn down his player option and enter free agency during the 2010 offseason well in advance. To give an idea of the impact of his choice, nearly 10 million viewers watched ESPN's airing of 'The Decision' live – more viewers than almost any single playoff game (Nielsen, 2010). Irrespective of the team he chose, James' decision would dramatically shift the balance of power in the NBA, as his new team would almost by default be the perennial title favorite.[63] As this occasion was telegraphed in advance, many free agents timed their previous contract to coincide with James' announcement, with the idea of capitalizing on the resulting mass musical chairs and securing a place on James' new team. This effect trickled down throughout all strata of the league, as everyone wanted to join the self-proclaimed 'King'. The result was a "free agent class … that would alter the face of the league for a decade to come" (Ciscell, 2013). Hyperbole aside, the 'LeBron effect' explains the massive jump in contract years in 2009-2010.

The small decreases in the past two seasons are counterintuitively explained by the 2011 CBA, and by the upcoming explosion of the salary cap (Lowe, 2014(a)). Although the 2011 CBA made contracts even shorter, it also decreased the number of contract years, by increasing the number of option contracts and thus reducing the number of 'pure' contract years and 'pure' non-contract years. In essence, while the 2005 CBA changed three and four year contracts into two and three year contracts, the 2011 CBA changed two and three year contracts into one and two year contracts with options on a second and third year, respectively. The salary cap explosion is tied to the huge new television deal the NBA signed

[63] Since the move, James' team has always been the preseason favorites to win the title for five straight seasons

with ESPN and TNT. Though only signed in October 2014, it was known far in advance that the money received from the networks would be significantly greater than under the previous deal. The deal comes into effect after the 2015-2016 season when the cap will explode from \$63 million to over \$90 million (Lowe, 2014(a)).[64] Operating under this knowledge that the cap would escalate dramatically when the current television deal expires, teams have been signing some players to longer deals, willing to stomach the additional risk as those deals will look extremely cheap when the cap is 50% larger.

Outside of changing the league's contract landscape, other potential avenues could have impacted performance from 2005-2014. Rule changes rendered some players more useful, others less so; improved conditioning and medical advances made recovery from injury quicker. In addition, the slow induction of statistics into NBA team management saw monumental increases in three-point attempts and reductions in midrange two-pointers. Yet, there is no reason to think that these changes affect players on contract years more or less than players in non-contract years. Crucially, all of my performance metrics are measured relative to league average and adjusted for pace. If we use this instrument, our dependent variable could not just be something simple such as points scored, as the league environment for scoring points has changed. Similarly, all players benefit from medical advancements, but a player's performance relative to league average stays constant, even as his absolute performance may increase.

The two best instruments I find to take advantage of this exogenous variation in contract years with seasons are firstly, an indicator of whether the season was from the 2009-10 season on; and secondly, using the number of contract years in the league that season

[64]To give some context, the cap has risen from \$49 million dollars over the last decade. A jump of this magnitude has never been seen before in any major American sports league

divided by the number of players who played at least one minute in the NBA that season as the indicator itself. Table VII reports Cragg-Donald F-statistic as a test of the strength of the instruments and the p-value returned from the Hansen-J statistic testing for overidentification. The first model is relevant at this point, while the latter is relevant later.

Table VII: First Stage Statistics

Model	Sample	Instrument			
		Year Indicator	CY Percent	Both	
		F-Stat	F-Stat	F-Stat	P-Value
With Player Fixed Effects	Full	15.56	13.20	8.06	0.4169
	Reduced	13.26	9.97	6.70	0.0236
Without Player Fixed Effects	Full	34.52	41.90	21.39	0.1700
	Reduced	69.71	51.49	34.72	0.0366

Source: Basketball-Reference.com, ShamSports.com & Spotrac.com
Full and reduced samples, as defined in text, are from 2005-2014. Table reports key statistics for first stage in instrumental variables framework, as outlined in equation (1) and (2) in text. F-Stat refers to Cragg-Donald F-Statistic. P-Value is that returned from Hansen-J statistic as test of overidentification

Using the approximate rule of thumb that the F-statistic should be greater than 10 (Stock, Wright and Yogo, 2002), both of these instruments bear up as sufficiently strong identifiers of being in a contract year. Player fixed effects have a dramatic impact on the strength of the instruments, because many players only appear once or twice in the dataset. Within my dataset, knowing only the name of a player thereby provides enormous insight into his contract year status. Using both instruments together may be a case of overidentifying, and my instruments are certainly correlated, but the extremely strong rejection of the null for the reduced sample is likely a statistical fluke attached to the weakness of the instrument, given the inability to reject the null for the full sample. Estimates using all three instrument approaches are thus included.

Table VIII reports the estimates for delta in equation (2) for ordinary least squares, and using equation (1) as a first stage for all three instrument approaches, for the full sample. Table IX repeats these estimates for the reduced sample, and includes estimates with the fitted probabilities from equation (3), formed from the respective instruments, as the instrument in equation (1). All standard errors are calculated robust to heteroskedasticity and are clustered by player for each table.

The results are undeniably muddled. My instruments likely do not identify a player's contract status sufficiently well, resulting in extremely large standard errors.[65] It is extremely telling that when using the probit approach for the first stage in Table VIII – which does a significantly better job of bounding the fitted value passed to the second stage – my standard errors shrink substantially. This suggests that the large standard errors for IV estimates in Tables VIII and IX are the result of outlying fitted values outside the bounds of zero and one.

The negative and significant estimate shown for xRAPM is unlikely to be indicative of an adverse contract year effect. If being in a contract year did negatively affect a player's xRAPM, we would heavily expect it to affect his statistical plus-minus too, but that effect is considerably more muted and insignificant. This implies that the result is more likely due to both the significant noise in measuring performance inherent to xRAPM, and the mechanism described earlier by which xRAPM's methodology is negatively biased against measuring contract year impact. The significance also disappears for the probit model, and indeed, the sign of the estimate changes for SPM estimates, making it extremely unlikely the effect on xRAPM is truly negative.

[65] Many studies in basketball arbitrarily cut off player-seasons under a certain minutes restriction, as they argue that the noise in measuring performance is too great unless enough minutes have been played. However, given the observed effect in baseball that players play more during a contract year (Perry, 2006), it is not clear that a cutoff is necessary or appropriate to this study. Nevertheless, all results are reported in Appendix 6 with only player-seasons of over 200 minutes included

Table VIII: Contract Year Effect Estimates for Full Sample

TSLS Estimates of Delta				
		Instrument		
Efficiency Metric	OLS	2010 Indicator	CY Percent	Both
Player Efficiency Rating	0.124	-0.857	-2.57	-1.35
	(0.215)	(1.617)	(1.96)	(1.61)
Win Shares per 48 Minutes	0.00319	0.00485	-0.00757	0.00125
	(0.00310)	(0.0243)	(0.0274)	(0.0237)
Statistical Plus-Minus (SPM)	-0.0420	0.334	-1.46	-0.186
	(0.151)	(1.08)	(1.31)	(1.06)
Expected Regularized Adjusted Plus-Minus (xRAPM)	-0.0411	-2.28*	-3.85**	-2.74*
	(0.108)	(1.01)	(1.47)	(1.08)
Offensive Win Shares per 48 Minutes	-0.000221	0.00649	-0.00913	0.00196
	(0.00333)	(0.0246)	(0.0282)	(0.0245)
Defensive Win Shares per 48 Minutes	0.00202	0.00937	0.00418	0.00786
	(0.000963)	(0.00804)	(0.00903)	(0.00792)
Offensive SPM	-0.0629	-0.1740	-1.43	-0.540
	(0.127)	(0.944)	(1.14)	(0.941)
Defensive SPM	0.0213	0.526	-0.0116	0.370
	(0.0609)	(0.486)	(0.537)	(0.463)
Offensive xRAPM	0.0216	-1.57*	-2.72*	-1.90*
	(0.0827)	(0.766)	(1.12)	(0.823)
Defensive xRAPM	-0.0643	-0.698	-1.09	-0.811
	(0.0668)	(0.544)	(0.688)	(0.558)
		Instrument		
Volume Metric	OLS	2010 Indicator	CY Percent	Both
Estimated Wins Added	0.313	0.0587	-0.905	-0.221
	(0.194)	(1.55)	(1.85)	(1.54)
Win Shares	0.0902	-0.00349	-0.560	-0.165
	(0.136)	(1.08)	(1.27)	(1.07)
Statistical Wins Above Replacement	0.156	-0.0845	-0.718	-0.268
	(0.147)	(1.25)	(1.52)	(1.25)
Wins Above Replacement	0.107	-1.847	-3.10	-2.21
	(0.169)	(1.445)	(1.94)	(1.50)
Offensive Win Shares	0.124	-0.0721	-0.419	-0.173
	(0.106)	(0.829)	(0.980)	(0.826)
Defensive Win Shares	-0.0382	0.0879	-0.998	0.0335
	(0.0536)	(0.463)	(0.541)	(0.457)

* p < 0.05; ** p < 0.01; *** p < 0.001. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com.

Full sample contains all 1870 player-seasons which were contract or non-contract years, as defined in the text, across 439 players from 2005-2014. Performance metrics and instruments used are described in the text. IV framework corresponds to equations (1) and (2) in the text. All standard errors were calculated robust to heteroskedasticity and were clustered by player

Table IX: Contract Year Effect Estimates for Reduced Sample

Estimates of Delta							
Efficiency Metric	OLS	TSLS			Probit First Stage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PER	0.163	-0.888	-3.60	-1.31	-0.773	-1.56	-1.14
	(0.208)	(1.57)	(2.27)	(1.59)	(1.03)	(1.00)	(1.00)
WS/48	0.00344	0.00522	-0.0269	0.000167	0.00529	-0.00425	0.000800
	(0.00302)	(0.0232)	(0.0305)	(0.0233)	(0.0148)	(0.0144)	(0.0145)
SPM	-0.0296	-0.0157	-2.01	-0.329	-0.0947	-0.683	-0.365
	(0.147)	(1.06)	(1.49)	(1.06)	(0.670)	(0.687)	(0.661)
xRAPM	-0.00613	-2.33*	-4.08*	-2.60*	-0.564	-0.830	-0.756
	(0.104)	(1.03)	(1.67)	(1.08)	(0.561)	(0.562)	(0.556)
Offensive WS/48	0.000389	0.00118	-0.289000	-0.00354	-0.000621	-0.00994	-0.00500
	(0.00326)	(0.0243)	(0.031)	(0.0244)	(0.0153)	(0.0152)	(0.0151)
Defensive WS/48	0.00195*	0.0089	0.00682	0.00858	0.00846	0.00704	0.00802
	(0.000934)	(0.00792)	(0.00979)	(0.00795)	(0.00540)	(0.00574)	(0.00545)
Offensive SPM	-0.0447	-0.356	-2.02	-0.618	-0.340	-0.800	-0.557
	(0.124)	(0.942)	(1.32)	(0.949)	(0.625)	(0.628)	(0.617)
Defensive SPM	0.0161	0.380	0.03130	0.325	0.281	0.147	0.226
	(0.0593)	(0.472)	(0.587)	(0.467)	(0.320)	(0.341)	(0.319)
Offensive xRAPM	0.0450	-1.46	-2.77*	-1.67*	0.179	-0.0434	0.0174
	(0.0798)	(0.754)	(1.23)	(0.793)	(0.531)	(0.536)	(0.525)
Defensive xRAPM	-0.0530	-0.843	-1.25	-0.906	-0.706	-0.742	-0.733
	-0.0648	(0.559)	(0.772)	(0.572)	(0.418)	(0.434)	(0.419)
Volume Metric	OLS	TSLS			Probit First Stage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EWA	0.311	-0.540	-2.06	-0.780	2.12	2.17	2.020
	(0.189)	(1.51)	(1.99)	(1.51)	(1.23)	(1.23)	(1.21)
WS	0.0747	-0.439	-0.027	-0.586	0.295	0.279	0.234
	(0.132)	(1.06)	(1.39)	(1.06)	(0.717)	(0.697)	(0.695)
Statistical WAR	0.151	-0.321	-1.41	-0.492	1.93*	2.04*	1.88*
	(0.144)	(1.18)	(1.59)	(1.09)	(0.888)	(0.913)	(0.876)
WAR	0.147	-2.23	-3.69	-2.46	1.21	1.35	1.13
	(0.165)	(1.45)	(2.10)	(1.48)	(0.974)	(1.01)	(0.969)
Offensive WS	0.119	-0.389	-0.993	-0.484	0.657	0.701	0.622
	(0.103)	(0.821)	(1.06)	(0.824)	(0.600)	(0.592)	(0.585)
Defensive WS	-0.0486	-0.0482	-0.338	-0.0938	-0.355	-0.404	-0.376
	(0.0525)	(0.445)	(0.583)	(0.450)	(0.322)	(0.336)	(0.321)

* p < 0.05; ** p < 0.01; *** p < 0.001. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com.

