Show Me the Money: An Analysis of the Impact of Free Agency on NFL Player Performance

Ben Singer, 2009

Abstract: Contract theory states that individuals are more likely to expend greater effort when they have incentives that reward them for better performance. Presumably, this effort can be observed in the individual's performance in whatever pursuit or employment to which the contract applies. Professional sports provide an excellent environment for analysis of contract theory through examining how players respond to contract incentives such as free agency. Previous research within Major League Baseball (MLB) and the National Basketball Association (NBA) revealed evidence to varying degrees that players: 1) play better in the year prior to becoming a free agent; and 2) play worse in the year immediately after signing a multiyear contract. In this paper, I apply similar analysis to the National Football League (NFL). No study of free agency or player performance has been attempted previously for the NFL. This is likely because of a combination of factors that distinguish the NFL from MLB or the NBA, including more complex teamwork components as well as a unique contract system with less guaranteed money than other major professional sports. In this study, I use data on free agency status (dummy) and offensive player performance variables from 1998 through 2007 (10 full NFL seasons) for quarterbacks, running backs, tight ends, and wide receivers. The performance variables chosen are a mixture of traditional metrics as well as newly designed metrics (which take into account strength of defense and a player's value relative to the average player at his position, among other things). The other independent variables I use in examining free agency's effect on player performance include length of contract, years of experience in the NFL, the number of team wins, the year after a multiyear contract signing (dummy), whether a player switched teams (dummy), and the number of plays in which the player touched the ball. I analyze each of the four positions separately while using many of the same performance metrics. Although there are mixed results, the preponderance of the evidence indicates that free agency does not have a statistically significant impact on player performance, either for the year prior to free agency or the year after signing a multiyear contract. This suggests that the conventional wisdom that NFL players play harder when they are about to become free agents and then slack off after signing a multiyear contract is unsubstantiated.

Introduction

A commonly espoused conventional wisdom in professional sports is that players in the last year of their contracts will exert extra effort to perform better in the hopes of securing better contracts in free agency. The idea seems logical that people would respond to incentives, and anecdotal evidence supports it. In the National Basketball Association (NBA), Erick Dampier "doubles his rebounds and increases his scoring by 50 percent" in his contract year with the Golden State Warriors in 2003-2004 (W1). In Major League Baseball (MLB), Manny Ramirez's batting average jumped 100 points when he was traded to the Los Angeles Dodgers and became eligible for free agency. Mere months ago in the National Football League (NFL), Kurt Warner went from borderline starting quarterback (QB) to the Super Bowl and threw for 1000 more yards than he did in any of his previous seasons with the Arizona Cardinals.

There certainly are players who fit the criteria for this contract year phenomenon. But are they outliers or the norm? Is their elevated performance due to increased effort or some other factor that is outside of their control, such as the acquisition of a crucial teammate or a coach who knows how to better utilize their abilities? Even if only a small fraction of players are capable of significantly improving their performance by trying harder, being able to identify those players a priori would substantially impact contract negotiations.

In the highly lucrative and highly competitive world of professional sports, figuring out how to maximize team performance relative to costs is paramount. However, while the contract year phenomenon has been examined in the NBA and MLB previously, this study is the first to statistically analyze the phenomenon within the NFL. In order to understand the design of this study, it is necessary to comprehend the previous work that has been done in the NBA and MLB and how the three leagues differ with respect to player performance and contract rules and structures. After reviewing the relevant differences in game and contract structures in the three leagues, I outline a simple economic model for the expected interactions between free agency and player performance. Using this model, I delineate the hypotheses and methodology for data gathering and the design of my statistical analyses. From there I review the results found in my analysis of the contract year phenomenon and discuss the significance of these results for the NFL. Finally, I explore the significance of the different findings across the NBA, MLB, and NFL and propose suggestions for future research in these areas.

Review of Major League Baseball (MLB) Findings (Note: a list of commonly used abbreviations beginning in this section is located in the Appendix)

MLB is a game comprised of two different types of players: those who bat and field (batters) and those who pitch (pitchers). The majority of the game's interactions are discrete events, known as at-bats, that involve the pitcher and the batter. It's a zero-sum interaction; either the batter is successful and gets on base or the pitcher is successful and records an out. This is significant for two reasons. First, teamwork components do not hold much influence over an individual player's performance relative to other sports, making it easier to gauge a player's value in MLB. Second, despite whatever specialized fielding position or pitching role players may have, they can be easily substituted for each other when batting or pitching. This is an important contrast with the NFL because one can imagine substituting Manny Ramirez into the lineup for the Los Angeles Dodgers without much of a hitch, but it would be nearly impossible to take a quarterback midseason from one NFL team and put him into another because of the complexity of team interaction and differences in offensive strategies between teams. Simply put, the game of baseball is more homogenous than football.

Another distinguishing feature of MLB is that there are no conflicts of interest between players on the same team. A batter wants his teammate to get a hit because it will give him the opportunity to get an RBI (run batted in) if he gets on base or to score a run if he is already on base. In the NFL and NBA, where players are working offensively and defensively simultaneously rather than individually, there is more room for moral hazard. Terrell Owens might want to get the ball more because it will increase his personal catching statistics, but doing so might sometimes be at odds with the team goal of choosing the play that gives the team the best chance to move the ball downfield and score.

Now that some of the important structural differences of MLB have been described, what have studies found with regards to the contract year phenomenon? MLB has the most concentrated research on this topic of any of the three sports. While the results vary from study to study, the general consensus is that free agency has a significant positive impact on player performance the year prior to becoming a free agent. There is also some indication that player performance significantly declines the year immediately following the signing of a multiyear contract. This “shirking” phenomenon would make sense given that a player’s incentives to try hard to improve his free agency value would be lowest during this time period.

Starting back in 1993, Paul Sommers began examining the link between salary arbitration and player performance in MLB (Sommers 1993). Salary arbitration is a feature of MLB where a player with at least 2-6 years of experience, who is not eligible for free agency, may apply for arbitration. This results because of a dispute over the compensation the player receives in his contract. The player and the team each submit compensation figures for what they think the player is worth. A neutral arbitrator then evaluates the player in terms of “Statistics covering productivity, longevity, potential and comparable worth as compared to like-situated players...The arbitrator must use these statistics to decide” (W2) which of the two figures to award the player.

Arbitration differs from free agency in a few significant ways. First, one would expect a greater selection effect for players “outperforming” their current contracts to apply more often for arbitration. Why would a player try to renegotiate his salary if he was underperforming his contract? With free agency, players are eligible when their contract is terminated. If anything, this would lead to a greater representation of underperforming players because teams would be less inclined to extend their contracts prior to their free agent year. Additionally, the timing of salary arbitration is different from free agency. Free agency occurs when a player’s contract ends or a player is without a contract for whatever reason. Salary arbitration occurs when the player applies for it. This timing is determined solely by the player for arbitration, but not for free agency.

There is a lag between when a player files for arbitration and when his case is heard, and players know ahead of time that they will be eligible after their second MLB season. Sommers hypothesized that players have incentives to put in their best effort in the season before their case is heard in order to make the best case for the arbitrator that they are worth more money. He examined 234 players (pitchers and batters) whose arbitration cases were heard between 1980 and 1990. He evaluated pitcher performance in terms of earned run average (ERA) and strikeout to walk ratio (K/BB), and batter performance in terms of batting average (BA) and slugging average (SA). He then segregated each of these categories by age and whether the player or the team won the arbitration dispute. Although Sommers's performance statistics were far from comprehensive and many of his results were not statistically significant at the 10% level, he did find uniformly that player performance across all categories decreased from the season before arbitration to the season afterward. His most significant findings were that pitchers over 28 years of age increased their ERAs by over half a run (significant at the 5% level) and batters under 27 lost an average of 17 points on their batting average and 28 points on their slugging average (both significant at the 10% level) following arbitration.

Perhaps intrigued by Sommers's work and armed with a decade's worth of improved analysis, two more extensive studies examined the effects of free agency on player performance in 2002 and 2003. The authors of "The Effectiveness of Incentive Mechanisms in Major League Baseball" (Maxcy et al. 2002) examined whether players in the final years of their contracts performed significantly better than those who had just signed multiyear contracts. They inspected only one performance variable (SA for batters and K/BB for pitchers) and controlled using the number of days a player spent on the disabled list (DL), their age, the number of at bats (AB) or innings pitched (IP). They found that players in the last year of their contract had significantly decreased DL time compared to players in the first year of multiyear contracts. Specifically, batters spent almost 5 fewer days on the DL (significant at the 5% level, one-tailed) and pitchers spent over 8 fewer days on the DL (significant at the 1% level, one-tailed) in the last years of their contracts. These results suggested that perhaps players were more likely to play through or conceal injury in order to improve their negotiating value. However, because managers control playing time, it could be that they tried to play players as much as possible while they were on their team with only one season left rather than being more cautious as they would with players signed long-term. Ultimately, across 1972 player observations, Maxcy et al. found no significant differences in player performance either in the last year of the contract or the first year of a multiyear contract when playing time was controlled for. It is important to note that the authors did take into account the conclusions of Maxcy (1996) that long term contracts were significantly more common among top players entering the prime years of their playing careers. The ramifications of this selection bias for free agency are important and will be discussed later on in this paper in relation to the NFL.

However, less than a year after Maxcy et al.'s study, Daniel Marburger (2003) conducted a similar study of his own and obtained very different results. He examined performance changes based on the length of contract for player's in the free agency era and those in the reserve era (no free agency, could alter incentives) of MLB and compared them. One of his cleverer techniques was computing player productivity as player performance relative to mean player performance within a given year. Doing so helped control for increases in player performance due to league-wide phenomena such as weaker pitching in a given year. However, at the same time, such changes could be due to the fact that there were more good batters in a given year, so this technique could have overcontrolled for player performance as well. Rather than using SA, Marburger adopted a total bases formula for productivity. Total bases is the sum of total bases got on hits, plus walks, plus hit by pitch, plus stolen bases, minus caught stealing. Controlling for age and position, he used ordinary least squares (OLS) to compare the performance of free agents to themselves over the life of their careers. He then analyzed player performance as a function of whether they are free agents, or have one, two, three, four, or five years as the remaining length of their contracts. In the end, he found that players with 1-2 year contracts in the free agent era showed significant performance increases over similar players in the reserve era, but after 2 years there was no statistically significant difference. Although it's possible that there existed significant control variables that were not taken into account, the study presented solid evidence that the prospect of being a free agent caused players to perform better, presumably to some degree due to increased effort.

Aside from Maxcy et. al (2002) and Marburger (2003), other studies on free agency, player incentives, and performance in MLB have been conducted. Woolway

(1997) found that player performance drops off significantly after signing a multiyear contract, although his study focuses extensively on the 1992 and 1993 seasons and is therefore less robust. Another study (Krautmann & Oppenheimer, 2002) found a significantly negative tradeoff between the length of a contract given to a player and the returns on his performance. Although this study did not attempt to explore the possible impact of free agency incentives on this negative tradeoff, what remains clear is that there is a lack of consensus on the effects of free agency on MLB player performance. Despite this lack of consensus and potential room for various selection biases in their methodologies, some studies such as Marburger (2003) have found effects that do not prove but provide support for a boost in performance due to free agency. Similarly, others such as Sommers (1993) have found evidence of a decline in performance following the negotiation and signing of a multiyear contract. Although many of these studies could be more rigorous, their results suggest the existence of players increasing their effort before and decreasing their effort immediately after their contract years in accordance with the contract year phenomenon.

Review of National Basketball Association (NBA) Findings

Unlike the series of discrete events that define baseball, basketball is a much more fluid game with greater teamwork components. In this way, it is more similar to football because the interactions of players with their teammates are much more significant and also much harder to quantify.

Unlike the NFL, in the NBA the players who play defense are the same as the players who play offense. And unlike MLB, in the NBA these players have to shift quickly and constantly between playing defense and offense. Another factor that distinguishes the NBA from MLB is that players may sometimes have conflicts of interest between acting in a way that gives their team the best chance to win and acting in a way that helps their individual performance. For example, a player might give his team the best chance to win if he passes the ball to an open teammate rather than try and shoot the ball himself. However, that player might shoot the ball anyway because he wants to increase the number of points he scores to improve the appearance of his individual performance, which will presumably increase his value in free agency. Obviously, these types of conflicts of interest depend on the individual player's set of values and are often more complex in reality. More importantly, they are virtually impossible to quantify in a streamlined manner. Still, it is important to understand that they exist when analyzing player performance.

Yet one of the largest differences between the NBA and the other two sports leagues is that only five players play per side in an NBA game, roughly half of the nine men teams in MLB and the eleven man sides in the NFL. Perhaps this allows for an individual to influence the outcome of the game through his performance, meaning that increasing effort would have more noticeable effects in the NBA.

Kevin J. Stiroh found in "Playing for Keeps: Pay and Performance in the NBA" (2007) results that support such a theory. Using the same template as Maxcy et al. (2002) with a robust 6195 player observations from 1988-2002, he found that individual performance improved significantly in the year before signing a multiyear contract but declined significantly in the year after signing a multiyear contract. Specifically, a player's composite rating (a performance metric that factors over 9 performance metrics and controls for playing time) increased by .381 (5% significance level) the season before free agency and decreased by .325 (5% significance level) the season after signing a contract. He also examined contract pay specifically in relation to performance and found that a one-point scoring increase is associated with an annual increase in salary of over $300,000. In addition, he found that "performance declines tend to be smallest for those who signed the very longest contracts, suggesting that the moral hazard of a multi-year contract may be offset by the selection effect of who receives contracts." What this means is that there was a selection bias where better players were more likely to receive multiyear contracts. Because the players who received multiyear contracts were not randomly selected, but chosen after scrutiny by the team's management, they might not exhibit the shirking that the average player would. This suggests that the selection effects that Maxcy (1996) found in MLB apply to multiple sports. Furthermore, Stiroh found that a contract shift from last year of a contract to first year of a multiyear deal was associated with a 4.5 game decrease in the number of team wins, suggesting that individual performance incentives were largely positively aligned with team performance.

As far as Stiroh's data is concerned, he used a very comprehensive array of performance and control variables to strengthen the validity of his findings. In terms of player performance, he focused on composite rating. Regarding contract information, he included the signing date of the contract, the end year, the length, the overall contract value, and the annual salary. Additionally, he controlled for age and used team, position, year, and traded (=1 if the player was traded) dummy variables. He used weighted least squares (WLS) regression for his estimates, and his methods presented no major limitations other than the fact that he does not have salary information for all 6000 players (only about 2000). Still, his findings were robust and remain the most thorough and current analysis of the contract year phenomenon in the NBA.

If we are to believe Stiroh's findings, then the contract year phenomenon appears to be more significant in the NBA than in MLB. This could be the result of having a much greater diversity of studies in MLB concerning this phenomenon as opposed to just one major (albeit very robust) study in the NBA. Regardless, there is reason to believe the contract year phenomenon exists to some degree in both leagues, and that its effects may be stronger in the NBA. In order to link these findings to analysis of the NFL, differences in contract negotiations and rules must be understood.

Structural and Contractual Differences between the NFL, the NBA, and MLB

i) Structural Differences

Some of the structural differences between how the games are organized and played differently in the NFL from the NBA and MLB have been addressed, but there are still other important differences. For instance, in the NBA and MLB, all players can be compared across a similar range of performance metrics. In MLB, pitchers can all be compared by pitching metrics (ERA, K/BB, etc) and batters by batting metrics (BA, runs, etc). In the NFL there is more specialization within each player position. A quarterback (QB) can be compared to other quarterbacks using his quarterback rating and completion percentage, but these statistics don't exist for wide receivers or any other position. Furthermore, for many positions there do not exist adequate performance metrics to measure player performance. For example, one could measure a defensive lineman by the amount of sacks or tackles he records, but this is a far from perfect reflection of his contribution to the team. What if the defensive lineman's role on his specific team is to preoccupy two of the offensive lineman so that another defensive lineman can more effectively pursue the QB? His success would not be accurately measured in by the performance metrics that are used today. Generally, these measurement issues are most prevalent for defensive players. It is for this reason that tests in this paper examine only offensive players.

The previous example highlights another salient aspect of the NFL game: the large role of teamwork. Similar to the NBA and unlike MLB, every play in the NFL is not a discrete event between two players; it is an event involving eleven men on each side of the ball. One can only speculate whether teamwork plays a greater role in the NFL or the NBA, but there are some reasons to think that it is the NFL. First, the number of players on each side is over double the number in the NFL, meaning that theoretically each player is more reliant on his teammates and has less opportunity to take over the game himself by controlling the ball. One could argue that positions with a disproportionate share of control over the plays, such as QB, can influence a game through their play more than any single player on an NBA team. This might be true, but counterexamples such as LeBron James in the NBA suggest the opposite. Second, NFL players are in many ways more specialized than players in the NBA or MLB. All baseball players either pitch or bat, and similarly, all NBA players play offense and defense and switch between the two fluidly regardless of their position. In the NFL, players either play offense, defense, or special teams and never change their roles during a play (the occasional fumble or interception is the exception to this rule). Furthermore, among the offensive players, not all advance the ball (e.g.: linemen), whereas all NBA players shoot the ball and all MLB batters hit the ball. Third, the structure of NFL games as a mixture of discrete plays involving many players may mean that coaching plays the largest role in the NFL of the three leagues. It is widely known that for most teams, the first fifteen or so offensive plays are scripted before the game (W3). As the game progresses, because each play is a discrete event, coaches will still design and call plays for their teams to execute throughout the game, leading to less improvisation on behalf of the players than in the

NBA. This increased role of coaching in the NFL may increase the impact of teamwork relative to the NBA because it decreases the ability of individual players to take over the game.

Greater specialization in player positions and a large teamwork component (within discrete plays) are two of the most distinguishing structural features of the NFL game. One other factor to keep in mind is that the NFL has by far the fewest games played of the three leagues. With only 16 games per season (excluding playoffs) per team compared to 82 in the NBA or 162 in MLB, the magnitude of each game's result on a team's season is much greater. This also has implications for the degree to which short-term fluctuations in team performance, such as going on a winning streak, affects a team. However, the ramifications of these dynamics between leagues are complex and not necessary to address for the analysis of this paper. On the other hand, the differences between the contract structures and league monetary policies (such as salary caps) are important to discuss.

ii) Contractual Differences

In order to apply the work done examining the contract year phenomenon in the MLB and NBA to the NFL, it is necessary to understand how the three leagues differ. There are five basic criteria: free agency eligibility and types, salary cap, team revenue sharing, player stake in revenue sharing and player salaries, and player contract mechanisms. Free agency eligibility and type and contract mechanisms are important because they determine when and to what extent the player can exert influence over his contract status. In other words, they directly affect player incentives. Player stake in revenue sharing and player salaries are important because they provide information on how much money players are directly provided, which also directly affects free agent incentives. Salary cap and team revenue sharing are important because they restrict the amount of money a team can spend on players and the amount of money they have to spend, respectively. In other words, they indirectly affect player incentives by restricting the resources teams can devote to individual player contracts.

Free agency eligibility and type comparisons

The first point is how one becomes eligible for free agency. In MLB, as previously discussed, players are eligible for salary arbitration if they have between slightly over two seasons to six seasons of experience. Free agency is open to any player with at least six years of experience who is currently not under contract for any subsequent seasons (W4). All players eligible for free agency must apply for it within fifteen days after the World Series ends. Those fifteen days are known as an Exclusivity Period where the player's former team is the only one who can re-sign him. There are many rules governing the compensation teams receive when a player signs with another team as a free agent. Although these rules affect the strategic interaction between the player and the team, they do not influence the player's incentives to exert effort either before or after a contract and so will not be discussed here. There are two points of note: 1) a team limit for free agent signings is determined by the overall number of free agents in a given year; 2) team compensation for having a free agent sign with another team is based upon the performance of that player relative to other players at his position in a given year. For example, a team would have to give up more draft picks to sign a catcher who performed in the top 20% of catchers that year than they would for one who performed in the bottom 60%.

In the NBA, free agents are lumped into one category, but divided into restricted and unrestricted free agents. Unrestricted free agents (UFA) may sign with whatever team they want. Restricted free agents (RFA) may receive contract offers from other teams, but their current team has "Right of First Refusal," meaning that if they match the other teams offer within fifteen days the player has to resign with his current team (W5) First round draft picks are allowed to become RFAs after the fourth year of the rookie scale contract. All other players can become RFAs in their first three seasons, and UFAs after that.

The NFL has a similar free agent structure to the NBA. There are RFA and UFA. There are also Exclusive Rights Free Agents, who are players in their first two years in the NFL and may only sign with their current team if their team offers the minimum qualifying offer. This type of free agent will not be discussed further because he does not have anything close to the types of performance incentives that RFA and UFA have. What distinguishes RFA and UFA in the NFL is that RFA must have three years experience but no more than four years experience, and UFA must have more than four years experience (W6). As in all sports, players cut, released, or without any contract qualify as UFA too. Again, as in all three leagues, there are a myriad of rules regarding team compensation and qualifying offer formalities that will not be discussed in this paper because they should not affect player performance incentives.

