SALARY DETERMINATION IN THE NATIONAL FOOTBAL LEAGUE

A Dissertation
Submitted
to the Temple University Graduate Board

In Partial Fulfillment
of the Requirements for the Degree of
Doctor of Philosophy

By
Sandra Kowalewski
August 2010

Examining Committee:
Michael A. Leeds, Temple University
Erwin Blackstone, Temple University
William Dunkelberg, Temple University
Lynne Andersson, Temple University
Department of Economics

ABSTRACT

This paper examines salary determination in the National Football League (NFL). The heterogeneity of teams and players in the league leads to thin labor markets. Under such circumstances, the neoclassical model in which labor supply and labor demand uniquely determine wages is too simple. Instead, a competing model of salary determination is tested – McLaughlin's (1994) rent-sharing model. This is the only study of its kind to investigate salary determination at a disaggregated level for all of the non-kicking positions in the NFL. A comprehensive model of salary determination, using many unique variables, is constructed and tested for each position. Quantile regression techniques are employed to examine the bargaining aspects of the model. Although, little support is found for the rent-sharing model, this study lays the groundwork and presents the argument for further investigation.

ACKNOWLEDGEMENTS

I would like to thank my parents, my husband and my son without their help, support and inspiration, I would not have been able to finish. I would also like to thank my committee for their help and determination; especially, Mike Leeds, for his patience, guidance, support and friendship throughout this process.

TABLE OF CONTENTS

PAGE

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1 INTRODUCTION

Professional sports are a huge business in America. In 2006, professional sports, including players' salaries, television contracts, gate receipts, and merchandise sales generated $213 billion in revenue[1]. In many cases, star athletes are paid more than CEOs of Fortune 500 companies. The average salary in the 2002-03 season was $4.9 million in the National Basketball Association (NBA), $2.49 million in Major League Baseball (MLB), $1.79 million in the National Hockey League (NHL), and $1.26 million in the National Football League (NFL).[2] These high salaries lead many to conclude that athletes are paid too much, but are they really?

According to economic theory, in a competitive market a worker's wage should equal his marginal revenue product (MRP). In reality, it is very difficult to get good estimates of workers' marginal revenue products, which makes it difficult to conclude whether workers are paid what they are worth. However, professional sports, with readily available salary data and relatively clear individual performance data, provide an excellent arena for investigating an important question in labor economics: whether workers (the athletes) are paid what they are worth (their MRPs).

Many researchers have tried to estimate athletes' marginal revenue products and then to compare their estimates with the athletes' salaries. Most of the studies (Scully, 1974, 1989; Zimbalist, 1992; Vrooman, 1996; Krautmann, 1999) have focused on

---

[1] This figure is for the year 2006 as reported in Street and Smith Sports Business Journal (2006), taken from http://www.willamette.edu/wucl/pdf/review/42-4/williams.pdf.

[2] Average salary figures are obtained from ESPN Magazine, May 10, 2004.

baseball. Baseball has the most directly comparable[3] (across positions) and independent (of teammate performance) measures of individual player performance of the major American professional sports, allowing for relatively easier estimation of marginal products and MRPs.

The problem with focusing on MRPs is that most workers, including athletes, are not paid their MRPs. As McLaughlin (1994) states, workers are paid more than necessary to do their jobs but less than they are worth to their employers. Most workers participate in relatively thin labor markets; those of athletes are even thinner. The neoclassical model in which labor supply and labor demand uniquely determine wages is too simple. Therefore, it is not surprising that prior studies, regardless of the method used to estimate the MRPs, have all come to the conclusion that athletes are not paid according to the competitive model and are not paid their MRPs.

Instead of once again applying the standard models to investigate whether athletes are paid their MRPs (Scully, 1974, 1989; Zimbalist, 1992) or assuming that free agents are paid according to their MRPs (Krautmann, 1999), this study builds upon earlier findings. I assume, as prior researchers have found, that players are not necessarily paid their MRPs and instead build and test a competing model of salary determination.

This dissertation tests whether McLaughlin's (1994) rent-sharing model is more applicable than the competitive model to salary determination in the National Football League. The rent-sharing model combines elements of matching and marginal analysis, resulting in an equilibrium in which workers match with the employers that pay them the

[3] Individual performance statistics are comparable across all positions in baseball with the exception of pitchers. Researchers have handled this by using only non-pitchers, sometimes referred to as hitters. Pitchers are generally valued for specific pitching roles and are not usually good hitters nor are they expected to be.

most, in the jobs where they are most productive. However, this model does not mandate, as the competitive model does, that players are paid their marginal revenue products. Instead, heterogeneity leads to thin markets with players and owners bargaining over rents. Wages thus depend on bargaining strength.

I use a two-step process to decompose the relevant factors determining wages in the NFL: market factors and bargaining strength. First, I combine McLaughlin's theoretical model with Krautmann's (1999) empirical methodology to produce a superior empirical model of salary determination in professional football. This empirical model captures the market forces responsible for salary determination in the NFL. Like Krautmann, I create sub-samples of players based on their free agency status.[4] Free agents' contracts have expired and are able to negotiate with any team. Restricted players are able to negotiate only with the team that owns their rights; they are not able to enter the market and negotiate with other teams. Therefore, the regressions are run only on the free agents to obtain the market returns attributable to the independent variables.[5] A key difference from Krautmann is that this study builds upon the *findings* of the existing salary determination literature and not upon its methods and models. This research incorporates a different model that does not assume, as Krautmann and previous researchers have, that these estimated returns are competitive market returns.

---

[4] For a complete description of free agency guidelines see section 3.1.1.

[5] The regressions are run on players that are eligible for free agency even though they may not be free agents because they are currently under contract. I am unable to obtain contract duration and therefore cannot isolate the players that are truly free agents. Using the players who are eligible for free agency should not be a problem, though, because, while they may be under contract, the players' salaries are not guaranteed, so they are treated similar to free agents.

Then, assuming my empirical model has captured the relevant market factors determining salaries, I use quantile regression to investigate the other main factor at work in determining salaries- bargaining strength. Quantile regression complements and expands upon the initial OLS regression results.[6] It allows me to describe the relationship between players' salaries and the independent variables more accurately. In particular, estimates based on the conditional quantile functions and not just the conditional mean show the effects of bargaining strength on salary more clearly. This is important because bargaining strength is particularly difficult to quantify, which is one reason why the rent-sharing model has not been tested.

This research contributes to the existing literature in several ways. First, I apply McLaughlin's rent-sharing model to a new market, that for professional football players. Because previous researchers have provided evidence that athletes are not paid their MRPs, one cannot assume that athletes operate in competitive markets. Taking a fresh look at the market for athletes, specifically the NFL, provides insight into salary determination in all sports leagues and into the labor market as a whole, especially where markets are thin and workers' skills are heterogeneous. Second, realizing that a structural model of McLaughlin's theory is not testable, I develop a reduced form-empirical model based upon his theoretical model that allows me to create testable hypotheses. Third, I present a more comprehensive and realistic empirical model of salary determination in sports than currently exists. I use the standard variables from the existing literature and combine them with new variables that were added to capture some of the real world

[6] For an introduction to quantile regression see Buchinsky (1998), Koenker and Hallock (2001) and Buhai (2004).

phenomena that occur today in the compensation of professional football players. Finally, I use quantile regression, a relatively new and more powerful statistical technique than those typically used in sports economics research, to more accurately characterize the relationship between salary and its determinants, at all ranges of salary, in the NFL.

Prior studies of salary determination in football have been conducted by Kahn (1992), Kowalewski and Leeds (1999), and Leeds and Kowalewski (2001). However, these studies did not distinguish between restricted and unrestricted players, so the returns to individual performance may be biased. Combining both types of players dilutes the returns to individual performance since restricted players have no option to shop their talent to the highest bidder. Another shortcoming of the previous research on salary determination that I address is the effect of teammate performance on individual pay. A study by Idson and Kahane (2000) examined salary determination in the NHL by including measures of teammate performance in addition to the individual performance measures. These additional variables account for the coworker effects on productivity that are present in hockey and affect individual salary. I include position-specific interaction terms where possible to capture the effects of teammate performance on individual performance and hence pay.

Estimating the determinants of salary in football is more challenging than for the other professional team sports. Football does not have one individual statistic that summarizes a player's performance and applies to all or most positions, such as total bases and batting average in baseball, or points and plus/minus in hockey. Therefore, one cannot directly compare the performance of a quarterback with that of a tackle. Football does have complex interactions among its players, with the play of others directly affecting the performance of the individual. One cannot easily isolate the performance of a wide receiver without considering the quality of the quarterback throwing to him. For these reasons, salary determination in football is significantly more difficult to model and estimate than for the other professional team sports and therefore, rarely attempted.

In addition to the complexities created by the nature of the game, salary determination in football is further complicated by the fact that the NFL does not have guaranteed contracts[7] and has a salary cap[8] in place. In recent years, payroll determination has resembled a chess game, with teams trying to assemble and keep their talent for the current year while staying within the salary cap and not causing severe cap ramifications in the following years.[9] Teams that are constrained by the cap have little room to maneuver and in many cases cannot sign new talent without restructuring current contracts or releasing some of their leaders, the expensive, veteran starters. Many, including Harold Henderson, the league's chief labor negotiator, argue that these veteran cap casualties reduce the continuity of teams and that league play could suffer as a result (Forbes, 2001). In this study, I include variables to account for salary cap constraints and free agency effects on individual salary determination.

This study encompasses every position in the NFL with the exception of punters and kickers. This is the only study of its kind to investigate salary determination at a

---

[7] This means that when a player signs a $10 million dollar contract over five years, he is not necessarily going to receive $2 million per year, he can be forced to renegotiate and/or restructure his contract based on his actual performance or just to stay with his current team and free up some salary cap room. Salary restructuring is the norm in the NFL today.

[8] The salary cap in 1998 was $52.4 million per team; in 1999 it was $58.4 million per team; in 2000 it was $62.2 million per team. See section 3.1.2 for more information on the salary cap.

[9] Cap ramifications refers to a team's restructuring contracts and/or making personnel changes that it would not otherwise make but, is forced to make to stay within the salary cap.

disaggregated level for all of the non-kicking positions in the NFL. My detailed estimates allow me to calculate the returns to performance of free agents in the NFL. This research will be useful for salary negotiations both in the NFL and in other leagues that do not have easily comparable measures of performance, such as the National Basketball Association. Research of this type performed by Scully (1974) on MRPs of baseball players has been used in arbitration hearings for professional baseball players.

The remainder of the paper is organized as follows: Chapter 2 is a literature review presenting previous theoretical and empirical research on salary determination in professional sports. Chapter 3 outlines the important details of the NFL Collective Bargaining Agreement (CBA) and presents stylized facts regarding the current state of the NFL. Chapter 4 presents the theoretical model and adapts it to model salary determination in the NFL. Chapter 5 describes the data used in the analysis. This section also contains the generalized empirical model and describes how I go from the abstract theoretical model to my testable empirical model. OLS positional regression results are presented in Chapter 6. Chapter 7 introduces the reader to the quantile regression technique and briefly reviews the relevant literature. The results of the quantile regressions are also presented in this chapter. Conclusions and ideas for future research are contained in the final chapter.