(1) is OLS estimates based off equation (2). (2), (3), (4) use equations (1) and (2) in a two stage least squares framework; while (5), (6), (7) use fitted probabilities from equation (3) as the instrument passed to the first stage.(2), (5) use 2010 indicator as the instrument; (3), (6) use the contract year percent as the instrument; and (4), (7) use both. Full and reduced samples, performance metrics and instruments described in the text. All standard errors are calculated robust to heteroskedasticity and clustered by player

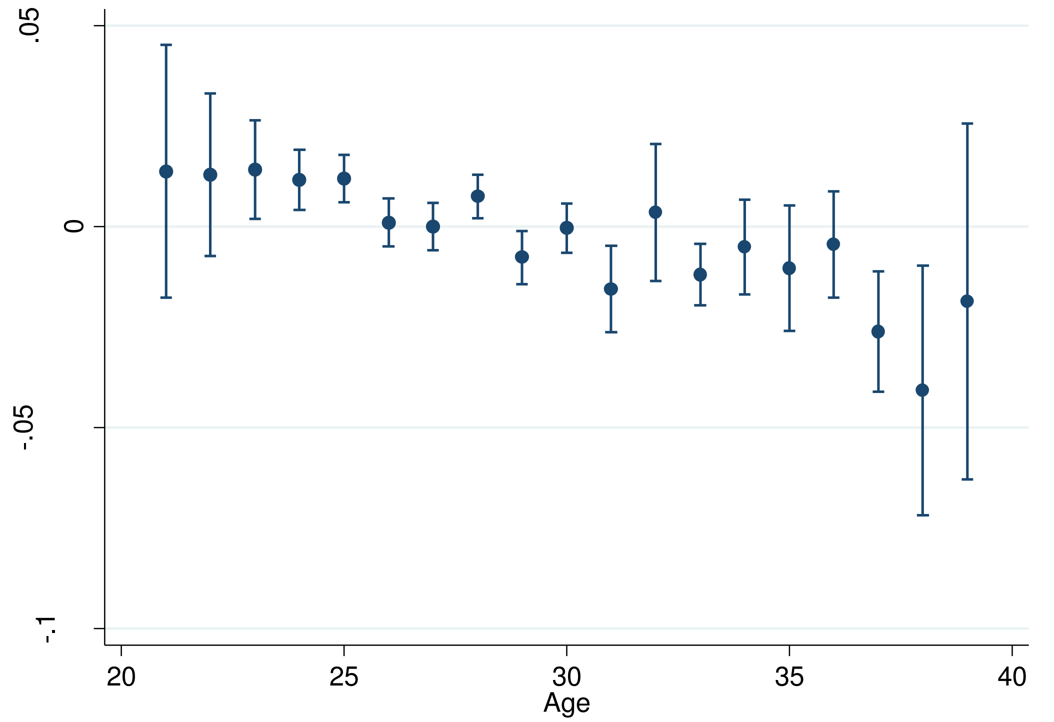
Rather than concluding that there is no contract year effect, it is possible that the true contract year effect is masked by the poorly identified standard errors. Hence, I present another approach for correcting for endogeneity bias. Rather than using a player fixed effects model, instead we can use performance relative to individual expectation as our dependent variable. Paine's projection system enables one to provide an expectation of a player's efficiency metrics for the upcoming season, based off past performance and adjusted for age based off a globalized aging curve (Paine, 2008). It can only be used for efficiency metrics which have a volume corollary (see Appendix 4 for details).[66] This leads to the following basic framework.

$$Y_{it} - \mathbb{E}(Y_{it}|Y_{i,t-1}, Y_{i,t-2}, Y_{i,t-3}, Age_{it}) = \alpha + \beta \cdot X_{it} + \delta CY_{it} + \epsilon_{it} \quad (4)$$

Height, weight, position dummies, and team quality are included to further refine the model – for example to improve accuracy if the projection systematically underestimates point guards. Because Paine's system accounts for age in its expectation, we do not necessarily have to include age as a background covariate. Figure II shows the mean residual for each age group after running the regression in equation (4), with a 95% confidence interval if age is omitted.[67] It should be noted that Paine's aging adjustment is very simplistic, and though the intervals would widen substantially and all would contain zero with a multiple comparisons adjustment (20 group means plotted), the downwards trend is undeniable. It appears that older players are overly optimistically projected by his system and therefore it is necessary to include an age covariate in our regression.

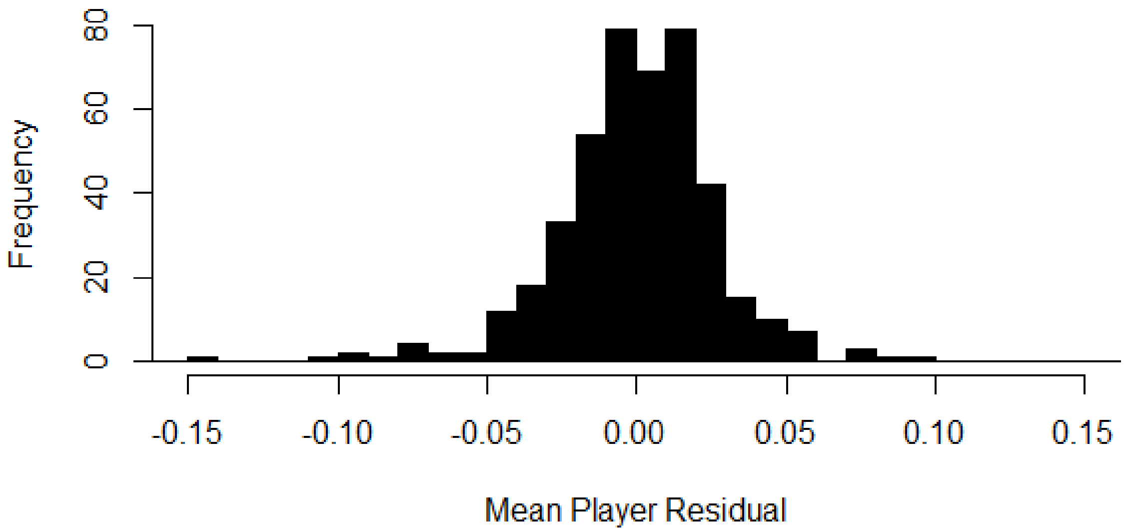
[66] It cannot project volume metrics as minutes are notoriously difficult to project for a player. It is based off Tom Tango's infamous 'Marcel the Monkey' forecasting system and despite its simplicity has held up well against Pelton's SCHOENE and other more advanced prediction systems (Kubatko, 2009(b))
[67] The performance variable used is win shares per 48 minutes

Figure II: Average Residual by Age for Equation (4)



Source: Basketball-Reference.com, ShamSports.com & Spotrac.com
Note: Shows the average residual and 95% confidence interval, not adjusted for multiple comparisons, for each age group for equation (4), as outlined in the text, with win shares per 48 minutes over expectation as the dependent variable. Results are for the full sample of player-seasons, as defined in the text, for all seasons from 2005-06 to 2013-14

Figure III: Histogram of Average Player Residual for Equation (4)



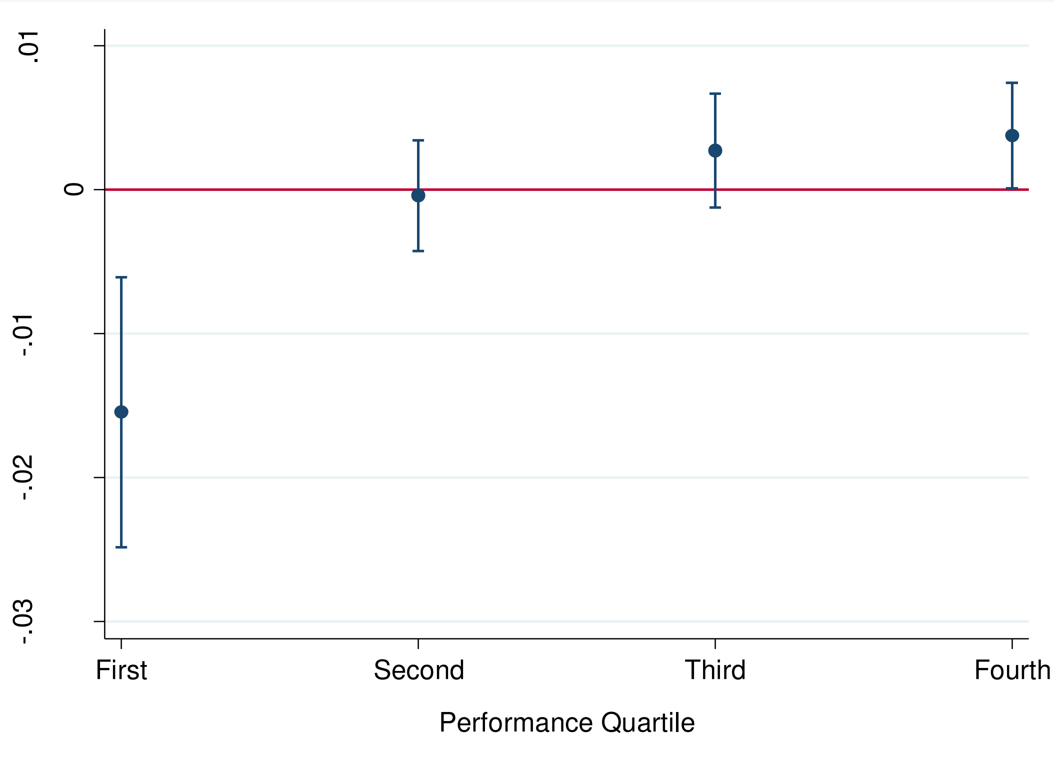
Source: Basketball-Reference.com, ShamSports.com & Spotrac.com
Note: After running the regression for equation (4), as outlined in the text, with win shares per 48 minutes over expectation as the dependent variable, the residuals were averaged for each player. Shown is a histogram of those average residuals, displaying that no player significantly and substantially deviates from zero. Results are from full sample, as outlined in the text, from 2005-2006 to 2013-2014

One could argue that player fixed effects are no longer relevant, as they should be taken into account by the personalized expectation in the dependent variable. Figure III shows a histogram of the average residual for each player after running this regression for the full sample on equation (4) with win shares per 48 minutes as our performance variable. The vast majority being at (or almost exactly at) zero further supports the argument that player effects are correctly accounted for.

However, Paine's system regresses all players to the same average mean. While this adjustment is important for players playing for few minutes due to exogenous factors such as injury, it could overestimate the projected performance of bad players around replacement level with limited playing time. Similarly, the system may underestimate elite players who missed time due to injury, though most top players are on the court for a significant enough amount of time that the regressed portion of their expectation is trivial. Figure IV confirms the fears that in particular weaker players are overestimated, showing the average residual for the full sample by performance quartile across the NBA, as before in Table I.