In addition, the NFL has the Transition Tag and Franchise Tag, both of which give teams more leverage over player contracts. Every year, each NFL team is limited to either two Transition Tags or one Transition Tag and one Franchise Tag. A Transition Tagged player must be paid the greater sum of 1) 120% of his prior year salary or 2) the average of the top ten highest paid players' salaries at his position the previous year. In each, his current team maintains the "Right of First Refusal," which means that they can demand compensation (usually in terms of draft picks) if another team signs him. In essence, teams will apply the Transition Tag to a player who will be a highly sought after free agent to the point that other teams would be willing to give the team draft picks just to get to sign him. A Franchise Tagged player may only negotiate contracts with his current team, but in exchange they must give the player a one year contract worth the greater sum of 1) 120% of his prior year salary or 2) the average of the top 5 highest paid players' salaries at his position as calculated at the end of the current year's free agency period. What is important about both tags is that they restrict a player from being able to test his full market value in free agency, and that a player does not know until after he has completed the season whether he will be tagged.

The order of player contract negotiating power in the three leagues from greatest to least is: MLB, NBA, NFL. Although MLB players have to have played for the longest time to qualify for free agency status, once they do they are all UFAs. Because this paper is only interested in comparing player incentives once they qualify for free agency, the longer pre-eligibility period in the MLB is irrelevant. In the NBA, the prevalence of RFA restricts the contract negotiating power of younger players. In the NFL, on top of RFA and UFA, there are two additional tagging tools that teams can apply to players who would be UFAs that restrict the players' negotiating power. However, because these tags are limited and applied after the season is completed, the player's incentives to perform during the season should be largely unaltered.

Salary cap comparisons

The second distinguishing criteria of the three leagues is a salary cap, or a limit set by the league on the amount of money a team can pay the players on its roster. In MLB, there is no salary cap. However, there is a luxury tax. The luxury tax comes into effect if a team's payroll in a given year exceeds the luxury tax limit (e.g., $162 million in 2009). If it does, the team must pay a percentage of their excess spending (which increases each successive year the team incurs the tax) to the league (W7). Overall, the luxury tax has not achieved much in terms of payroll parity between teams, as the gap between the payrolls of the wealthiest team and the poorest team is over $184 million (W8).

In the NBA, a soft salary cap exists in addition to a luxury tax. What this means is that teams are equally limited on what they can pay their players, but there are rules that allow certain teams to spend more in a given season. If a team qualifies under one of these rules and is allowed to spend more, and if they do and it exceeds a predetermined amount (changes every year, like MLB), then they will have to pay the league in the form of the tax (W9). The significance of the soft cap is that NBA teams are not as uniformly restricted in terms of player salaries as NFL teams.

In the NFL, there is a hard salary cap. All teams have an equal limit on the amount of money they can spend on player salaries each year, and there are no exceptions. There is no need for a luxury tax as a result. Much like the NBA, the NFL has 1) a minimum salary requirement as well to deter teams from not spending money in order to reap the profits from revenue sharing (explained more fully in *Revenue sharing comparisons)* and 2) a formula for determining its salary cap based on the projected revenues from ticket sales, television contracts, and NFL merchandise sales. Because of the NFL's commercial success, the projected revenues have increased every year and the salary caps have increased in parallel. As an example, the 2009 salary cap is $127 million per team, up over $10 million from 2008 and over $41 million from 2005 (W6).

In terms of rigidity of salary cap structure, the order from strongest to weakest is: NFL, NBA, MLB. MLB is the weakest because there is no salary cap, although there is a luxury tax that functions as a similar (albeit weaker) parity mechanism. The NBA is stronger than MLB because it has a soft salary cap in addition to a luxury tax. The NFL is the strongest of the three leagues because it has a hard salary cap, the most rigid team payroll parity mechanism that exists.

Revenue sharing (between teams) comparisons

Another mechanism used to enforce parity among teams is revenue sharing. Revenue sharing functions similarly in all three leagues. Each team contributes a portion of its total revenues every season to a common pool, which is then divided up and redistributed among them. The idea behind revenue sharing is that certain team, because they have a larger market, better management, or any number of reasons, will generate greater revenues than other teams. Over time, these revenue disparities between teams could snowball, causing lower revenue teams to not be able to successfully operate or renovate their franchises. By sharing a certain percentage of their revenues, teams help ameliorate franchise parity problems.

Unlike the other contractual features discussed in this section, revenue sharing's effect on free agency incentives for players is more ambiguous. If there is no hard salary cap, then it could be that revenue sharing is irrelevant to free agency incentives. This is because larger revenue teams can afford to pay players more, counteracting the inability of smaller market teams to afford these players. However, it is more likely that players will be able to generate greater salaries for themselves if they have more teams competing for their services in free agency. Hence, revenue sharing with no hard salary cap is likely to lead to more teams being able to competitively bid for a players services, driving up his market value and his free agency incentives. Under a hard salary cap, player free agency incentives most likely diminish because all teams know there is a rigid limit set on what they can pay their players regardless of revenue sharing.

Across the three leagues, the significance of revenue sharing from greatest to least is: NFL, MLB, NBA. Although it is unclear to what degree team revenue sharing actually affects free agency incentives, it is speculated that greater revenue sharing leads to more teams being able to competitively bid for free agents, increasing free agent values and incentives. In MLB, each team must contribute 31% of their yearly revenues, and the sum of those contributions are divided and distributed evenly among the 30 teams (W10). In the NFL, television contract money and merchandise sales are split equally among all teams, and ticket revenues are split between the home and visiting teams 60%:40%, respectively (W11). This results in approximately 70-75% of all NFL revenues being shared among teams. The NBA is by far the least equitable in terms of revenue sharing. There are a host of complex rules for how revenues are split between teams, but two salient facts emerge: 1) all ticket sale revenues go to the home team and 2) the total estimated percentage of revenues that are shared is 20-25%, the lowest of the three leagues (W12).

Player stake in revenue sharing and minimum, maximum, and average player salary comparisons

Revenue sharing has implications for the players as well as the teams. Players in all three leagues take home a portion of the revenues, as defined by the terms of their leagues collective bargaining agreement (CBA). A CBA determines the various contractual rights of players, and the two key features that will be looked at here that have not already been discussed (i.e.: free agency eligibility requirements) are the percentage of league revenues that players receive as well as salary maximums and minimums. It is commonly held that the strength of the players union is greatest in MLB and weakest in the NFL, and this is reflected in terms of player salaries. The data do not necessarily support this theory. Although the CBA in MLB sets a minimum salary of $390,000 with no maximum, the percentage of MLB revenues players receive is 51%, the lowest of the three leagues (W13). Back in 2003, MLB had the highest percentage at 63%, but it has been declining ever since. Meanwhile, the NBA and NFL pay their players 57% and 59%, respectively. However, in the NFL, the minimum salary is $310,000 with no maximum, and in the NBA, it is $442,114 with a maximum of $14 million for a player with ten or more years of experience (W14).

A closer look at average player salary presents a slightly different picture. The average annual NBA salary is by far the highest of the three leagues at $5.585 million despite having a salary cap and being the only league with a maximum player salary (W9). This is likely due to the fact that NBA teams feature by far the fewest players and still achieve comparable revenues to the NFL and MLB. With a number of players more comparable to that of the NFL but lacking a salary cap, it is no surprise that the average MLB player earns $2.82 million while their NFL counterparts earn roughly $1.5 million

(W15). For all three leagues, the order from greatest to least for average player salary is the same for minimum player salary: NBA, MLB, NFL.

What is relevant about these CBA and salary differences is how they affect player free agency incentives. Whether one expects to be an unrestricted or restricted free agent, if the salary but not the specific team is the main objective for the player, theoretically the same incentives would apply. The free agency structure is not dissimilar enough across the three leagues that incentives to try harder in the contract year should be significantly different. Despite having the highest percentage of player-received league revenues, the NFL's hard salary cap might influence free agent salaries teams can afford to a degree that significantly alters player effort indirectly (because the players know they can only earn so much). Still, it seems logical that team spending limits would probably not have a significant effect on player effort unless that player has already attained one of the best salaries available and has no more he can gain (a very rare if not impossible feat).

Player contract mechanism comparisons: bonuses, salary renegotiations, and guaranteed money

There remain a few more interactions between the salary cap and the CBA that could impact player incentives. First, the restructuring of player contracts in order to manipulate the salary cap. This happens only in the NBA and NFL because there is no salary cap in MLB. Players can renegotiate or backload their contracts so that their team has more spending flexibility in the short term. This happens because the annual salary cap figure for each contract isn't based on the total value of the contract, but what the player is being paid that year. This is a common practice in the NBA and NFL.

Second, there is the issue of incentive bonuses. In the NBA, performance incentives are divided into "likely to be achieved" and "not likely to be achieved" categories determined by the league office. For example, superstar Dwyane Wade starting half of the games for the Miami Heat would be a "likely to be achieved" bonus, but winning the NBA Most Valuable Player award would be "not likely to be achieved." The former count against the salary cap while the latter do not (W9). There is leeway for NBA teams to keep players motivated through use of "not likely to be achieved" incentives. Additionally, signing bonuses, or money that is guaranteed and given directly to the player when he signs his contract, are spread out evenly over the length of the contract and counted against the cap. The same salary cap rules for incentives and signing bonuses are used in the NFL.

The third, and arguably most important difference in terms of player incentives, is the degree to which contracts are guaranteed in each sport. In MLB and the NBA, the vast majority of contracts are guaranteed, meaning players do not have to fear losing the money they signed for if they are released from the team (W9). This is not the case in the NFL, where if a player is cut or released before June 1, he loses all remaining money on his contract (W6) that is not guaranteed (the majority of NFL contracts are not guaranteed). This gives NFL team executives incentive to cut players whose contracts are too burdensome to free up salary cap space, it impacts how much money players will want in guaranteed signing bonuses to renegotiate their contracts, and perhaps most importantly, it adds significant incentives for NFL players to work as hard as they can and try to remain healthy so that they don't lose the money they've already "earned." This feature of the NFL is probably the most distinguishing in terms of player incentives compared with the other leagues, and it is taken into account in the Analysis Design of this paper.

Summary of contractual comparisons

There are five notable categories of contractual information summarized in the previous sections: free agency eligibility and types (UFA, RFA, tags), salary cap, revenue sharing, player stake in revenue sharing and player salaries, and player contract mechanisms such as salary renegotiations, bonuses, and guaranteed money. The five most salient elements in which this information is anticipated to affect free agent incentives are summarized in Chart 1. It is important to note that not each of these categories has equal weight in affecting free agent incentives. Specifically, I expect the percentage of a player's contract that is guaranteed money, average player salary, and free agency eligibility and types to have the greatest effect on free agent incentives because these are the categories that directly affect players. Therefore, I expect salary cap and revenue sharing between teams to have the least effects on free agency incentives because they indirectly affect players. Average player salary is used in Chart 1 instead of the percentage of league revenue sharing that goes to the players because I expect the quantity of money that players make to have a stronger effect on their free agency incentives than what percentage of the league revenues they receive. In general, the order of expected free agent effects from greatest to least across the leagues is: NBA, MLB, NFL. This order gives greater weight to categories that directly affect free agent incentives than to categories that indirectly affect free agent incentives. The general pattern of greater, more significant free agent effects in the NBA than in MLB is consistent with the results of previously reviewed studies. Without this weighting, MLB and the NBA switch places. However, the underlying point is that MLB and the NBA have contractual features in place that should encourage free agent incentives much more strongly than those of the NFL.

Chart 1: Contractual features of MLB, NBA, and the NFL and their expected influence on free agent incentives (incentives to perform harder in free agency year rated greatest, 1, to least, 3, of three leagues)

	Free agency eligibility and types	Salary cap	Revenue sharing (per team)	Average player salary	% contract money guaranteed
MLB	All UFA	None	31%	2.82	Most
Incentives	1	1	Unclear, 2	2	1
NBA	UFA and RFA	Soft	Roughly 20-25%	5.585	Most
Incentives	2	2	Unclear, 3	1	1
NFL	UFA, RFA, tags	Hard	Approximately 70-75%	1.5	Little (mainly some bonuses)
Incentives	3	3	Unclear, 1	3	3

Economic Model

Although the contractual and structural differences are important in understanding the specific Analysis Design of this study, there is an underlying economic model that I must first outline. This model examines the interactions between player performance and contract value (salary). The same basic model applies to all three leagues, but I will focus specifically on the NFL here.

The basic idea is that there is a positive tradeoff between player performance and player compensation. Better performing players earn more money because they are more valuable to their teams. Performance itself is decomposed into multiple components of varying magnitudes. For the purpose of this study, these components fall under two general categories: intrinsic performance and factors that affect player performance that are outside of a player's control. Factors that affect a player's performance that are outside of his control include such factors as how good the team surrounding him is, how good his coaching staff is, how good he fits into the team system, how much playing time the player gets (depending on how performance is measured), and how experienced the player is. Theoretically, all of these factors, with the exception of age, have positive correlations with player performance. Experience likely starts out positively correlated with player performance, then at higher levels becomes negatively correlated as the physical processes of aging set in. Intrinsic player performance consists of two components: the player's natural ability and his level of effort. Both of these are positively correlated with player performance. In addition to intrinsic player performance and the component of player performance that is out of the player's control, there is also a random component, ε, that affects player performance. From these components, I generate a model for estimating player performance, P, below.

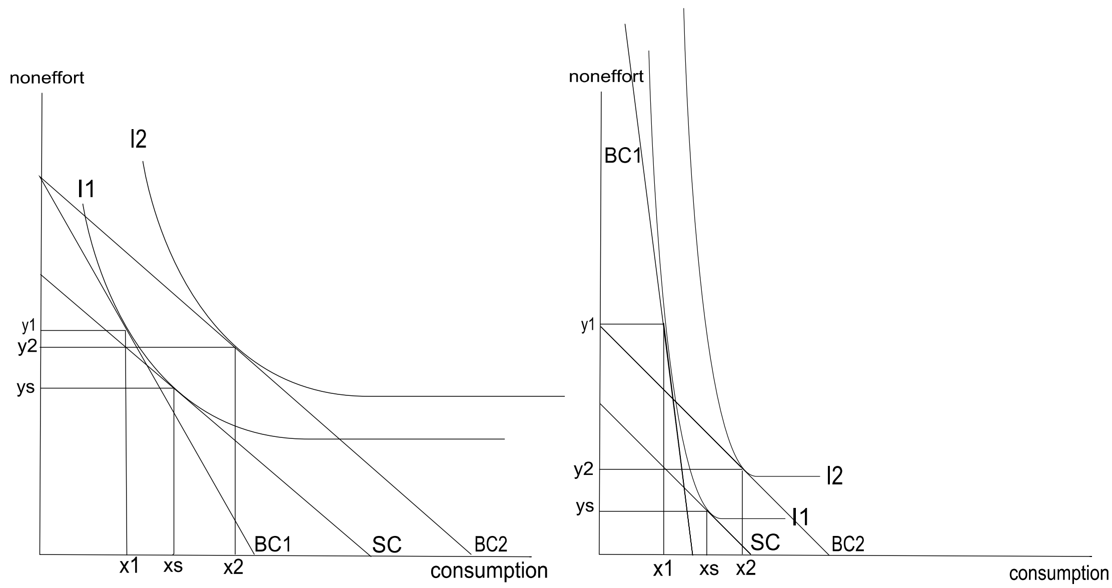
$$\mathbf{P = \beta_1(\text{player performance outside of a player's control}) + \beta_2(\text{intrinsic player performance}) + \varepsilon = \beta_3(\text{team quality}) + \beta_4(\text{coaching}) + \beta_5(\text{player-team fit}) + \beta_6(\text{playing time}) + \beta_7(\text{years of experience}) - \beta_8(\text{years of experience squared}) + \beta_9(\text{natural ability}) + \beta_{10}(\text{effort}) + \varepsilon}$$

From this model, the only thing that a player has control over to alter his performance is his level of effort. During normal years, a player theoretically has no added incentive to improve his performance because he receives no compensation (incentive bonuses excluded) in the form of a higher salary for doing so. However, in a year when a player will become a free agent at the end of the season, he has incentives to increase his effort so that teams will think that he is more valuable and reward him with a better contract (in terms of longer duration and/or higher salary). Similarly, in a year following the signing of a multiyear contract, a player's effort should theoretically decrease from the previous year because he has just gone from a period of having extra incentives to improve his performance to a period where he has no incentives to add additional effort beyond what is needed to keep his contract. In fact, knowing that he has just been given a multiyear contract and the team is invested in him, he may exert less than normal effort because the team has demonstrated its need for him and is thus less likely to release him.

However, players are human beings, and not all human beings have the same motivations. There are two types of players to distinguish between here: players who are more motivated by their career and players who are more motivated by short-term incentives. In reality players are more complex than this simplification, but for the purposes of illustrating this model they are not. Similarly, effort is a function of both short-term effort and an intrinsic desire to succeed. Players motivated by their careers have much larger effort components for their intrinsic desire to succeed than their short-term effort, and the opposite is true of players motivated by short-term incentives.

These two types of players respond very differently to the presence of free agency incentives. Players who value their careers show little or no change in effort because they always want to succeed regardless of whether they can get a better contract. On the other hand, players who value short-term incentives significantly increase their effort in the season prior to free agency and significantly decrease it in the season afterward because they care more about short-term incentives than they do about intrinsic motivation (e.g.: always trying hard to preserve one's integrity). The two graphs below diagram the behavior of both of these types of players. The left graph represents players motivated more by their careers and the right graph represents players motivated more by short-term incentives. The y-axis represents noneffort (opposite of effort) and the x-axis represents player consumption. Player consumption equals income (in the form of a better contract with a higher salary, longer duration, etc.); income equals potential income a player would have earned if he worked full time minus leisure. The more a player is motivated by his career, the more inelastic his indifference curves are with respect to noneffort (horizontal lines); the more he is motivated by short-term incentives, the more inelastic his indifference curves are with respect to consumption (vertical lines). These indifference curves for both players are I1 and I2. The initial budget constraint (BC1) is what these players face in most years. Free agency causes a price effect. The cost of noneffort becomes greater relative to consumption because exerting more effort theoretically yields a greater payoff. So both types of players will substitute a degree of more effort in order to accommodate this change in their budget constraint from BC1 to

SC (substitution effect). Because players can now attain greater consumption for the same amount of effort, their budget constraints shift out from SC to BC2 to accommodate this change in what the noneffort-consumption bundle they can now "afford" (income effect).



Motivated more by career Motivated more by short-term incentives

The introduction of free agency causes the players motivated by short-term incentives to increase their effort greatly whereas the players motivated by their careers do not show a very significant change in effort at all. The reason for their greatly differing responses is that players motivated by short-term incentives have much more elastic preferences for effort than they do for consumption. Because of this, they are willing to substitute much more noneffort for consumption than players motivated by their careers. To summarize, the degree to which players alter their effort in response to free agency incentives depends on the elasticity of substitution between noneffort and consumption.

An interesting issue is what type of players teams actually want to sign to long-term deals. Perhaps teams will want talented players who they know they can motivate through short-term deals with incentive bonuses. If talent is equal, it is more likely that teams want to sign players who are motivated by their careers because these players are more likely to always put in a high amount of effort and less likely to shirk once signed.

The degree to which altering player effort changes player performance (P) is unknown. The other performance determining variables outside of a player's control may in fact determine the majority of P. If this is the case, then even if players motivated by short-term incentives are aware that teams prefer players who demonstrate consistent effort, they might still have an incentive to increase effort prior to free agency. This is because the teams do not observe player effort directly, only player performance. Because of this asymmetric information, teams may frequently assume a player who improves his performance significantly in his free agent year is developing his talent when in fact he is only increasing his effort. This type of situation is important because it illustrates that free agency effects can still exist even if teams demonstrate a preference for players with records of consistent effort because the teams cannot directly observe effort. The purpose of this study, however, is to try and isolate effort from the other variables affecting performance. I will describe my methods for doing this in the next section detailing the Analysis Design.