CHAPTER 2 LITERATURE REVIEW

There is a very small literature related to salary determination in professional football. Most of the salaries studies in sports focus on baseball. Scully (1974) was the first to study pay and performance in professional sports in an effort to determine whether baseball players were paid what they were worth. Scully's method estimates a player's value by imputing his MRP from three equations:

$$(2.1)\quad TR_j = \alpha_0 + \alpha_1 X_j + \alpha_2 WPCT_j$$

$$(2.2)\quad WPCT_j = \beta_0 + \beta_1 PERF_j$$

$$(2.3)\quad PERF_j = f(PERF_{i,j}, Z_j) \text{ for all } i \text{ on team } j$$

Where *j* indexes the team, *i* indexes the player, TR_j is total revenue, X_j is a vector of team-specific factors, such as city size or team popularity that affect team revenue, $WPCT_j$ is team *j's* winning percentage, $PERF_j$ is the team's performance, $PERF_{i,j}$ is the *i*th player's performance on team *j*, and Z_j is a vector of other inputs that determine the team's performance, such as the team's management.

Equation (2.3) relates how player and other inputs affect team performance. Researchers using Scully's method ignore Z_j and assume that equation (2.3) is additively separable. They then use a measure of the player's individual performance, such as batting average, to measure his marginal revenue product. However, the equation may not be separable and more importantly, ignoring Z_j gives the individual players full credit for the team performance and ignores factors such as managerial decisions, coaching moves and player cross complementarities.[10]

[10] This systematically overstates the players' MRPs.

Using equations (2.1) and (2.2), Scully computes the MRP for the *jth* team:

$$(2.4) \quad MRP_j = (\partial TR_j/\partial WPCT_j)\ (\partial WPCT_j/\partial PERF_j) = (\alpha_2)(\beta_1).$$

To get the MRP of player *i* on team *j*, we need to know how the addition of player *i* to the roster of team *j* affects team *j's* performance and therefore its revenues. Denoting the *ith* player's marginal product on the *jth* team as $(\Delta PERF_j/\Delta I_j)$, then

$$(2.5) \quad MRP_{ij} = (MRP_j)(\Delta PERF_j/\Delta I_j) = (\alpha_2)(\beta_1)(\Delta PERF_j/\Delta I_j).$$

The estimate of the player's marginal revenue product depends upon how one measures his marginal product.

Scully's method to measure the player's marginal product, called the proportional method, credits the player with a proportion of his individual performance. He multiplied the player's slugging average (SA) by the player's share of team at-bats. For example, if the player had 10% of the team's at-bats and had a .300 slugging average, his marginal product would be (.1)(.300) = 0.030. Scully (1989) tested his own method and found very large estimates of MRPs. The correlation between his estimates and actual player salaries were quite low, and he acknowledged that the estimates of player MRPs are crude.

Zimbalist (1992) tried to improve upon Scully's work by using a different method to measure the marginal product. He hoped to find a higher correlation between MRPs and actual salaries. His approach, called the incremental method, was based upon the difference in the team's performance with the player versus without the player. He, like Scully, used the slugging average but he used it to compare the team's performance with and without a particular player. His results, when averaged over his sample, reported very low estimates of MRP, thus, concluding that the players were generally, overpaid. He also found low correlations between MRPs and actual salaries.

Krautmann (1999) pointed out a problem with Zimbalist's method. Zimbalist used the slugging average as his measure of performance without taking into account the fact that the team's performance will necessarily improve when it gets rid of a below average player. This would mean that player had a negative marginal product, which is not allowed by second order conditions. Thus, Zimbalist's method of measuring the marginal product cannot be correct. Krautmann claimed that Zimbalist should have used a statistic based on a player's total performance such as total bases, so as to guarantee positive marginal products.

Krautmann presented a different method to obtain the marginal revenue product. The previous empirical research had found inconsistent results that did not correlate well with actual player salaries. Therefore, he developed a completely different method to compute marginal value. His method is based on the logic that a competitive bidding process sets free agent salaries. This process should align wages with marginal revenue products, thereby allowing Krautmann to estimate the competitive returns to performance. Once he estimated the competitive market returns to performance, he applied these estimates to the performance of restricted players, allowing him to estimate the imputed market value of these restricted players.

He regressed free agent salaries on their performance in order to generate competitive market returns to performance using the following fixed effects model:

$$(2.6) \quad W_{ij} = \delta_j + \delta_1 PERF_i + \delta_2 TREND + \varepsilon_{ij}.$$

He used a large panel of data including numerous free agent signings per team so that teams could be viewed as cross-sectional units in the fixed effects model to control for team-specific factors affecting wages. In the model, W_{ij} is the *i*th free agent's wage on the *j*th team, $PERF_i$ is an ex ante measure of free agent *i*'s performance, *TREND* is included to control for any time trend in the data and δ_j is the fixed effects parameter for team *j*. By using a fixed effects model, Krautmann controlled for team invariant factors, such as coaching and managerial quality; Scully and Zimbalist ignored these factors.

These free market regression estimates were then used to impute the value of the restricted players.[11] Using player-specific performance data, he estimated the *i*th reserved player's market value on team *j* ($VALUE^*_{ij}$) as:

$$(2.7) \quad VALUE^*_{ij} = \hat{\delta}_j + \hat{\delta}_1 PERF_j + \hat{\delta}_2 TREND.$$

Where $\hat{\delta}$ is the vector of regression estimates obtained from equation (2.6), $PERF_i$ is the restricted player's ex ante performance. This equation allows Krautmann to impute the restricted player's value by applying the same competitive market returns to performance obtained for free agents in equation (2.6) to show what the player would have earned if he were a free agent.

Although Krautmann's methodology implicitly assumes away collusion and the winner's curse, it is superior to previous methods because it uses the available market information to impute a player's value. It also allows him to impute the values of restricted players, a group whose MRP is generally very difficult to calculate. Krautmann's empirical results are more realistic than those of previous researchers. His

[11] Restricted players are those players who are not free agents and are restricted to signing a contract with the team that owns their rights. Because they are restricted their salaries are not determined according to a competitive bidding process.

results show that starters and better players are paid more. He finds that restricted players are paid less than they are worth, with the degree of restriction negatively affecting the ratio of actual earnings to value. For example "apprentices" who are the most restricted of the major league baseball players earn the least compared to what they should earn, whereas "journeymen" earn almost 85% of their value.[12]

Blass (1992) presented evidence that most experienced baseball players are relatively overpaid. He tested whether the labor market in baseball contradicts the human capital model of investment, in other words whether experienced players are paid more because they are more productive. He used a cross section of all players in 1987 and used a panel with eight observations (one for each year from 1980-87) for each player with at least ten years of experience in 1988. He found no evidence to support the human capital model of investment at work in major league baseball. Instead, he found evidence consistent with implicit contract models; wages increased with experience beyond any association with productivity. The experienced players were not paid more because they are better players; in fact from a productivity standpoint they were overpaid.[13]

Idson and Kahane (2000) expand upon the existing literature by including team effects in their model of individual salary determination in the NHL. Their paper is one of few to measure the complex, cross productivity in sports. They investigate whether coworker productivity affects individual salaries, affects the rate at which individual

[12] Apprentices referred to the most restricted baseball players. They were not eligible for salary arbitration and were bound to their team and contract. After two years in the league, players became journeymen and were eligible for salary arbitration. These terms are no longer used in these contexts for baseball players.

[13] The results could also be consistent with an omitted variables bias.

productivity is valued by the team, and if it is complementary to individual productivity. They employ the model:

$$(2.8) \quad ln(Salary_i) = \beta_0 + \beta_1\mathbf{X_i} + \beta_2\mathbf{t\_X_i} + \beta_3\mathbf{X_i} * \mathbf{t\_X_i} + \beta_4\mathbf{Z_i} + \varepsilon_i ,$$

where $\mathbf{X_i}$ is a vector of individual performance measures and $\mathbf{t\_X_i}$ is a vector of team performance measures, which are calculated without the *i*th player's individual contribution. The fourth term is a vector of interaction variables of individual performance measures multiplied by the corresponding team performance measures. $\mathbf{Z_i}$ is a vector of additional regressors, including franchise variables such as franchise revenues.

Taking partial derivatives, they show that an individual player's performance affects his salary in two ways:

$$(2.9) \quad \partial ln(Salary_i)/ \partial\mathbf{X_i} = \beta_1 + \beta_3 \mathbf{t\_X_i},$$

through the direct productivity effect, β_1 and through the indirect effect, β_3. The latter coefficient measures how average player productivity for the team affects the value of an individual player's productivity. If β_3 is not zero, it captures the fact that individual player attributes are valued differently in different work environments. For example, a high-scoring player will be more highly valued on a relatively low scoring team.

Likewise, there are direct and indirect team effects on individual players' salaries:

$$(2.10) \quad \partial ln(Salary_i)/ \partial\mathbf{t\_X_i} = \beta_2 + \beta_3\mathbf{X_i} .$$

Here β_2 represents the direct effect of team performance on individual player salary, and β_3 captures the indirect effect of the interaction of the team's average performance and player salaries.

In their model, individual and teammate attributes can combine to affect individual player salaries in three distinct combinations: (1) If $\beta_3 = 0$, there are no indirect effects. Individual productivity and salary are not affected by the corresponding team values of these productivity measures. The standard models are a special case of Idson and Kahane's model in which $\beta_3 = 0$. Production is strictly additive in inputs. This is most likely the case in baseball. (2) If $\beta_3 > 0$, inputs are complementary. Individual performance is rewarded more on a team with players who, on average also have higher values for that particular productivity measure. (3) If $\beta_3 < 0$, then inputs are substitutes. Individual performance is not rewarded as much on a team that already, on average, performs better in this particular area. For example, a good defensive player may not be as valuable on a team that already has, on average, players with good defensive skills.

Idson and Kahane use two years of NHL salary and performance data to test their model. They find that team attributes have direct and indirect effects on individual player salaries. Their results show that when the team attributes are added to the regression equation, the coefficients on the individual performance measures decrease, suggesting that these coefficients were biased upwards when the team variables were left out of the equation. They also find that, on average, players generally seem to be complements in the production process in hockey. However, they find that this complementarity is not found across all performance measures, and they posit that certain combinations of positions, for which they did not test, are stronger complements than others.[14]

[14] The degree of complementarity is also likely to vary by sport, with the effects being stronger in football, hockey and basketball compared with baseball.

Although an excellent start, it is likely that their model overstates the importance of the individual on the team's performance and the team's performance on the player's salary. They calculate the team performance measures without the individual contribution of player *i*. The problem is that if the *i*th player were not on the team, he would be replaced with another player of unknown quality. Excluding his contribution and assuming no replacement, overstates the worsened condition of the team with the missing player.

Kowalewski and Leeds (1999) expanded the existing literature by examining the impact of free agency and a salary cap on players' salaries in the NFL. They used data on all players in the years 1992 and 1994. The 1992 data represented the period prior to free agency and the salary cap and the 1994 data represented the period after the implementation of the new collective bargaining agreement which brought about the salary cap and free agency.

They found that these changes significantly altered the determinants and distribution of salaries in the league. The Gini coefficient, which they use to measure the inequality of income in the league, increased 22% between these two years. They found that superstars and veteran starters gained dramatically under the new regime while the pay of the bottom two thirds of the income distribution has fallen. The pay of the marginal players deteriorated dramatically under the new system.