Tables IX and X show the estimates for the contract year effect in this framework, with equation (4) as either the OLS regression, or the second stage to equation (1). Table IX uses the instruments outlined earlier in a two stage least squares framework, while Table X uses the fitted values from the probit model in equation (3) as the instrument as before. When player fixed effects are omitted, the probit alternative can now be used also for the full sample. All standard errors are calculated robust to heteroskedasticity and clustered by player. As shown in Table VI, my instruments are significantly stronger in the absence of player fixed effects. Though there is a concern of overidentification, estimates with both my seasonal instruments are included.

Figure IV: Average Residual for Equation (4) by Performance Quartile



Source: Basketball-Reference.com, ShamSports.com & Spotrac.com
Note: Shows the average residual and 95% confidence interval, not adjusted for multiple comparisons, for each performance quartile, as described in Table I, for equation (4), as outlined in the text, with win shares per 48 minutes over expectation as the dependent variable. Results are for the full sample of player-seasons, as defined in the text, for all seasons from 2005-06 to 2013-14 and results do not differ substantially for the reduced sample

When omitting player fixed effects, the IV standard errors are substantially lower than under the previous framework, approximately half of what they were for the lower probit errors in Table IX. Even with the strength of the seasonal instrument (F > 30 for all single instruments, Table VII) in the absence of fixed effects, when trying to detect an effect which White and Sheldon estimated at 0.75 PER (White and Sheldon, 2013, 4), a standard error of about one for the full sample is very large. The simple truth is that because of the extreme difficulties in accurately measuring player performance, even with almost two thousand observations, the error in measuring our dependent variable causes sufficient noise to drown out the signal we seek, and IV estimates alone cannot provide insight.

Table X: Performance over Expectation Estimates of Contract Year Effect

Efficiency Metric	TSLS Estimates of Delta							
	Without Player Fixed Effects				With Player Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample							
PER	0.0400	0.295	-0.626	-0.414	0.492*	0.475	-0.770	0.0763
	(0.172)	(1.20)	(1.05)	(1.05)	(0.226)	(1.75)	(1.83)	(1.67)
WS/48	0.00519	0.000603	-0.00308	-0.00223	0.00896**	0.0137	0.00389	0.0105
	(0.00277)	(0.0201)	(0.0180)	(0.0179)	(0.00341)	(0.0278)	(0.0296)	(0.0268)
SPM	0.164	1.03	0.182	0.377	0.263	0.579	-0.918	0.0996
	(0.118)	(0.834)	(0.763)	(0.756)	(0.158)	(1.21)	(1.33)	(1.17)
xRAPM	0.0605	1.26	-0.424	-0.100	0.201	-1.52	-2.60	-1.87
	(0.0778)	(0.687)	(0.535)	(0.523)	(0.109)	(1.04)	(1.33)	(1.08)
OWS/48	-0.00223	0.00446	-0.000838	0.000385	0.00461	0.0198	0.00832	0.0161
	(0.00272)	(0.0186)	(0.0179)	(0.0176)	(0.00351)	(0.0267)	(0.0282)	(0.0259)
DWS/48	0.00242***	0.00485	0.00362	0.00390	0.00338**	0.00405	-0.00239	0.00199
	(0.000885)	(0.00672)	(0.00602)	(0.00593)	(0.00127)	(0.0104)	(0.0118)	(0.0104)
	Reduced Sample							
PER	0.126	0.229	-0.849	0.171	0.488*	0.381	-1.96	0.00614
	(0.183)	(0.799)	(0.891)	(0.770)	(0.221)	(1.75)	(2.12)	(1.73)
WS/48	0.00573*	0.00896	-0.00300	0.00832	0.00915**	0.0171	-0.0113	0.0125
	(0.00280)	(0.0115)	(0.0142)	(0.0116)	(0.00332)	(0.0269)	(0.0323)	(0.0267)
SPM	0.0985	0.356	-0.428	0.314	0.261	0.363	-1.48	0.0680
	(0.128)	(0.555)	(0.648)	(0.553)	(0.154)	(1.20)	(1.53)	(1.19)
xRAPM	0.115	0.279	-0.826	0.220	0.204	-1.62	-3.27*	-1.89
	(0.0866)	(0.403)	(0.475)	(0.402)	(0.106)	(1.07)	(1.62)	(1.11)
OWS/48	0.00138	0.00560	-0.00455	0.00505	0.00466	0.0171	-0.00905	0.0129
	(0.00290)	(0.0121)	(0.0148)	(0.0122)	(0.00345)	(0.0267)	(0.0304)	(0.0263)
DWS/48	0.00318***	0.00528	0.00555	0.00529	0.00336**	0.00394	0.00197	0.00362
	(0.000974)	(0.00459)	(0.00529)	(0.00458)	(0.00124)	(0.101)	(0.0125)	(0.0101)

* p < 0.05; ** p < 0.01; *** p < 0.001. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com.

(1), (5) are OLS estimates based off equation (4), without and with player fixed effects respectively

All others are two stage least squares estimates with an instrument in equation (1) as the first stage, and equation (4) as the second stage

(2), (6) use 2010 indicator as the instrument; (3), (7) use the contract year percent as the instrument; and (4), (8) use both

Full and reduced sample as described in the text, are from 2005-2014. All standard errors are robust to heteroskedasticity and clustered by player. Instruments are also described in the text

Table XI: Performance over Expectation Estimates of Contract Year Effect

	Probit First Stage Estimates of Delta							
Efficiency Metric	Without Player Fixed Effects				With Player Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Full Sample				
PER	0.0400	0.806	-0.102	0.102	0.492*	-	-	-
	(0.172)	(1.17)	(1.00)	(1.01)	(0.226)	-	-	-
WS/48	0.00519	0.00565	0.00220	0.00281	0.00896**	-	-	-
	(0.00277)	(0.0199)	(0.0176)	(0.0176)	(0.00341)	-	-	-
SPM	0.164	1.27	0.414	0.628	0.263	-	-	-
	(0.118)	(0.829)	(0.746)	(0.739)	(0.158)	-	-	-
xRAPM	0.0605	1.29*	-0.214	0.153	0.201	-	-	-
	(0.0778)	(0.583)	(0.505)	(0.491)	(0.109)	-	-	-
OWS/48	-0.00223	0.00986	0.00547	0.00628	0.00461	-	-	-
	(0.00272)	(0.0185)	(0.0177)	(0.0174)	(0.00351)	-	-	-
DWS/48	0.00242***	0.00490	0.00317	0.00370	0.00338**	-	-	-
	(0.000885)	(0.00631)	(0.00578)	(0.00564)	(0.00127)	-	-	-
				Reduced Sample				
PER	0.126	0.371	-0.576	0.300	0.488*	0.231	-0.297	-0.0206
	(0.183)	(0.767)	(0.875)	(0.767)	(0.221)	(0.974)	(0.884)	(0.930)
WS/48	0.00573*	0.0110	0.00081	0.0102	0.00915**	0.00710	0.000129	0.00387
	(0.00280)	(0.0115)	(0.0141)	(0.0116)	(0.00332)	(0.0156)	(0.0148)	(0.0151)
SPM	0.0985	0.439	-0.297	0.385	0.261	-0.292	-0.786	-0.512
	(0.128)	(0.551)	(0.642)	(0.551)	(0.154)	(0.634)	(0.621)	(0.618)
xRAPM	0.115	0.396	-0.739	0.312	0.204	0.181	-0.0140	0.0139
	(0.0866)	(0.393)	(0.467)	(0.391)	(0.106)	(0.533)	(0.517)	(0.525)
OWS/48	0.00138	0.00751	-0.000593	0.00688	0.00466	0.00720	0.000508	0.00413
	(0.00290)	(0.0123)	(0.0150)	(0.0124)	(0.00345)	(0.0137)	(0.0129)	(0.0132)
DWS/48	0.00318***	0.00567	0.00586	0.00569	0.00336**	0.00198	0.000575	0.00151
	(0.000974)	(0.00454)	(0.00527)	(0.00452)	(0.00124)	(0.00623)	(0.00617)	(0.00613)

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com.

(1), (5) are OLS estimates based off equation (4), without and with player fixed effects respectively

All others use an instrument in equation (3) to produce fitted probabilities, which are then passed as an instrument to equation (1) in the first stage and equation (4) in the second

(2), (6) use 2010 indicator as the instrument; (3), (7) use the contract year percent as the instrument; and (4), (8) use both

Full and reduced sample as described in the text, are from 2005-2014. All standard errors are robust to heteroskedasticity and clustered by player. Instruments are also described in the text

Furthermore, as we can see from comparing columns (1) and (5), omitting player fixed effects negatively biases estimates of the contract year effect, since worse players, who are disproportionately likely to be in a contract year, are projected too optimistically (see Figure IV). In contrast to the previous OLS results, it could now be argued that being in a contract year is no longer endogenous. Players are being compared to their own personal expectation, and then subsequently the effect of being in a contract year is measured (adjusted for position, height, weight, and team effects). Although worse players are more likely to be in a contract year, they are now being compared to themselves rather than the rest of the NBA. On account of the bias in the projection system, player quality, which is negatively correlated with being in a contract year, is not independent of the residual so the contract year dummy is not purely endogenous.

Nonetheless, the contract year dummy no longer shows a significant correlation with our dependent variable as it did previously (Table V), and can be interpreted as representative of the true effect after player fixed effects are included. Although there is multicollinearity between the contract year dummy and the other covariates, and particularly with the player dummies as a group, the variance inflation factor of the contract year dummy is only 1.57 for the full sample, and 1.32 for the reduced sample so the concern is limited. Comparing the OLS estimates in (5) to their IV counterparts, the Durbin-Wu-Hausman test for endogeneity is passed very easily (p-value > 0.95 for all comparisons) but there are two further reasons to have some confidence in interpreting column (5) as representative of the contract year effect.

Firstly, although the IV estimates have too large standard errors attached to be interpreted, if they showed consistency in their point estimates with the OLS estimates, then that would give us reason to trust the OLS results. Paine designed the weights in his system primarily to project win shares efficiency and thus team win totals for the upcoming season, by making broad assumptions about the distribution of playing time (Paine, 2008). Hence while the other three measures of performance show no pattern of consistency between IV and OLS estimates, there is good reason to believe that win shares estimates being more accurate is no statistical fluke. It is eminently plausible that with the weights established in this fashion, the win shares projections are more accurate and less noisy. All the OLS estimates are within the margin of error for their IV corollaries, and this holds particularly true for the biased estimates without fixed effects. These estimates are broadly consistent and are simply inflated in terms of the point estimates – a phenomenon we might expect given the approximation to contract status in the two stage framework would be less susceptible to the negative bias against worse NBA players from omitting fixed effects. The estimates with fixed effects included also demonstrate some consistency across OLS and IV, but less so on account of the wider standard errors.

Secondly, column (5) is the first time we find consistency in estimates across our measures of performance. Allowing for the fact that the noisy plus-minus based estimates are not significant, and that there are still fairly wide error bounds on each individual measure of performance, when taken as a whole these results do seem to suggest a poorly defined, but definitely present, contract year effect. All performance measures are correlated with each other, so while each individual estimate is poorly defined, reading them as a group of estimates which largely agree with each other indicates a real contract year effect. Table XII shows this stability across measures by taking those point estimates at face value, and calculating the resulting league-wide performance percentile for the median player after the estimated contract year boost. The different estimates broadly agree on a 3-5 percentile increase, though with varying confidence intervals attached.