Analysis Design

Even though there have been studies that have examined the links between free agency and player performance in MLB and the NBA, no similar study has been conducted in the NFL. This is why the previously mentioned differences between the NFL, MLB, and NBA are important in designing a template for this study based on similar contract year phenomenon studies done in the NBA and MLB. First, I obtain data on players qualifying for restricted and unrestricted free agency for the decade 1998-2007 from Mark Levin, Director of Salary Cap and Agent Administration at the NFL Players Association (NFLPA). These data are corroborated by various websites for the years when free agency information is available (no websites consulted had any free agency data on years before 2000). Because of the previous problems mentioned with the limitations of performance metrics in the NFL, I only examine the positions of quarterback (QB), running back (RB), tight end (TE), and wide receiver (WR). Defensive and special teams positions and lineman have too few recorded performance metrics and too many teamwork components contributing to their on-field performance. I obtain performance metrics from the website footballoutsiders.com (W16). I then obtain additional independent variables including years experience in the NFL, contract length, and team wins from the NFLPA website (W18). A comprehensive list of performance metrics and independent variables can be found in the Appendix. I explain the specific effects of each of these variables on performance and their interactions with free agency status in the Analysis section. Initially, I examine the data to obtain trends in performance metrics and free agency across positions. Then using the statistical software package Stata, I run a series of Ordinary Least Squares (OLS) regressions on the player observations data (separately for each position) to determine the effects of free agency on player performance. For the reasons the Economic Model illustrates, in doing so I take into account other independent variables to isolate effects due to player effort from the effects of other variables not under the player's control.

i. Data

There are two types of data in this study: data on performance statistics and data on independent variables such as free agency. I treat all free agency variables as dummy variables (FA=1 if the player is a free agent, FA=0 if he is not). Both sets of data apply to players playing from the years 1998-2007. Ideally, I would have examined player data earlier than 1994 (the year the salary cap was implemented) to estimate the effects of the introduction of the salary cap in the NFL, but the performance metrics provided by footballoutsiders.com only extend back to the 1995 season and obtaining the necessary free agency data for this time period proved too difficult. There are 1090 individual players recorded in the data for this time period, accounting for 3594 player observations. This means the average NFL career among players in this data set is 3.29 years, which is in line with the overall average playing career of three and a half years reported on the NFLPA website. The data for performance metrics are from the website, footballoutsiders.com. This website contains databases of traditional player performance metrics as well as innovative metrics (Note: the term "metrics" is used in place of “statistics” or “stats” in order to avoid confusion with terms relating to econometric statistical analysis). Traditional metrics are metrics used in NFL box scores, such as yards gained, quarterback rating, and completion percentage for quarterbacks. What distinguishes traditional metrics from innovative metrics is that traditional metrics do not attempt to control for a player’s performance in comparison to other player’s at his position, within his team’s offensive scheme, or taking into account the strength of the defense he plays against.

The following sections describe the data as well as some notable patterns I found prior to the actual regression analysis. They describe in order, performance metrics, player observation categories, the distribution of free agency across years and positions, the independent variables used in the regressions, and finally some of the shortcomings of the data.

Description of performance metrics

Footballoutsiders has developed two innovative metrics that I use in this study: Defense-adjusted Value Over Average (DVOA) and Defense-adjusted Yards Above Replacement (DYAR). The advantages and drawbacks of these metrics are explained extensively on the footballoutsiders.com website; here is a brief summary. DVOA ranks the success of each play a player makes according to the following scale: “On first down, a play is considered a success if it gains 45 percent of needed yards; on second down, a play needs to gain 60 percent of needed yards; on third or fourth down, only gaining a new first down is considered success” (W16). Successful plays are awarded one point, unsuccessful plays 0 points, and big plays are awarded points as follows: “Extra points are awarded for big plays, gradually increasing to three points for 10 yards, four points for 20 yards, and five points for 40 yards or more. There are fractional points in between” (W16). Similarly, “Losing four yards is -1 point, losing 12 yards is -1.8 points, an interception is -6 points, and a fumble is worth anywhere from -1.70 to -3.98 points depending on how often a fumble in that situation is lost to the defense - no matter who actually recovers the fumble. Red zone plays are worth 20 percent more, and there is a bonus given for a touchdown” (W16). After these success values are assigned, the success values of plays in similar situations are compared for all plays, controlling for variables such as down and distance, field position, time remaining, and current score lead or deficit. Among these criteria, passing plays are only compared to passing plays, rushing to rushing, and players involved in the plays are only compared to other players making those plays at their position. Then, to adjust for defense, the play is compared against the defensive team's average success rate in stopping that type of play. Finally, after these variables have been controlled for, comparable plays are ranked in terms of percentage according to the average success of those plays. These plays are then aggregated for each player, and his percentage ranking according to how he compares to average players at his position will rank somewhere from around 30% (among the best) to -30% (among the worst).

The definition for DVOA may sound confusing. The main idea behind DVOA is to provide a nuanced metric that compares player performance among all players at a given position in a way that takes into account the situation of a play rather than just its outcome.

DYAR follows a similar construction. It measures how well a player plays relative to a replacement level player (the average player in the league) in terms of absolute yards gained. A replacement level player typically has a DVOA of around -13.3% for reasons explained on footballoutsiders.com (W16). Once a player is compared to this replacement level, the same defensive adjustments used in DVOA are calculated. Finally, DYAR calculates the percentage difference in success rate of the player over the replacement level player into yards.

There are some drawbacks of DVOA and DYAR. These include the fact that they cannot be computed until each play of an NFL season is complete and the defensive calculations are not perfect quantitative estimates of defense. Still, DVOA and DYAR contribute statistical estimates of player performance that control to an extent for teamwork and strength of defense, which traditional metrics do not.

There are two main reasons I use DVOA and DYAR in this study. First, they are metrics that can be used for all four positions analyzed. Second, they contribute a blend of percentage and absolute performance measures. DVOA is a percentage metric that sums to zero (approximately) when aggregated for all players in a year. DYAR measures players in terms of an absolute metric, yards, which is not zero sum when aggregated. A priority for the performance metrics used in this study is to include a range of measurement types (aka: percentage, absolute) in case free agency affects one type but not the others.

This diversification of performance metrics is important in selecting the traditional metrics used as well. I use total yards gained (yards) partly because it is the most recognizable statistic in all of football. If a player leads all players at his position in yards, he is generally held to be one of the best players at his position. What is interesting about yards is that it is not necessarily a very good indicator of performance. A player could be mediocre, but if he touches the ball enough, he can accumulate a lot of yards over the course of a season. In turn, these touches are dependent upon the coach's decision to give the player the ball, which is not a variable the player controls.

For this reason, I also include yards per touch (yards/touch). There are three types of yards/touch: yards per pass (YP) for QB, yards per catch (YC) for TE and WR, and yards per rush (YR) for RB. Yards/touch is an average metric, so that the amount of touches a player has won't inflate or deflate his performance. It is generally held to be a better metric than yards, however it is not without drawbacks. Players have different roles even within positions. Some WR run short routes and others run long routes. Yet a short route WR such as Wes Welker who more successfully does his job than a long route WR such as Randy Moss may still have a lower YC.

The final metric included is one that varies according to each position. While DVOA, DYAR, yards, and yards/touch are metrics that can be applied across positions, giving each position a more position specific metric adds more depth to the analysis. For QB, this position specific metric is quarterback rating. Quarterback rating is a composite metric that is calculated as:

a = (((Completions/Passes) * 100) -30) / 20
b = ((Touchdowns/Passes) * 100) / 5
c = (9.5 - ((Interceptions/Passes) * 100)) / 4
d = ((Yards/Passes) - 3) / 4
a, b, c and d can not be greater than 2.375 or less than zero.
QB Rating= (a + b + c + d) / .06

It is generally held to be the best traditional metric for evaluating QB because it deals with many separate performance metrics (completion percentage, touchdown rate, interception rate, and yards per pass) in a nuanced manner. For WR and TE, the position specific metric used is catchrate (CR). CR is the percentage of passes thrown to a player that the player successfully catches. For RB, the position specific metric is the difference between the number of touchdowns and the number of fumbles (TFD). While I exclude touchdowns (TD) from this analysis because they are very context-dependent and only measure positive contributions by a player, I include TFD because it looks at both negative (fumbles) and positive (TD) aspects of player performance. So while a player may accumulate a lot of touchdowns because he touches the ball a lot, if he also manages to fumble a lot, TFD takes this into account.

Player Observation Categories

The footballoutsiders database only includes data on certain metrics, such as quarterback rating, for players who have a number of touches above a certain threshold in a season. The importance of touch thresholds is that I use them as general boundary lines to differentiate between players who have a significant amount of playing time during a season and those who do not. This boundary generally separate players who are established NFL players from players who are not as good or who have not established a routine role on the team. Additionally, this boundary helps control to an extent for injury because injured players typically do not pass the touch threshold. In sum, the touch threshold boundaries serve as an interesting way to test NFL regulars from NFL non-regulars and show some distinct differences in patterns of free agency.

For QB, TE, and WR I refer to touches as passes, for RB they are runs. The threshold for positions are 100 passes for QB, 100 rushes for RB, 25 passes for TE, and 50 passes for WR. Players with touches above the threshold are type 1 players, and players under the threshold are type 2 players. Obviously, a player can switch between being a type 1 and type 2 player from year to year.

The strict player categorization I use here imperfectly describes certain exceptional players who excel in performance areas not generally recorded as their position's metrics. For instance, QB Michael Vick is an excellent runner. In this study, rushing statistics for QB are not taken into account. Although excluding these statistics makes it so that certain players' performances are not as accurately represented, these players are the exception rather than the norm. Overall, including these statistics proved too complicating because the vast majority of players at each position do not have enough performance data for comparison.

The following are some useful statistics on the number of player observations (Obs) and free agency (FA) status in the data:

Table 1: FA and Player Observation breakdown by type

Position	Players (n)	Total Obs.	Type 1 Obs.	Type 2 Obs.	1:2 Obs.%	Type 1 FA (n)	Type 1 FA %	Type 2 FA (n)	Type 2 FA %
QB	190	673	465	208	69:31	110	23.6	76	36.5
RB	297	908	433	475	48:52	71	16.3	108	22.7
TE	189	638	408	230	64:36	84	20.5	73	31.7
WR	415	1375	817	558	59:41	137	16.7	120	21.5

There are some noteworthy trends illustrated by Table 1. First, there is a noticeably higher rate of FA among type 2 players than among type 1 players for each position. Second, while QB and TE have the same number of players, RB and WR have significantly more. This makes sense, given that most teams employ one QB and TE for each play, while teams frequently substitute RB every few plays and often use 2-3 WR per play. Third, the only position with more type 2 than type 1 player observations is RB. This could be the result of the fact that teams have increasingly adopted multiple RB schemes (95% of the time) in order to increase RB role specialization and reduce the risk of injury for each RB (W17). The first trend is the most important, and one would assume type 2 players have a higher FA percentage because they do not have as crucial a role with the team. Therefore, they are not signed to long contracts and are more frequently released. Table 2 presents the mean values of each performance metric across each player position and type category in order to further illustrate performance trends across player observation categories.

Table 2: Performance trends across position and type categories

Position	DVOA	DYAR	Total Yards	Yards/Touch
QB 1	-.05004	250.8215	2202.314	5.89219
QB 2	-.24403	-30.52885	227.3798	5.17083
RB 1	-.02002	69.12933	917.2286	4.09753
RB 2	-.05268	7.54105	190.5116	3.94371
TE 1	-.00568	33.32598	378.2157	6.58359
TE 2	-.10193	-3.39565	93.08696	5.75036
WR 1	.00905	113.4614	765.8446	7.66218
WR 2	-.10898	6.33512	183.9928	6.72042

According to Table 2, type 2 players perform worse than their type 1 counterparts across every performance metric. This supports the argument that type 2 players are up more frequently for FA because they are worse players and less likely to be signed to long contracts and more likely to be released.

The distribution of free agency across years and positions

To be a RFA, a player must be in his fourth year in the NFL. To be a UFA, a player can either be cut, without a contract, or be in his fifth+ year in the NFL. The distribution for FA, RFA, and UFA for each position across years is listed below. The data for this study treat Transitional Tag and Franchise Tag players as UFA because these tags are applied after the player has completed his season, and up until he is tagged he thinks he will be a UFA at the end of the year. Table 3 illustrates the number of players who are FA, RFA, and UFA for each position for each year 1998-2007.

Table 3: FA, UFA, RFA (n) breakdown by year

	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Total (%)
QB FA	17	23	17	12	15	24	22	21	14	21	186 (100)
QB RFA	2	3	3	2	4	5	2	3	3	1	28 (15.0)
QB UFA	15	20	14	10	11	19	20	18	11	20	158 (85.0)
RB FA	12	10	16	17	15	17	26	20	25	21	179 (100)
RB RFA	3	6	7	6	4	7	6	3	4	3	49 (27.3)
RB UFA	9	4	9	11	11	10	20	17	21	18	130 (72.7)
TE FA	15	11	16	15	12	15	22	19	19	13	157 (100)
TE RFA	6	7	4	6	4	6	7	4	5	2	51 (32.4)
TE UFA	9	4	12	9	8	9	15	15	14	11	106 (67.6)
WR FA	23	17	23	18	26	15	34	38	30	33	257 (100)
WR RFA	11	8	9	7	13	7	6	7	7	3	78 (30.3)
WR UFA	12	9	14	11	13	8	28	31	23	30	179 (69.7)

Table 3 shows that there are some yearly fluctuations in the number of free agents. This could result for number of reasons and because none of these fluctuations are of a very significant magnitude, they are most likely incidental. For RB, TE, and WR, RFA make up about 30% of the FA. However, for QB, RFA make up only half of that (15%). Perhaps this occurs because QB are more likely to be signed to long-term contracts or cut before their fourth year. This could be the case because QB are at the center of the offense, so teams tend to evaluate quickly whether they have a QB who they can use long-term or whether they need a replacement.

Description of independent variables

Because free agency is not randomly assigned throughout the sample of NFL players, I use a host of independent variables in this study. Players are not awarded contracts at random. Teams specifically choose to sign or not sign them based on a number of reasons, not all of which pertain to a player's intrinsic effort. I use these independent variables to isolate the effects of player performance that can actually be attributed to free agency or player effort as opposed to factors that the player does not control. Ultimately, for reasons explained in the analysis section, I choose not to use teamwins and contract length in my primary regressions after exploring their interactions with other dependent and independent variables. Nonetheless, I include them here because they are an important element of my Analysis process.

First, team wins (teamwins) are the number of wins (0-16) a player's team has within a given year. This is one of the more uncertain independent variables because while teamwins may reflect the strength of the team around the player, it is difficult to extract how much of the team's success is a product of the player himself. Additionally, there may be significant correlations between teamwins and DVOA and DYAR, which include estimates of team strength.

Second, contract length. This is the number of years a player has remaining on his contract. Because NFL players can be released before the expected completion date of their contracts, it is difficult to accurately estimate the true length of contracts. Given this obstacle, I calculate contract length as the number of years before a player hits free agency. There are some potential issues with the fact that players may become free agents because they are released due to a poor performance year or similar factors (negative selection effects). However, because access to a database of all contracts signed for the 1090 players in this study is unavailable, the contract length variable I use is the best available estimate of contract length despite its potential selection effects.

Third, the years of NFL experience a player has (yearsexp). The data for these years comes from the nfl.com website (W18). A player's first year does not necessarily count as the first year signed with a team, but rather the first year in which he records touches in a regular season NFL game. This is important because some players only contribute in practice for their first one or two years. I use years of experience instead of age because there are variations in the age at which players enter the NFL, and for this reason the years of experience players have are more likely to influence the improvement and wear on a player than age alone. There is a strong correlation between years of experience and age.

Fourth, whether a player switches teams following his free agency season (newteam). The free agent data list both players who finish their contracts and players who are cut and do not have a team as free agents. For this reason, controlling for whether a player switches teams in free agency limits the free agent pool exclusively to players who finish their contract and re-sign with their previous team. Using this variable excludes free agents who finish their contracts and then sign with different teams, and I explore this tradeoff and its ramifications in the Analysis.

Fifth, touches. This final independent variable most often takes the form in this study of dividing players into type 1 and type 2 categories previously explained. I expect that in general players with more touches are better players because if they were not better players, their coaches would not allow them to get as many touches.

Description of shortcomings of the data

The two most salient shortcomings of the data relate to injuries and retirement status. One of these is that injuries are not recorded in the data. Part of the reason for this is because such data was inaccessible. Additionally, there are differences in how coaches use the Physically Unable to Perform (PUP) list and Injured Reserve list. Those familiar with the New England Patriots know that head coach Bill Belichick frequently lists major players' statuses as "questionable" each week despite the fact that many of these players are healthy in order to stem the flow of information about his players' health to opposing teams. This paper tries to account for injuries through touches. In other words, if a player is injured for a significant portion of the year, this will be reflected in his decreased touches, demotion to type 2 status, as well as decreased Yards and DYAR.

With regard to retirement, it is true that free agents do not have the same incentives if they are also players planning on retiring at the end of their contracts. They are not planning on re-signing with any team, so why should they exert extra effort in the year before their contracts expire? For this reason, I would expect most of these players to show declining performance prior to retirement even when I control for age. Furthermore, I expect retirement to correlate positively with age and years of experience. So, years of experience is the main variable to control for potential retirement effects in the data.

I omit player salary as an independent variable. The reason for this is because theoretically a player will try harder at the end of his contract to secure the best value for himself in free agency, regardless of his current salary. Perhaps there are players who have earned enough money to have become content, and therefore do not expend additional effort heading into free agency or shirk after signing a multiyear contract. However, engaging in analysis of the psychology of player satiation presents an even greater host of challenges. How does one definitively test whether there is a salary range at which players feel content? What happens if this range is different for each individual, as is likely the case? In this study I acknowledge that players may have satiation points in terms of their salary and that these effects may have significant overall effects in the data, but I assume out of reasonable simplicity (and to avoid psychological analysis) that all players have incentives to increase their value in free agency.

As a final note regarding the data, I recognize that NFL performance metrics do an incomplete job at best of controlling for or measuring coaching and teamwork variables. I acknowledge that these variables likely play a very large role in both player performance and game outcomes, and are probably the main reason no similar research on this topic has been undertaken in the NFL. I do not claim that this study's methods perfectly extract the influence of free agency on player performance; they are merely attempts to analyze these effects given the limitations of the data.

ii. Methodology

With the data previously mentioned, in this study I employ the statistical software package Stata to test my predictions through regression analysis. I run these regressions using Ordinary Least Squares (OLS), and I examine all positions (QB, RB, TE, WR) separately in the analysis. The two main components of the contract year phenomenon tested are the free agency effect (FAE) and the year after effect (YAE). To qualify for the

FAE, a player must be a free agent at the end of the season. In other words, this regression can be completed simply by regressing FA (independent variable) on any performance metric (dependent variable). To qualify for the YAE, a player must have been a free agent in the past season and not be a free agent after his current season. I use an independent variable called YA in regressions on performance metrics to examine the YAE. If a player would qualify for FAE or YAE status but has missing values for performance metrics in one of the required seasons (did not play that season, for whatever reason), he does not qualify.

First, I analyze all player data in standard OLS (grouping all player observations belonging to the same player) to see what the net effects of FAE and YAE are on performance. I do this using the other independent variables to a certain degree. Because of the influence of selection biases noted in the data section, I run these regressions again taking into account fixed effects. Taking into account fixed effects controls for bias by using a dummy indicator for each player. Better players tend to perform well throughout their careers, and worse players tend to perform poorly throughout their careers. In addition, player performance is correlated with free agency because worse players are more frequently free agents than better players. As a result, because free agency is not randomly assigned and players tend to perform at a certain level (according to their ability) throughout their careers, it is important to control for fixed effects to mitigate the selection bias of worse players having more free agency player observations. Controlling for fixed effects does this by comparing free agency and non-free agency player observations years within individual players rather than treating all player observations as independent observations. In other words, all players are given equal weight and compared to themselves for free agency analysis, regardless of how many times they have been free agents.

The next step involves adding independent variables to the initial regressions of FA or YA on performance metrics. I add these independent variables because free agency is not randomly assigned throughout the sample. Without random assignment, other variables correlated with free agency could skew its coefficient estimates in the regressions. As explained in the Economic Model, free agency consists of a player effort/intrinsic performance component and components of variables that are correlated with free agency that the player does not control, such as years of experience. The purpose of including the non-FA, non-YA independent variables in these regressions is to try and isolate the effect of free agency on performance due to player effort/intrinsic performance.

After observing results from these regressions that include the entire population of each position, I run specialized regressions. Specialized regressions involve splitting up the position populations into segments and testing the FAE and YAE effects on each of these segments. For example, type 1 and type 2 players are two segments of players analyzed separately. Another example is to examine the FAE and YAE on QB who perform in the top 33% of quarterback ratings. The purpose of such a test is to examine if players who are the best at their position show different FAE and YAE patterns than players who are not. I will explain these specialized regressions as they arise in the Analysis section.

After I run these regressions and analyze their results, I will compare the results of each position against each other. Doing so will help distill whether there are generalized phenomena regarding FAE and YAE or whether each position exhibits unique patterns.

iii. Hypotheses

The following are a list of hypothesis generated based on the initial findings in the Data section, the previous literature on the contract year phenomenon, and the differences between the NFL and the NBA and MLB:

1) Because of the free agent effects (FAE) and year after signing a multiyear contract effects (YAE) found in many studies of the NBA and MLB and the similar incentives all professional athletes face with respect to FA, I expect some degree of positive FAE and negative YAE (Note: FAE and YAE are collectively referred to as effects in the following hypotheses).