Their results, although an interesting early exploration of salaries in the NFL, were limited by the lack of independent variables in their regressions. There is no uniform performance measure across all players in the NFL. In a follow-up paper, Leeds and Kowalewski (2001) improve upon their earlier work by more closely examining the determinants of individual salary determination on a positional level.

Studying salary determination at a positional level allowed them to use more and better performance indicators. Leeds and Kowalewski (2001) were also the first to use quantile regression techniques in the analysis of salaries in professional sports. Their 2001 findings reinforced their earlier findings that performance was a much more important determinant of salaries after the new collective bargaining agreement. The salary cap and free agency combined to allow superstars and veteran starters to gain a disproportionate amount at the expense of the rookies and marginal players. They also found that the performance effects were more pronounced for the skill positions of quarterback and running back, than they were for receivers.

A shortcoming of both of their papers is that they did not distinguish between restricted players and free agents, so their results are biased. Combining both types of players dilutes the returns to free agency resulting in artificially smaller estimated coefficients for free agents and artificially larger coefficients for restricted players. Their research was also conducted in the years immediately surrounding the inception of free agency and the salary cap, 1992 and 1994 respectively. The time period of my study, with all of the data at least five years removed from the inception of free agency and the salary cap, allows for better detection of changes in salaries brought about by the new regime. My study is more comprehensive than prior studies. I test all of the positions in the NFL with the exception of kickers. I include variables to capture effects of the salary cap and free agency on player salaries. I test for the presence of differences in bargaining strength among players.

CHAPTER 3 THE NFL LABOR AGREEMENT & THE CURRENT STATE OF THE NFL

3.1. Specifics of the Collective Bargaining Agreement

In 1993 the NFL Management Council and the NFL Players Association (NFLPA) signed a new collective bargaining agreement (CBA). The agreement has since been extended five times. The most recent extension in 2006 is set to expire after the 2010 season.[15] The new CBA brought dramatic changes to the labor market for and the compensation received by professional football players.[16] The most important of these changes are free agency and the salary cap. The specifics of the important aspects of the collective bargaining agreement are below.

3.1.1 Free Agency

In 1993, a series of court rulings reestablished free agency in the NFL. The league responded by quickly negotiating a new collective bargaining agreement with the newly re-established NFLPA. The new CBA brought free agency to the league in two phases depending on a player's tenure. First, players become eligible for a restricted form of free agency. A couple of years later, they are eligible for unrestricted free agency.

[15] In May 2008 the NFL owners exercised the opt-out clause built into the CBA. Without a further extension of the CBA, 2010 is the "Final League Year". The "Final League Year" differs from any other league year in that there is no salary cap and there are substantial, additional restrictions on player free agency. This is creating much anxiety over the upcoming 2010 season and beyond.

[16] For a brief history of free agency in the NFL prior to the 1993 CBA see Kowalewski and Leeds (1999).

A veteran player with three or more accrued seasons, but less than five accrued seasons (or less than four accrued seasons in any capped year[17]) is a *restricted free agent* upon the expiration of his contract.[18] He is able to negotiate and sign a contract with any club subject to the restrictions of the CBA. However, as long as his prior club tenders a qualifying offer as set forth in Article XIX of the CBA on or before the first day of the restricted free agency signing period, it has the right of first refusal and/or draft choice compensation with respect to the restricted free agent. Therefore the old club has the option to match any offer made to the player and retain him under its right of first refusal. If the old club does not match the offer it may receive draft choice compensation for losing this player; compensation depends on the amount of its initial qualifying offer to this player as outlined in Article XIX (NFLPA, 1998).

Any player with five or more accrued seasons (or four or more accrued seasons in any capped year) is an *unrestricted free agent* upon the expiration of his contract.[19] He is

[17] A capped year is any year in which the salary cap is in effect.

[18] A player receives one accrued season for each season in which he spends six or more regular season games on a club's active/inactive, injured-reserved or physically unable to perform lists (NFL Press Release 2000).

[19] Exceptions to this are those players designated as franchise or transition players. Each team is permitted to designate one of its players who would otherwise be eligible for unrestricted free agency as a franchise player each season. The salary offer determines what type of franchise player he is. An exclusive franchise player must be offered the greater of the average of the top five salaries at the players' position as of April 12 (for 1999 designation) or 120% of his previous year's salary. He is then able to negotiate and/or sign only with the team who designated him as such. If the franchise player is offered a minimum of the average of the top five salaries *of the previous season* at his position, he is a non-exclusive franchise player and can negotiate with other clubs. However, the designating club has the right to match any new club's offer or to receive two first round draft picks as compensation if it decides not to match and loses the player (NFL 1999).
Transition players are a little more complicated. A team was able to designate two in 1993, one in 1994 and one in the final year of the CBA. The salary offer to a transition player must be the minimum of the average of the top ten salaries of the previous year at the player's position or 120% of his previous year's salary, whichever is greater. The transition player designation gives his team the right of first refusal. It has seven days to match a competing offer given to the player upon his contract expiration. If the team

free to negotiate and sign a contract with any team; any team is likewise, free to negotiate and sign him without penalty, restriction or compensation to his prior team subject to the signing period established in the CBA. When I refer to free agents throughout the paper, I am referring to unrestricted free agents (NFLPA, 1998).

3.1.2 The Salary Cap & Minimum Salaries

The NFL salary cap is the absolute maximum each team is able to spend on player salaries in a capped year. The salary cap in 1998-2001, which covers the timeframe of this study, was set at "63% of the Projected Defined Gross Revenues (DGR)[20], less League-wide Projected Benefits, divided by the number of teams playing in the NFL during such year" (NFLPA, 1998, p.95).[21] Table 3.1 shows the salary cap figures since the cap was first instituted in 1994, the relevant years for this study are in bold.

---

matches the offer, it retains its transition player; if the team does not match it loses the player and receives no compensation for the player's departure (NFL, 1999).

[20] DGR means "the aggregate revenues received or to be received on an accrual basis, for or with respect to a league year during the term of this agreement, by the NFL and all NFL teams, from all sources, whether known or unknown, derived from, relating to or arising out of the performance of players in NFL football games, with only the specific exceptions set forth below. The NFL and each NFL team should in good faith act and use their best efforts, consistent with sound business judgment, so as to maximize DGR for each playing season during the term of this agreement." DGR includes pre-season, regular season and post-season gate receipts (net of admission taxes and surcharges paid to municipal authorities), including ticket revenue from luxury boxes, suites and premium seating subject to gate receipt sharing among teams and any proceeds from the broadcast or rights to broadcast any NFL game (NFLPA, 1998, p.86).

[21] Revenues derived from concessions, parking, local advertising and promotion, signage, magazine advertising, local sponsorship agreements, stadium clubs, luxury box income other than ticket sales, sales of programs and novelties, and revenue generated by NFL Films and NFL Properties, Inc and its subsidiaries are considered "Excluded DGR" meaning they are not included in the calculation of the DGR (NFLPA, 1998, p.87).

Table 3.1 Yearly Team Salary Cap

YEAR	**Salary Cap per Team** (in millions of dollars)	YEAR	**Salary Cap per Team** (in millions of dollars
2009	$128.0	2001	$67.4
2008	$116.7	**2000**	**$62.2**
2007	$109.0	**1999**	**$58.4**
2006	$102.5	**1998**	**$52.4**
2005	$85.5	1997	$41.5
2004	$80.6	1996	$40.8
2003	$75.0	1995	$37.1
2002	$71.1	1994	$34.6

The salary cap remains in effect at all times in the NFL.[22] The salaries of a team's players that are on the roster and under contract cannot exceed the cap.[23] If a team exceeds the cap, the NFL can waive players from the team, beginning with the lowest paid players, until the team's payroll has fallen under the cap. Additionally, the NFL can impose a fine, up to $1 million per day, on a team exceeding the cap.

The CBA stipulates both a maximum and a minimum league wide salary, referred to as the "Guaranteed League-wide Salary". League-wide player costs cannot fall below 58% of the *actual* DGR for any season. In the event that they do, the NFL will, by April 15 of the next year, pay an amount equal to the deficiency directly to the players who played on the NFL teams during such season. Additionally, there is a guaranteed minimum team salary, requiring each team to spend at least 54% of Projected DGR, less League-wide Projected Benefits, divided by the number of teams in the League.

[22] Exception being for the upcoming 2010 season, see footnote 15.

[23] There are certain restrictions as to which players' salaries are counted towards the cap. For example, from February 24 until the day before the start of the 2005 season, *only a team's top 51 salaried players count against the cap*, plus the prorated signing bonuses, incentives, etc, *but not the base salaries of other players* on the roster of up to 80 (Brooks, 2005).

In addition to the minimum team salary, Article XXXVIII of the Collective Bargaining Agreement establishes minimum salaries for players based on their tenure in the League. The actual salaries for 1998 and 1999 are specified in the CBA. A formula is given to calculate the minimum salaries for subsequent years. The abridged formula states, that after 1999, the minimum salaries increase each year by the same percentage as the increase in the projected DGR during that time period, up to a maximum of ten percent per year. Minimum salaries cannot decrease in any event, regardless of the change in the projected DGR. Table 3.2 shows the yearly minimum salaries for the time period of the study and for the 2005 and 2009 seasons for comparison.

Table 3.2 Player Minimum Salaries[24]

Length of Service	**1998**	**1999**	**2000**	**2005**[25]	**2009**[26]
Less than one accrued season	$144,000	$175,000	$192,500	$230,000	$310,000
One accrued season	$180,000	$250,000	$275,000	$305,000	$385,000
Two accrued seasons	$216,000	$325,000	$357,500	$380,000	$460,000
Three accrued seasons	$216,000	$350,000	$385,000	$455,000	$535,000
Four accrued seasons	$216,000	$375,000	$412,500	$540,000	$620,000
Five accrued seasons	$216,000	$400,000	$440,000	$540,000	$620,000

[24] These figures are for players on the active/inactive list. For minimum salaries for players not a team's active/inactive list see p.173-174 of the CBA.

[25] The paragraph 5 minimum salaries were revised in 2002 to allow the pay scale to increase for accrued seasons up to 10. Therefore, the remainder of the minimum salary scale for 2005 is as follows: players with 4-6 accrued seasons earn at least $540,000; players with 7-9 accrued seasons earn at least $665,000; players with 10+ accrued seasons earn at least $765,000 (NFLPA, 2003).

[26] The remainder of the minimum salary scale for 2009 is as follows: players with 4-6 accrued seasons earn at least $620,000; players with 7-9 accrued seasons earn at least $745,000; players with 10+ accrued seasons earn at least $845,000 (NFLPA, 2006).

3.1.3 Salary Cap Accounting

In this study, salary data are reported using the same method the NFL uses to calculate individual players' salaries and determine the team salary. A player's salary is reported as his base salary plus most bonuses and incentives with the exception of signing bonuses. Incentives are counted towards the current year salary if they are "likely to be earned" during the season based on the player's and/or team's prior season performance. For example, if a player's contract contains an incentive where he will receive $100,000 for reaching 200 yards rushing in the current season, and he reached that mark in the prior season, the $100,000 incentive is considered "likely to be earned" and counts towards his current salary. Any incentive entirely in the control of the player, such as a weight bonus or workout bonus, is considered likely to be earned and is included in his current salary (NFLPA, 2003).