So perhaps the contract year phenomenon is real but small. It is hence worth exploring where it is observed in the box score. Using simple measures like per-minute points or assists as the dependent variable requires the use of year dummies as the league environment has changed over my dataset. Table XIII shows the estimates of delta from equation (4) with performance over expected box score statistics per 36 minutes as the dependent variable.

Table XII: Impact of Contract Year Effect

Performance Metric	Estimated Percentile of Median Player under Contract Year Effect
PER	54.3
WS/48	55.1
SPM	53.4
xRAPM	54.2

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com
OLS point estimates taken for full sample from column (5) of Tables X and XI with player fixed effects. Given those estimates, the new leaguewide percentile of the median player is shown

Table XIII: Contract Year Effect Estimates on Box Score Statistics

Estimates of Delta		
Box Score Statistic	Sample	
	Full	Reduced
Points per 36 Minutes	0.0898	0.0822
	(0.168)	(0.164)
Assists per 36 Minutes	0.0585	0.0644
	(0.0549)	(0.0537)
Offensive Rebounds per 36 Minutes	0.0878*	0.0851*
	(0.0361)	(0.0353)
Defensive Rebounds per 36 Minutes	0.115	0.116*
	(0.0617)	(0.0599)
Blocks per 36 Minutes	0.0234	0.0191
	(0.0255)	(0.0250)
Steals per 36 Minutes	0.0468	0.0507*
	(0.0243)	(0.0237)
Turnovers per 36 Minutes	0.00601	0.00695
	(0.0340)	(0.0335)

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in parentheses
Source: Basketball-Reference.com, ShamSports.com & Spotrac.com.
Full and reduced sample as described in the text, are from 2005-2014. OLS estimates based off equation (4) in text. All standard errors are robust to heteroskedasticity and clustered by year. Baseline covariates include position dummies, height, weight, age, year dummies and SRS as a team quality measure, as outlined in the text

Year dummies and player fixed effects are included, and IV estimates are no longer relevant as the seasonal instrument is no longer uncorrelated with the residuals in the second stage because of the changing league environment. The year dummies of course dovetail with being in a contract year (Figure I) but the variance inflation factor of the contract year dummy for the full sample is still only 1.59, so the estimates can still be interpreted as approximately representative. All standard errors are calculated robust to heteroskedasticity and clustered at the player level, and all box score numbers were first adjusted to the average league pace of 2013-2014, thereby correcting for the effect of the changing pace of the league.

In contrast to White and Sheldon's result that "no CY [contract year] boosting effect emerged for any of the other non-scoring statistics (steals, blocks, defensive rebounds, offensive rebounds)" (White and Sheldon, 2013, 4), with a primarily offensive contract year phenomenon observed, my results show the exact inverse. This is likely because scoring decreased over White and Sheldon's period, and there were more 'contract years' in their dataset pre-2005 because more players were waived, which they defined as being in a contract year, as there was a reduced opportunity cost of waiving a player. Hence, they associated an overly positive offensive effect with being in a contract year. On the other hand, I find most of the contract year effect to be in rebounding and getting steals, which is consistent with the significant estimate on defensive win shares in Tables X and XI, though the offensive equivalent is similar in magnitude just with larger standard errors.

While the contract year effect on individual performance is calculated to be positive, we should temper conclusions that a player has a meaningful positive effect on team performance. It is a plausible hypothesis that being in a contract year affects a player's marginal choices. Whenever a shot is taken by a teammate, a player faces a choice: backpedal to stop the other team in transition, or 'crash the glass' and go for an offensive rebound.[68] Similarly, when an opponent takes a shot, the player must choose whether to box out and try

[68] For more information on this decision and its importance in general, see Wiens et al. (2013)

to grab a defensive rebound or start moving away from the basket in anticipation of a fast break. There are numerous factors which play into this decision, such as one's own position, the positions of one's teammates, the positions of the opponents, the score of the game and myriad more, but given the sheer volume of shots in a season, there are certainly times when the decision is right on the margin. It is reasonable that knowing you are in a contract year could lead a player to chase box score events and go for rebounds more often, as that choice has a higher probability of being recorded in the box score, even if it is not ultimately beneficial to your team. The same logic goes for steals, as players on defense always face the risky choice of going for a steal. There is evidence that steals are the most important part of the box score (Morris, 2014) and a steal is useful in a vacuum, but not if it follows three failed attempts, allowing easy points to the other team in the process. Players face fewer marginal decisions regarding points, assists, and blocks in general, as for rebounds and steals, the decision occurs on every single possession. The results shown here could be contract year performers valuing themselves over the team.

Alternatively, it could be contract year players exhibiting better performance from exhorting superior effort during 'garbage time'. Over the course of the NBA season, many games will be all but over as a team heads into the last few minutes of a game down by twenty, and while most players start conserving effort at this point, contract year performers could artificially boost their stats by still playing with full exertion. Expanding my analysis to look at play-by-play data and filtering out 'garbage time' situations could rule out this possibility.

For these reasons, we cannot be certain if this observed increase in a player's box score statistics during a contract year ultimately helps his team.[69] The estimated contract year impact of a 3-5 percentile boost is about half of what Perry observed in baseball (Perry, 2006), and my PER estimate is roughly two-thirds what Sheldon and White estimated to be the contract year effect in the NBA. The science of precisely measuring basketball performance is still in its infancy, particularly in the defensive side of the game. All box score metrics especially are ill-equipped to measure defensive contributions. As we move into the age of spatial data, better defensive statistics will be produced. Franks and Miller recently presented a paper which argued that "the combination of player tracking, statistical modelling, and visualization enable a far richer characterization of defense than has previously been possible" (Franks et al., 2015, 1). The field is advancing, but metrics available in the public sphere are not yet sufficiently well calibrated to produce definitive results at such a small magnitude. In addition, if a more accurate projection system was developed,[70] the framework provided could yield more definitive results. Regardless, this paper can only conclude that the contract year phenomenon does indeed exist in the NBA.

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[69] The estimates of delta for SPM and xRAPM are not significant owing to the noise associated with those measures of performance. But the point estimates being in line with those for the box-score metrics could be seen as very weak evidence of a player helping his team's performance too during a contract year

[70] Baseball has addressed the issue of regressing to one mean and having one globalized aging curve by comparing a player to historically similar players, and observing how their career progressed. Pelton's SCHOENE has tried to embrace this methodology but is neither publicly available any more, nor was it better than Paine's approach the last time it was (Kubatko, 2009(b))

V. CONCLUSION

We find evidence for an estimated contract year effect of an increase of 0.009 win shares per 48 minutes in the NBA, with the effect most heavily impacting rebounding and steals of the box score statistics. As methods of measuring individual performance in the NBA improve, the precision of this estimate will increase. The methodology outlined in this paper, particularly with regard to contract states, can be adapted to embrace new definitions of performance, which will further refine this estimate.

The estimated effect is of lesser magnitude in basketball as compared to baseball, and there are two major reasons to believe why the contract year phenomenon may be more strongly felt in baseball. Firstly, baseball is at its core an individual sport. Crucially, it is also a far more mentally demanding sport. A continuous and dynamic game, basketball requires making lightning fast, physically-motivated decisions, reacting instantaneously to nine other players on the court. There is constant pressure to perform from fans and teammates, as well as the constant threat of media criticism in the digital age. Baseball players face these pressures as well, but in the game theoretical battle between hitter and pitcher, the basis of the sport, mental decision-making is arguably easier to improve than physical performance. If one knows that every hit, every at-bat could end up determining millions of contract dollars, one would reasonably spend all the extra hours available watching film of one's opponent and better perfecting one's mental strategy. Film sessions matter in basketball too, but nowhere near to the same extent (Lindbergh, 2013). Additionally, one relies on other players' cooperation and collaboration – players who may or may not be on contract years – in stark contrast to baseball's individualized sport.

The second reason is more conjectural, but it is potentially extremely important. Even in the face of the strong evidence Perry's study in baseball provides (Perry, 2006), the editor argues in the notes that he still does not fully believe in the contract year phenomenon. Although players performed better, this analysis was done in the steroids era of baseball, and it is his belief that the contract year phenomenon is related to steroid use (Keri, 2006, 406). Under the incentive of a future contract, then, starting or increasing steroid use may be desirable, even when considering the penalties, financial and otherwise, of being caught. Cheating in this manner would explain the increase in playing time, as injuries would be recovered from more quickly; and the increase in performance, as players' hits travel further and pitches are thrown faster.

The narrative on performance-enhancing drugs in the NBA is far less explored than it is for baseball or football.[71] "Of all the running-and-jumping sports that feature world-class athletes competing at the highest level, only the NBA hasn't had a single star get nailed for performance enhancers" (Simmons, 2013). Testing is so limited that, as Simmons (2013) observes, "NBA players [only] get tested up to four times during the course of a season," such paucity that "it's a running joke within NBA circles". The question of the extent to which NBA players are or are not doping is beyond the scope of this thesis, but it seems reasonable that the inability to affect one's play via doping – either because everyone already is or because it is not as beneficial as in baseball – would explain the limited impact of the contract year effect in basketball.

By rigorously defining a true contract and non-contract year, expanding the description of performance to more advanced metrics, and correcting for endogeneity bias in its analysis, this paper dramatically questions the large contract year effect found in the literature thus far. While sports analytics as a field has had a tendency to emphasize results

[71] American Football, to clarify

over process, particularly with regard to internet-based studies, this paper demonstrates the benefits of bringing more rigorous econometric and academic analysis to the subject. The contract year phenomenon is a media narrative that almost makes too much sense not to exist, but the basketball community as a whole overstates its magnitude.

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Appendix Glossary

Table A.1 outlines all the acronyms used in the upcoming equations in the appendix. Without any subscript, the acronyms refer to a player's seasonal totals. A '*tm*' subscript refers to a player's team totals for the season; an '*opp*' subscript refers to a player's team's opponents totals for the season, in games against them; while a '*lg*' subscript refers to the league totals for the season.

Table A.1: Acronyms used in Appendix

Acronym	Statistic
MP	Minutes Played
3PM	Three-Point Field Goals Made
AST	Assists
FGM	Field Goals Made
FGA	Field Goals Attempted
FTM	Free Throws Made
FTA	Free Throws Attempted
TOV	Turnovers
DRB	Defensive Rebounds
ORB	Offensive Rebounds
STL	Steals
BLK	Blocks
PF	Personal Fouls
PTS	Points
PACE	Possessions per 48 minutes
PtsPerPoss	Points per Possession
PossOff	Offensive Possessions
PtsPerGame	Points per Game
POSS	Possessions
PossDef	Defensive Possesions

Appendix 1: PER

This section is a summary to the guide for calculating PER at Basketball-Reference.com. To begin one calculates what is known as a player's unadjusted PER (uPER) as follows:

$$uPER = \left(\frac{1}{MP}\right) \cdot [3PM + \frac{2}{3} \cdot AST + \left(2 - factor \cdot \frac{AST_{tm}}{FGM_{tm}} \cdot FGM\right) + \left(FTM \cdot 0.5 \cdot \left(2 - \frac{5}{3} \cdot \frac{AST_{tm}}{FG_{tm}}\right)\right) - VOP \cdot \left[TOV + DRB\% \cdot (FGA - FGM) - 0.44 \cdot \left(0.44 + (0.56 * DRB\%)\right) \cdot (FTA - FTM) + (1 - DRB\%) \cdot DRB + DRB\% \cdot ORB + STL + DRB\% \cdot BLK\right] - PF \cdot \left(\frac{FTM_{lg}}{PF_{lg}} - 0.44 * \frac{FTA_{lg}}{PF_{lg}} \cdot VOP\right)] \quad \text{(A.1.1)}$$

Where:

$$factor = \frac{2}{3} - \frac{1}{4} \cdot \frac{AST_{lg} \cdot FTM_{lg}}{FGM_{lg}^2} \quad \text{(A.1.2)}$$

$$VOP = \frac{PTS_{lg}}{FGA_{lg} - ORB_{lg} + TOV_{lg} + 0.44 \cdot FTA_{lg}} \quad \text{(A.1.3)}$$

$$DRB\% = \frac{DRB_{lg}}{DRB_{lg} + ORB_{lg}} \quad \text{(A.1.4)}$$

uPER is then adjusted for pace to form adjusted PER (aPER):

$$aPER = \frac{PACE_{lg}}{PACE_{tm}} \cdot uPER \quad \text{(A.1.5)}$$

Finally, aPER is standardized such that the league average PER is 15. The league average aPER ($aPER_{lg}$) is first calculated and then PER itself is finally produced:

$$PER = aPER \cdot \frac{15}{aPER_{lg}} \quad \text{(A.1.6)}$$

Estimated Wins Added (EWA) is then calculated from PER as follows:

$$EWA = (PER - 10.82) * \frac{MP}{2010} \quad \text{(A.1.7)}$$

Appendix 2: Win Shares

This section combines the salient points of Chapters 14 and 17 and Appendices 1 and 3 of *Basketball on Paper* by Dean Oliver (2004), with Justin Kubatko's definition of win shares on Basketball-Reference.com (Kubatko, 2009).