2) There are a greater number of players, more teamwork/coaching effects, and less clear-cut measures of success (hits are always good in MLB, but yards have a more ambiguous significance in the NFL) in the NFL compared to MLB and the NBA. Additionally, players have a shorter careers in the NFL than MLB or the NBA, there are more injuries,

there is a hard salary cap, there is less guaranteed money, and there are more 1 year/short-term deals. For all of these reasons, I expect less significant effects for the NFL than the other two leagues.

3) Because QB are in every passing play and have multiple WR and TE of varying skills to interact with, I expect QB to have the most influence over their own performance. Therefore I expect QB to show the most significant effects.

4) Because WR and TE typically only receive passes from one QB, I expect their performance to be much more dependent on their QB. Hence, I expect their effects to be less significant than those of QB.

5) Because TE have a blocking function that is not taken into account by the performance metrics, I expect TE to have less significant effects than WR.

6) Because RB largely do not interact with anyone on their team other than the offensive line (which the QB, and therefore the WR and TE do as well) but do not have as much playing time as QB, I expect RB effects to be more significant than TE and WR but less significant than QB.

6a) An alternative expectation for RB: It could also be that QB only need their offensive line up to a certain threshold (e.g.: 3 seconds of protection) in order to achieve their full ability, whereas RB have a more continuous interaction with the offensive line. If this is true, then I expect RB to be the position most affected by team/omitted variable bias.

7) Because RB receiving statistics are not measured, I expect undervaluation of certain RB and thus diminished effects relative to their true value.

Analysis

Analysis overview

In this section, I discuss the results of each regression as I present them. I start by estimating the effects of free agency on player performance with and without fixed effects, without using any independent variables other than free agency. I then examine the impact of years of experience on player performance as an independent variable. Afterwards, I examine the impact of switching teams on player performance as an independent variable to control for free agent selection bias. Following this, I discuss other potential methods for dealing with free agent selection bias. Once I have decided upon a set of independent variables that accurately control for free agent selection bias, I estimate the effects of the year after a multiyear contract signing on player performance for the whole sample. Because players of different skill levels in the sample may have different interactions between free agency and performance, I separate players into groups for two series of specialized subgroup analysis. Finally, after explaining these two specialized analyses and discussing their results, I summarize the findings of my analysis with regards to my initial hypotheses.

Initial estimates of free agency's effects on performance with and without fixed effects

The most basic analysis is the starting point: regressing FA (dummy variable=1 if a player will be a free agent at the end of the season and =0 otherwise) on performance variables for all positions and controlling for fixed effects. I control for fixed effects in order to reduce selection bias for reasons I previously described in the Methodology. Theoretically, doing so corrects for the potential bias from below-average players traveling from team to team on estimates of the impact of free agency on player performance. Overall, these regressions provide very rough estimates for free agent effects (I will discuss year after multiyear signing effects after free agent effects) because the only independent variable I use is FA. The following is a summary of the results (the first number is the coefficient, the parenthetical number is the standard error, and ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively):

Table 4: FA effect on performance across player position and type categories (metrics applicable to all positions)

	Yards	Yards fe	Yards/touch	Yards/touch fe	DVOA	DVOA fe	DYAR	DYAR fe
QB	-533.4795*** (97.952)	-429.483*** (107.045)	-.159 (.120)	-.073 (.137)	-.012 (.029)	.006 (.032)	-142.495*** (37.388)	-89.190** (41.152)
QB1	-565.990*** (111.908)	-427.026*** (130.380)	-.261*** (.096)	-.168 (.109)	-.055** (.022)	-.035 (.025)	-186.840*** (54.436)	-124.337* (63.666)
QB2	-18.056 (23.810)	-12.558 (38.074)	.131 (.300)	.255 (.490)	.086 (.074)	.143 (.115)	2.533 (16.321)	21.040 (26.593)
RB	-112.741*** (32.106)	-114.363*** (34.547)	.005 (.069)	.018 (.077)	.001 (.015)	.005 (.017)	-14.439* (8.163)	-11.854 (9.435)
RB1	-149.299*** (44.928)	-161.14*** (50.064)	-.157** (.073)	-.157** (.082)	-.029** (.016)	-.030* (.018)	-31.709** (16.458)	-29.075 (18.741)
RB2	11.767 (11.098)	8.748 (14.771)	.128 (.113)	.110 (.143)	.029 (.024)	.029 (.033)	8.336* (4.613)	9.100 (6.853)
TE	-56.830*** (16.106)	-40.402** (17.199)	-.320** (.158)	-.213 (.183)	-.029 (.020)	-.017 (.023)	-13.394** (5.783)	-5.550 (6.424)
TE1	-66.148 *** (21.480)	-45.560** (23.541)	-.158 (.172)	-.110 (.199)	-.015 (.023)	-.015 (.028)	-12.116 (8.714)	-5.897 (10.039)
TE2	-1.791 (5.828)	-8.836 (9.153)	-.286 (.294)	-.551 (.477)	-.029 (.037)	-.040 (.057)	-3.027 (4.072)	-4.208 (6.434)
WR	-75.500*** (22.087)	-62.770*** (23.248)	.041 (.124)	.051 (.137)	.016 (.014)	.017 (.015)	-23.884*** (8.327)	-3.760 (8.740)
WR1	-121.740*** (26.602)	-87.622*** (29.473)	-.141 (.135)	-.026 (.159)	-.000 (.015)	.009 (.018)	-28.655** (12.322)	-6.603 (14.016)
WR2	15.700 (10.535)	9.703 (15.787)	.284 (.227)	.221 (.334)	.039 (.026)	.032 (.035)	7.387 (4.994)	11.530 (7.297)
FE	NO	YES	NO	YES	NO	YES	NO	YES

Table 5: FA effect on performance across player position and type categories (metrics specific to position)

	QB Rating	QB Rating fe	TFD	TFD fe	Catchrate	Catchrate fe
QB	-2.371* (1.327)	-1.450 (1.501)				
QB1	Same as above	Same as above				
QB2	NA	NA				
RB			-.464 (.299)	-.310 (.335)		
RB1			-.515 (.562)	-.093 (.636)		
RB2			.088 (.198)	.181 (.282)		
TE					.000 (.010)	.008 (.012)
TE1					.009 (.010)	.005 (.012)
TE2					-.010 (.020)	-.018 (.032)
WR					.004 (.006)	.007 (.007)
WR1					.004 (.007)	.009 (.007)
WR2					.005 (.013)	-.004 (.017)
FE	NO	YES	NO	YES	NO	YES

The results for Table 4 indicate a very significant decline in performance associated with free agency when fixed effects are not taken into account. For example, quarterbacks throw for 533 fewer yards in the year prior to free agency, which is the opposite of the expected FAE. The position-specific performance metrics (Table 5) show no very significant results. Yards and DYAR show the most statistically significant changes due to FA. Since these are the only two absolute performance metrics, perhaps there is something about absolute metrics that makes them more predisposed to significant fluctuations. Specifically, yards and DYAR both compute some form of yards gained; yards gained is a factor of playing time as well as skill, whereas yards/touch controls for playing time. Because yards and DYAR encounter two sources of variation (touches and skill) instead of one, the variation in performance between players is magnified.

Nevertheless, FA has a very significant negative effect on yards when fixed effects are not taken into account. This result is not surprising considering that the majority of the free agent pool is below-average players. However, there are two results that are very surprising about yards. First, while fixed effects slightly reduce the negative coefficient, the results are still very statistically significant. Second, type 2 players do not show a significantly negative relationship while type 1 players do. This pattern is replicated to a degree in DYAR, although controlling for fixed effects eliminates any statistical significance outside of QB. Furthermore, even for the two performance metrics that show the least significant results (yards/touch and DVOA), type 1 QB and RB show the most significant effects (although in QB these are eliminated after fixed effects), while TE and WR show the least statistically significant results.

These results are interesting for a number of reasons. First, regardless of how good of an indicator of performance yards and DYAR are relative to the other performance metrics, there appears to be a pattern in terms of which metrics show the most significant results. From greatest to least significance: Yards, DYAR, yards/touch, DVOA. This pattern essentially takes the form of greatest to least in terms of metric type: absolute, average, percentage. This pattern is strengthened by the fact that DYAR is an innovative metric with lots of controls for unobserved variables while yards is a traditional metric with no controls (in a sense, yards is more of an absolute metric than

DYAR). With only four metrics, it's difficult to reasonably extrapolate a generalized pattern regarding metric type and position, but the fact that absolute metrics have a much larger range of values could partially determine this pattern. Second, the fact that RB and QB show more significant results than WR and TE is interesting considering the hypothesis that QB and RB would have the most significant results because they have the most control over their performance. Whether this is the case or not, it fits in well with the third, and most interesting result: that the type 1 players show very significant negative effects for yards and DYAR while the type 2 show less negative and insignificant effects, even when I control for fixed effects.

While one could read these results and say that the players with the most touches and greatest incentives to perform well played the worst (exactly the opposite of the expected result), there is a problem with this conclusion. If yards/touch does not significantly change while yards does, then what is most likely happening is that free agents are getting fewer touches. This theory is in line with the fact that type 1 free agents are greatly affected while type 2 free agents are not because type 2 free agents have a very limited number of touches to begin with. In other words, the amount of touches type 2 players have might not be robust enough to display any significant free agent effects even if they do exist. Additionally, if free agents are getting fewer touches because their coaches think they are becoming less effective, it makes sense that this phenomenon would be confined to the players (type 1) that the coach thought were good enough to play a lot in the first place.

However, this interpretation of the results raises questions as well. Most notably, why would a player get fewer touches if his yards/touch did not get significantly worse? Furthermore, there is intriguing consistency across these results that lends credibility to the argument that free agents are playing worse as opposed to just getting fewer touches. QB and RB, the players that theoretically have the most control over their own performance, show the most significantly negative results. Taken together, there are three likely conclusions, not all of which are necessarily mutually exclusive. Either free agents play worse because of something inherent in free agency, they play less because coaches do not want to play free agents as much, or there is an unobserved variable (maybe multiple variables) correlated with free agency that negatively impacts player performance.

The effect of years of experience as an independent variable

One unobserved variable in the previous regression that likely accounts for some of the bias in the results is years of experience (variable: yearsexp). Players get worse as they age and their bodies cannot perform at the same physical level as they could when they were younger. How might this be correlated with free agency? Perhaps as players age (and years of experience increases), their physical capabilities continually decrease, causing their on-field performance to suffer, leading teams to be less inclined to give those players long-term contracts, which in turn results in those players being overrepresented in the free agent pool. Why would fixed effects not account for this? Because all players get worse as they age, meaning almost every player at some point should have a free agency period where he is worse than when he was younger, healthier, and more likely to be under a long-term contract. Why would type 1 players show this degeneration effect while type 2 players do not? Two reasons. Maybe type 1 players are hit affected more by age than type 2 players because type 2 players are not as good to begin with and degeneration due to aging takes a disproportionate toll on players who were once at a higher level of play. Or perhaps this occurs because type 1 players by definition have a greater amount of touches than type 2 players, and the negative effects of aging are exacerbated by the greater sample size of plays. Alternatively, it could be that older players simply cannot handle the same workload (touches), and so their coaches play them less. Whatever the reason, it seems logical to examine the effects of years of experience.

Because yards is the variable most significantly impacted by FA, I start by examining the impact of yearsexp on yards. I first do this by looking at the relationship between mean yards as a function of yearsexp across all positions (note: yearsexp=0 means that the player is in his first year playing in the NFL, and all yards values are rounded to the nearest whole number). Table 6 shows the results. This is not a statistically rigorous analysis, but rather a preliminary means of approaching the data to help conceptualize the relationship between yearsexp and yards.

Table 6a: Mean yards as a function of yearsexp (number of observations)

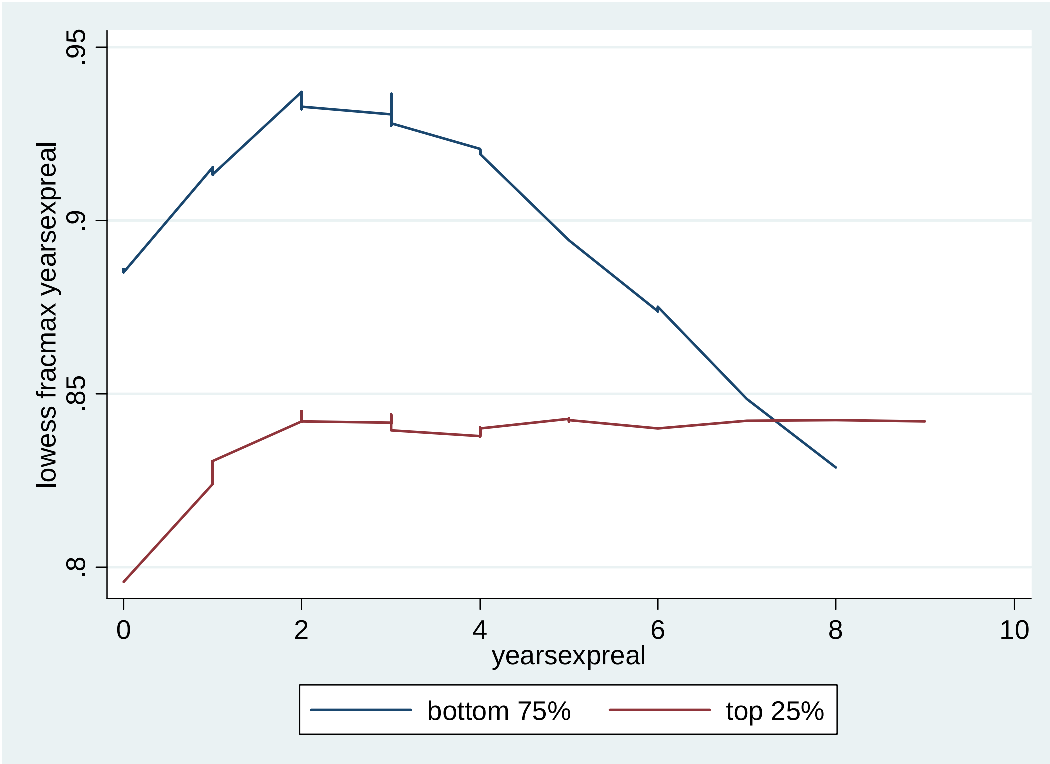
	Yearsexp																			
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
QB	840 (126)	1664 (79)	1682 (63)	1717 (63)	1723 (50)	1858 (47)	1902 (37)	1939 (36)	1793 (33)	1782 (29)	1930 (21)	2071 (20)	1839 (15)	1631 (21)	1553 (12)	2072 (8)	1628 (6)	1206 (4)	462 (2)	942 (1)
RB	368 (216)	522 (129)	547 (105)	556 (97)	589 (87)	726 (75)	623 (57)	693 (43)	634 (36)	664 (26)	410 (22)	628 (7)	818 (4)	295 (3)	937 (1)					
TE	181 (141)	263 (99)	304 (76)	338 (71)	324 (68)	318 (47)	313 (39)	289 (28)	283 (23)	239 (18)	326 (14)	238 (7)	370 (4)	506 (2)	222 (1)					
WR	298 (300)	474 (193)	543 (174)	624 (141)	623 (120)	598 (102)	707 (80)	673 (68)	633 (53)	681 (38)	661 (34)	598 (26)	704 (12)	785 (9)	698 (8)	355 (9)	544 (5)	1211 (1)	859 (1)	429 (1)

Across all positions, a pattern of improvement takes place with yearsexp, then gradually levels off, and then degeneration sets in. QB appear to level off at around 7 yearsexp, RB at 5 yearsexp, TE at 3 yearsexp, and WR at 6 yearsexp. Similar patterns are seen for yards/touch and DVOA in Tables 6b and 6c, respectively (Appendix). The uniformity of these performance trends across performance metrics suggests correlation between these performance metrics, which is expected. However, these data do not necessarily capture a uniform trend applicable to all players. More likely, there are two distinct trends occurring at each position: one for the regular players who play a long career and one for the players who are not as good or whose physical capabilities diminish quickly with age (yearsexp). The significant drop-off in the number of player observations in the first few years attests to the viability of this double-trend. Hence, it could be the case that below-average players make up a large share of the players with early career exits, and the omission of their performance data from the later years makes it appear as though all players keep getting better, when in reality the above-average players were playing well for most of their careers.

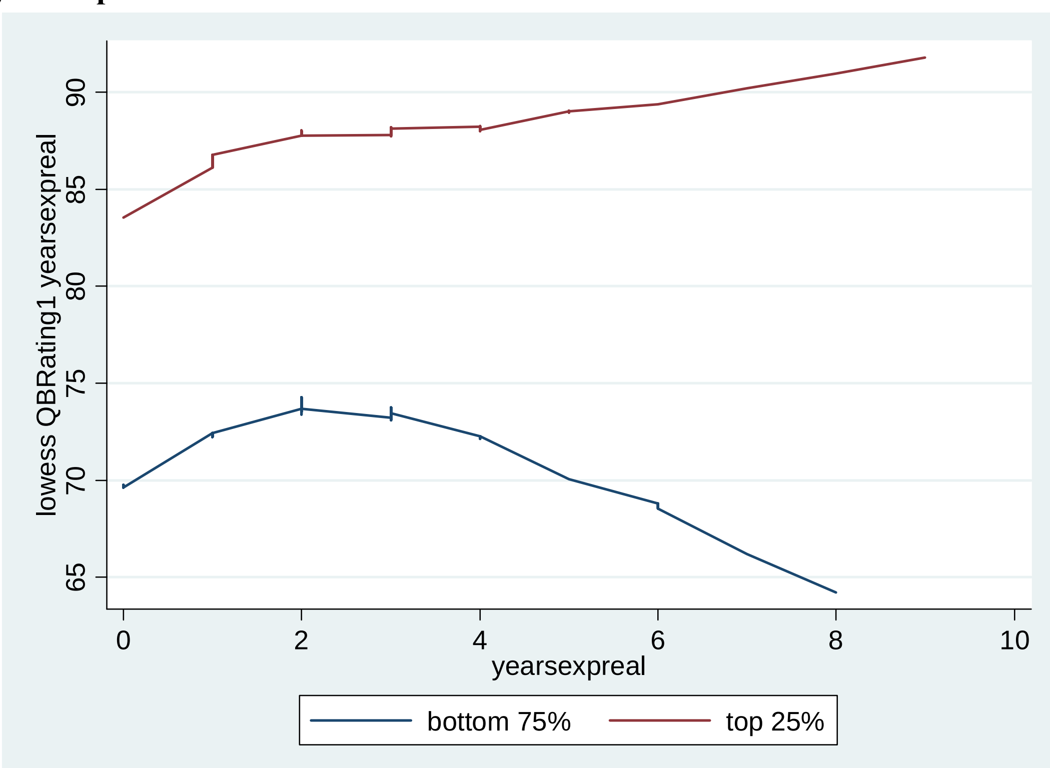
This theory is best tested using QB because they have one of the cleanest metrics available: quarterback rating (QB Rating). QB Rating is ideal because it only applies to type 1 players the way that it is coded in the data, and because it is nuanced composite metric that ranks players on their efficiency, regardless of playing time (touches). In order to test this theory, I must create a new variable: MaxQBR. MaxQBR is the highest quarterback rating that any QB achieves in his career. MaxQBR enables the best QB to be separated from the rest of the population. Within MaxQBR, the top 25% of QB have ratings greater than 91. The reason MaxQBR is needed to properly cull the top 25% of QB is because simply taking the top 25% of QB ratings would likely result in the same players having multiple observations crammed within the top 25%, which is not an accurate representation of the QB pool as a whole. Furthermore, MaxQBR allows the creation of the variable fracmax. Fracmax is the fraction of a player's MaxQBR that he accomplishes with his rating in a given season. It is useful because it acts as an indicator of how well a player is performing relative to his peak career performance. In other words, it illustrates player growth and deterioration more effectively.

In order to effectively illustrate how the top 20% of QB perform differently from the rest of the type 1 pool, I plot the MaxQBR of both groups as a function of yearsexp. However, the data do not pick up the start of the careers of all the players included. Approximately one third of the players in the data began playing prior to 1998. Because these players only have performance data for their later years of experience but not the earlier ones, their inclusion in the plot (graph) could skew the curves. For the following graphs, I only include players whose rookie season is recorded in the data. Additionally, I do not include players whose careers are shorter than three years (maximum yearsexp<2) because theoretically a) they don't have long enough careers to properly experience the effects of aging even though they make early exits and b) these players can never qualify for non-release free agency (free agency where the player knows ahead of time that he will be a free agent at the end of the season as opposed to being released before the expected expiration date of his contract), and are therefore irrelevant to later analysis. Graph 1a plots fracmax as a function of yearexp for players in the top 25% of MaxQBR and players in the bottom 75% of MaxQBR. Graph 1b plots QB Rating as a function of yearsexp for players in the top 25% of MaxQBR and players in the bottom 75% of MaxQBR.