In contrast, the salary cap allows signing bonuses to be prorated over the life of multiyear contracts.[27] Therefore, a signing bonus is not reported as a lump sum in the year it is paid. Instead, the prorated amount is used to calculate the player's salary for salary cap purposes. For example, suppose a player signs a three-year contract with a $9 million dollar signing bonus. The player receives the $9 million signing bonus immediately. However, under the salary cap accounting, his salary is reported as his base salary, likely to be earned incentives and $3 million from the signing bonus (one-third of the total signing bonus).

[27] Signing bonuses are prorated on a straight-line basis unless subject to acceleration or some other treatment as set forth in the CBA (NFLPA, 2006, p. 104).

The treatment of the signing bonuses provides a huge loop-hole allowing teams a simple way to legally circumvent the salary cap and offer players more money. Teams also commonly "backload" contracts to afford themselves additional dollars to spend under the salary cap. These contracts, with much of the money not guaranteed, are later renegotiated under more favorable terms for the team (extending the contract and exchanging base salary for a signing bonus) or the player is simply released (Ritter, 2008; Weisman, 2006).

3.2 Current State of the NFL

According to the press, television ratings, and popular opinion, football has overtaken baseball as America's favorite pastime. Super Bowl XLIV was watched by more than 106 million people, making it the most-watched television program in U.S. history (NFLPA, 2010). NFL games draw the largest average crowds in world sport at 67,509 people per game (Harris, 2010). Financial parity, labor peace and competitive play have helped the league increase its fan base by making the NFL more unpredictable, more fun to watch and extremely successful financially.

3.2.1 Profits and Team Values

The NFL is most valuable and profitable sports league in the world. However, even the NFL is not immune to the economic downturn. According to Forbes, 2009 was the first time in ten years that the value of a team had decreased, with eight teams losing value. Nonetheless, Forbes reports the average team enterprise (equity plus debt) value at $1 billion in 2009. Compare this value to those of their competitors: The average MLB team at $491.9 million, the average NBA team at $379 million, and the average NHL team at $219 million (NFLPA, 2010). The NFL is doing well. The Dallas Cowboys are the most valuable franchise, estimated to be worth $1.65 billion; the Oakland Raiders are the least valuable franchise with an estimated worth of $797 million (Badenhausen, Ozanian, & Settimi 2009).

Combined revenues for the league's teams rose 7% in 2009 to reach more than $7.6 billion. Revenues in the NFL are driven mainly by broadcasting rights, with the television deals paying each team about $116 million in 2008. Ticket and concession revenue resulted in an additional $59 million per team. These revenues, combined with contained player costs due to the salary cap, lead to healthy profits for NFL teams. In fact, Forbes reports that the 2008 season was one of the NFL's most profitable ever. The Washington Redskins were the League's most profitable team with 2008 operating income of $90 million, more than half of that generated from luxury suites (Badenhausen et al. 2009).

3.2.2 Player Salaries

The NFLPA (2010) reported that in 2008, while team operating income increased 31% to an average of $32 million per team, labor costs increased only 4%. Players in the NFL received about 58 percent of league-wide revenue. Badenhausen (2009) reporting on the world's highest paid athletes, writes (there is a) "notable omission: the entire NFL." Despite being the world's richest sporting league, no players from the NFL are on the Forbes list of the world's highest paid athletes. In fact, NFL players are paid less on average then players in the NBA, IPL (India's Premier League which plays cricket), MLB and NHL (Harris, 2010).

3.2.3 Competitiveness

Many attribute the success of the NFL to the fact that revenue sharing coupled with the salary cap has led to relatively more financial parity than in other professional sports leagues and thus, to more competitive play within the League. In theory the salary cap forces teams to make tough choices regarding their rosters and spreads talent around the league. The strict revenue sharing, as described earlier in the chapter, allows smaller market teams to compete with large market teams.

The NFL lacks a perennially dominate team and instead has numerous teams which rise and fall in the rankings every year. Each season brings with it the excitement that any team can win on "any given Sunday" (Economist, 2006). In the 2002 season, 0.063 was the difference in the winning percentage between the last place team in the AFC East and the rest of the teams in the division (Fleming, 2003). Since 2000, fifteen of the league's thirty two teams have appeared in the Super Bowl. The New Orleans Saints climbed from the bottom of the NFC South just two seasons ago to defeat the Indianapolis Colts and win the 2010 Super Bowl.

CHAPTER 4 THEORETICAL MODEL

4.1 Background

McLaughlin (1994) blends features of marginal analysis and search theory into a general equilibrium model of rent sharing in which trade takes place in efficiency units of labor. His model applies to labor markets where the heterogeneity of workers and firms leads to thin markets and contestable rents. Equilibrium is characterized by efficient matching, with a worker going to the firm that pays him the most, where his productivity value is the greatest.

Firm *j*'s production function, F_j, maps efficiency units of labor, L_j, and physical capital, K_j, into output, q_j:

$$(4.1) \qquad q_j = F_j\,(L_j, K_j).$$

The firm's production technology is given, and the number of firms is fixed at J.[28] Given the heterogeneity of workers, the firm's labor input, L_j, values each worker's skills and aggregates these valuations across all workers. Each individual worker, *i*, possesses a set of n skills represented by the vector $s_i = (s_{i1},\ldots, s_{in})$. The valuation of skills is firm-specific because some firms can make better use of specific skills than others can.[29] Let $X_j(s_i)$ be a firm-specific function that maps worker *i*'s skills into a scalar value, x_{ij}, of efficiency units of labor:

$$(4.2) \qquad X_j(s_{i1},\ldots, s_{in}) = x_{ij}$$

[28] The restriction to fix the number of firms in the model is highly applicable to the NFL and professional sports in general, but it is not as applicable to most other industries.

[29] For example in the NFL factors that could make the skill values firm specific are the surrounding players, other players at the same position, or the team's "philosophy".

Summing the x_{ij}'s over all employees yields firm j's labor input L_j:

$$(4.3) \quad L_j \equiv \sum_{i=1}^{I} X_j(s_{i1},...,s_{in}) \cdot E_{ij} \equiv \sum_{i=1}^{I} x_{ij} \cdot E_{ij},$$

where E_{ij} is a dummy variable that equals one if worker *i* is employed in firm *j* and zero otherwise.

The model does not impose price-taking behavior. Instead, the marginal productivity schedule is used to define ω_j, the shadow price of labor for firm *j*:

$$(4.4) \quad \omega_j \equiv P_j \cdot \partial F_j / \partial L_j,$$

which is a function of capital, labor and the price of *j*'s product.[30] The marginal value of worker *i* to firm *j* is the shadow price of labor in firm *j* multiplied by the amount of labor supplied by worker *i* to firm j:

$$(4.5) \quad M_{ij} \equiv (P_j \cdot \partial F_j / \partial L_j) \cdot x_{ij}$$

$$\equiv \omega_j \cdot x_{ij},$$

where M_{ij} is worker *i*'s marginal productivity in firm *j*, which varies across firms.

4.2 Efficient Matching

For efficient matching to occur, worker *i* must be matched with the firm in which his productivity value is the highest.[31] This match ensures that the value of output in the market is maximized so that workers cannot be rearranged to increase the value of the output. Any movement of worker *i* from firm *j* to firm *k* would reduce the value of *j*'s

[30] This assumes the output market is competitive. This assumption is just for convenience and is not a realistic assumption for the NFL. However, it does not alter the nature of the results.

[31] This match is conditional on the firm's existing workforce and working environment. For example: Brett Favre's value to the Eagles depends on whether Donovan McNabb is already there.

output more than it would increase the value of firm *k*'s output, so this movement would be inefficient.[32]

In contrast to the competitive model, a worker is not necessarily paid his marginal revenue product in an efficient match. The shadow price of labor, $\omega_{j,}$ determines his productivity value but not his wage. In fact, only the marginal worker in firm *j* (for whom $M_{ij} = M_{ik,}\ j \neq k$) must be paid the value of his marginal product; the firm can wage discriminate against the inframarginal workers. However, each inframarginal worker has some bargaining strength, so one of a variety of mechanisms could determine wages. McLaughlin's approach analyzes bargaining over *wage contracts* not the wages per say. The solution to a simple bargaining game determines the wage contract parameters.

The wage contract is a rent sharing agreement. The contract between worker *i* and firm *j* pays worker *i*, if employed, a wage equal to his opportunity wage plus a share of the rent generated by the match. The wage contract generates wage offers to all workers. However, if worker *i*'s opportunity wage is greater than his productivity value in firm *j*, firm *j* will still offer him a wage equal to his value to the firm, M_{ij} and he will not accept the offer.[33]

Assume that each worker's wage is set by an auction with J firms simultaneously bidding for I workers. Each firm makes a bid on all workers. In each round, worker *i* receives J bids. Worker *i* privately announces his best alternative wage offer to each firm, and the firms, guided by the wage contract, constantly revise their offers. The

[32] See McLaughlin (1994) for a formal proof of efficient matching in this model.

[33] In the case of the marginal worker, worker *i*'s opportunity wage equals his productivity value in firm *j* ($M_{ij} = M_{ik}$ for $j \neq$ k, in other words, the worker whose value to firm j is equal to his value to firm k). This worker's wage offer equals his productivity value and he is paid exactly what he is worth.

bidding ends when a set of mutually consistent wage offers is on the table so that no firm revises its wage offer to any worker. Then each worker accepts his highest wage offer.

4.3 Wage Offers

Wage offers are interrelated since a firm's offer to worker *i* depends on *i*'s opportunity wage, which depends on his outside wage offers. Let w_{ij} represent worker *i*'s wage offer from firm *j* and let $w_{ik} \equiv \max_{k \neq j} w_{ij}$ be defined as worker *i*'s opportunity wage, his next best wage offer. The wage contract is a piecewise linear function of worker *i*'s productivity value in firm *j* and worker *i*'s opportunity wage:

$$(4.6) \qquad w_{ij} = \begin{cases} w_{ik} + \beta_{ij} (M_{ij} - w_{ik}) & \text{if } M_{ij} \geq w_{ik} \\ M_{ij} & \text{if } M_{ij} < w_{ik} \end{cases}$$

where $0 < \beta_{ij} \leq 1$ is the rent sharing parameter. This parameter reflects the worker's bargaining strength, other than threat points, in a cooperative bargaining game. According to McLaughlin, "one may think of β_{ij} as the generalized Nash solution to the bargaining game that is played if the firm employs the worker (p 506)."

To fully understand equation (4.6) let us look at it from firm *j*'s perspective. If worker *i* is worth more to firm *j* than to firm *k*, the top equation is applicable. Firm *j* will offer worker *i* his opportunity wage, w_{ik}, plus some portion of the rent generated by the match of worker *i* with firm *j*. Conversely, if worker *i* is worth more to firm *k* than to firm *j*, the bottom equation applies, and firm *j* will offer worker *i* his value to the firm, M_{ij}. In most cases, except for the marginal worker, this offer will be rejected and worker *i* will contract with firm *k*, which is willing to pay him more.