To calculate win shares, there are two separate processes for the offensive and defensive components. Beginning with the offensive component, first the points produced (PProd) for each player is calculated as follows:

$$PProd = (PProd_{FG} + PProd_{AST} + FTM) \cdot \left(1 - \frac{ORB_{tm}}{ScoringPoss_{tm}} \cdot TmORBweight \cdot TmPlay\%\right) + PProd_{ORB} \quad \text{(A.2.1)}$$

Where:

$$PProd_{FG} = 2 \cdot (FGM + 0.5 \cdot 3PM) \cdot \left(1 - \frac{PTS - FTM}{4 \cdot FGA}\right) \cdot q_{AST} \quad \text{(A.2.2)}$$

$$PProd_{AST} = \frac{FGM_{tm} - FGM + 0.5 \cdot (3PM_{tm} - 3PM)}{FGM_{tm} - FGM} \cdot \frac{(PTS_{tm} - FTM_{tm}) - (PTS - FTM)}{2 \cdot (FGA_{tm} - FGA)} \cdot AST \quad \text{(A.2.3)}$$

$$PProd_{ORB} = ORB \cdot TmORBweight \cdot TmPlay\% \cdot \frac{PTS_{tm}}{FGM_{tm} + \left(1 - \left(1 - \frac{FTM_{tm}}{FTA_{tm}}\right)^2\right) \cdot 0.4 \cdot FTA_{tm}} \quad \text{(A.2.4)}$$

$$ScoringPoss_{tm} = FGM_{tm} + (1 - \left(1 - \frac{FTM_{tm}}{FTA_{tm}}\right)^2) \cdot FTA_{tm} \cdot 0.4 \quad \text{(A.2.5)}$$

$$TmORBweight = \frac{(1 - TmORB\%) \cdot TmPlay\%}{(1 - TmORB\%) \cdot TmPlay\% + TmORB\% \cdot (1 - TmPlay\%)} \quad \text{(A.2.6)}$$

$$TmPlay\% = \frac{ScoringPoss_{tm}}{FGA_{tm} + FTA_{tm} \cdot 0.4 + TOV_{tm}} \quad \text{(A.2.7)}$$

$$TmORB\% = \frac{ORB_{tm}}{ORB_{tm} + DRB_{opp}} \quad \text{(A.2.8)}$$

$$q_{AST} = 1.14 \cdot \frac{5 \cdot MP}{MP_{tm}} \cdot \frac{AST_{tm} - AST}{FGM_{tm}} + (1 - \frac{5 \cdot MP}{MP_{tm}}) \frac{\frac{5 \cdot MP}{MP_{tm}} \cdot AST_{tm} - AST}{\frac{5 \cdot MP}{MP_{tm}} \cdot FGM_{tm} - FGM} \quad \text{(A.2.9)}$$

From points produced, we calculate the marginal offense (MO) produced by a player in a season, and the marginal points per win (MPW) required for that season:

$$MO = PProd - 0.92 \cdot PtsPerPoss_{lg} \cdot PossOff \quad \text{(A.2.10)}$$

$$MPW = 0.32 \cdot PtsPerGame_{lg} \cdot \frac{PACE_{tm}}{PACE_{lg}} \quad \text{(A.2.11)}$$

Putting it all together, and we can accredit offensive win shares (OWS) to a player via:

$$OWS = \frac{MO}{MPW} \quad \text{(A.2.12)}$$

The starting point for calculating a player's defensive win shares is to calculate his defensive rating (DRtg), a measure of as his individual points allowed per 100 possessions, against average opposition with average teammates.

$$DRtg = DRtg_{tm} + 0.2 \cdot [100 \cdot DPtsPerScPoss \cdot (1 - Stop\%) - DRtg_{tm}] \quad \text{(A.2.13)}$$

Where:

$$DRtg_{tm} = 100 \cdot \frac{PTS_{opp}}{POSS_{tm}} \quad \text{(A.2.14)}$$

$$DPtsPerScPoss = \frac{PTS_{opp}}{FGM_{opp} + \left(1 - \left(1 - \frac{FTM_{opp}}{FTA_{opp}}\right)^2\right) \cdot FTA_{opp} \cdot 0.4} \quad \text{(A.2.15)}$$

$$Stop\% = \frac{(Stops_1 + Stops_2) \cdot MP_{opp}}{Poss_{tm} \cdot MP} \quad \text{(A.2.16)}$$

$$Stops_1 = STL + BLK \cdot FMwt \cdot (1 - 1.07 \cdot DOR\%) + DRB \cdot (1 - FMwt) \quad \text{(A.2.17)}$$

$$FMwt = \frac{DFG\% \cdot (1 - DOR\%)}{DFG\% \cdot (1 - DOR\%) + (1 - DFG\%) \cdot DOR\%} \quad \text{(A.2.18)}$$

$$DOR\% = \frac{ORB_{opp}}{ORB_{opp} + DRB_{tm}} \quad \text{(A.2.19)}$$

$$DFG\% = \frac{FGM_{opp}}{FGA_{opp}} \quad \text{(A.2.20)}$$

$$Stops_2 = \left[\frac{FGA_{opp} - FGM_{opp} - BLK_{tm}}{MP_{tm}} \cdot FMwt \cdot (1 - 1.07 \cdot DOR\%) + \frac{TOV_{opp} - STL_{tm}}{MP_{tm}}\right] \cdot MP + \frac{PF}{PF_{tm}} \cdot 0.4 \cdot FTA_{opp} \cdot (1 - \frac{FTM_{opp}}{FTA_{opp}})^2 \quad \text{(A.2.21)}$$

Once a player's defensive rating has been calculated, we proceed as before to calculate a player's Marginal Defense (MD) as a contribution, and then use the Marginal Points per Win (MPW) from earlier to apportion defensive win shares (DWS):

$$MD = \frac{MP}{MP_{tm}} \cdot PossDef_{tm} \cdot 1.08 \cdot (PtsPerPoss_{lg} - \frac{DRtg}{100}) \quad \text{(A.2.22)}$$

$$DWS = \frac{MD}{MPW} \quad \text{(A.2.23)}$$

Offensive and defensive win shares combine to form the overall win shares metric, a measure of how many wins a player produces in a season. Dividing this total by his number of minutes played and multiplying by 48 gives the efficiency equivalent of win shares per 48 minutes.

Appendix 3: Box Plus-Minus

This section is a summary of Myers' technique for calculating his version of statistical plus-minus, box plus-minus (BPM). Please refer to Section III for more details on the theoretical underpinnings of this method of evaluating player performance, and see Myers (2015) for discussion of why he chose the following regression formula (A.3.1).

$$Y = a \cdot MPG + b \cdot ORB\% + c \cdot DRB\% + d \cdot STL\% + e \cdot BLK\% + f \cdot AST\% - g \cdot USG\% \cdot TOV\% + h \cdot USG\%(1 - TOV\%) \cdot [2 \cdot (TS\% - TmTS\%) + i \cdot AST\% + j \cdot (3PAr - Lg3PAr) - k] + l \cdot \sqrt{AST\% \cdot TRB\%} + \varepsilon \quad \text{(A.3.1)}$$

Myers first ran the regression with Y as overall xRAPM (see Section III), using data from 2002-2014 and weighting by a player's total possessions. He termed the linearly calculated right-hand side as Raw BPM, measured in points above or below average per 200 possessions. He then ran the regression again with Y as offensive xRAPM, defining raw offensive BPM as the right-hand side of that equation, and raw defensive BPM as the difference between Raw BPM and raw offensive BPM. The coefficients chosen in the second regression were chosen to minimize the squared errors of offensive and defensive BPM on their xRAPM counterparts. Table A.2 shows the coefficient estimates and provides a description of the terms in the regression.

Once the raw estimates have been calculated, they are adjusted to improve accuracy. In general, errors are going to be correlated at the team level, and because we know the team's overall efficiency,[72] we can adjust individual BPMs.[73] Adjustments are equally divided for all players on a team and calculated separately for defense, offense, and overall components.

$$BPM_{adj} = (TeamEff * 120\% - \sum_{p \in players} \frac{MP_p}{MP_{tm}} \cdot Raw\ BPM_p) \cdot \frac{1}{5} \qquad \text{(A.3.2)}$$

Finally, a player's BPM (for each component) is calculated as a sum of the raw calculation, from the coefficients in Table A.2 and equation A.3.1, and the team adjustment:

$$BPM = Raw\ BPM + BPM_{adj} \qquad \text{(A.3.3)}$$

As per footnote 57, replacement level is currently considered to be -2.0 points below average per 200 possessions (Tango, 2014). Using this number, wins above replacement (WAR), the volume corollary to xRAPM, and statistical wins above replacement (SWAR), the volume corollary to BPM, are calculated by the following formulas:

$$WAR = \left(xRAPM - (-2.0)\right) * \frac{MP}{MP_{tm}} \cdot 2.7 \qquad \text{(A.3.4)}$$

$$SWAR = \left(BPM - (-2.0)\right) * \frac{MP}{MP_{tm}} \cdot 2.7 \qquad \text{(A.3.5)}$$

[72] The efficiency is adjusted by the strength of schedule component of SRS (see Basketball-Reference.com for details)

[73] The 120% multiplying factor comes from the 'elastic effect' that players play better when behind than when ahead, ceteris paribus (Goldman and Rao, 2013; Engelmann, 2014)

Table A.2: Coefficient Estimates for Box Plus-Minus

Coefficient	Term	Explanation	Raw BPM Value	Raw OBPM Value
a	MPG	Player's minutes per game	0.123391	0.064448
b	ORB%	Percentage of available offensive rebounds grabbed by a player while on the floor	0.119597	0.211125
c	DRB%	Percentage of available defensive rebounds grabbed by a player while on the floor	-0.151287	-0.107545
d	STL%	Percentage of opponent possessions that end with a steal by the player while on the floor	1.255644	0.346513
e	BLK%	Percentage of opponent two-point field goal attempts blocked by the player while on the floor	0.531838	-0.052476
f	AST%	Percentage of teammate field goals a player assisted while on the floor	-0.305868	-0.041787
g	TOV%*USG%		0.921292	0.932965
h	Scoring		0.711217	0.687359
	USG%	Percentage of team plays used by a player (via a turnover, field goal attempt or free throw attampt) while on the floor		
	TOV%	Turnovers per 100 offensive possessions		
	TS% & TmTS%	True shooting percentage is a measure of shooting efficiency that takes into account field goals, 3-point field goals and free throws		
i	AST Interaction		0.017022	0.007952
j	3PAr Interaction	3-point attempt rate is the percentage of field goal attempts which are 3-point attempts	0.297639	0.374706
k	Threshold Scoring		0.213485	-0.181891
l	sqrt(AST%*TRB%)	Total rebound percentage is the percentage of all available rebounds grabbed while on the floor	0.72593	0.239862