Graph 1a: Fracmax for the top 25% and bottom 75% of QB as a function of yearsexp



Graph 1b: QB Rating for the top 25% and bottom 75% of QB as a function of yearsexp



Graph 1b indicates that, in fact, the top 25% of QB keep their form for much longer than the bottom 75%. Both groups appear to make the most progress during their first three years (yearsexp 0-2). Afterwards, the bottom 75% start fading dramatically while the top 25% essentially stay where they are. Because the data only ranges from 1998-2007 and only players with their rookie season data are recorded, this graph is limited to ten seasons of experience. However, from the data available on players with more yearsexp whose rookie data does not appear, I know that the top 25% eventually decline like the rest of the QB pool, only the timing is delayed. The underlying causes of these performance patterns is a matter open to speculation. Nevertheless, because QB Rating is a metric that is impartial to playing time, it is clear that the best QB are not as quickly or dramatically affected by the negative effects of aging as the rest of QB, even though both groups improve over their first three seasons at the same rate.

One might think that because there are more observations at lower values of yearsexp than at higher values, that there is selection bias influencing the results of the previous graphs. How is it that QB Rating improves slightly with yearsexp for the top 25% while fracmax for the top25% remains unchanged? The answer is that the players left in the sample at higher values of yearsexp are better players. Overall, QB Rating increases but the players remaining have higher maxQBR as well. Yet this trend does not occur with the bottom 75% of QB. So even though it is likely that a more select group is present for both the top 25% and bottom 75% at greater levels of experience, the fraction of that group that is still playing at a high level is much greater in the top 25%. Because of this, the evidence of Graphs 1a and 1b still suggest that the bottom 75% are adversely affected by aging to a greater degree (at least, within their first 10 years of NFL experience).

How are these patterns of performance with yearsexp manifested in the other three positions? Graphs 2a, 2b, 3a, 3b, 4a, and 4b (Appendix) illustrate these same plots for RB, TE, and WR, respectively. None of the other positions have as nuanced a performance metric that is impartial to playing time as QB Rating. Since playing time is important to control for because it is largely not the player's decision, yard/touch is the variable chosen for these positions. Admittedly, certain players at these positions have roles that are more conducive to greater yards/touch even with poorer performance (think of a mediocre deep threat WR verses an excellent short yardage slot WR). Yet, these are not significant concerns because I control for fixed effects and players rarely change their roles in that regard throughout their careers.

These graphs show that the top 25% percent of players maintain better performance than the bottom 75% throughout their careers, but RB, TE, and WR do not show a clear disparity in the effects of yearsexp on performance like QB. While these graphs do not demonstrate how these two groups of players (top 25% and bottom 75%) perform with respect to free agency, they suggest that at least for QB, the broader trend of aging affects the performance of top players differently than the rest.

How much is yearsexp correlated with FA? Across all positions, yearsexp has a positive relationship with FA significant at 1% level. Specifically, based on a linear model, the estimated percentage increase in likelihood of becoming a free agent with each year of experience is 3.4% for QB, 4.2% for RB, 2.9% for TE, and 4% for WR.

Now that I have explained some of the patterns and context for years of experience, the next step is to examine the impact of years of experience in the earlier regressions on player performance metrics. Since FA has the most significant effects on yards, yards will be examined using yearsexp as a control variable.

Table 7: FA and yearsexp regressed on yards (fixed effects (FE) and non-fixed effects regressions)

	FA	Yearsexp	FA	Yearsexp
QB	-564.998*** (98.796)	27.656** (12.106)	-381.140*** (108.469)	-46.645** (19.639)
QB1	-615.034*** (113.277)	28.443** (12.945)	-377.452*** (131.698)	-45.441** (21.189)
QB2	-19.183 (23.614)	5.222** (2.455)	-13.378 (38.399)	2.726 (9.212)
RB	-128.161*** (32.776)	15.574*** (5.014)	-102.238*** (35.343)	-10.743 (6.780)
RB1	-165.606*** (46.034)	15.028** (6.434)	-133.924*** (50.876)	-22.465** (9.251)
RB2	11.026 (11.185)	.937 (1.662)	10.014 (15.142)	-1.249 (3.165)
TE	-61.114*** (16.307)	5.088* (2.899)	-37.839** (17.373)	-3.761 (3.612)
TE1	-66.818*** (21.600)	.896 (3.715)	-42.105** (23.771)	-4.894 (4.707)
TE2	-1.445 (5.878)	-.474 (.903)	-7.516 (9.318)	-1.790 (2.240)
WR	-97.778*** (22.582)	18.960*** (3.076)	-48.344** (23.684)	-13.120*** (4.520)
WR1	-127.979*** (26.763)	6.128* (3.362)	-74.377** (29.593)	-15.162*** (5.018)
WR2	13.041 (10.635)	2.302* (1.363)	27.055 (16.488)	-12.849*** (4.176)
FE	NO	NO	YES	YES

The results of Table 7 indicate that yearsexp does not account for the significant portion of the negative relationship between FA and yards. Yearsexp across almost all positions has a very significant positive effect on yards without controlling for fixed effects but a very significant negative effect on yards with controlling for fixed effects. This dramatic reversal suggests that once I weight equally the below average players who qualify for free agency most frequently with all other free agents, yearsexp has only a degenerative effect on player performance. In other words, this supports the hypothesis that most players' performance declines on average as they age. However, because this coefficient is a function of a linear model, it does not rule out the possibility that players initially improve in their first few years and then get much worse later on as they age, a trend indicated by the previous graphs. Because the decline due to yearsexp may be greater as yearsexp increases, I use yearsexp^2 (squared) as another independent variable in future regressions.

Nonetheless, the result that free agency has a significant negative relationship on yards even when I account for years of experience is surprising. One potential reason for this is the lack of separation between players who are free agents because they have played poorly and have been released and players who are free agents because they fulfilled their previous contract and want to test their value in free agency. Distinguishing between these two types of free agents is difficult. Perhaps it is a very significant obstacle to analyses of free agency in the NFL more than other leagues because the lack of guaranteed contracts allows teams to cut costs by getting rid of underperforming players. Ideally, analysis of free agency would only include the players who fulfill their entire contract.

The effect of switching teams as an independent variable

One solution is to create a variable that distinguishes between free agents who sign with a different team than their previous team. This variable is newteam. The theory behind newteam is that players who re-sign with their previous teams during free agency have most likely not underperformed their previous contracts with their teams. This accounts for players who are released because teams release players when they feel the players' value is too low relative to their contract. However, this variable is not a perfect control. It still does not account for the bias created by players who sign midseason contract extensions. Presumably players who sign midseason contract extensions are above-average players because their teams actively sign them before having a full season of performance rather than letting them hit the free agency market. These players do not count as free agents in this analysis even though many of them may enter the final year of their contracts and adjust their effort accordingly prior to receiving their extensions. Similarly, newteam does not capture scenarios such as when a player underperforms his previous contract but re-signs for less money with his team anyway because no other team wanted his services, or he wanted to stay in the same city, or the team's offensive system still suited him better than that of any other team, or any other similar reason. In other words, I expect that newteam will account for some bias, but not all of it.

The first step is to include newteam in the regression on yards to see if it diminishes the negative free agent effect observed previously. If it does, then I run a similar regression using yard/touch as the dependent variable to ascertain whether newteam affects the amount of playing time (touches) for players or the quality of their play. Afterwards, I run a regression of newteam on touches to test this hypothesis directly. Finally, because yards and yards/touch both are traditional performance metrics, I run similar regressions with newteam on DYAR because it is the innovative metric that exhibits the most significant negative free agent effects so far.

Table 8a lists the results for what happens when I add newteam as an independent variable to the previous regression on yards. Table 8b does this same regression but with yearsexp^2 in addition to yearsexp. The reason for including both forms of years of experience is to model a quadratic years of experience variable. This is done based on the previous evidence that indicates that players initially improve at lower levels of years of experience but then get increasingly worse at higher levels. These regressions and all regressions from this point on in the Analysis control for fixed effects because doing so has demonstrated to be crucial in controlling for bias in the previous regressions. Because of the very low number of player observations where newteam=1 for type 2 players, I only include type 1 players.

Table 8a: Yards regressions using newteam, FA, yearsexp as independent variables

	newteam	FA	Yearsexp	Obs/Total Obs
QB1	-338.972** (139.879)	-253.158* (140.407)	-44.803** (21.030)	75/465
QB2	40.658 (54.446)	-22.122 (40.250)	3.359 (9.277)	24/208
RB1	-150.83*** (58.107)	-95.961* (52.434)	-21.081** (9.172)	47/433
RB2	-5.906 (19.132)	10.408 (15.225)	-1.332 (3.182)	46/475
TE1	-69.224** (29.783)	-21.688 (25.167)	-4.794 (4.670)	42/408
TE2	9.866 (12.653)	-9.709 (9.752)	-1.375 (2.307)	24/230
WR1	-89.731*** (30.428)	-38.120 (31.865)	-14.735*** (4.987)	128/817
WR2	33.746* (18.098)	24.658 (16.446)	-12.706*** (4.153)	56/558

Table 8b: Yards regressions using newteam, FA, yearsexp, yearsexp^2 as independent variables

	newteam	FA	Yearsexp	Yearsexp^2
QB1 (75)	-392.105*** (137.658)	-221.822 (137.718)	116.995** (46.946)	-11.097*** (2.894)
RB1 (47)	-164.154*** (57.816)	-109.923** (52.249)	35.704 (24.593)	-5.047** (2.031)
TE1 (42)	-74.768*** (28.865)	-23.998 (24.374)	41.787*** (11.522)	-4.292*** (.976)
WR1 (128)	-102.390*** (29.901)	-37.265 (31.209)	40.152*** (11.936)	-4.187*** (.831)

As seen in Tables 8a and 8b, newteam greatly diminishes the significance of the negative FA effect on yards but does not eliminate its significance entirely for all positions (specifically, RB1). At the same time, newteam has a more significant negative relationship with yards than FA does when both are included in the regression. Yearsexp (and yearsexp^2) maintains its significant negative relationship with yards regardless of whether I include newteam in the regression. These results show that players who switch teams (on average) gain significantly fewer yards in the season prior to the switch. Because newteam diminishes the negative effects of FA on yards, this suggests that players who switch teams in free agency are on average worse players (in terms of yards gained in their contract year) than those who re-sign with their former teams. However, to determine whether these players are playing worse or whether they are getting fewer touches (eg: their coaches are playing them less for some reason), I run the regressions of Tables 8a and 8b on yards/touch.

Table 9a: Yards/touch regressions using newteam, FA, yearsexp as independent variables

	Newteam	FA	Yearsexp
QB1	-.144 (.118)	-.098 (.119)	-.016 (.018)
QB2	.593 (.668)	.221 (.494)	-.301*** (.114)
RB1	-.329*** (.095)	-.034 (.085)	-.031** (.015)
RB2	-.140 (.185)	.091 (.147)	.027 (.031)
TE1	-.731*** (.249)	.163 (.210)	-.080** (.039)
TE2	.080 (.658)	-.453 (.507)	-.154 (.120)
WR1	-.404** (.164)	.212 (.172)	-.085*** (.027)
WR2	.689* (.388)	.417 (.353)	-.178** (.089)

Table 9b: Yards/touch regressions using newteam, FA, yearsexp, yearsexp^2 as independent variables

	Newteam	FA	Yearsexp	Yearsexp^2
QB1	-.185 (.117)	-.074 (.117)	.108*** (.040)	-.008*** (.002)
RB1	-.337*** (.095)	-.042 (.086)	.002 (.040)	-.003 (.003)
TE1	-.742*** (.249)	.158 (.210)	.012 (.099)	-.009 (.008)
WR1	-.404** (.165)	.212 (.172)	-.080 (.066)	-.000 (.005)

Switching teams has a very significant negative effect on yards/touch for type 1 RB, TE, and WR even though FA has no significant effect on yards/touch. Taken together with the results of Table 8, this suggests that type 1 RB, TE, and WR who switch teams do in fact play worse, as both yards and yards/touch significantly decrease. This also lends credibility to the theory that these players switch teams because of their decline in performance. In other words, a significant amount of the players who switch teams in free agency most likely do so because they were released by their former teams. Additionally, because FA shows no significant relationship with yards/touch while it shows a significant negative relationship with yards when I use newteam, it is likely that the free agents who do not switch teams are gaining fewer yards because their coaches play them less, not because they are performing worse. This explanation does not account for the insignificant result in Tables 9a and 9b for type 1 QB. Given the results of Graphs 1-4, this suggests that type 1 QB are affected much more by age than other type 1 position players. However, this result could simply reflect the much greater variation in performance among QB because of their greater number of touches and greater variation in yards and touchdowns relative to other positions. In other words, the effects of aging are magnified for QB because they are the most heavily involved offensive players.

Regardless, because DYAR is an innovative, non-traditional metric that also shows significant negative FA effects, it makes sense to examine the effects of newteam on DYAR. This is done in Tables 10a and 10b.

Table 10a: DYAR regressions using newteam, FA, yearsexp as independent variables

	Newteam	FA	Yearsexp
QB1	-169.952** (68.758)	-65.950 (69.017)	3.924 (10.337)
QB2	-1.240 (38.000)	22.997 (28.092)	-5.639 (6.475)
RB1	-56.415** (21.989)	-15.096 (19.842)	.699 (3.471)
RB2	-2.282 (8.821)	6.643 (7.020)	2.541* (1.467)
TE1	-36.948*** (12.644)	6.001 (10.684)	-1.363 (1.983)
TE2	.386 (8.949)	-4.005 (6.897)	-.376 (1.632)
WR1	-34.304** (14.546)	12.443 (15.233)	-5.773** (2.384)
WR2	12.244 (8.566)	12.016 (7.784)	-.952 (1.966)

Table 10b: DYAR regressions using newteam, FA, yearsexp, yearsexp^2 as independent variables

	Newteam	FA	Yearsexp	Yearsexp^2
QB1	-199.812*** (67.182)	-48.340 (67.211)	94.854*** (22.911)	-6.237*** (1.412)
RB1	-59.831*** (22.012)	-18.676 (19.893)	15.259 (9.364)	-1.294* (.773)
TE1	-38.571*** (12.479)	5.325 (10.537)	12.275 (4.981)	-1.256*** (.422)
WR1	-37.179** (14.540)	12.637 (15.173)	6.688 (5.803)	-.950** (.404)

The results of Tables 10a and 10b show that when newteam, FA, and yearsexp are regressed on DYAR, only newteam and yearsexp have significant effects. In order to tell how much the effect of FA on DYAR changes without newteam, Table 11 (Appendix) shows the results for the regressions of Table 10a when I do not use newteam as an independent variable.

In terms of newteam's effect on FA for DYAR, the only significant result is for type 1 QB. This contrasts with the result that type 1 QB are the only type 1 position without a significant negative correlation between newteam and yards/touch (Table 9). This likely means that type 1 QB either have their playing time (touches) reduced more than other positions when they switch teams or that their performance in terms of yards and DYAR is more affected than other positions from a similar decrease in playing time.

As a final confirmation of FA getting fewer touches, Tables 12a and 12b examine the impact of newteam, FA, and yearsexp on touches for each position. Due to the quantity of tests performed up to this point that all show largely insignificant results for type 2 players, it appears that type 2 players most likely as a sample do not have enough touches to show robust effects for any control variable related to effort. For this reason, I do not include them in any further analysis unless I mention otherwise.

Table 12a: Touches regressions using newteam, FA, and yearsexp as independent variables

	newteam	FA	yearsexp
QB1	-40.534* (21.020)	-36.734* (21.100)	-7.690** (3.160)
RB1	-20.304* (12.056)	-22.027** (10.879)	-3.622* (1.903)
TE1	-5.513 (3.772)	-3.853 (3.187)	-.400 (.591)
WR1	-6.102* (3.268)	-8.264** (3.422)	-.780 (.536)

Table 12b: Touches regressions using newteam, FA, and yearsexp as independent variables

	Newteam	FA	Yearsexp	Yearsexp^2
QB1	-46.730** (20.876)	-33.080 (20.885)	11.176 (7.119)	-1.294*** (.439)
RB1	-23.066* (11.996)	-24.922** (10.841)	8.149 (5.103)	-1.046** (.421)
TE1	-6.215*** (3.656)	-4.146 (3.087)	5.503*** (1.459)	-.544*** (.124)
WR1	-7.716** (3.183)	-8.155** (3.321)	6.217*** (1.270)	-.534*** (.088)

From the results of Tables 12a and 12b, it is clear that switching to a new team is more indicative of a drop in quality of performance as well as a decrease in playing time, whereas FA is correlated only with a decline in playing time.

Overall, newteam appears to do a decent job of controlling for players who are free agents because they were released prior to their end of their contract. This is because it significantly diminishes the negative free agent effects previously observed for performance metrics while not diminishing the significant negative effects of aging. It does not, however, eliminate entirely the negative effect of FA on yards for type 1 players. Because it does this to only a degree, there are still likely some unobserved variable effects. Newteam itself might even over-control to some degree because not all of the players who switch teams do so because they were released; some simply choose to go elsewhere. Excluding these players from the free agent pool means distorting the pool so that it no longer reflects all of the players who face free agency incentives, but only the ones who did and re-signed with the same teams.

Discussion of alternative methods to deal with potential bias affecting free agency variables: years of experience thresholds, team wins (independent variable) and contract length (independent variable)

Another way to exclude free agents who do not face true incentives is to limit the regression to free agents who have more than three years of experience. The reason for this is because players become eligible to become RFA when yearsexp=2 (three years of NFL experience) and eligible to be UFA when yearsexp>=3. Any free agents with fewer years of experience are free agents because they have been released from a team, and thus do not face the same incentives as a player who plays out his contract.

It turns out that there are only a few FA player observations eliminated under these criteria (20 type 1 and 24 type 2 QB, 5 type 1 and 23 type 2 RB, 16 type 1 and 28 type 2 TE, 15 type 1 and 22 type 2 WR). For this reason, their exclusion from the sample does not influence the size or the results of the sample significantly.

But there are still two independent variables that have not been used in the study: number of team wins (teamwins) and contract length. When regressed on every performance statistic for all positions, teamwins returns a positive correlation significant at the 1% level. This is expected since players who play on better teams will be positively impacted by the higher level of play that surrounds and interacts with them. The problem is that the causality of teamwins positive effect on performance is unclear. To what degree is an individual player on a team playing well enough to bring his team's wins up, and to what degree are the players and coaching around him making him better? The causality can only be speculated, and it likely varies for each individual player. Furthermore, if free agents try harder in a way that impacts team performance, teamwins would absorb some of the significance of the effect of FA on performance. For these reasons, I do not use teamwins as an independent variable in my regressions.

Contract length is another independent variable that may be able to help isolate the true effects of free agency of performance. As has been previously demonstrated, free agents are generally below-average players. By extension, players with shorter contracts should be statistically worse because contract length is not randomly assigned; better players on average receive longer contracts. However, when I regress contract length on FA, there is correlation significant at the 1% level. In addition to this very significant correlation, contract length observations of 1 year overlap directly with FA (because both variables signify the last year of a contract). Because this variable overlap significantly skews the true effect of free agency, I do not use contract length as an independent variable in my regressions.

Generally, newteam, yearsexp, and yearsexp^2 account for the significant negative free agent effects on performance variables observed previously. Because of this and the problems posed by the three additional means I describe in this section (threshold for years of experience, teamwins, and contract length), I proceed with the remainder of this analysis using newteam, yearsexp, yearsexp^2, and FA as my primary independent variables.

Estimates of the effects of the year after signing a multiyear contract (YA) on performance

To recap, the free agency effect (FAE) is negative but mostly insignificant for type 1 players across all positions. But how does the year after signing a multiyear contract effect (YAE) compare? Theoretically, the same incentives apply to the YAE as the FAE, so the independent variables used in the regression are the same. However, only a small fraction of players qualify for the YAE. Specifically, 42 QB, 48 RB, 43 TE, and 82 WR. This is because in order to qualify for the YAE a player must have been a free agent the prior year and must have performance data for at least two consecutive years after his free agency year. The reason for this is to exclude players who sign one year contracts, such as players who are about to retire. I exclude these players because they do not face the same incentives to decrease effort as other players who qualify for the YAE. A potential but likely insignificant problem with defining the YAE in this way is that it will eliminate players who become injured and miss their second season into the multiyear deal. I do not have data on injury status, but I think it is safe to assume that the number of players that fall into this category is not significant.

Table 13a lists the results of standard performance variable regressions using YA and yearsexp, and Table 13b lists the results of these regressions for position specific performance variables. Tables 13c and 13d (Appendix) do not include yearsexp^2 as an independent variable. I do not use newteam in these regressions because a player's incentive to shirk after signing a multiyear deal would theoretically always be present regardless of whether he switches teams. Despite their lack of a robust sample size of playing time or player observations, I include type 2 players in Tables 13a-d in order to provide a complete picture of the YAE. As noted previously, I control for fixed effects.