4.4 Equilibrium

McLaughlin shows that a unique, mutually consistent set of wage offers $w_i = (w_{i1}, \ldots, w_{iJ})$ exists for each worker. For convenience, he indexes firms in order of the wage offer they make to worker *i*, so that $w_{i1} \leq \ldots \leq w_{iJ}$. Since $w_{ij} \leq w_{iJ}$, the rejected wage offers equal the productivity values for firms $j = 1, \ldots, J\text{-}1$,

$$(4.7a) \qquad w_{ij} = M_{ij}, \quad j \leq J\text{-}1.$$

The accepted wage, w_{iJ}, is a convex combination of the worker's productivity values in his two best matches:

$$\begin{aligned}(4.7b) \qquad w_{iJ} &= \beta_{iJ}M_{iJ} + (1-\beta_{iJ})w_{iJ-1} \\ &= \beta_{iJ}M_{iJ} + (1-\beta_{iJ})M_{i\,J-1} \\ &= M_{iJ-1} + \beta_{iJ}(M_{iJ} - M_{iJ-1}).\end{aligned}$$

A firm does not need to know the worker's productivities in all other firms, the market wage offers are sufficient to reveal the only necessary information which is the worker's productivity value in his next best offer.

In equilibrium, there is a mutually consistent set of wage offers for any vector of shadow prices of labor $\boldsymbol{\omega} = (\omega_1, \ldots, \omega_J)$. The equilibrium simultaneously equates the marginal productivity schedules to the labor supply schedules across all firms to yield solution vectors $\boldsymbol{\omega}^* = (\omega^*_1, \ldots, \omega^*_J)$ and $\mathbf{L}^* = (L^*_1, \ldots, L^*_J)$. The equilibrium shadow prices of labor, $\boldsymbol{\omega}^*$, are used to determine the equilibrium productivity values M^*_{ij} and the equilibrium wage offers w^*_{ij}. Adopting the same indexing as above where $w_{i1} \leq \ldots \leq w_{iJ}$, worker *i*'s vector of equilibrium wage offers is:

$$(4.8a) \quad w^*_{ij} = M^*_{ij}, \qquad j = 1, \ldots, J\text{-}1,$$

and

$$(4.8b) \quad w^*_{iJ} = \beta_{iJ} M^*_{iJ} + (1 - \beta_{iJ}) M^*_{iJ-1}.$$

The equilibrium wage offers are flexible and vary with the productivity values. The accepted wage offer is increasing in the rent sharing parameter, the worker's productivity value in the optimal match, and the worker's best alternative productivity. The accepted wage offer is independent of the worker's bargaining power in any other firm. Although each worker is paid less than his productivity value in equilibrium, these workers are still matching with the firms where they are most productive and therefore the equilibrium wage offers are inducing efficient matching.

4.5 Justification for use of this model

The focus of this study is salary determination in the National Football League, in other words w_{ij} is the key variable and equation (4.6) is the key equation. Before going into the details of applying the model to the NFL, it is important to shed light on the aspects of the model that make it a particularly good fit for salary determination, especially for free agents, in the league.

McLaughlin's model extends Roy's (1951) model of self-selection across markets. Roy's model shows how competition among identical firms within a market for heterogeneous workers retains the neoclassical features of supply and demand. McLaughlin extends Roy's model to a "thinner" environment (p 502) by relaxing the assumption of identical firms. McLaughlin's environment is thin due to the heterogeneity of workers *and* firms.

There are only 32 teams in the NFL, and, given the teams' existing rosters, only a fraction of these teams is looking for a player at a particular position at any given time.[34] The imposition of the salary cap creates an even thinner market. The salary cap constrains some teams that would otherwise want a particular player, from pursuing him. As a result, only a handful of teams bids for even the most desirable free agent. Therefore, it is hard to reconcile the use of the competitive framework to model salary determination in the NFL. Instead, I follow the rent-sharing model.

The players in the league also fit the definition of heterogeneous workers. Their skills and skill levels vary by position and across teams. A running back has different skills than a quarterback or a defensive lineman. He is better than a tight end at rushing the football. Additionally a running back performs better on a team with good blockers than on a team with poor blockers. Thus, a player's value to a particular team depends on his own skills and those of his teammates. His skills and his overall fit on the team determine his value to his own team and to other teams. As described in Equation 7b, his wage is a convex combination of these two values. The rent sharing parameter in this model, β, determines what portion of the difference between these two values the player receives. The player's wage is a function of his productivity value on his own team, his opportunity wage and the rent sharing parameter:

$$(4.9) \qquad wage_{ij} = f(M_{ij}, w_{ik}, \beta_{ij}).$$

[34] There were only 31 teams in the league during the time period of this study; the Houston Texans became the 32nd team when they entered the league in the 2002 season.

CHAPTER 5 DATA DESCRIPTION & GENERALIZED EMPIRICAL MODEL

5.1 Data Description

I have assembled a pooled-time series-cross section of over 4,000 observations on players' salaries from the 1998- 2000 NFL seasons.[35] I would prefer to use panel data and follow the same players through the years so that more variables could be held fixed, but that would be nearly impossible. Because the average NFL career is between three and four years, most of the players do not make it to free agency. Therefore, the data set would need to encompass many years to provide enough observations of free agents at each position in order to carry out any useful analysis of panel data.

The salary data are taken from the *USA Today*. The newspaper assembled much of its information from NFLPA reports and from players' agents.[36] I use data for all non-practice squad players on each team's roster at the beginning of the season, excluding kickers. The salary data are reported using the same method the NFL uses to determine team salary caps. A player's salary is reported as his base salary plus most bonuses except for any signing bonuses. The salary cap allows signing bonuses to be prorated

[35] I know of no available data sets for the information other than the sources specified and therefore I had no choice other than to painstakingly assemble my own extensive data set. I have assembled and manually entered the data set in its entirety. The difficulty of this task does somewhat limit my analysis particularly with respect to the length of the time frame studied and to comparisons with salaries in other sports.

[36] Unfortunately there is no way for me to verify the accuracy of the salary data reported in the *USA Today*. The NFLPA denied my request for salary data saying that it is a stipulation of the CBA that each player provides a copy of his contract to the Player's Association; in return they are unable to disclose this information to anyone else. However, the contractual details of many veterans and free agents, who are the primary focus of this study, usually make the news and newspapers anyway. Therefore, if accuracy is a problem it should be limited to the marginal, lesser known and less tenured players and should have little effect on my main results.

over the life of a multiyear contract and therefore it is not reported as a lump sum.[37] For example, suppose a player signs a three-year contract with a $9 million dollar signing bonus. Under salary cap accounting, his salary would be reported as his base salary plus $3 million in bonuses (one-third of the total signing bonus).

The majority of the individual and team performance data, along with player-specific data such as college and draft position are taken from the *Sporting News Pro Football Guide* and the *Sporting News Pro Football Register* for the 1998 -2000 seasons. Additional performance and player-specific data are gathered from *espn.com*, *nfl.com* and the official web sites of the NFL teams. The stadium-specific data are from *ballparks.com*.[38]

5.2 Rent-Sharing Model Applied to Salary Determination of Free Agents in the NFL

Free agents are able to contract with whatever team they choose. As in Equation (4.9) a free agent's salary depends on his productivity value to his own team, his opportunity wage and his rent sharing parameter. Three scenarios relating to the opportunity wage are worth highlighting:

(i) The opportunity wage is equal to the player's second-best offer, which is greater than the applicable minimum salary. ($w_{ik} = w_{i,j-1}$, $w_{ik} > w_{min}$)

This scenario applies to most free agents in the league. They typically have at least two contract offers. Their accepted offer, the one that we view, is at least equal to their

[37] A more detailed description of salary cap accounting for bonuses will appear in Section 3.1.3 of the dissertation.

[38] Certain information on the old Tampa Bay Buccaneers' stadium was obtained from a phone interview with the stadium manager as the information was not available on *ballparks.com*.

second-best offer plus some portion of the difference between their value to their team and this opportunity wage. In this scenario the applicable minimum salary has no effect because the opportunity wage is strictly greater than the minimum salary.

(ii) The opportunity wage is equal to the applicable minimum salary. ($w_{ik} = w_{min}$)

This is the scenario where the player's second-best wage offer is equal to the minimum salary or where there is only one contract offer, the accepted offer that we view. In this case the applicable minimum salary is a lower bound for the accepted salary offer. If the player signs a contract, his value to the team with which he signs has to be at least equal to the league minimum. In this situation, a player will be paid the applicable minimum salary or something close to it. The lack of competition for this player ensures that his rent sharing parameter and hence, his bargaining power, is low and he is paid close to his opportunity wage.

(iii) The opportunity wage is less than the league minimum and the player's value is not greater than the league minimum to any team.

If the player's value is less than the league minimum for every team he will not receive any contract offers and will be forced to exit the league. Teams might be willing to sign him if they could pay him less than the applicable minimum salary for his level of experience but this is not an option. This player is forced to leave the sport or play for a lesser, rival league.[39]

[39] If the NFL had a minor league the player could play there but since there is no minor league the player is forced to play for a rival league such as the Canadian Football League, if he plays at all.

5.3 Generalized First Stage Empirical Model

Clearly, the opportunity wage and minimum salaries play an important role in salary determination this model. Unfortunately, the opportunity wage is not observable. The difficulty with applying McLaughlin's theoretical model is that none of the factors that determine the wage are directly observable. The opportunity wage, rent sharing parameter, and player's value to his own team are unknown. Therefore, the structural equations in the theoretical model are not identifiable and not testable.

I use a two-stage process to test this model. In the first stage, I develop a reduced form regression model of the market factors relevant to salary determination; these factors affect the player's opportunity wage, bargaining strength, and value to his team. Many of the variables included may affect more than one, and in some cases, all three of the key variables in the rent sharing model. It is not important to distinguish which variables they affect, only that they affect the dependent variable, the player's salary. What is important for my purposes in this study is that the independent variables accurately capture the market forces at work in determining the player's salary.

In order to distinguish McLaughlin's rent sharing model from other models, I need to investigate the bargaining aspect of the model separately. I do this in the second step when I apply quantile regression techniques to the first-stage empirical model. Assuming that the first-stage estimation captures the market forces determining wages, the quantile regressions capture any differences in bargaining strength that exist across the salary distribution. This second step is key to distinguishing the rent-sharing model from competing models of salary determination.

My empirical model contains a variety of independent variables that affect the three independent variables in the theoretical model, and therefore affect the player's salary. The general regression model is tailored for each position and the regressions are carried out separately for each of the eight positional equations. I have a salary equation for each of the following positions: quarterback, back (running back and fullback), receiver (wide receiver and tight end), defensive lineman (defensive end and tackle), cornerback, safety, offensive lineman (center, guard and offensive tackle) and linebacker.

To calculate the determinants of salary for free agents in the NFL, I estimate the following equation:

$$(5.1) \qquad \ln(y_i) = \boldsymbol{\beta}' \boldsymbol{X}_i + \varepsilon_i$$

where $\mathbf{X}_i$ is a vector of explanatory variables[40] defined in the text and in the Appendices. The dependent variable, y_i, is the log earnings of player *i*.[41] This variable is constructed as the player's base salary plus all bonuses including the prorated signing bonus for a particular year.[42]

McLaughlin's theoretical model predicts that a player's salary is a function of his value to his own team, his opportunity wage and his rent sharing parameter. Equation 5.1 can thus be expressed for an NFL player in very general terms as:

(5.2) *ln (Salary$_i$) = f (individual performance and statistics, team performance and statistics, interaction between individual & team performance and current negotiating environment in the league).*

[40] The set of explanatory variables varies by position.