Source: Myers (2015). See text for description and interpretation of results

Appendix 4: Paine's Projection System

Paine designed his system based off Tango's Forecasting System (Tango, 2004). It uses volume metrics (e.g. steals, wins above replacement) from the last three seasons ($Y_{t-1}, Y_{t-2}, Y_{t-3}$) to provide an expectation of an efficiency metric (e.g. points per minute, steals per minute, wins above replacement per minute) for the upcoming season (Paine, 2008). The expectation is a weighted average of the past three years of performance, regressed to the league average by 1000 minutes.

$$\mathbb{E}(Y_t/_{Min}) = \frac{(6 \cdot Y_{t-1} + 3 \cdot Y_{t-2} + Y_{t-3}) + \frac{1000}{MPWeight} \cdot LgAverage}{MPWeight + 1000} \cdot (1 + AA) \quad \text{(A.4.1)}$$

Where:

$$MPWeight = 6 \cdot MP_{t-1} + 3 \cdot MP_{t-2} + MP_{t-3} \quad \text{(A.4.2)}$$

$$LgAverage = 6 \cdot MP_{t-1} \cdot \frac{Y_{lg,t-1}}{MP_{lg,t-1}} + 3 \cdot MP_{t-2} \cdot \frac{Y_{lg,t-2}}{MP_{lg,t-2}} + MP_{t-3} \cdot \frac{Y_{lg,t-3}}{MP_{lg,t-3}} \quad \text{(A.4.3)}$$

$$AA = \begin{cases} (28 - Age) \cdot 0.004 \text{ if } Age \leq 28 \\ (28 - Age) \cdot 0.002 \text{ if } Age > 28 \end{cases} \quad \text{(A.4.4)}$$

From $\mathbb{E}(Y_t/_{Min})$, we can form expectations such as 'Steals per 36 minutes' or xRAPM (using A.3.4). Some minor alterations are that the sign of the aging adjustment (AA) is reversed for turnovers, and projected points are computed using projected field goals made, projected 3-point field goals made, and projected free throws made.

Appendix 5: Sensitivity Check with Team Dummies Included

As outlined in footnote 61, this appendix repeats all results for Tables VII, VIII, IX, X, XI and XIII with team dummies for each of the 30 franchises included. This could potentially pick up some element of team culture, not captured by my team quality measure, which is constant over the course of my dataset and impacts performance.

Table A.5.VII: First Stage Statistics

Model	Sample	Instrument			
		Year Indicator	CY Percent	Both	
		F-Stat	F-Stat	F-Stat	P-Value
With Player Fixed Effects	Full	14.29	12.26	7.43	0.5153
	Reduced	12.86	9.61	6.50	0.0326
Without Player Fixed Effects	Full	30.72	37.38	19.08	0.1491
	Reduced	66.51	49.64	33.31	0.0283

Source: Basketball-Reference.com, ShamSports.com & Spotrac.com.

Full and reduced samples, as defined in text, are from 2005-2014. Table reports key statistics for first stage in instrumental variables framework, as outlined in equation (1) and (2) in text. F-Stat refers to Cragg-Donald F-Statistic. P-Value is that returned from Hansen-J statistic as test of overidentification. Team dummies now included in specification

Table A.5.VIII: Contract Year Effect Estimates for Full Sample

TSLS Estimates of Delta

Efficiency Metric	OLS	Instrument: 2010 Indicator	Instrument: CY Percent	Instrument: Both
Player Efficiency Rating	0.122 (0.215)	-0.608 (1.70)	-2.24 (1.97)	-1.11 (1.67)
Win Shares per 48 Minutes	0.00298 (0.00315)	0.00425 (0.0258)	-0.00608 (0.0285)	0.00110 (0.0251)
Statistical Plus-Minus (SPM)	-0.0236 (0.153)	0.510 (1.18)	-1.39 (1.38)	-0.0703 (1.14)
Expected Regularized Adjusted Plus-Minus (xRAPM)	-0.0180 (0.110)	-2.09* (0.998)	-3.60* (1.43)	-2.55* (1.07)
Offensive Win Shares per 48 Minutes	-0.000299 (0.00342)	0.0103 (0.0265)	-0.00247 (0.296)	0.00643 (0.0263)
Defensive Win Shares per 48 Minutes	0.00234** (0.000888)	0.00699 (0.00765)	0.000673 (0.00808)	0.00507 (0.00739)
Offensive SPM	-0.0752 (0.130)	0.00743 (1.01)	-1.28 (1.17)	-0.384 (0.991)
Defensive SPM	0.0523 (0.0602)	0.515 (0.505)	-0.112 (0.538)	0.324 (0.474)
Offensive xRAPM	0.0329 (0.0827)	-1.48 (0.773)	-2.65* (1.12)	-1.84* (0.830)
Defensive xRAPM	-0.0535 (0.0680)	-0.596 (0.550)	-0.910 (0.665)	-0.692 (0.556)
Volume Metric	**OLS**	**Instrument: 2010 Indicator**	**Instrument: CY Percent**	**Instrument: Both**
Estimated Wins Added	0.339 (0.194)	0.492 (1.59)	-0.388 (1.80)	0.224 (1.56)
Win Shares	0.122 (0.138)	0.228 (1.13)	-0.234 (1.28)	0.0871 (1.11)
Statistical Wins Above Replacement	0.204 (0.148)	0.147 (1.29)	-0.520 (1.53)	-0.0564 (1.29)
Wins Above Replacement	0.151 (0.170)	-1.43 (1.44)	-2.51 (1.87)	-1.76 (1.49)
Offensive Win Shares	0.128 (0.108)	0.181 (0.850)	-0.0548 (0.970)	0.109 (0.838)
Defensive Win Shares	-0.00954 (0.0514)	0.0637 (0.474)	-0.133 (0.519)	0.00364 (0.458)

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com.

Full sample contains all 1870 player-seasons which were contract or non-contract years, as defined in the text, across 439 players from 2005-2014. Performance metrics and instruments used are described in the text. IV framework corresponds to equations (1) and (2) in the text. All standard errors were calculated robust to heteroskedasticity and were clustered by player. Team dummies are now included in the specification

Table A.5.IX: Contract Year Effect Estimates for Reduced Sample

Estimates of Delta							
Efficiency Metric	OLS	TSLS			Probit First Stage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PER	0.250	-1.49	-5.17	-1.70	-0.0242	-0.0594	-0.299
	(0.185)	(1.90)	(3.50)	(1.93)	(0.989)	(0.967)	(0.968)
WS/48	0.00436	0.0117	-0.0206	0.00985	0.0126	0.00727	0.0103
	(0.00259)	(0.270)	(0.0342)	(0.0268)	(0.0140)	(0.0135)	(0.0136)
SPM	0.0994	-0.367	-2.45	-0.484	0.258	-0.0522	0.111
	(0.117)	(1.12)	(1.86)	(1.12)	(0.617)	(0.611)	(0.608)
xRAPM	0.0145	-2.91	-5.54	-3.06*	0.0999	-0.173	-0.0829
	(0.112)	(1.49)	(2.97)	(1.53)	(0.610)	(0.607)	(0.601)
Offensive WS/48	0.00232	0.00617	-0.221	0.00458	0.00268	-0.00297	0.000330
	(0.00258)	(0.0270)	(0.0349)	(0.0269)	(0.0136)	(0.0132)	(0.0133)
Defensive WS/48	0.00176*	0.00671	0.00508	0.00661	0.0106*	0.0114	0.0109*
	(0.000731)	(0.00963)	(0.0114)	(0.00961)	(0.00502)	(0.00507)	(0.00497)
Offensive SPM	0.0334	-0.466	-2.38	-0.574	-0.0220	0.0114*	-0.171
	(0.107)	(1.07)	(1.77)	(1.08)	(0.562)	(0.00507)	(0.556)
Defensive SPM	0.0668	0.146	-0.0334	0.136	0.317	-0.351	0.319
	(0.0471)	(0.535)	(0.681)	(0.533)	(0.324)	(0.561)	(0.320)
Offensive xRAPM	0.0249	-2.05	-4.38	-2.18	0.310	0.334	0.128
	(0.0840)	(1.13)	(2.41)	(1.17)	(0.545)	(0.327)	(0.537)
Defensive xRAPM	-0.0129	-0.794	-1.07	-0.809	-0.192	0.000231	-0.190
	(0.0678)	(0.734)	(1.03)	(0.740)	(0.405)	(0.541)	(0.410)
Volume Metric	OLS	TSLS			Probit First Stage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EWA	0.369	-0.981	-3.44	-1.12	2.45	-0.152	2.36
	(0.197)	(2.00)	(3.08)	(2.01)	(1.33)	(0.427)	(1.30)
WS	0.174	-0.276	-1.35	-0.337	0.588	2.43	0.578
	(0.143)	(1.45)	(1.96)	(1.45)	(0.819)	(1.30)	(0.797)
Statistical WAR	0.199	-0.493	-2.64	-0.614	2.44*	0.626	2.35*
	(0.158)	(1.65)	(2.54)	(1.66)	(1.08)	(0.797)	(1.06)
WAR	0.189	-2.81	-5.15	-2.94	2.03	2.40*	1.94
	(0.178)	(2.02)	(3.44)	(2.05)	(1.09)	(1.07)	(1.08)
Offensive WS	0.151	-0.286	-0.995	-0.326	0.619	2.08	0.593
	(0.113)	(1.14)	(1.53)	(1.14)	(0.659)	(1.10)	(0.641)
Defensive WS	0.0198	0.0129	-0.290	-0.00423	-0.0123	0.614	0.00850
	(0.0505)	(0.597)	(0.745)	(0.592)	(0.319)	(0.642)	(0.314)

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com.

(1) is OLS estimates based off equation (2). (2), (3), (4) use equations (1) and (2) in a two stage least squares framework; while (5), (6), (7) use fitted probabilities from equation (3) as the instrument passed to the first stage.(2), (5) use 2010 indicator as the instrument; (3), (6) use the contract year percent as the instrument; and (4), (7) use both. Full and reduced samples, performance metrics and instruments described in the text. All standard errors are calculated robust to heteroskedasticity and clustered by player. Team dummies are now included in the specification

Table A.5.X: Performance over Expectation Estimates of Contract Year Effect

Efficiency Metric	TSLS Estimates of Delta							
	Without Player Fixed Effects				With Player Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample							
PER	0.0480	0.554	-0.472	-0.235	0.463*	0.432	-0.918	-0.0202
	(0.176)	(1.26)	(1.12)	(1.11)	(0.230)	(1.83)	(1.90)	(1.75)
WS/48	0.00515	-0.0000922	-0.00432	-0.00335	0.00857*	0.00940	-0.00247	0.00542
	(0.00280)	(0.0210)	(0.0192)	(0.0190)	(0.00346)	(0.0289)	(0.0309)	(0.0278)
SPM	0.172	1.11	0.204	0.413	0.269	0.593	-1.14	0.0108
	(0.123)	(0.901)	(0.828)	(0.817)	(0.162)	(1.27)	(1.42)	(1.23)
xRAPM	0.0840	1.08	-0.351	-0.0210	0.209	-1.46	-2.50	-1.81
	(0.0785)	(0.638)	(0.556)	(0.544)	(0.110)	(1.05)	(1.34)	(1.09)
OWS/48	0.00124	0.00679	0.00120	0.00249	0.00393	0.0190	0.00778	0.0152
	(0.00286)	(0.0196)	(0.0191)	(0.0187)	(0.00363)	(0.0284)	(0.0298)	(0.0275)
DWS/48	0.00294***	0.00172	0.0000190	0.000411	0.00366**	0.00265	-0.00656	-0.000437
	(0.000872)	(0.00719)	(0.00638)	(0.00634)	(0.00124)	(0.0103)	(0.0119)	(0.0103)
	Reduced Sample							
PER	0.112	0.305	-0.835	0.219	0.448	0.378	-2.15	-0.0172
	(0.190)	(0.779)	(0.898)	(0.778)	(0.228)	(1.78)	(2.18)	(1.76)
WS/48	0.00518	0.00641	-0.00680	0.00542	0.00858*	0.0138	-0.0178	0.00884
	(0.00288)	(0.0116)	(0.0143)	(0.0116)	(0.00342)	(0.0273)	(0.0333)	(0.0272)
SPM	0.0997	0.377	-0.461	0.314	0.264	0.378	-1.66	0.0593
	(0.134)	(0.568)	(0.666)	(0.568)	(0.161)	(1.24)	(1.59)	(1.23)
xRAPM	0.125	0.408	-0.720	0.323	0.209	-1.47	-3.06	-1.72
	(0.0873)	(0.401)	(0.466)	(0.399)	(0.109)	(1.03)	(1.57)	(1.07)
OWS/48	0.000887	0.00539	-0.00553	0.00457	0.00382	0.0171	-0.0102	0.0128
	(0.00308)	(0.0119)	(0.0145)	(0.0120)	(0.00361)	(0.0279)	(0.0318)	(0.0275)
DWS/48	0.00302**	0.00255	0.00226	0.00253	0.00360**	0.00280	-0.00129	0.00216
	(0.000949)	(0.00471)	(0.00532)	(0.00469)	(0.00121)	(0.00983)	(0.0122)	(0.00989)

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com.