Table 13a: YA effect on performance (metrics available to all positions)

	Obs.	YA (Yards)	Yearsexp (Yards)	Yearsexp^2 (Yards)	YA (yards/touch)	Yearsexp (yards/touch)	Yearsexp^2 (yards/touch)
QB1	31	314.503* (186.550)	88.922* (47.779)	-10.260*** (2.936)	.098 (.156)	.097** (.040)	-.008*** (.002)
QB2	11	13.514 (70.877)	10.856 (19.129)	-.754 (1.463)	.077 (.874)	-.238 (.236)	-.006 (.018)
RB1	29	-12.384 (68.807)	13.797 (24.947)	-3.737* (2.080)	.022 (.113)	-.027 (.041)	-.001 (.003)
RB2	19	-22.799 (26.265)	10.802 (8.131)	-1.113 (.751)	-.078 (.256)	.036 (.079)	-.000 (.007)
TE1	33	5.199 (31.957)	38.121*** (11.768)	-4.095*** (.993)	-.242 (.274)	.009 (.101)	-.008 (.009)
TE2	10	29.720* (16.651)	.852 (5.265)	-.315 (.490)	1.135 (.871)	-.394 (.276)	.022 (.026)
WR1	55	46.526 (40.121)	32.254*** (12.080)	-3.837*** (.840)	-.145 (.219)	-.088 (.066)	.000 (.001)
WR2	27	8.264 (28.751)	-9.150 (8.458)	-.177 (.849)	-.814 (.612)	-.255 (.180)	.015 (.018)
	Obs.	YA (DVOA)	Yearsexp (DVOA)	Yearsexp^2 (DVOA)	YA (DYAR)	Yearsexp (DYAR)	Yearsexp^2 (DYAR)
QB1	31	.025 (.035)	.027*** (.009)	-.002*** (.001)	99.978 (90.774)	83.358*** (23.249)	-5.814*** (1.429)
QB2	11	.012 (.953)	.017 (.056)	-.007 (.004)	105.635* (47.749)	8.620 (12.887)	-1.543 (.986)
RB1	29	.019 (.024)	.000 (.009)	-.000 (.001)	-.503 (25.903)	9.199 (9.391)	-.918 (.783)
RB2	19	.099* (.058)	.014 (.018)	-.000 (.002)	21.041* (12.097)	5.315 (3.745)	-.295 (.346)
TE1	33	-.018 (.038)	.012 (.014)	-.002 (.001)	-10.799 (13.781)	11.851** (5.074)	-1.208*** (.428)
TE2	10	.197* (.103)	-.024 (.033)	.003 (.003)	24.077** (11.676)	-3.619 (3.692)	.304 (.343)
WR1	55	-.005 (.024)	-.002 (.007)	-.000 (.001)	7.686 (19.318)	5.052 (5.816)	-.854*** (.405)
WR2	27	-.071 (.065)	-.006 (.019)	.001 (.002)	-13.093 (13.527)	2.729 (3.979)	-.263 (.399)

Table 13b: YA effect on performance (position specific metrics)

	YA (QB Rating)	Yearsexp (QB Rating)	Yearsexp^2 (QB Rating)	YA (TFD)	Yearsexp (TFD)	Yearsexp^2 (TFD)	YA (Catchrate)	Yearsexp (Catchrate)	Yearsexp^2 (Catchrate)
QB1	1.886 (2.129)	1.910*** (.545)	-.139*** (.034)						
QB2	NA	NA	NA						
RB1				-1.001 (.874)	.041 (.317)	.004 (.026)			
RB2				1.440*** (.494)	.185 (.153)	-.020 (.014)			
TE1							.017 (.017)	.006 (.006)	-.000 (.001)
TE2							.140** (.058)	.013 (.018)	-.001 (.002)
WR1							.001 (.010)	.004 (.003)	-.000 (.000)
WR2							.037 (.032)	.002 (.009)	.000 (.001)

Tables 13a-d show that the YAE is largely insignificant across all positions. This is not surprising given the small sample size of YA players. What is surprising is that when this effect does show significance, it is positively correlated with performance. The results supporting this correlation are not robust enough to merit detailed discussion, but they reflect selection bias for better players receiving multiyear contracts when they are still getting better. Specifically for QB, remember that Graph 1b showed that the top 25% of QB improve slightly with age throughout the first 10 years of their career. Still, the yearsexp quadratic (yearsexp and yearsexp^2) has a fairly strong negative effect. This is because players who have signed multiyear deals are most likely older players, and the negative effects of aging affect them more than younger players who still might be improving their performance through their on-field experience. The fact that years of experience (aging) still affects the sample of year after multiyear contract signing players the same as other players suggests that these players are not completely different from the overall sample because they share common performance trends.

Overview of specialized analysis

It is clear that position-wide analysis of the free agent effect (FAE) and year after multiyear contract signing effect (YAE) does not yield very significant results. For this reason, it makes more sense to decompose each position into more specialized categories in order to see if the FAE and YAE hold true for specific subgroups. I make use of two specializations: 1) categorizing players according to their level of performance along a particular metric (yards, DYAR, etc) and 2) categorizing players according to how many times they have been a free agent given a certain level of years of experience. Both specializations test the hypothesis that only the best players have the ability to significantly improve their performance due to motivation. The first specialization does this by separating players into groups according to their performance. For instance, players in the top 33% of DYAR are one group, players in the second 33% below that are another, etc. Within each of these groups, I then regress FA on player performance. The second specialization does this by examining the number of times players at specific positions with a certain amount of years of experience have previously been free agents. For example, players with under seven years of experience who have been free agents once are one category, players with under seven years of experience who have been free agents twice are another, etc. I regress FA and YA on player performance in each of these categories. The purpose of these specializations is to gain a more nuanced perspective of potential FAE and YAE that the broader, position-wide regressions cannot provide. I explain these categories and their specific regressions as they arise.

First specialization: free agency and year after signing a multiyear contract effects on player performance by player performance thirds

For the first specialization, I expect that FA will have the most positive significant effect on QB Rating for the top third of players and the least for the bottom third. Players are organized into thirds based on their MaxQBR. Because each of these groups has a smaller sample size than the previous regressions, I use the natural log of QB Rating as the dependent variable in order to diminish the potential skewing effect of outliers. FA (or YA), yearsexp and yearsexp^2 are the independent variables. Switching teams (newteam) has a uniformly negative impact in all of these regressions significant at the 1-5% level. Nevertheless, I exclude newteam as an independent variable because separating players into performance thirds already attempts to control for players who would be cut or released (because they would perform worse). Within these specialized groups, only counting the free agents who re-sign with their previous teams would likely significantly reduce the pool of free agents such that it would no longer reflect a large quantity of the players who face the relevant free agent incentives.

Tables 14 (a and b) show the results for these performance thirds regressions for QB. Tables 15-17 (Appendix) show similar regressions for RB, TE, and WR. Because a comprehensive metric like QB Rating doesn't exist for these positions, I use YR and DYAR. Despite the smaller sample size in each of these regressions, I do not apply any natural logs to YR because it is already a variable with very little variance, nor DYAR because there are too many observations with negative values (and altering these to be positive distorts the metric).

Table 14a: ln(QB Rating) regression on FA, yearsexp, yearsexp^2 by MaxQBR thirds

	Obs	FA	yearsexp	Yearsexp^2
Top 33%	252	-.034 (.026)	.029*** (.009)	-.002*** (.001)
Mid 33%	145	.012 (.032)	.018 (.014)	-.002 (.001)
Bottom 33%	68	.010 (.097)	.104* (.052)	-.013** (.006)

Table 14b: ln(QB Rating) regression on YA, yearsexp, yearsexp^2 by MaxQBR thirds

	Obs	YA	yearsexp	Yearsexp^2
Top 33%	252	.036 (.033)	.028*** (.009)	-.002*** (.001)
Mid 33%	145	-.033 (.051)	.019 (.014)	-.002 (.001)
Bottom 33%	68	dropped	.106** (.045)	-.013** (.006)

Throughout all of the performance thirds regressions in Tables 14-17, no consistently significant free agent effect (FAE) or year after signing multiyear contract effect (YAE) occur. This is most likely because of the small sample size of each of the groups (thirds). The strongest results are for QB, where I observe no FAE or YAE, but the negative effects of yearsexp and yearsexp^2 are very significant. There is one very significant (1% level) negative relationship between FA and yards/touch for the top third of RB, but there are no other results in line with this trend and therefore it is most likely an anomaly. The only other interesting result from these regressions is that better performance is positively correlated with more player observations for QB, TE, and WR, but not for RB. This supports the theory that better players have longer careers for these three positions. I postulate that this result may reflect the fact that RB endure much more physical contact because of the nature of their position (running into the line, getting tackled more frequently than QB, TE, WR), and therefore even better RB frequently wear down physically much more quickly than players at the other positions.

Second specialization: free agency and year after signing a multiyear contract effects on player performance by how many times players with certain levels of years of experience have been free agents

Although a greater sample size would provide confirmation of the previous results, it seems that the FAE and YAE do not vary significantly depending on the level of player skill. Maybe the second specialization will provide more insight. The second specialization separates players according to two categories: the number of times a player has been a free agent (sum of FA, or sFA) and the amount of seasons he has played so far in his career (measured by yearsexp). I do not include players with yearsexp<2 because they cannot qualify for non-release free agency (their incentives are not the same as the free agents relevant to this study). I expect for all positions that greater FAE and YAE are correlated with fewer free agency periods and greater years of experience. This is because players who are free agents least frequently throughout their careers are most likely the best players (the reason why they are signed long-term). Therefore, they possess the greatest ability to alter their performance through the effort they expend. Tables 18 (a and b) list the results of the second specialization regressions for QB, and Tables 19-21 (Appendix) list the results for RB, TE, and WR, respectively.

Table 18a: QB Rating regression on FA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	FA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	45	-26.244* (13.774)	-1.403 (22.130)	-.548 (2.538)
sFA>1	32	-.175 (5.726)	-10.957 (23.248)	1.311 (2.455)
Yearsexp>=6				
sFA=1	59	1.311 (5.984)	-4.336 (5.718)	.096 (.257)
sFA>1	46	-2.916 (3.845)	3.551 (3.610)	-.283* (.158)

Table 18b: QB Rating regression on YA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	YA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	45	-6.819 (9.739)	-17.428 (26.274)	1.335 (2.898)
sFA>1	32	1.238 (5.558)	-9.434 (23.095)	1.152 (2.417)
Yearsexp>=6				
sFA=1	59	2.432 (4.776)	-3.523 (5.848)	.058 (.257)
sFA>1	46	1.254 (3.561)	4.106 (3.551)	-.303* (.156)

Like the results of the first specialization, these results show very little evidence of either a FAE or YAE. Again, this could largely be a product of small sample sizes for each of the subgroups. Yet, the fact that yearsexp is significant negatively correlated with performance at every position suggests that despite the small sample size, some of the population-wide trends still hold and/or that the negative effects of aging are very strong.

A very interesting trend that emerges across positions with yearsexp is that the subgroups that are most affected are those where sFA>1, regardless of the value of yearsexp. In other words, regardless of how experienced a group of players is, they are more negatively affected by age the more frequently they are free agents. This relationship probably is not the result of a simple causal effect between sFA and the effects of yearsexp. Rather, it most likely reflects a more complex indirect causal effect. This more complex effect ties together the fact illustrated by Graphs 1 (and Graphs 2-4 to a lesser degree) that the best players do not decline as quickly/starkly with yearsexp as worse players with the fact that the best players are less frequently free agents than worse players. Hence, sFA is correlated with a steeper decline in player performance as yearsexp increases because worse players are more likely to have higher values of sFA as yearsexp increases.

The only other interesting result is that WR with more than seven years of experience who have been free agents more than once show a very significant positive FAE with both yards/catch and DYAR. This result makes sense from a theoretical standpoint. Players who have been playing for seven seasons are much more likely to be above-average players regardless of how many times they have been free agents. Therefore, the fact that they can try harder and improve their performance when they are eligible for free agency does not come as a surprise. However, because only 32 players make up this sample and no other position shows a similar trend of results, this result for WR is most likely a sampling anomaly.

Summary of analysis findings compared to hypotheses

Overall, I find no consistent significant free agent effects (FAE) or year after multiyear contract signing effects (YAE) when I account for switching teams and years of experience. Although I expected to find more significant results validating a positive FAE and a negative YAE, this result is still in line with my hypothesis that free agency affects player performance to a less significant degree in the NFL than in MLB or the NBA.

Regarding patterns of performance by position, I expected QB performance to be more significantly affected by free agency than WR or TE performance. When I use years of experience and switching teams as independent variables, I find that there are no significant differences in the significance of FAE and YAE among all positions. However, it appears that QB are more dramatically impacted by age than the other positions. I think this result reflects the fact that the data for QB magnify the adverse effects of aging relative to other positions. This is because age negatively impacts player performance in a very significant way at higher levels, and QB have the most robust sample size of performance data in terms of yards gained and the amount of plays they are involved in on offense. Still, I have no explanation for why the pattern that the top 25% are so much less adversely affected by aging over the first ten years of their careers than the bottom 75% only results for QB and not for RB, TE, or WR.

There are performance aspects of certain positions that my data do not record. Specifically, I do not record data for blocking performance for TE. I speculated that this would cause TE to have less significant effects than WR because I analyze both in terms of their effectiveness as receivers. However, I do not find any differences in significance between WR and TE for FAE or YAE.

I cannot comment on whether evaluating RB in terms of their receiving performance in addition to their running performance would have created any significant changes in my results. Yet, due to the small number of RB who perform significant receiving roles, I suspect that incorporating this data would not have significantly altered my results. Similarly, I cannot say to what degree the results for RB (or any position) are affected by the omission of performance data for the offensive line. However, the result that the number of RB player observations is uniquely uncorrelated with player performance indirectly suggests that the physical interaction of RB with the offensive and defensive line adversely affects RB physical condition more significantly than any other position.

Significance of Findings

Ultimately, the vast majority of the results in this study do not show significant evidence of the free agent effect (FAE) or the year after multiyear contract signing effect (YAE) in the NFL for QB, RB, TE, or WR. Additionally, this insignificance pervades both traditional and innovative metrics, indicating that these metrics are significantly correlated despite a fair amount of variation in how they are derived. Although many of the findings are insignificant, the fact that there are somewhat consistent negative FAE and positive YAE likely attests to the fact that my analysis does not control perfectly for the two primary selection biases (worse players more likely to be free agents, better players more likely to receive multiyear contracts).

However, there are some significant findings in relation to player performance. First, below average players are much more highly represented in the free agent pool. Second, the top 25% of QB and the bottom 75% are not affected symmetrically by age. While both player categories improve during their first 2-3 seasons, the bottom 75% drop off sharply and quickly thereafter while the top 25% plateau for a while longer before their decline. This suggests that QB performance follows a more unique trend with age than that of any other position. Third, the amount of years of experience a player has and whether that player switches teams the following season are two variables that account for most of the negative FAE observed. The significant negative correlation between switching teams and performance indicates that a significant number of players are free agents because they are released by their teams, likely due to their poor performance. The very significant negative relationship between performance and years of experience across all player positions and specializations attests to the fact that no player can escape the effects of aging.

That being said, the data leave some questions to be answered. Why is it that free agents have significantly less playing time without showing significant declines in performance? Why is it that QB show a much more unique response to aging than any other position? I can only speculate the answers to these questions with the data I use. If anything, these questions reveal the inadequacy of statistics to tell the whole story for dynamic games that are more than a series of calculations. Perhaps coaches have some knowledge of player performance that causes them to be aware of when a player is about to decline in performance before his metrics show significant decline? One certainly hopes coaches can identify player performance better than a statistical software program.

The inadequacy of the data is perhaps a defining feature of the NFL compared to MLB and the NBA. It is not surprising that a game with over 22 players, each playing specialized positions where each of them has an impact on every play, shows much less conclusive results in terms of FAE and YAE than a game with five players on a team (NBA) or a game comprised of largely one-on-one discrete events (MLB). For these reasons, the magnitude of coaching, of teamwork, and of unobserved variables are likely much greater. More importantly, these variables are much more difficult to quantify.

How does it appear the three leagues compare now in terms of FAE and YAE? The NBA has clear evidence of both FAE and YAE, MLB has inconsistent support of these phenomena, and the NFL shows no evidence of either one. That is not to say that these phenomena do not exist in the NFL; perhaps the data are not strong enough or the performance metrics accurate enough to capture these effects. More likely there are two main factors contributing to the difference in results.

The first is the degree to which a player's effort can alter his performance. In other words, how much can a player influence the outcome of a game just by trying harder? It appears players have the greatest ability to do this in the NBA, due to the largest observed shifts in performance associated with contract incentives. Considering that NBA games are decided by five individuals per team playing interchangeable positions, there is the greatest capacity for a player to be able to affect the game outcome (and his performance metrics) by trying harder. This appears to be less clear-cut in MLB, where even though the majority of the game is decided by one-on-one interactions between pitchers and batters, each of these players plays only one position (pitching or batting—at best affecting half of the game) while still depending on the performance of the other eight players who are fielding. In the NFL, there is even more position specialization within offense, defense, and special teams. Furthermore, there are more players (eleven) on the field at one time than any other sport, and unlike the NBA or MLB, no fewer than two players (including the snapper) on a team can touch the ball during a single play. What this means is that the NFL has a much lesser capacity for how much one player can influence his team's performance, let alone his individual performance.

The second factor contributing to the difference in results is the differences in player contracts between leagues. There are many nuances in the salary structures and rules of each league, but the most important factor concerning player performance is the amount of guaranteed money included in contracts. Player salaries are effectively entirely guaranteed in MLB and the NBA. This is not the case the NFL, where the only real guaranteed money a player has is his signing bonus. If a player knows that he can be cut any year and not receive the money for the remaining years on his contract, essentially he always faces heightened incentives to keep his performance at a high level relative to MLB and NBA players. This by no means eliminates the added incentive to work harder right before a contract year or to shirk after a big signing, as there is a broad range of performance that a player can exhibit that is likely good enough to ensure his job security. Nonetheless, non-guaranteed contracts keep him on his toes in a way his MLB and NBA counterparts are not, and even if the performance metrics accurate reflect player effort, this could diminish the FAE and YAE.

Conclusion

In this study, I establish a model where players face a tradeoff between expending less effort and obtaining greater consumption (income). Free agency introduces potential short-term increases in the consumption returns to effort, creating incentives for players to work harder in their contract years. This is the basis for the conventional wisdom that players work harder and therefore perform better in their contract years.

Within this economic framework, not all players have the same motivations. Some players may be more motivated by short-term incentives; others may be more driven to consistently try their best. The elasticity of effort varies among players.

Aging has a more consistent effect on players, but it is not entirely uniform. All players improve in their first few seasons, and then worsen as they get older. Yet, the best players (at least for QB) are adversely affected by age in a more gradual manner than other players. This confirms that players differ in their physical limitations in addition to their intrinsic motivations.

Regardless of these variations, there is no evidence in the analysis of this study that players in the final years of their contracts perform significantly better than they do in other years, nor is there evidence that they perform significantly worse in the year after they sign multiyear contracts. This contrasts greatly with the NBA, where there is significant evidence of both of these phenomena, and MLB, where there is inconsistent but significant evidence for these phenomena. The two primary factors I propose to account for the lack of any such findings in the NFL are the lesser degree to which individual players can affect team outcomes and their own performance as well as the lack of guaranteed contracts.

One of the crucial issues that still remain is figuring out to what degree teams want to reward players who perform significantly better in their contract years. Teams give contracts to players commensurate with their expected future performance. Additionally, free agency is not static; it is dynamic. In other words, a player is not always in his contract year. If a team knows that a player is no longer developing his talent and his performance increases in his contract year, then that player is revealing that he is the type of player who does not put in maximum effort all of the time. If a team is deciding between signing long-term this player or another player of comparable talent who shows consistent performance throughout his career, the team likely chooses the more consistent player because there is reason to think the former will decrease his effort when he no longer needs a contract. That is to say, it may be that players who increase their performance heading into free agency do themselves a disservice.

More likely, there is too much asymmetric information for teams to operate in this manner. Teams do not know with certainty when a player's development has reached its plateau. Nor can teams observe player effort directly. They can only observe trends in player performance. For this reason, teams cannot ascertain what causes an increase in player performance during the contract year. Only a player knows his level of effort. Hence, there is likely still a payoff for exerting more effort in the contract year because generally there is too much asymmetric information for teams to assume that players exert effort only when there are short-term rewards. Moreover, because of the demonstrated difficulty of improving performance noticeably through increased effort, any players who are able to do this are most likely talented enough to merit the risk.

While the lack of significant findings for either aspect of the contract year phenomenon suggests that it does not exist in the NFL, it does not provide definitive proof for this. Specifically, large potential unobserved variable bias in the form of teamwork and coaching likely play a very significant role in determining individual and team performance. I recognize that I do not establish ironclad conclusions in this analysis. My goal is to try and provide an initial attempt to tackle the contract year phenomenon in the NFL and hopefully provide a foundation for future research in this area.