[41] A log transformation of salary data is commonly used to better approximate a normal distribution. It dramatically compresses the variance of the distribution.

[42] I use this definition of salary because it is the team's cost to employ a player within the salary cap structure in the NFL (Mirabile 2004). It is also the way the data is reported in my source for the time period of this study. It is important to note that this figure is not necessarily the same as the player's actual salary for a given year, differences can arise because of the salary cap accounting of bonuses.

The equations vary by position, particularly the individual and team performance measures used and the interaction terms constructed. Specific regression equations for each position are presented in the next chapter.

CHAPTER 6 POSTIONAL REGRESSION EQUATIONS & OLS RESULTS

This study encompasses every position in the NFL with the exception of punters and kickers. This is the only study of its kind to investigate salary determination at a disaggregated level for all of the non-kicking positions in the NFL. The general form equation for all positions is:

$$(6.1) \quad \ln(Salary_i) = \alpha_0 + \alpha_{1\text{-}4}\,(\textit{individual performance/characteristics}) + \alpha_5\,(\textit{team performance/characteristics}) + \alpha_{6\text{-}9}\,(\textit{interaction of individual and team performance}) + \alpha_{10}\,(\textit{quality of college football program}) + \alpha_{11}\,(1^{st}\textit{ round}) + \alpha_{12}\,(\textit{round}) + \alpha_{13}\,(\textit{profitability}) + \alpha_{14}\,(\textit{games played}) + \alpha_{15}\,(\textit{games started}) + \alpha_{16}\,(\textit{experience}) + \alpha_{17}\,(\textit{experience squared}) + \alpha_{18}\,(\textit{player status in negotiations}) + \varepsilon_i.$$

Since the responsibilities and nature of each position are so different, many of the specific variables, especially those used to evaluate performance, vary significantly by position.

6.1 Regression Model and OLS Results for Quarterbacks

By far the best-known and most studied position in the NFL is the marquee position, quarterback. The quarterback is in many cases the team leader and the highest paid player on a team.[43] There are numerous relatively clear performance measures for the quarterback, which explains the attention given to the position in the existing literature.

Table 6.1 contains the descriptive statistics for the variables used in the final, parsimonious regression model for free agent quarterbacks. Appendices A and B define

[43] For a gentle introduction to the game of football including a description of each position and the rules of the game see *Football Rules Illustrated* (Sullivan 1981).

all of the variables attempted in different specifications of the quarterback regression model.

Table 6.1
Descriptive Statistics for Free Agent Quarterbacks

VARIABLE	MEAN	STD DEVIATION
Log of total salary (t)	14.097	0.927
Attended BCS eligible school	0.893	0.310
Height	74.855	1.754
Released (t)	0.137	0.346
Not drafted	0.107	0.310
Drafted as Junior	0.115	0.320
Number of Super Bowls	0.282	0.797
Total Pro Bowl selections to t-2	1.046	2.108
Games played (t-1)	9.458	5.360
Starter (t-1)	0.458	0.500
Completion percentage (t-1)	0.524	0.165
Rushing yards (t-1)	81.504	105.699
Draft number (recoded)	165.328	100.234
Team win % (t-1)	0.475	0.235
Team points scored (t-1)	308.191	120.097
Free agent who switched teams	0.137	0.346
Super Bowl winner (t-1)	0.023	0.150
N = 131		

The final specification of the regression model for free agent quarterbacks is:

$$(6.2)\quad \ln(Salary_i) = \alpha_0 + \alpha_1\,\textit{Attended BCS Eligible School} + \alpha_2\,\textit{Height} + \alpha_3\,\textit{Released} + \alpha_4\,\textit{Not Drafted} + \alpha_5\,\textit{Drafted as Junior} + \alpha_6\,\textit{Number of Super Bowls} + \alpha_7\,\textit{Total Pro Bowl Selections (to t-2)} + \alpha_8\,\textit{Games Played} + \alpha_9\,\textit{Starter} + \alpha_{10}\,\textit{Completion Percentage} + \alpha_{11}\,\textit{Rushing Yards} + \alpha_{12}\,\textit{Draft Number(recoded)} + \alpha_{13}\,\textit{Team Win Percentage} + \alpha_{14}\,\textit{Team Points Scored} + \alpha_{15}\,\textit{Free Agent who Switched Teams} + \alpha_{16}\,\textit{Super Bowl Winner} + \varepsilon_i.$$

The results of the OLS regression for free agent quarterbacks are contained in Table 6.2. It is important for the reader to remember that many additional variables were used in alternative specifications of the quarterback model.

Table 6.2
Results of the OLS Estimation for Free Agent Quarterbacks

Variable	Estimated Coefficient	Standard Error	t statistic	Pr > |t|
Constant	7.705**	2.168	3.555	< 0.001
Attended BCS Eligible School	-0.287	0.171	-1.676	0.096
Height	0.078**	0.029	2.682	0.008
Released (t)	-0.602**	0.134	-4.493	< 0.001
Not Drafted	-0.946**	0.207	-4.570	< 0.001
Drafted as Junior	0.327	0.170	1.919	0.056
Number of Super Bowls	0.154*	0.073	2.121	0.036
Total Pro Bowl selections to t-2	0.121**	0.029	4.243	< 0.001
Games played (t-1)	0.040**	0.014	2.837	0.005
Starter (t-1)	0.322*	0.158	2.039	0.044
Completion percentage (t-1)	0.536	0.308	1.739	0.085
Rush Yards (t-1)	0.001*	0.001	2.221	0.028
Draft Number (recoded)	-0.001	0.001	-1.720	0.088
Team Win% (t-1)	-0.825*	0.392	-2.103	0.038
Team Points Scored (t-1)	0.002*	0.001	2.346	0.020
Free agent who switched teams	-0.476**	0.135	-3.528	< 0.001
Super Bowl Winner (t-1)	-1.055**	0.322	-3.282	0.001
Adjusted R^2 = 0.715 N = 131	F = 21.417	Dependent Variable = LNTOTSAL		
* significant at 5% level ** significant at 1% level				

The dependent variable is the *natural logarithm of total salary* which is the player's base salary plus prorated bonuses which are explained in sections 3.1.4 and 5.1.[44] The independent variables are *Attended BCS eligible school, Height, Released, Not drafted, Number of Super Bowls, Total Pro Bowl selections (to t-2), Games played, Starter, Completion percentage, Rush yards, Draft number (recoded), Team win percentage, Team points scored, Free Agent who switched teams, and Super Bowl winner.*

[44] Results of the regression were similar with total salary as the dependent variable but did not fit the data as well.

Not drafted is a dummy variable that equals one if the player was not drafted and zero otherwise.[45] It is not surprising that this variable shows a large, significantly negative effect on the player's salary. A quarterback who is not drafted has a 95% lower salary than a quarterback who is drafted. *Drafted as a Junior* equals one if the quarterback was drafted prior to his senior year and zero otherwise. Only those thought to be the best college players usually enter the draft early. It is not surprising that this variable has a strong positive return of 33%. The positive effect of this variable indicates that those quarterbacks drafted early continue to be rewarded in the NFL independent of their performance. This variable may be a proxy for football intelligence, natural skill or some other factor(s) not picked up by the other independent variables.

Total Pro Bowl selections is the total number of Pro Bowls in which a free agent quarterback has been selected up to year t-2. For example, if the year is 1999, *total Pro Bowl selections* equals the number of Pro Bowls that a player participated in, up to and including 1997. Regressions not shown here included a separate dummy variable for being selected to the prior year's Pro Bowl but it had no effect on the quarterback's salary in year t. The *total Pro Bowl selections* variable shows a strong and significant 12% return for each additional Pro Bowl selection. The Pro Bowl is essentially an All-Star game for the NFL. This result is driven by superior performance, skill and/or leadership at the quarterback position, above and beyond that detected from the other individual performance measures included in the equation. The coefficient estimate is not surprising and is consistent with previous studies.

[45] There could be competing forces affecting the salary of an un-drafted player. Since an un-drafted player is free to negotiate his own deal, he is not subject to the monopsony power in place for those players who are drafted. However, his not being drafted sends a signal that he should be paid less than the lowest draft choice. The results show the latter effect dominates.

Number of Super Bowls equals the total number of Super Bowls in which the quarterback started. Leading your team to the Super Bowl is one of the biggest accomplishments in sports and can establish a player's reputation as a "winner." We see a significant 15% return for each additional Super Bowl that a quarterback starts. A surprising result is that of *winning the Super Bowl.* This dummy variable equals one if a quarterback started and won the prior year's Super Bowl. I expected a positive spike in salary from winning the prior year's Super Bowl. Instead there is a large negative return on a quarterback's salary. This result could be driven by specific circumstances for the three quarterbacks in this category. It could be the result of quarterbacks' taking pay cuts[46] to keep a winning team together. The result could also be misleading if quarterback's salary was re-negotiated after winning the "big game". In actuality, he could be receiving more money over the life of the contract. However, if a larger portion of that money is guaranteed in the form of signing bonuses that are spread out of the life of the contract[47] - for salary cap purposes, the player's salary could appear to be decreasing. The available data does not allow us to test exactly what is happening with this variable.

Free agent who switched teams is an interaction of the dummy variable f*ree* a*gent* and the dummy variable *switching teams*. This interaction variable is picking up the effect of a free agent quarterback who switched teams from one season to the next. This variable has a strong negative effect, with a -48% return. This means that quarterbacks who have four years of experience, are not currently under contract, AND

---

[46] At least for salary cap purposes, in reality though they may not be taking a pay cut.

[47] See Section 3.1.3 for a description of the NFL salary cap accounting.

switch teams are paid less, all else equal, than other quarterbacks. Free agency does not necessary lead to big money for quarterbacks, especially those who do not re-sign with their current team. There are numerous reasons for this. First, the fact that the quarterback is not re-signed and is allowed to become a free agent indicates that the current team does not value him enough to keep him at his current salary. His team is essentially willing to let him go. Second, the specific human capital accumulated by a quarterback is probably larger than that for any other position. Team offenses are so complicated in the NFL that unless he goes to a team with the same system, he may need to learn a new offense. Finally, there is more uncertainty for a quarterback on a new team; he must adapt to a different coaching staff, system, and teammates. It is also interesting to note that this coefficient is negative and significant only for quarterbacks and running backs. We will see that the coefficient is positive and significant for most other positions.

The variable *starter* is a dummy variable that equals one if the quarterback started at least eight games in the previous regular season and zero otherwise. The variable was included instead of the number of games started[48], although that variable was attempted, to distinguish between a starting quarterback and backup quarterback. The positive and significant 32% return to being a starter is as expected. The variable *games played* is the number of games in which a quarterback played during the previous regular season. The significant 4% return for each additional game played is not surprising. Quarterbacks, more than any other position, gain valuable experience just from entering games.

[48] Starter was chosen as opposed to games started due to a better fit and also due to the expected job of the quarterbacks on the roster. One person is usually the starter and the other quarterbacks are designated as the second and third string respectively. The effect of being a starter is seen better with the dummy variable starter as opposed to the number of games started.

Height is the quarterback's height in inches. There is an 8% additional return to each inch of a quarterback's height. Taller quarterbacks have become the standard in the NFL. Additional height makes is easier for a quarterback to see over the large men in front of him and get a better view down field. A taller quarterback may also be more difficult to sack and is likely to have fewer blocked passes. Additional inches give the quarterback a potential on-field advantage that translates into more money.