(1), (5) are OLS estimates based off equation (4), without and with player fixed effects respectively

All others are two stage least squares estimates with an instrument in equation (1) as the first stage, and equation (4) as the second stage

(2), (6) use 2010 indicator as the instrument; (3), (7) use the contract year percent as the instrument; and (4), (8) use both

Full and reduced sample as described in the text, are from 2005-2014. All standard errors are robust to heteroskedasticity and clustered by player. Instruments are also described in the text. Team dummies are now included in the specification

Table A.5.XI: Performance over Expectation Estimates of Contract Year Effect

	Probit First Stage Estimates of Delta							
Efficiency Metric	Without Player Fixed Effects				With Player Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample							
PER	0.0480	-0.494	-0.0484	-0.0488	0.463*	-	-	-
	(0.176)	(0.0223)	(0.0223)	(0.0224)	(0.230)	-	-	-
WS/48	0.00515	0.00634	0.00110	0.00220	0.00857*	-	-	-
	(0.00280)	(0.0205)	(0.0183)	(0.0183)	(0.00346)	-	-	-
SPM	0.172	1.44	0.486	0.708	0.269	-	-	-
	(0.123)	(0.882)	(0.781)	(0.776)	(0.162)	-	-	-
xRAPM	0.0840	1.40*	-0.130	0.216	0.209	-	-	-
	(0.0785)	(0.601)	(0.517)	(0.503)	(0.110)	-	-	-
OWS/48	0.00124	0.0112	0.00559	0.00666	0.00393	-	-	-
	(0.00286)	(0.0193)	(0.0183)	(0.0180)	(0.00363)	-	-	-
DWS/48	0.00294***	0.00389	0.00154	0.00221	0.00366**	-	-	-
	(0.000872)	(0.00670)	(0.00600)	(0.00593)	(0.00124)	-	-	-
	Reduced Sample							
PER	0.112	-0.0434	-0.0432	-0.0434	0.448	0.359	-0.124	0.129
	(0.190)	(0.0245)	(0.0244)	(0.245)	(0.228)	(0.880)	(0.785)	(0.836)
WS/48	0.00518	0.0108	-0.00128	0.00963	0.00858*	0.00730	0.000229	0.00427
	(0.00288)	(0.0113)	(0.0137)	(0.0113)	(0.00342)	(0.0137)	(0.0128)	(0.0132)
SPM	0.0997	0.551	-0.263	0.472	0.264	-0.160	-0.613	-0.360
	(0.134)	(0.557)	(0.638)	(0.556)	(0.161)	(0.603)	(0.572)	(0.582)
xRAPM	0.125	0.592	-0.567	0.478	0.209	0.0993	-0.0940	-0.0452
	(0.0873)	(0.383)	(0.448)	(0.380)	(0.109)	(0.489)	(0.480)	(0.482)
OWS/48	0.000887	0.00866	-0.00104	0.00771	0.00382	0.00556	-0.00160	0.00267
	(0.00308)	(0.0117)	(0.0140)	(0.0117)	(0.00361)	(0.0126)	(0.0113)	(0.0119)
DWS/48	0.00302**	0.00379	0.00356	0.00379	0.00360**	0.00471	0.00355	0.00423
	(0.000949)	(0.00452)	(0.00518)	(0.00450)	(0.00121)	(0.00576)	(0.00564)	(0.00567)

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com.

(1), (5) are OLS estimates based off equation (4), without and with player fixed effects respectively

All others use an instrument in equation (3) to produce fitted probabilities, which are then passed as an instrument to equation (1) in the first stage and equation (4) in the second

(2), (6) use 2010 indicator as the instrument; (3), (7) use the contract year percent as the instrument; and (4), (8) use both

Full and reduced sample as described in the text, are from 2005-2014. All standard errors are robust to heteroskedasticity and clustered by player. Instruments are also described in the text. Team dummies are now included in the specification

Table A.5.XIII: Contract Year Effect Estimates on Box Score Statistics

Estimates of Delta		
Box Score Statistic	Sample	
	Full	Reduced
Points per 36 Minutes	0.106	0.0901
	(0.169)	(0.166)
Assists per 36 Minutes	0.0537	0.0651
	(0.0528)	(0.0521)
Offensive Rebounds per 36 Minutes	0.0860*	0.0801*
	(0.0367)	(0.0361)
Defensive Rebounds per 36 Minutes	0.112	0.114
	(0.0608)	(0.0589)
Blocks per 36 Minutes	0.0315	0.0285
	(0.0256)	(0.0251)
Steals per 36 Minutes	0.0409	0.0421
	(0.0243)	(0.0239)
Turnovers per 36 Minutes	0.0159	0.0197
	(0.0341)	(0.0338)

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com & Spotrac.com.

Full and reduced sample as described in the text, are from 2005-2014. OLS estimates based off equation (4) in text. All standard errors are robust to heteroskedasticity and clustered by year. Baseline covariates include position dummies, height, weight, age, year dummies and SRS as a team quality measure, as outlined in the text. Team dummies are now included in the specification

Appendix 6: Sensitivity Check with Minutes Restriction

As outlined in footnote 65, this appendix repeats all results for Tables VII, VIII, IX, X, XI and XIII while removing player-seasons of less than 200 minutes played. This could potentially remove some of the noisier observations in my dataset, as the performance metric may not have had time to stabilize in such a short period of time. With this restriction, the full sample reduces to 1,780 player-seasons across 434 players and the reduced sample to 1,334 player-seasons across 255 players.

Table A.6.VII: First Stage Statistics

Model	Sample	Instrument			
		Year Indicator	CY Percent	Both	
		F-Stat	F-Stat	F-Stat	P-Value
With Player Fixed Effects	Full	9.48	7.01	4.78	0.0412
	Reduced	7.90	4.99	3.95	0.0226
Without Player Fixed Effects	Full	32.26	34.59	18.45	0.1117
	Reduced	56.40	36.56	28.29	0.0869

Source: Basketball-Reference.com, ShamSports.com & Spotrac.com.
Full and reduced samples, as defined in text, are from 2005-2014. Table reports key statistics for first stage in instrumental variables framework, as outlined in equation (1) and (2) in text. F-Stat refers to Cragg-Donald F-Statistic. P-Value is that returned from Hansen-J statistic as test of overidentification. Player-seasons are removed if less than 200 minutes

Table A.6.VIII: Contract Year Effect Estimates for Full Sample

TSLS Estimates of Delta				
Efficiency Metric	OLS	Instrument		
		2010 Indicator	CY Percent	Both
Player Efficiency Rating	0.192	-0.675	-4.17	-1.12
	(0.194)	(1.81)	(2.82)	(1.84)
Win Shares per 48 Minutes	0.00417	0.0272	-0.00372	0.0232
	-0.00266	(0.0264)	(0.0295)	(0.0258)
Statistical Plus-Minus (SPM)	0.0498	0.021	-1.83	-0.214
	(0.121)	(1.06)	(1.50)	(1.06)
Expected Regularized Adjusted Plus-Minus (xRAPM)	-0.642	-3.20*	-5.79*	-3.53*
	(0.113)	(1.47)	(2.65)	(1.56)
Offensive Win Shares per 48 Minutes	0.00263	0.0211	-0.00844	0.0173
	(0.00266)	(0.0262)	(0.0301)	(0.0258)
Defensive Win Shares per 48 Minutes	0.00123	0.00734	0.00696	0.00729
	(0.000884)	(0.00965)	(0.0120)	(0.00967)
Offensive SPM	0.0218	-0.195	-1.91	-0.412
	(0.112)	(1.03)	(1.47)	(1.04)
Defensive SPM	0.0281	0.240	0.106	0.223
	(0.0494)	(0.490)	(0.624)	(0.488)
Offensive xRAPM	-0.0175	-2.34*	-4.51*	-2.61*
	(0.0859)	(1.11)	(2.11)	(1.19)
Defensive xRAPM	-0.0482	-0.813	-1.21	-0.863
	(0.0671)	(0.697)	(0.956)	(0.708)
Volume Metric	OLS	Instrument		
		2010 Indicator	CY Percent	Both
Estimated Wins Added	0.305	-0.866	-2.80	-1.11
	(0.201)	(2.05)	(2.89)	(2.08)
Win Shares	0.134	-0.106	-1.05	-0.226
	(0.143)	(1.39)	(1.83)	(1.39)
Statistical Wins Above Replacement	0.122	-0.752	-2.06	-0.918
	(0.159)	(1.68)	(2.31)	(1.69)
Wins Above Replacement	0.0622	-3.28	-5.52	-3.56
	(0.179)	(2.09)	(3.29)	(2.17)
Offensive Win Shares	0.147	-0.235	-0.948	-0.326
	(0.113)	(1.10)	(1.47)	(1.11)
Defensive Win Shares	-0.0173	0.150	-0.0419	0.126
	(0.0547)	(0.582)	(0.731)	(0.581)

* p < 0.05; ** p < 0.01; *** p < 0.001. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com.