I have some concrete suggestions for further analysis. First, either the NFL or some independent source should design a free agency database that clearly distinguishes between players who are free agents because they are released before finishing their contracts and players who are free agents because they finish their contracts. Additionally, it would be informative to gather free agency and player performance data predating implementation of the salary cap in 1994 and examine whether there are changes in the contract year phenomenon before and after the salary cap rule. Furthermore, it would be interesting to compile a list of player salary data and examine to what extent increased contract year performance correlates with higher salary thereafter. Ultimately, perhaps the most helpful research going forward is to develop better estimates for teamwork, coaching, and the other intangibles that pervade the NFL in order to better estimate player effort. It may even be the case that some players increase effort in a way that subjugates their individual performance for the good of the team. Such motivations create an even more complex picture of player motivations and raise the question of whether individual performance is really the relevant performance area to analyze in the first place? Nevertheless, until these factors can be better measured (assuming they can be measured), it is unclear to what degree player effort can be observed in the NFL.

Appendix

List of commonly used abbreviations:
MLB=Major League Baseball, **NBA**=National Basketball Association, **NFL**=National Football League, **NFLPA**=National Football League Players Association, **CBA**=Collective Bargaining Agreement, **FA**=Free Agent, **RFA**=Restricted Free Agent, **UFA**=Unrestricted Free Agent, **YA**=Year After signing a multiyear contract, **FAE**=Free Agent Effect (expected increase in performance when FA=1), **YAE**=Year After Effect (expected decrease in performance when YA=1), **DVOA**=Defense-adjusted Value Over Average, **DYAR**=Defense-adjusted Yards Above Replacement, **TFD**=Touchdown Fumble Differential, **maxQBR**=maximum QB Rating in a player's career, **max(x)=**a player's highest recorded single season performance of x performance metric, **fracmax(x)**= a player's performance in x in a given year divided by his best performance in x during his career, **yearsexp**=years of experience playing in the NFL, **teamwins**=the number of wins a particular NFL team had in a given year, **newteam**=whether a player switched teams (=1) during a season or not (=0), **QB**=quarterback, **RB**=running back, **TE**=tight end, **WR**=wide receiver, **sFA**=sum of instances during a players career where he has been a Free Agent, **OLS**=Ordinary Least Squares, **fe**=fixed effects

List of performance metrics:
Position specific: Quarterback (QB) Rating—QB, Touchdown Fumble Differential (TFD)—RB, Catchrate—TE and WR
Applicable to all positions: Yards, Yards/touch, Defense-adjusted Value Over Average (DVOA), Defense-adjusted Yards Above Replacement (DYAR), Touches (Passes—QB, TE, and WR; Runs—RB)
Changes to conventional performance metrics: max(x), fracmax(x)

List of independent variables:
Free Agent (FA), Year After signing a multiyear contract (YA), Unrestricted Free Agent (UFA), Restricted Free Agent (RFA), type 1 and type 2 players, contract length, yearsexp, teamwins, newteam, sum of instances during a players career where he has been a Free Agent (sFA)

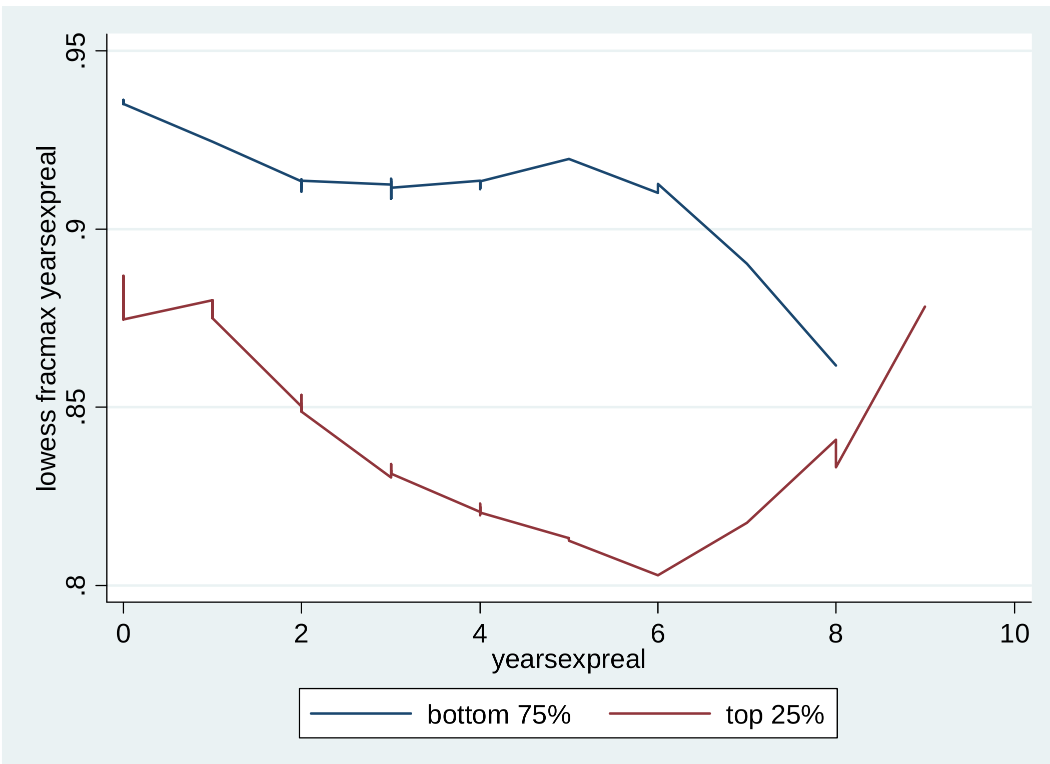
Table 6b: Mean yards/touch as a function of yearsexp (number of observations)

	Yearsexp																			
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
QB	5.24 (126)	5.66 (79)	5.40 (63)	5.84 (63)	5.51 (50)	6.03 (47)	5.95 (37)	6.07 (36)	5.94 (33)	5.84 (29)	5.65 (21)	5.68 (20)	5.90 (15)	6.27 (21)	4.97 (12)	5.84 (8)	5.96 (6)	5.831 (4)	7.06 (2)	5.15 (1)
RB	3.96 (216)	4.14 129	4.06 105	3.98 (97)	3.91 (87)	4.10 (75)	3.88 (57)	4.05 (43)	4.08 (36)	4.12 (26)	4.02 (22)	4.34 (7)	4.09 (4)	3.38 (3)	3.51 (1)					
TE	6.16 (141)	6.38 (99)	6.06 (76)	6.47 (71)	6.31 (68)	6.51 (47)	6.46 (39)	6.20 (28)	6.28 (23)	6.05 (18)	5.96 (14)	6.07 (7)	6.54 (4)	7.44 (2)	6.73 (1)					
WR	6.84 (300)	7.52 193	7.51 174	7.35 141	7.29 120	7.02 102	7.53 (80)	7.52 (68)	7.34 (53)	7.57 (38)	7.86 (34)	7.29 (26)	7.14 (12)	7.22 (9)	6.95 (8)	6.68 (9)	7.54 (5)	8.07 (1)	6.93 (1)	6.81 (1)

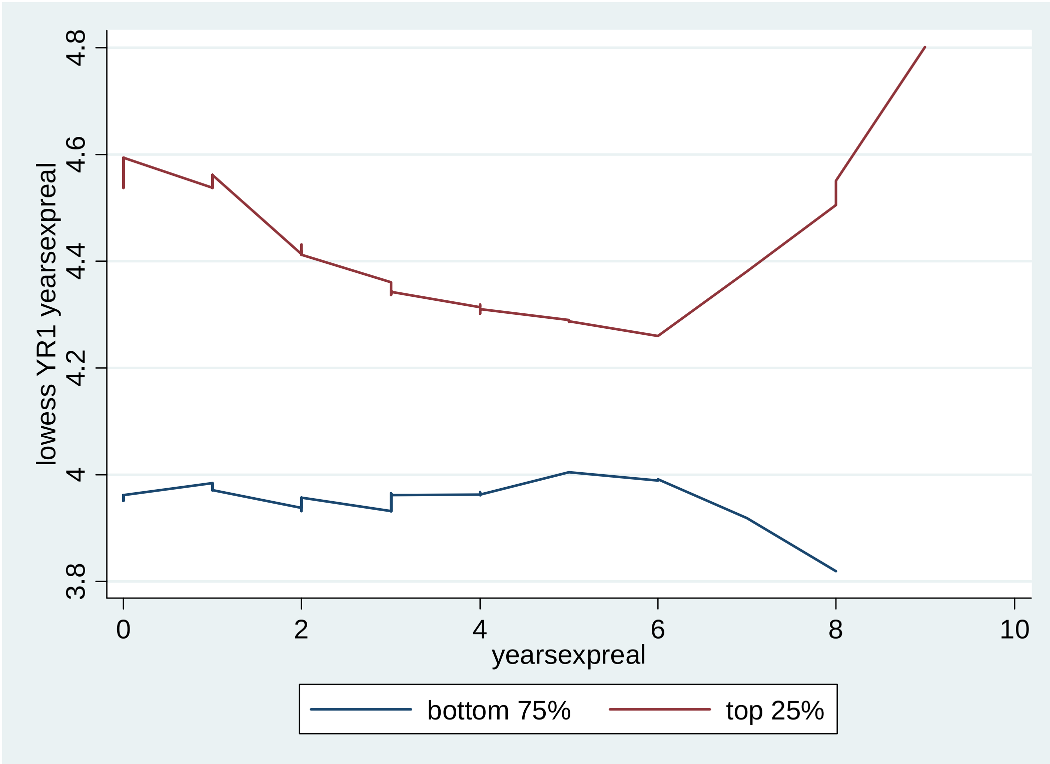
Table 6c: Mean yards/touch as a function of DVOA (number of observations)

	Yearsexp																			
	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
QB	-.22 (126)	-.10 (79)	-.15 (63)	-.06 (63)	-.13 (50)	-.02 (47)	-.03 (37)	.00 (36)	-.07 (33)	-.09 (29)	-.17 (21)	-.09 (20)	-.03 (15)	-.04 (21)	-.32 (12)	.01 (8)	-.16 (6)	.02 (4)	-.16 (2)	-.29 (1)
RB	-.06 (216)	-.03 (129	-.03 (105)	-.04 (97)	-.04 (87)	-.01 (75)	-.04 (57)	-.02 (43)	-.01 (36)	.01 (26)	-.02 (22)	.09 (7)	.02 (4)	-.20 (3)	-.15 (1)					
TE	-.09 (141)	-.03 (99)	-.05 (76)	-.03 (71)	-.02 (68)	.00 (47)	-.02 (39)	-.03 (28)	-.02 (23)	-.07 (18)	-.05 (14)	-.03 (7)	.07 (4)	.15 (2)	-.16 (1)					
WR	-.11 (300)	-.02 (193)	-.02 (174)	-.02 (141)	-.03 (120)	-.06 (102)	-.00 (80)	.01 (68)	-.03 (53)	.01 (38)	.05 (34)	-.01 (26)	-.03 (12)	-.00 (9)	-.06 (8)	-.06 (9)	.04 (5)	.10 (4)	-.12 (1)	-.05 (1)

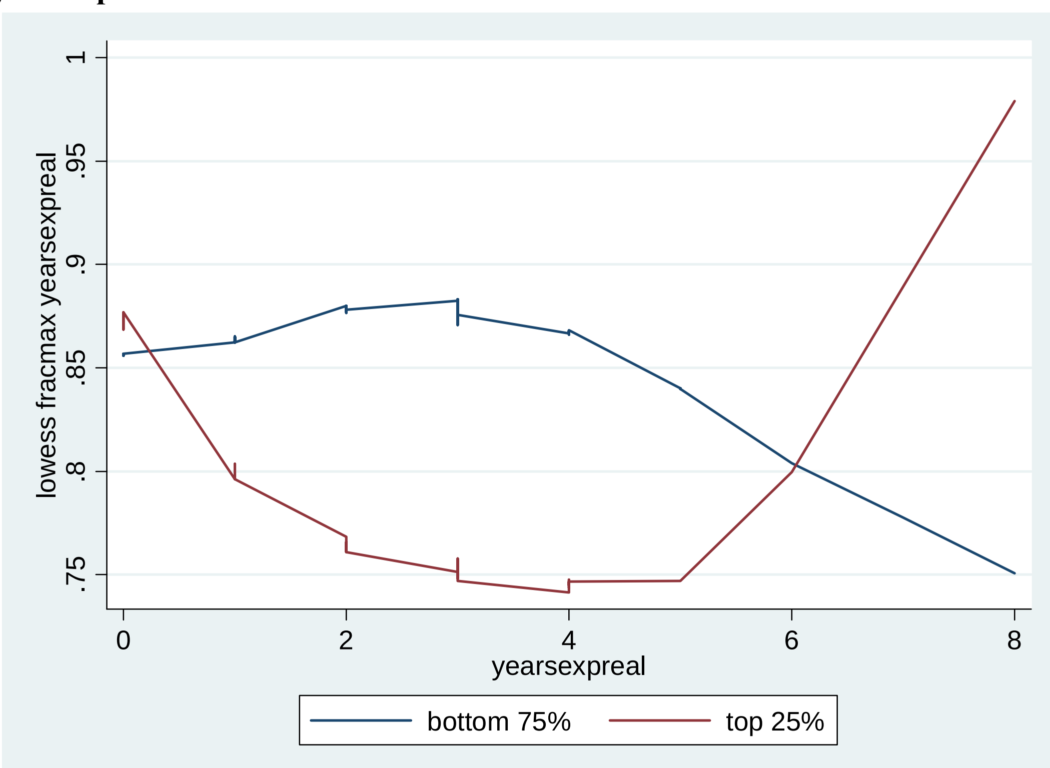
Graph 2a: Fracmax for the top 25% and bottom 75% of RB as a function of yearsexp



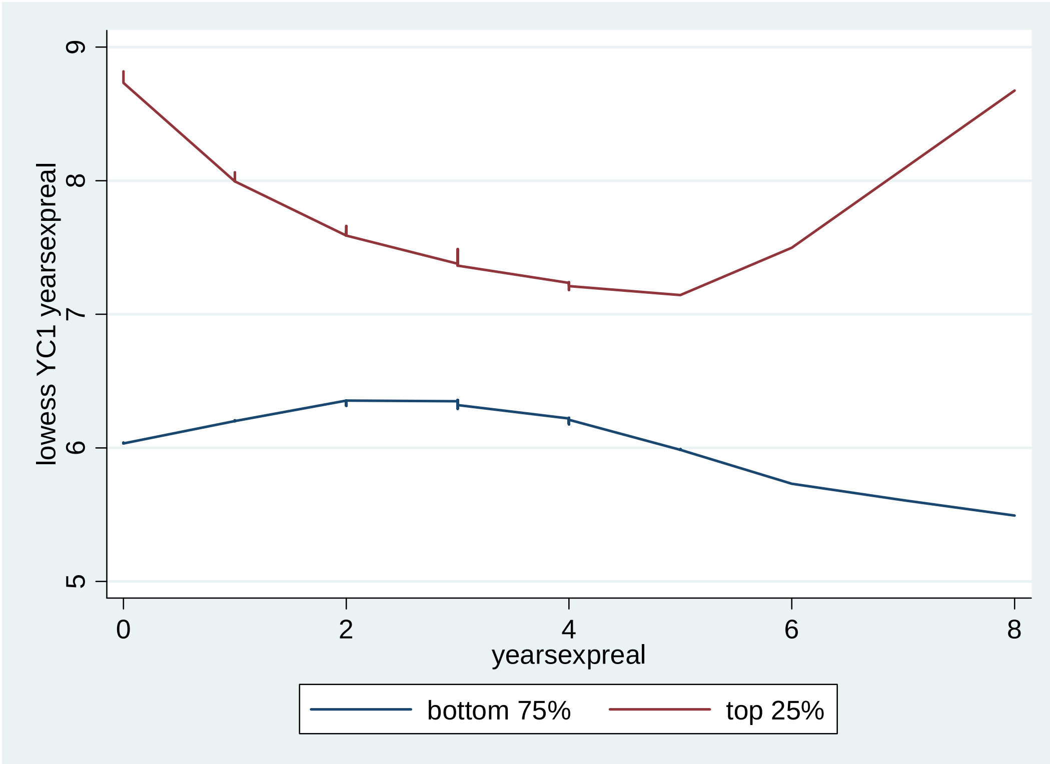
Graph 2b: YR for the top 25% and bottom 75% of RB as a function of yearsexp



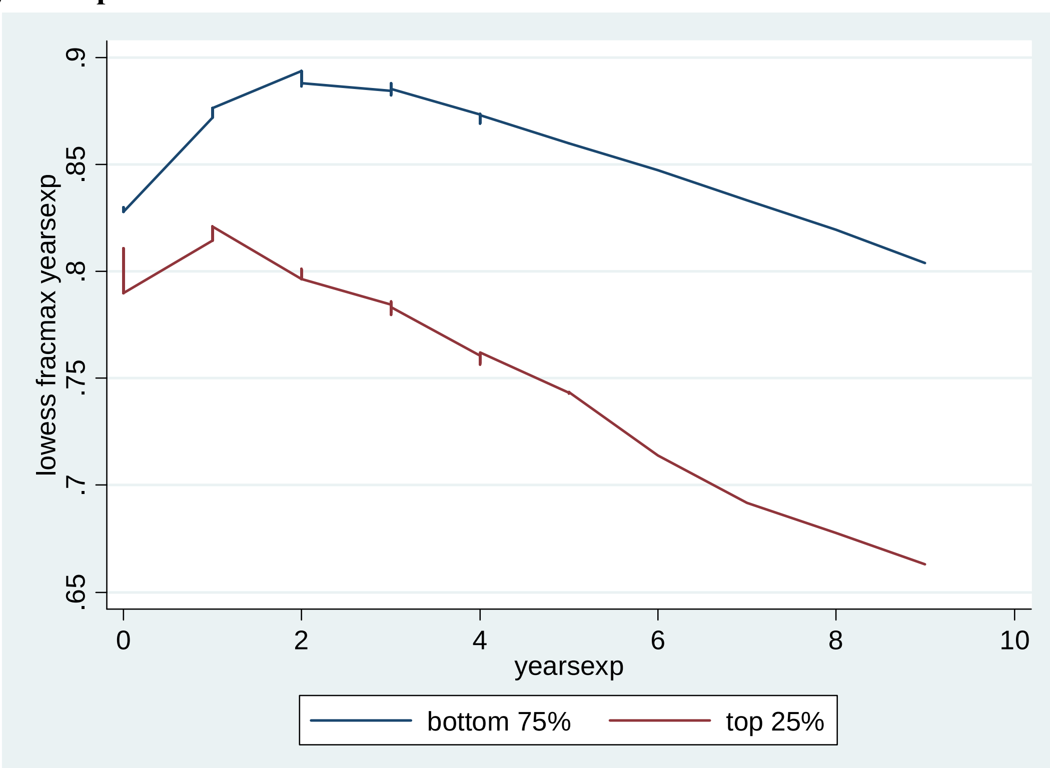
Graph 3a: Fracmax for the top 25% and bottom 75% of TE as a function of yearsexp



Graph 3b: YR for the top 25% and bottom 75% of TE as a function of yearsexp



Graph 4a: Fracmax for the top 25% and bottom 75% of WR as a function of yearsexp



Graph 4b: YR for the top 25% and bottom 75% of WR as a function of yearsexp

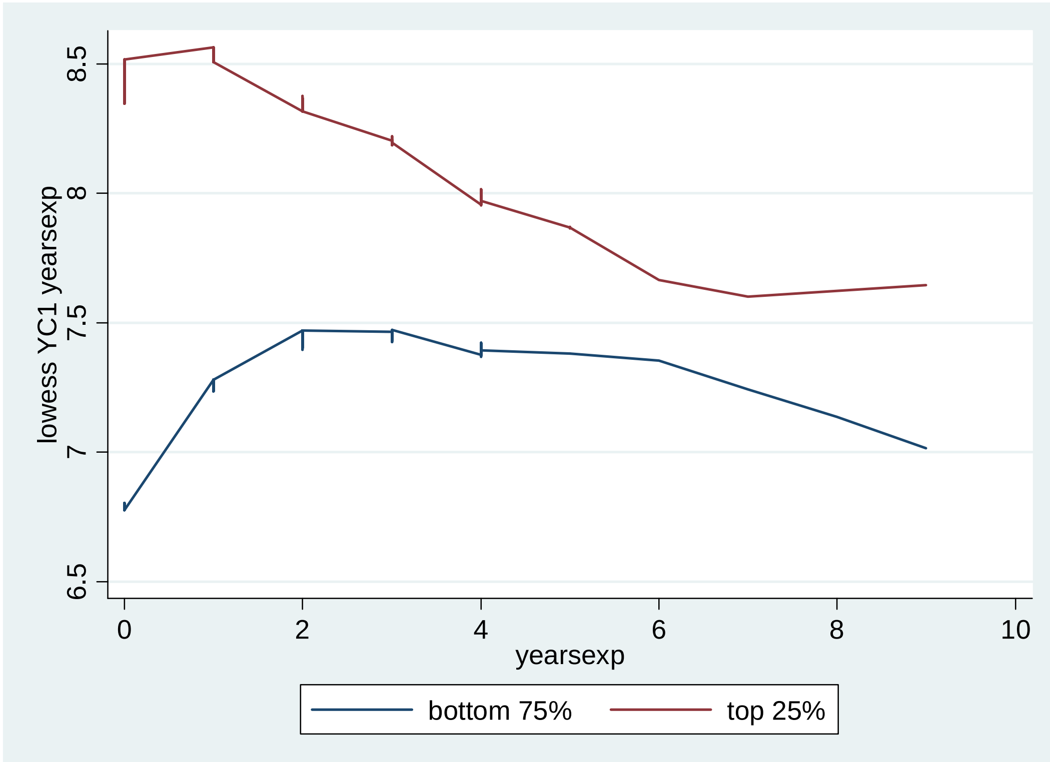


Table 11: DYAR regressions using FA, yearsexp as independent variables (Note: Change in FA denotes whether FA changed from statistical insignificance in Table 10a to statistical significance in Table 11)