Completion percentage is a standard performance measure for quarterbacks. It is calculated as the number of passes completed divided by the number of passes attempted. This is an important efficiency measure for a quarterback. There is a 0.54% return to each 1% increase in the completion percentage. A quarterback with a 10% higher completion percentage than his counterpart will see a 5% higher salary than his counterpart, all else equal. The significant impact from this important performance measure is not surprising. The variable *rush yards* is the number of yards that a quarterback rushed in the prior season. This is another standard performance statistic for quarterbacks which measures ability and agility. Being able to run the ball provides additional options for a passer and makes him more of a threat than an immobile quarterback. We see a positive and significant 0.13% return for each additional rushing yard. Although this coefficient is small, if a quarterback has 500 yards more rushing than another, this would amount to a 65% return.

The variable *released* is a dummy variable that equals one if a quarterback was released and zero otherwise. Usually, the key players on a team are not released.[49] It is

[49] The team can unilaterally abrogate a player's contract. With few guarantees (beyond the up-front money from bonuses), this would have a major impact on the player and the team.

not surprising that there is large, negative 60% return to being released.[50] The variable *attended a BCS eligible school* is a dummy variable that equals one if a quarterback attended a university that is eligible to participate in the Bowl Championship Series (BCS) and zero otherwise. Initially, I found the significant negative impact surprising but upon further thought, it makes sense. Only veterans are included in the sample and the rest of the positional regressions. Holding all else constant, there is no reason to expect that a player coming from a BCS eligible school would have a positive impact on his salary after four or more years in the league. In fact, the opposite could be expected if, for example, a player were better known because he came from a non-BCS school. Basically, this result is indicating the presence of an "underdog" or "unlikely to succeed" effect. We are comparing two quarterbacks who are performing equally well from different college backgrounds. The player from a BCS eligible school might be regarded as a bust because more was expected from him, whereas the other player is a pleasant surprise.

Team points scored is the number of points a team scored in the prior season. Scoring points is one of the primary goals of a quarterback. The variable captures any complementarity or substitutability effects of a quarterback on an "offensive minded team." We see a positive and significant 0.18% return for each additional point scored. The result indicates that a quarterback is complementary to an "offensive minded team." He is paid more on a high scoring team than he would be on a low scoring team, all else equal.

[50] Players are usually released if they are no longer living up to the expectations at the time the contract was signed. Being released sends a strong negative signal to other teams and may result in difficulty in the matching system relative to a player who chooses another team as a free agent or who is traded.

Team win percentage is the team's number of games won divided by the number of games played in the prior regular season. There is a negative return of 83% for this variable. This means that a team with a 50% win percentage pays its quarterback 8.3% more than a team with a 60% record, all else equal. This result is somewhat surprising. It indicates that a losing team is willing to pay a quarterback significantly more than a winning team, all else equal. Perhaps once everything else is held constant, a team with an unusually high win percentage relies more on factors other than the quarterback (e.g., a top-notch defense or offensive line), so the team allocates its resources elsewhere.

6.2 Regression Model and OLS Results for Backs

Another recognizable position in the NFL is the back. This position includes both running backs and fullbacks. Both are offensive players. The running back's main job is to run the ball. The fullback is mainly a blocker, leading the way for the running back or protecting the quarterback. The back is a skill position and typically he is highly paid. Similar to the quarterback there are numerous relatively clear performance measures for the back.

Table 6.3 contains the descriptive statistics for the variables used in the final, parsimonious regression model for free agent backs. Appendix A defines all of the variables attempted in different specifications of the backs regression model.

Table 6.3
Descriptive Statistics of Free Agent Backs

VARIABLE	MEAN	STD DEVIATION
Log of total salary (t)	13.722	0.695
Attended BCS eligible school	0.871	0.337
Weight	222.306	17.768
Injured Reserve (t-1)	0.083	0.672
Traded (t)	0.026	0.159
Not drafted	0.145	0.353
Year (t)	1999.005	0.807
Games played (t-1)	13.876	3.654
Games started (t-1)	7.140	6.092
Rush yards (t-1)	391.450	476.388
Yards receiving (t-1)	174.202	169.014
Drafted in first round	0.181	0.386
Total Pro Bowl selections to t-2	0.694	1.460
Free agent who switched teams	0.290	0.455
Team win percentage (t-1)	0.492	0.207
Super Bowl winner (t-1)	0.026	0.159
Team net passing yards (t-1)	3386.715	619.477
N = 193		

The final specification of the regression model for free agent backs is:

$$(6.3)\quad \ln(Salary_i) = \alpha_0 + \alpha_1\, Attended\ BCS\ Eligible\ School + \alpha_2\, Weight + \alpha_3\, Injured\ Reserve + \alpha_4\, Traded + \alpha_5\, Not\ Drafted + \alpha_6\, Games\ Played + \alpha_7\, Games\ Started + \alpha_8\, Year + \alpha_9\, Rush\ Yards + \alpha_{10} Yards\ Receiving + \alpha_{11}\, Drafted\ in\ First\ Round + \alpha_{12}\, Total\ Pro\ Bowl\ Selections\ (to\ t\text{-}2) + \alpha_{13}\, Free\ Agent\ who\ Switched\ Teams + \alpha_{14}\, Team\ Win\ Percentage + \alpha_{15}\, Super\ Bowl\ Winner + \alpha_{16}\, Team\ Net\ Passing\ Yards + \varepsilon_i.$$

The results of the OLS regression for free agent backs are contained in Table 6.4.

The dependent variable is the *natural logarithm of total salary*, which is the player's base salary plus prorated bonuses. The independent variables are *Attended BCS eligible school*, *Weight*, *Injured Reserve list*, *Traded*, *Not drafted*, *Year*, *Games played*, *Games started*, *Rush yards*, *Yards receiving*, *Drafted in the first round*, *Total Pro Bowl selections (to t-2)*, *Free Agent who switched teams*, *Team win percentage*, *Super Bowl winner*, and *Team net passing yards.*

A dummy variable for fullbacks was included in an earlier version of the regression to test if there was a significant difference in the salary of a fullback compared to that of a running back. The coefficient on the dummy variable was insignificant and therefore, the fullback variable was omitted from the final regression presented here.

Table 6.4
Results of the OLS Estimation for Free Agent Running Backs

Variable	**Estimated Coefficient**	**Standard Error**	**t statistic**	**Pr > |t|**
Constant	-124.125	71.801	-1.729	0.086
Attended BCS eligible school	0.104	0.089	1.175	0.241
Weight	0.002	0.002	1.113	0.267
Injured Reserve list (t-1)	-0.096**	0.044	-2.193	0.030
Traded (t)	0.322	0.190	1.700	0.091
Not drafted	-0.285**	0.086	-3.321	0.001
Year (t)	0.069	0.036	1.919	0.057
Games played (t-1)	-0.049**	0.009	-5.267	< 0.001
Games started (t-1)	0.021**	0.007	2.918	0.004
Rushing yards (t-1)	0.001**	0.000	6.412	< 0.001
Receiving yards (t-1)	0.001**	0.000	3.204	0.002
Drafted in first round	0.146	0.081	1.796	0.074
Total Pro Bowl selections to t-2	0.061**	0.022	2.820	0.005
Free agent who switched teams	-0.543**	0.069	-7.929	< 0.001
Team win percentage (t-1)	0.218	0.152	1.441	0.151
Super Bowl winner (t-1)	-0.237	0.187	-1.266	0.207
Team net passing yards (t-1)	< -0.001*	< 0.001	-1.978	0.050
Adjusted R^2 = 0.687 N = 193	F = 27.359	Dependent Variable = LNTOTSAL		
* significant at 5% level ** significant at 1% level				

As expected, being drafted, especially being drafted early, leads to higher salaries for free agent backs. *Not drafted* is a dummy variable that equals one if the player is not drafted and zero otherwise. It is not surprising that an undrafted back has a salary that is 29% lower than his drafted counterpart, all else equal. *Drafted in the first round* is a dummy variable that equals one if the player is drafted in the first round and zero otherwise. Those backs that are expected to have the most success in the NFL are drafted in the first round. Backs see a 15% return to being drafted in the first round.

Total Pro Bowl selections is the total number of Pro Bowls a free agent back has been selected to up to year t-2. Additional regressions, whose results are not reported here, include a separate dummy variable for being selected to the prior year's Pro Bowl but this variable has no effect on the back's salary in the current year. The *total Pro Bowl selections* variable has a significant 6% return for each additional Pro Bowl selection. It is interesting to note that this coefficient estimate is only half of the return a quarterback receives for each additional Pro Bowl selection.

Free agent who switched teams is an interaction of the dummy variable *free* a*gent* and the dummy variable *switching teams*. This interaction variable picks up the effect of a free agent back who switched teams from one season to the next. Similar to the results for quarterbacks, free agent backs who switch teams see a strong, negative 54% salary reduction. This means that backs who have at least four years of experience, are not currently under contract, AND switch teams, are paid less, all else equal than other backs. Generally speaking, free agency does not lead to a big payoff for the skill positions (quarterback, running back and fullback). Those skill position players who are not re-signed by their current team experience an especially large decrease in their salaries. As with quarterbacks, these results are driven by specific human capital. The amount of specific human capital accumulated is likely to be greater for skill positions than for the other positions on the team. This specific human capital does not transfer as well as general human capital. Therefore skill position players who switch teams through free agency many times see a reduction in their salaries. In later sections discussing salary determination for the other positions, we see very different results for the coefficient estimate on this variable.

In sharp contrast, backs who are traded see a 32% increase in salary after the trade. Economically speaking, it makes sense that a player would see an increase in his salary resulting from a trade as opposed to the decrease in salary resulting from switching teams through free agency. When a player switches teams through free agency, the cost of the player must be more than the benefit for his old team and therefore, it will not re-sign him. Whereas a trade in the NFL, like a trade in any market, has to be mutually beneficial for both parties otherwise it would not occur. When a back is traded to another team, the new team must value him more highly than the old team and therefore, it is not surprising that a traded player sees an increase in pay.

Individual performance, when it can be accurately measured, is an important factor in salary determination for any job. Two variables are included to measure the individual performance of backs. *Rushing yards* measures the total number of yards a back ran the ball in the prior season. *Receiving yards* measures the total number of yards a back gained catching the ball in the prior season. Both individual performance statistics are highly significant in the salary regression for backs. A back sees an additional 0.1% increase in salary for each additional rushing or receiving yard. Although the magnitude of the return per yard is small, if a back has 500 more yards rushing or receiving than another, this translates to a 50% increase in pay.

Games started is the number of games a back started in the previous season. *Games played* is the number of games he played in the previous season. The *games started* variable is a measure of performance and a proxy for experience. We expect a positive relationship between experience and pay. A back receives an additional 2% increase in pay for each game started. The better players start the games; starting every game in the 16-game season translates to a 32% return. The variable *games played* has a negative return of 5% per game. Unfortunately, we do not have data on number of plays or minutes played in a game. However, we can say that generally a player, who starts a game, will spend more time playing in that game, than a player who does not start the game, but still plays in the game. The *games played* variable is not a proxy for experience but instead picks up the marginal player who enters the game[51] and plays but does not start. Since the variables distinguish between starting and just playing in a game, we expect that the games played variable would be negative.