Full sample contains all 1870 player-seasons which were contract or non-contract years, as defined in the text, across 439 players from 2005-2014. Performance metrics and instruments used are described in the text. IV framework corresponds to equations (1) and (2) in the text. All standard errors were calculated robust to heteroskedasticity and were clustered by player. Player-seasons are removed if less than 200 minutes

Table A.6.IX: Contract Year Effect Estimates for Reduced Sample

	Estimates of Delta						
Efficiency Metric	OLS	TSLS			Probit First Stage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PER	0.211	-1.74	-5.58	-1.66	-0.947	-1.65	-1.21
	(0.187)	(1.82)	(3.58)	(1.81)	(1.09)	(1.11)	(1.08)
WS/48	0.0421	0.00891	-0.0275	0.00964	0.0101	0.00375	0.00784
	(0.00257)	(0.0238)	(0.0341)	(0.0238)	(0.0142)	(0.0139)	(0.0139)
SPM	0.631	-0.379	-2.53	-0.336	0.0813	-0.259	-0.0497
	(0.118)	(1.02)	(1.84)	(1.02)	(0.664)	(0.687)	(0.663)
xRAPM	-0.0340	-3.31*	-6.26	-3.26	-0.627	-0.909	-0.796
	(0.109)	(1.54)	(3.23)	(1.52)	(0.644)	(0.657)	(0.643)
Offensive WS/48	0.00267	-0.00054	-0.0358	0.000169	0.000473	-0.00574	-0.00176
	(0.00257)	(0.0242)	(0.0362)	(0.0242)	(0.0150)	(0.0150)	(0.0148)
Defensive WS/48	0.00124	0.0104	0.0112	0.01040	0.0101	0.0104	0.0102
	(0.000852)	(0.00993)	(0.0136)	(0.00991)	(0.00636)	(0.00698)	(0.00646)
Offensive SPM	0.0367	-0.653	-2.73	-0.612	-0.321	-0.692	-0.456
	(0.108)	(1.02)	(1.85)	(1.01)	(0.638)	(0.666)	(0.640)
Defensive SPM	0.0270	0.326	0.238	0.327	0.445	0.472	0.448
	(0.0477)	(0.496)	(0.702)	(0.495)	(0.349)	(0.376)	(0.351)
Offensive xRAPM	0.0015	-2.29*	-4.73	-2.24*	-0.0161	-0.304	-0.172
	(0.0828)	(1.14)	(2.50)	(1.12)	(0.626)	(0.648)	(0.625)
Defensive xRAPM	-0.0374	-0.956	-1.43	-0.947	-0.555	-0.546	-0.566
	(0.0649)	(0.714)	(1.12)	(0.711)	(0.465)	(0.498)	(0.470)
Volume Metric	OLS	TSLS			Probit First Stage		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
EWA	0.298	-1.56	-4.24	-1.50	1.78	1.84	1.69
	(0.194)	(1.99)	(3.38)	(1.98)	(1.38)	(1.41)	(1.37)
WS	0.113	-0.670	-1.97	-0.644	0.171	0.223	0.145
	(0.139)	(1.36)	(2.07)	(1.36)	(0.792)	(0.780)	(0.777)
Statistical WAR	0.114	-0.798	-2.95	-0.755	1.76	1.86	1.71
	(0.154)	(1.56)	(2.59)	(1.56)	(1.05)	(1.10)	(1.04)
WAR	0.102	-3.46	-6.34	-3.41	1.17	1.34	1.09
	(0.174)	(2.06)	(3.84)	(2.05)	(1.06)	(1.16)	(1.10)
Offensive WS	0.137	-0.682	-1.67	-0.662	0.470	0.527	0.446
	(0.109)	(1.10)	(1.68)	(1.10)	(0.679)	(0.681)	(0.669)
Defensive WS	-0.0282	0.0178	-0.243	0.0229	-0.288	-0.280	-0.286
	(0.0533)	(0.557)	(0.796)	(0.556)	(0.387)	(0.410)	(0.388)

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com.

(1) is OLS estimates based off equation (2). (2), (3), (4) use equations (1) and (2) in a two stage least squares framework; while (5), (6), (7) use fitted probabilities from equation (3) as the instrument passed to the first stage.(2), (5) use 2010 indicator as the instrument; (3), (6) use the contract year percent as the instrument; and (4), (7) use both. Full and reduced samples, performance metrics and instruments described in the text. All standard errors are calculated robust to heteroskedasticity and clustered by player. Player-seasons are removed if less than 200 minutes

Table A.6.X: Performance over Expectation Estimates of Contract Year Effect

Efficiency Metric	TSLS Estimates of Delta							
	Without Player Fixed Effects				With Player Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample							
PER	0.2330	0.961	-0.251	0.260	0.479*	0.790	-1.930	0.338
	(0.148)	(0.995)	(0.939)	(0.912)	(0.208)	(2.03)	(2.43)	(2.00)
WS/48	0.00791***	0.0183	0.00913	0.0130	0.00917**	0.03680	0.00801	0.0321
	(0.00218)	(0.0146)	(0.0144)	(0.0137)	(0.00310)	(0.0334)	(0.0353)	(0.0324)
SPM	0.299**	0.752	0.148	0.403	0.333*	0.422	-1.18	0.157
	(0.0961)	(0.638)	(0.596)	(0.583)	(0.137)	(1.30)	(1.55)	(1.28)
xRAPM	0.0624	0.945	-0.613	0.0438	0.177	-2.15	-4.12	-2.48
	(0.0805)	(0.630)	(0.598)	(0.570)	(0.114)	(1.42)	(2.23)	(1.50)
OWS/48	0.00467*	0.0163	0.00783	0.0114	0.00614*	0.0340	0.0119	0.0303
	(0.00205)	(0.0135)	(0.0134)	(0.0128)	(0.00294)	(0.0315)	(0.0321)	(0.0306)
DWS/48	0.00298**	0.00177	0.00146	0.00159	0.00267	0.00253	-0.00271	0.00166
	(0.000897)	(0.00655)	(0.00634)	(0.00608)	(0.00125)	(0.0130)	(0.0159)	(0.0131)
	Reduced Sample							
PER	0.217	0.117	-1.18	0.238	0.456*	-0.562	-3.50	-0.0059
	(0.164)	(0.661)	(0.834)	(0.661)	(0.202)	(1.99)	(3.09)	(1.99)
WS/48	0.00738	0.0107	-0.00187	0.0119	0.00916**	0.0251	-0.0105	0.0257
	(0.00247)	(0.0102)	(0.0132)	(0.0102)	(0.00302)	(0.0312)	(0.0390)	(0.0313)
SPM	0.251*	0.364	-0.422	0.437	0.330*	0.306	-1.77	0.339
	(0.106)	(0.428)	(0.533)	(0.429)	(0.133)	(1.28)	(1.86)	(1.28)
xRAPM	0.0846	0.169	-1.23*	0.300	0.178	-2.23	-5.14	-2.18
	(0.0906)	(0.433)	(0.555)	(0.435)	(0.111)	(1.47)	(2.98)	(1.46)
OWS/48	0.00434	0.00720	-0.00475	0.00831	0.00600*	0.0175	-0.0137	0.0180
	(0.00229)	(0.00938)	(0.0120)	(0.00935)	(0.00288)	(0.0294)	(0.0356)	(0.0294)
DWS/48	0.00278**	0.00303	0.00319	0.00301	0.00280*	0.00661	0.00418	0.00665
	(0.000991)	(0.00465)	(0.00587)	(0.00466)	(0.00121)	(0.0128)	(0.0170)	(0.0128)

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com.

(1), (5) are OLS estimates based off equation (4), without and with player fixed effects respectively

All others use an instrument in equation (3) to produce fitted probabilities, which are then passed as an instrument to equation (1) in the first stage and equation (4) in the second

(2), (6) use 2010 indicator as the instrument; (3), (7) use the contract year percent as the instrument; and (4), (8) use both

Full and reduced sample as described in the text, are from 2005-2014. All standard errors are robust to heteroskedasticity and clustered by player. Instruments are also described in the text. Player-seasons are removed if less than 200 minutes

Table A.6.XI: Performance over Expectation Estimates of Contract Year Effect

Efficiency Metric	Without Player Fixed Effects (1)	(2)	(3)	(4)	With Player Fixed Effects (5)	(6)	(7)	(8)
	Probit First Stage Estimates of Delta							
	Full Sample							
PER	0.2330	1.51	0.349	0.824	0.479*	-	-	-
	(0.148)	(0.942)	(0.884)	(0.859)	(0.208)	-	-	-
WS/48	0.00791***	0.0214	0.0131	0.01660	0.00917**	-	-	-
	(0.00218)	(0.0137)	(0.0138)	(0.0130)	(0.00310)	-	-	-
SPM	0.299**	0.921	0.317	0.577	0.333*	-	-	-
	(0.0961)	(0.602)	(0.570)	(0.552)	(0.137)	-	-	-
xRAPM	0.0624	1.24	-0.386	0.304	0.177	-	-	-
	(0.0805)	(0.599)	(0.572)	(0.538)	(0.114)	-	-	-
OWS/48	0.00467*	0.0195	0.0123	0.0152	0.00614*	-	-	-
	(0.00205)	(0.0128)	(0.0129)	(0.0122)	(0.00294)	-	-	-
DWS/48	0.00298**	0.00185	0.00108	0.00153	0.00267	-	-	-
	(0.000897)	(0.00605)	(0.00608)	(0.00569)	(0.00125)	-	-	-
	Reduced Sample							
PER	0.217	0.172	-1.05	0.2570	0.456*	-0.0473	-0.615	-0.253
	(0.164)	(0.641)	(0.811)	(0.642)	(0.202)	(0.991)	(0.930)	(0.967)
WS/48	0.00738	0.0114	0.000214	0.0121	0.00916**	0.01290	0.00680	0.0109
	(0.00247)	(0.00989)	(0.0129)	(0.00987)	(0.00302)	(0.0162)	(0.0154)	(0.0158)
SPM	0.251*	0.357	-0.411	0.409	0.330*	-0.204	-0.561	-0.326
	(0.106)	(0.415)	(0.520)	(0.415)	(0.133)	(0.614)	(0.593)	(0.605)
xRAPM	0.0846	0.248	-1.20*	0.349	0.178	-0.000770	-0.309	-0.171
	(0.0906)	(0.424)	(0.556)	(0.426)	(0.111)	(0.603)	(0.587)	(0.597)
OWS/48	0.00434	0.00732	-0.00327	0.00806	0.00600*	0.00690	0.00213	0.00534
	(0.00229)	(0.00916)	(0.0118)	(0.00914)	(0.00288)	(0.0136)	(0.0127)	(0.0132)
DWS/48	0.00278**	0.00361	0.00392	0.00358	0.00280*	0.00557	0.00482	0.00533
	(0.000991)	(0.00450)	(0.00578)	(0.00450)	(0.00121)	(0.00735)	(0.00734)	(0.00728)

* p < 0.05; ** p < 0.01; *** p < 0.001. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com, Spotrac.com & stats-for-the-nba.appspot.com.

(1), (5) are OLS estimates based off equation (4), without and with player fixed effects respectively

All others use an instrument in equation (3) to produce fitted probabilities, which are then passed as an instrument to equation (1) in the first stage and equation (4) in the second

(2), (6) use 2010 indicator as the instrument; (3), (7) use the contract year percent as the instrument; and (4), (8) use both

Full and reduced sample as described in the text, are from 2005-2014. All standard errors are robust to heteroskedasticity and clustered by player. Instruments are also described in the text. Player-seasons are removed if less than 200 minutes

Table A.6.XIII: Contract Year Effect Estimates on Box Score Statistics

Estimates of Delta		
Box Score Statistic	Sample	
	Full	Reduced
Points per 36 Minutes	0.0475	0.0236
	(0.168)	(0.163)
Assists per 36 Minutes	0.0620	0.0718
	(0.0543)	(0.0528)
Offensive Rebounds per 36 Minutes	0.0795*	0.0771*
	(0.0342)	(0.0334)
Defensive Rebounds per 36 Minutes	0.0828	0.0800
	(0.0591)	(0.0571)
Blocks per 36 Minutes	0.0137	0.00851
	(0.0240)	(0.0235)
Steals per 36 Minutes	0.0370	0.0405
	(0.0214)	(0.0208)
Turnovers per 36 Minutes	-0.00495	-0.00382
	(0.0295)	(0.0288)

* p < 0.05; ** p < 0.01; *** p < 0.001. Standard errors are in parentheses

Source: Basketball-Reference.com, ShamSports.com & Spotrac.com.

Full and reduced sample as described in the text, are from 2005-2014. OLS estimates based off equation (4) in text. All standard errors are robust to heteroskedasticity and clustered by year. Baseline covariates include position dummies, height, weight, age, year dummies and SRS as a team quality measure, as outlined in the text. Player-seasons are removed if less than 200 minutes