	FA	Yearsexp	Change in FA
QB1	-128.268** (64.760)	3.604* (10.419)	Yes
QB2	22.731 (26.702)	-5.619 (6.406)	No
RB1	-29.295 (19.247)	.182 (3.500)	No
RB2	6.490 (6.981)	2.573* (1.459)	No
TE1	-4.897 (10.148)	-1.416 (2.009)	No
TE2	-3.919 (6.569)	-.392 (1.579)	No
WR1	-1.418* (14.109)	-5.936** (2.392)	Yes
WR2	12.886* (7.779)	-1.004 (1.970)	Yes (barely P=.099)

Table 13c: YA effect on performance (metrics available to all positions)

	Obs.	YA (Yards)	Yearsexp (Yards)	YA (yards/touch)	Yearsexp (Yards/touch)	YA (DVOA)	Yearsexp (DVOA)	YA (DYAR)	Yearsexp (DVOA)
QB1	31	341.674* (189.634)	-61.291*** (21.216)	.119 (.158)	-.022 (.018)	.031 (.036)	-.004 (.004)	115.377 (92.881)	-1.771 (10.392)
QB2	11	3.564 (67.873)	2.346 (9.621)	.000 (.836)	-.304** (.118)	-.076 (.200)	-.058** (.028)	85.285* (46.376)	-8.785 (6.574)
RB1	29	4.513 (68.437)	-27.898*** (9.195)	.026 (.112)	-.039*** (.015)	.019 (.024)	-.000 (.003)	3.650 (25.678)	-1.047 (3.450)
RB2	19	-21.851 (26.325)	-.306 (3.149)	-.078 (.255)	.034 (.031)	.099* (.058)	.012* (.007)	21.292* (12.086)	2.375 (1.446)
TE1	33	12.345 (32.822)	-6.436 (4.792)	-.228 (.274)	-.076* (.040)	-.015 (.038)	-.009 (.006)	-8.692 (13.933)	-1.287 (2.034)
TE2	10	30.949* (16.490)	-2.228 (2.174)	1.050 (.864)	-.180 (.114)	.187* (.103)	.001 (.014)	22.891* (11.586)	-.647 (1.527)
WR1	55	55.051 (40.763)	-18.046*** (5.039)	-.145 (.219)	-.083*** (.027)	-.005 (.024)	-.006** (.003)	9.584 (19.355)	-6.148*** (2.392)
WR2	27	8.248 (28.688)	-10.699*** (4.005)	-.813 (.611)	-.122 (.085)	-.070 (.065)	-.001 (.009)	-13.116 (13.510)	.423 (1.886)

Table 13d: YA effect on performance (position specific metrics)

	YA (QB Rating)	Yearsexp (QB Rating)	YA (TFD)	Yearsexp (TFD)	YA (Catchrate)	Yearsexp (Catchrate)
QB1	2.255 (2.181)	-.129 (.244)				
QB2	NA	NA				
RB1			-1.017 (.865)	.082 (.116)		
RB2			1.457*** (.495)	-.012 (.059)		
TE1					.018 (.017)	.001 (.002)
TE2					.145** (.057)	.002 (.008)
WR1					.002 (.010)	.001 (.001)
WR2					.037 (.032)	.003 (.004)

Table 15a: Yards/run (RB) regression on FA, yearsexp, yearsexp^2 by MaxYR thirds

	Obs	FA	yearsexp	Yearsexp^2
Top 33%	147	-.488*** (.161)	-.044 (.080)	.001 (.007)
Mid 33%	142	.202 (.125)	-.017 (.060)	-.002 (.005)
Bottom 33%	144	-.071 (.124)	.034 (.056)	-.005 (.004)

Table 15b: Yards/run (RB) regression on YA, yearsexp, yearsexp^2 by MaxYR thirds

	Obs	YA	yearsexp	Yearsexp^2
Top 33%	147	-.128 (.210)	-.080 (.083)	.003 (.007)
Mid 33%	142	.198 (.061)	-.018 (.062)	-.002 (.005)
Bottom 33%	144	-.046 (.203)	.023 (.053)	-.005 (.004)

Table 15c: DYAR (RB) regression on FA, yearsexp, yearsexp^2 by MaxYR thirds

	Obs	FA	yearsexp	Yearsexp^2
Top 33%	145	-46.258 (35.056)	22.976 (19.203)	-1.736 (1.580)
Mid 33%	143	-16.842 (28.765)	-.497 (11.518)	-.637 (.875)
Bottom 33%	135	-20.058 (27.404)	-1.859 (16.212)	.626 (1.754)

Table 15d: DYAR (RB) regression on YA, yearsexp, yearsexp^2 by MaxYR thirds

	Obs	YA	yearsexp	Yearsexp^2
Top 33%	145	-39.304 (45.856)	23.183 (19.408)	-1.814 (1.600)
Mid 33%	143	64.018* (35.754)	-6.038 (10.876)	-.342 (.847)
Bottom 33%	135	21.322 (41.996)	-5.299 (16.543)	.662 (1.760)

Table 16a: Yards/catch (TE) regression on FA, yearsexp, yearsexp^2 by MaxYR thirds

	Obs	FA	yearsexp	Yearsexp^2
Top 33%	175	.101 (.386)	-.000 (.172)	-.006 (.013)
Mid 33%	158	-.028 (.228)	.143 (.139)	-.023* (.013)
Bottom 33%	75	-.697* (.405)	-.158 (.316)	-.003 (.036)

Table 16b: Yards/catch (TE) regression on YA, yearsexp, yearsexp^2 by MaxYR thirds

	Obs	YA	yearsexp	Yearsexp^2
Top 33%	175	-.836 (.547)	.025 (.171)	-.006 (.013)
Mid 33%	158	.023 (.293)	.138 (.137)	-.023* (.013)
Bottom 33%	75	.384 (.596)	-.242 (.327)	.007 (.034)

Table 16c: DYAR (TE) regression on FA, yearsexp, yearsexp^2 by MaxYR thirds

	Obs	FA	yearsexp	Yearsexp^2
Top 33%	190	-4.919 (18.628)	10.389 (7.656)	-1.141* (.598)
Mid 33%	145	-5.043 (12.144)	15.663* (8.174)	-1.513* (.765)
Bottom 33%	69	-10.165 (18.124)	-5.449 (13.133)	.972 (1.505)

Table 16d: DYAR (TE) regression on YA, yearsexp, yearsexp^2 by MaxYR thirds

	Obs	YA	yearsexp	Yearsexp^2
Top 33%	175	-21.923 (30.816)	10.839 (7.657)	-1.170* (.598)
Mid 33%	158	-6.465 (14.712)	15.613* (8.145)	-1.482* (.757)
Bottom 33%	75	-1.191 (25.023)	-7.344 (12.790)	1.226 (1.459)

Table 17a: Yards/catch (WR) regression on FA, yearsexp, yearsexp^2 by MaxYR thirds

	Obs	FA	yearsexp	Yearsexp^2
Top 33%	406	.003 (.267)	-.121 (.099)	.001 (.007)
Mid 33%	278	.071 (.202)	-.100 (.089)	.003 (.006)
Bottom 33%	133	-.015 (.343)	.099 (.209)	-.001 (.021)

Table 17b: Yards/catch (WR) regression on YA, yearsexp, yearsexp^2 by MaxYR thirds

	Obs	YA	yearsexp	Yearsexp^2
Top 33%	406	-.092 (.344)	-.119 (.099)	.001 (.007)
Mid 33%	278	-.345 (.285)	-.084 (.089)	.002 (.006)
Bottom 33%	133	.261 (.556)	.078 (.205)	-.001 (.021)

Table 17c: DYAR (WR) regression on FA, yearsexp, yearsexp^2 by MaxYR thirds

	Obs	FA	yearsexp	Yearsexp^2
Top 33%	444	-7.968 (22.188)	3.975 (8.100)	-.886 (.550)
Mid 33%	241	5.463 (18.019)	11.909 (8.626)	-.712 (.627)
Bottom 33%	132	-9.527 (23.471)	-31.000 (20.508)	3.575 (2.703)

Table 17d: DYAR (WR) regression on YA, yearsexp, yearsexp^2 by MaxYR thirds

	Obs	YA	yearsexp	Yearsexp^2
Top 33%	444	23.844 (27.655)	3.440 (8.118)	-.889 (.549)
Mid 33%	241	-23.387 (27.713)	13.446 (8.583)	-.797 (.629)
Bottom 33%	132	4.647 (35.545)	-32.011 (20.457)	3.529 (2.706)

Table 19a: Yards/run (RB) regression on FA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	FA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	47	-.263 (.338)	-1.554 (1.071)	.152 (.107)
sFA>1	34	-.566 (.389)	-2.419* (1.094)	.249* (.113)
Yearsexp>=6				
sFA=1	34	-.383 (.411)	.034 (.811)	-.012 (.041)
sFA>1	35	-.113 (.237)	.953** (.446)	-.059** (.023)

Table 19b: Yards/run (RB) regression on YA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	YA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	47	-.010 (.210)	-1.104 (1.001)	.114 (.106)
sFA>1	34	.266 (.257)	-2.185* (1.121)	.248* (.118)
Yearsexp>=6				
sFA=1	34	.143 (.356)	.164 (.822)	-.015 (.042)
sFA>1	35	-.154 (.243)	1.054** (.463)	-.064** (.025)

Table 19c: DYAR (RB) regression on FA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	FA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	47	-95.184 (89.738)	-3.683 (283.896)	-.762 (28.404)
sFA>1	34	-174.211* (93.958)	-759.667** (264.063)	78.534** (27.189)
Yearsexp>=6				
sFA=1	34	11.478 (91.558)	143.080 (180.760)	-7.353 (9.090)
sFA>1	35	30.883 (97.832)	186.602 (184.014)	-11.392 (9.608)

Table 19d: DYAR (RB) regression on YA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	YA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	47	6.269 (56.806)	142.157 (270.317)	-12.689 (28.552)
sFA>1	34	92.915 (62.303)	-693.503** (271.201)	79.025** (28.618)
Yearsexp>=6				
sFA=1	34	2.290 (77.497)	135.520 (179.012)	-7.057 (9.221)
sFA>1	35	-113.622 (96.953)	246.474 (184.525)	-15.213 (9.811)

Table 20a: Yards/catch (TE) regression on FA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	FA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	80	.202 (.498)	1.369 (1.430)	-.159 (.148)
sFA>1	25	.331 (.614)	-4.056 (2.664)	.381 (.295)
Yearsexp>=6				
sFA=1	18	1.782** (.540)	-.466 (2.255)	.010 (.118)
sFA>1	13	-.189 (.138)	dropped	-.004 (.005)

Table 20b: Yards/catch (TE) regression on YA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	YA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	80	-.051 (403)	1.186 (1.359)	-.147 (.146)
sFA>1	25	-.627 (.550)	-3.905 (2.462)	.352 (.275)
Yearsexp>=6				
sFA=1	18	-.954 (.548)	.464 (3.121)	-.061 (.161)
sFA>1	13	.094 (.069)	dropped	.001 (.004)

Table 20c: DYAR (TE) regression on FA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	FA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	80	33.966 (28.686)	-16.152 (82.400)	2.425 (8.543)
sFA>1	25	-1.102 (23.825)	36.848 (103.326)	-5.677 (11.445)
Yearsexp>=6				
sFA=1	18	34.623 (41.171)	-52.945 (171.858)	1.713 (8.976)
sFA>1	13	9 (74.478)	dropped	-1 (2.529)

Table 20d: DYAR (TE) regression on YA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	YA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	80	-18.968 (23.399)	-46.325 (78.974)	4.364 (8.475)
sFA>1	25	-30.409 (19.365)	56.345 (86.646)	-8.080 (9.683)
Yearsexp>=6				
sFA=1	18	-47.304 (23.633)	-53.392 (134.687)	1.225 (6.940)
sFA>1	13	-4.5 (37.239)	dropped	-1.265 (2.191)

Table 21a: Yards/catch (WR) regression on FA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	FA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	112	.034 (.484)	-1.894 (1.473)	.176 (.155)
sFA>1	44	-.890 (.985)	3.675 (2.960)	-.455 (.286)
Yearsexp>=6				
sFA=1	54	.287 (.729)	-3.263 (2.040)	.162 (.101)
sFA>1	32	1.767** (.786)	.420 (1.431)	-.006 (.063)

Table 21b: Yards/catch (WR) regression on YA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	YA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	112	-.076 (.329)	-1.906 (1.369)	.176 (.150)
sFA>1	44	-.006 (.594)	5.351* (2.800)	-.589* (.295)
Yearsexp>=6				
sFA=1	54	.061 (.565)	-2.976 (1.900)	.145 (.092)
sFA>1	32	-1.279 (.747)	.012 (1.500)	-.001 (.067)

Table 21c: DYAR (WR) regression on FA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	FA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	112	-4.767 (48.907)	-133.340 (148.828)	13.545 (15.634)
sFA>1	44	-71.120 (84.720)	266.085 (254.954)	-33.019 (24.582)
Yearsexp>=6				
sFA=1	54	30.992 (92.899)	-279.373 (259.846)	13.574 (12.887)
sFA>1	32	120.434*** (35.553)	-17.356 (64.717)	1.152 (2.856)

Table 21d: DYAR (WR) regression on YA, yearsexp, yearsexp^2 by sFA and yearsexp brackets

	Obs.	YA	yearsexp	Yearsexp^2
Yearsexp>1, <6				
sFA=1	112	23.374 (33.081)	-136.435 (137.598)	14.058 (15.060)
sFA>1	44	-4.894 (50.931)	410.955 (239.926)	-44.794* (25.245)
Yearsexp>=6				
sFA=1	54	21.616 (71.711)	-253.328 (241.312)	12.048 (11.660)
sFA>1	32	-52.417 (40.604)	-48.038 (81.534)	1.668 (3.636)

References

(W6) "Ask The Commish.com - Free Agency 101." Ask The Commish.com - The Fantasy Football Experts! Ed. Al Lackner. 15 Jan. 2009. 14 Mar. 2009 <http://www.askthecommish.com/freeagency/>.

(W15) "Average MLB salary up 4.6 percent to $2.82M - Baseball- nbcsports.msnbc.com." Sports News Headlines - NFL, NBA, NHL, MLB, PGA, NASCAR - Scores, Game Highlights, Schedules & Team Rosters - nbcsports.msnbc.com. 17 Jan. 2008. NBC Sports. 14 Mar. 2009 <http://nbcsports.msnbc.com/id/22717887/>.

(W7) Brown, Maury. "Breaking Down MLB's Luxury Tax: 2003-2007." The Biz of Baseball :: Part of the Business of Sports Network. 25 Dec. 2007. 14 Mar. 2009 <http://www.bizofbaseball.com/index.php?option=com_content&task=view&id=1805&Itemid=41>.

(W3) Clayton, John. "Early blitzes countering 'scripted-play' strategies - NFL - ESPN." ESPN: The Worldwide Leader In Sports. 28 Oct. 2005. ESPN. 10 Mar. 2009 <http://sports.espn.go.com/nfl/columns/story?columnist=clayton_john&id=3155267>.

(W2) Conrad, Mark. "Salary Arbitration." Mark's Sportslaw News. 1999. 9 Mar. 2009 <http://www.sportslawnews.com/archive/jargon/LJSArbitration.html>.

(W9) Coon, Larry. "NBA Salary Cap FAQ." NBA Salary Cap FAQ. 30 Aug. 1999. 11 Mar. 2009 <http://members.cox.net/lmcoon/salarycap.htm>.

(W10) Jacobson, David. "MLB's Revenue-Sharing Formula | BNET." BNET Today | Management, Strategy, Work Life Skills & Advice for Professionals. 10 Mar. 2009 <http://www.bnet.com/2403-13502_23-210897.html>.

(W12) Jones, Nate. "The NBA's Real Economic Problem: A Lack of Revenue Sharing." JONES ON THE NBA. 10 Mar. 2009. 14 Mar. 2009 <http://jonesonthenba.com/2009/03/nbas-real-economic-problem-lack-of.html>.

Krautmann, Anthony C., and Margaret Oppenheimer. (2002). "Contract Length and the Return to Performance in Major League Baseball." Journal of Sports Economics 3 (2002): 6-17.

(W11) Lawrence, Mark. "Revenue Sharing and The Salary Cap." Football 101. 8 Aug. 2005. 14 Mar. 2009 <http://football.calsci.com/SalaryCap.html>.

Marburger, Daniel R. (2003). "Does the Assignment of Property Rights Encourage or Discourage Skirking?: Evidence From Major League Baseball." Journal of Sports Economics 4 (2003): 19-34.

Maxcy, Joel G. (1996). "Efficient contract choice in the market for uniquely skilled labor." Unpublished Diss. Washington State University, 1996.

Maxcy, Joel G., et al. (2002). "The Effectiveness of Incentive Mechanisms in Major League Baseball." Journal of Sports Economics 3 (2002): 246-55.

(W16) "Methods to Our Madness." FOOTBALL OUTSIDERS: Football analysis and NFL stats for the Moneyball era - Authors of Pro Football Prospectus 2008. Football Outsiders. 16 Mar. 2009 <http://footballoutsiders.com/info/methods>.

(W14) "Minimum NBA Salary." InsideHoops.com - NBA Basketball News, Rumors - Pro, College Basketball, High School Hoops. 10 Aug. 2005. 14 Mar. 2009 <http://www.insidehoops.com/minimum-nba-salary.shtml>.

(W5) "NBA 101 Wednesday: Free Agency." Cavaliers Court. 4 July 2007. 11 Mar. 2009 <http://cavscourt.wordpress.com/2007/07/04/nba-101-wednesday-free-agency/>.

(W8) "New York Yankees Salaries - MLB Baseball - ESPN." ESPN: The Worldwide Leader In Sports. ESPN. 14 Mar. 2009 <http://sports.espn.go.com/mlb/teams/salaries?team=nyy>.

(W18) NFL.com - Official Site of the National Football League. National Football League. 26 Jan. 2009 <http://nfl.com>.

(W4) Ray, James L. "Baseball Free Agency Rules: MLB Player Eligibility and Draft Compensation Explained." Baseball @ Suite101.com: Major League teams, franchises, match-ups, off-field hijinx, salary debates, the pennant race, all-stars, promising minor league pitchers, standings, ownership battles, fantasy leagues and more. 23 Feb. 2008. 10 Mar. 2009 <http://baseball.suite101.com/article.cfm/baseball_free_agency_rules>.

(W1) Simmons, Bill. "ESPN.com: Page 2 : Curious Guy: Malcolm Gladwell." ESPN: The Worldwide Leader In Sports. 2 Mar. 2006. ESPN. 9 Mar. 2009 <http://sports.espn.go.com/espn/page2/story?page=simmons/060302>.

Sommers, Paul M. (1993). "The Influence of Salary Arbitration on Player Performance." Social Science Quarterly 74 (1993): 439-43.

Stiroh, Kevin J. (2007). "Playing For Keeps: Pay And Performance In The NBA." Economic Inquiry 45 (2007): 145-61.

(W17) Wong, Michael. "Analyzing the Efficiency of Using Multiple Running Backs in the NFL." Bleacher Report. 13 Feb. 2009. 31 Mar. 2009 <http://bleacherreport.com/articles/123587-utilizing-multiple-rbs-the-current-trend-in-nfl-examining-the-efficiency>.

Woolway, Mark D. (1997). "Using and Empirically Estimated Production Function for Major League Baseball to Examine Worker Disincentives Associated with Multi-Year Contracts." American Economist 41 (1997): 77-83.

(W13) Wulterkens, Jason. "MLB players receive the lowest percentage of leaguewide revenue." SportsAgentBlog.com | Sports Agent News. 11 Mar. 2008. 14 Mar. 2009 <http://www.sportsagentblog.com/2008/03/11/mlb-players-receive-the-lowest-percentage-of-leaguewide-revenue/>.