Injured reserve is a dummy variable that equals one if a back was on the injured reserve list for 8 or more games in the previous season and zero otherwise. I expect a player with a past serious injury to be paid less, all else equal. There is greater uncertainty surrounding the performance of player returning from an injury. A back plays one of the most grueling positions on the team. He is constantly being hit and faces much wear and tear on his body. It is not surprising that a back on the injured reserve list in the previous season sees a significant 10% decrease in his salary the next season.

The variable *team net passing yards* is the number of net passing yards for the team in the previous season. This variable captures complementarity or substitutability effects of a back on a "passing team." We have no a priori expectation regarding the sign of this variable. We see a negative and significant 0.1% return for each additional passing yard. This result indicates that a back is generally viewed as a substitute for a passer. A back is paid less on a high powered passing team, all else equal.

---

[51] Perhaps on special teams- and not even as a running back.

6.3 Regression Model and OLS Results for Receivers

The receiver is an offensive player whose main job is to catch passes and help advance the ball. There are two different types of receivers, tight ends and wide receivers. Wide receivers usually catch more passes while tight ends do more blocking. Speed, height and agility are important for receivers. Like quarterbacks and backs, receivers have numerous relatively clear performance measures.

Table 6.5 contains the descriptive statistics for the variables used in the final parsimonious regression model for free agent running backs. Appendix A defines all of the variables attempted in alternative specifications of the receivers regression model.

Table 6.5
Descriptive Statistics of Free Agent Receivers Estimation

VARIABLE	MEAN	STD DEVIATION
Log of total salary (t)	13.792	0.726
Tight End (dummy variable)	0.362	0.481
Attended BCS eligible school	0.761	0.427
Height	73.515	2.752
Not drafted	0.150	0.357
Drafted as a Junior	0.110	0.314
Year (t)	1999.006	0.819
Free Agent (t)	0.258	0.438
Traded (t)	0.034	0.181
Released (t)	0.092	0.290
Franchise/Transition Player (t)	0.015	0.123
Player who switched teams	0.242	0.429
Games played (t-1)	14.025	3.520
Games started (t-1)	8.472	6.623
Receiving yards (t-1)	476.972	407.498
Receiving touchdowns (t-1)	2.954	3.058
Experience (t)	6.632	2.676
Experience squared (t)	51.123	46.505
Free agent who switched teams	0.135	0.342
Draft number (recoded)	201.923	110.281
Round drafted (recoded)	8.945	4.151
Total Pro Bowl selections to t-2	0.709	1.787
Kick/Punt return touchdowns (t-1)	0.052	0.351
Kick/Punt return yards (t-1)	95.736	331.511
Team net passing yards (t-1)	3419.994	555.288
N = 326		

The final specification of the regression model for free agent receivers is:

$$(6.4)\quad \ln(Salary_i) = \alpha_0 + \alpha_1\, Tight\ End + \alpha_2\, Attended\ BCS\ Eligible\ School + \alpha_3\, Height + \alpha_4\, Not\ Drafted + \alpha_5\, Drafted\ as\ a\ Junior + \alpha_6\, Year + \alpha_7\, Free\ Agent + \alpha_8\, Traded + \alpha_9\, Released + \alpha_{10}\, Franchise/Transition\ Player + \alpha_{11}\, Player\ who\ Switched\ Teams + \alpha_{12}\, Games\ Played + \alpha_{13}\, Games\ Started + \alpha_{14}\, Receiving\ Yards + \alpha_{15}\, Receiving\ Touchdowns + \alpha_{16}\, Experience + \alpha_{17}\, Experience\ Squared + \alpha_{18}\, Free\ Agent\ who\ Switched\ Teams + \alpha_{19}\, Draft\ Number + \alpha_{20}\, Round\ Drafted + \alpha_{21}\, Total\ Pro\ Bowl\ Selections\ to\ (t\text{-}2) + \alpha_{22}\, Kick/Punt\ Return\ Touchdowns + \alpha_{23}\, Kick/Punt\ Return\ Yards + \alpha_{24}\, Team\ Net\ Passing\ Yards + \varepsilon_i.$$

The results of the OLS regression for free agent receivers are contained in Table 6.6.

The dependent variable is the *natural logarithm of total salary,* which is the player’s base salary plus prorated bonuses. The independent variables are *Tight End, Attended BCS eligible school, Height, Not drafted, Drafted as a junior, Year, Free Agent, Traded, Released, Franchise/Transition player, Player who switched teams, Games played, Games started, Receiving yards, Receiving touchdowns, Experience, Experience squared, Free Agent who switched teams, Draft number, Round drafted, Total Pro Bowl selections (to t-2), Kick/punt return touchdowns, Kick/punt return yards* and *Team net passing yards.*

Table 6.6
Results of the OLS Estimation for Free Agent Receivers

Variable	Estimated Coefficient	Standard Error	t statistic	Pr > |t|
Constant	-197.902**	54.953	-3.601	< 0.001
Tight End (dummy variable)	-0.097	0.071	-1.361	0.175
Attended BCS eligible school	-0.096	0.056	-1.706	0.089
Height	0.013	0.012	1.069	0.286
Not drafted	-0.126	0.140	-0.902	0.368
Drafted as a Junior	0.077	0.075	1.030	0.304
Year (t)	0.105**	0.028	3.821	< 0.001
Free Agent (t)	-0.325**	0.071	-4.558	< 0.001
Traded (t)	0.156	0.142	1.093	0.275
Released (t)	-0.421**	0.095	-4.455	< 0.001
Franchise/Transition Player (t)	0.711**	0.184	3.868	< 0.001
Player who switched teams	-0.363**	0.100	-3.628	< 0.001
Games played (t-1)	-0.012	0.008	-1.520	0.130
Games started (t-1)	0.029**	0.006	4.830	< 0.001
Receiving yards (t-1)	0.001**	< 0.001	3.578	< 0.001
Receiving touchdowns (t-1)	0.018	0.012	1.460	0.145
Experience (t)	0.094*	0.042	2.241	0.026
Experience squared (t)	-0.007**	0.003	-2.639	0.009
Free agent who switched teams	0.326**	0.130	2.511	0.013
Draft number (recoded)	0.006**	0.003	2.492	0.013
Round drafted (recoded)	-0.159*	0.074	-2.158	0.032
Total Pro Bowl selections to t-2	0.065**	0.018	3.596	< 0.001
Kick/Punt return touchdowns (t-1)	-0.114	0.075	-1.524	0.129
Kick/Punt return yards (t-1)	< 0.001**	< 0.001	2.628	0.009
Team net passing yards (t-1)	< 0.001	< 0.001	1.520	0.130
Adjusted R^2 = 0.713 N = 326	F = 34.696	Dependent Variable = LNTOTSAL		
* significant at 5% level ** significant at 1% level				

Overall the results for receivers differ significantly from those of quarterbacks and backs. While all are offensive players, one could argue that the receiver is "less skilled" than the other two. The receiver generally accumulates less specific human capital and more general human capital relative to the skilled positions. Additionally, the receiver is more dependent on other positions, mainly the quarterback, while the "skill positions" can be more independent players.

The effects of the being drafted and draft position on free agent receivers differ from the other skill positions. An undrafted receiver sees no significant negative impact on his salary. Whereas, an undrafted back sees a salary that is 29% less than his drafted counterpart and an undrafted quarterback has a 95% lower salary. Also, in contrast to the result for quarterbacks, a free agent receiver who is deemed one of the best from college and is drafted prior to his senior year (*drafted as a junior*) sees no significant positive effect on his pay.

A free agent receiver's draft number continues to have an impact on his salary even after he has accumulated four or more years of experience. The variable *draft number* is recoded[52] to reflect a positive relationship between perceived skill and draft position. A player who is perceived to be very good has a high draft number. This variable has the expected result with a receiver earning almost a one percent premium for a one spot higher position in the draft. However, a receiver drafted in a higher round (after similar recoding) sees a negative impact on his salary. Analyzing the draft effects together shows the draft has no clear impact on the salary of free agent receivers. The impact of the draft is not as strong for receivers as it is for the skill positions.

In contrast, the experience variables have a significant impact on the salary of a free agent receiver. However, they have no significant effect and are not even included in the final regressions for quarterback and running back. *Experience* is the number of seasons a player has participated in the league. A worker gains knowledge and perfects his skills as he accumulates experience. We assume the same for players in the NFL and

[52] The NFL uses a reverse order draft where the team that finishes last in the previous season has the first draft pick in each round and the team that finishes first gets the last pick. The first draft pick is usually perceived to be the best or at least one of the best players in the draft. Perceived player quality declines as the draft continues. So, a player drafted later (with a higher draft number) is perceived to be a lesser quality player all else equal. This variable is recoded to avoid discontinuity and to reflect a positive relationship between draft number and quality. Positive relationships are the norm when referring to quality: higher number = better quality.

expect a player with more experience to be paid more all else equal. A receiver earns an additional 9.4% for each additional year of experience in the league.

The variable *experience squared* is included to account for non-linearity[53] in the returns to experience. We see a negative and significant 0.7% coefficient on this variable. Combining the two experience effects we see a concave relationship between salary and experience. As a free agent receiver gains more experience he sees a positive effect on his salary but the effect increases at a decreasing rate. The breakeven point for experience occurs around the seventh year for receivers. Even if learning is still occurring for receivers after seven years, their physical skills are depreciating faster. The receiver's age and wear and tear on his body are slowing him down. It is logical that we would see the negative impacts of experience dominate in this range. These results are consistent with previous research.

As we see with the other positions, a receiver's individual performance has a strong impact on his pay. Numerous individual performance variables are included in the final regression, and other variables and different specifications of these variables were attempted in other regressions. Focusing on the significant variables, we find strong positive coefficients on r*eceiving yards* and *kick/punt return yards*. *Receiving yards* is defined as the total net yards a receiver gained catching the ball. Obviously, I expect a positive effect from this variable; catching the ball is a receiver's main job on the team. The total net yards a receiver gained while returning kickoffs and/or punts is the

[53] One could argue that non-linearites may exist in the returns to many of the variables included in this study, particularly some of the individual performance variables. However, there is a strong argument for including the squared term for experience: 1) Quadratics in experience are standard in wage equations and 2) NFL players have unusually short careers, which strongly suggests a quadratic in experience. There is nothing in the rest of the variables that makes such an *a priori* case for a quadratic.

receiver's *kick/punt return yards*. There is a 0.1% return to each additional yard receiving and approximately the same, 0.1% return to each additional yard gained returning a kick. These translate into a 50% increase in salary for a receiver with 500 more yards receiving (or returning kicks), all else equal. These results provide evidence that teams appear to place a high value on receivers who also return kicks. In the environment that exists in the NFL, with a salary cap and limited roster, it is not surprising that a multi-faceted player is rewarded accordingly.

The variables *games started* and *total Pro Bowl selections (t-2),* both defined earlier in the chapter, have the expected positive and significant results. The results for both variables are strikingly similar to those of free agent backs in the previous section and therefore do not warrant any additional discussion. Unlike with free agent backs, the coefficient for *games played* is insignificant for receivers. The variable *released*, defined earlier in the chapter, has the expected strong negative 42% impact on a receiver's salary. The variable *attended BCS eligible school,* defined earlier, has the similar, negative result we have seen for the other positions. The way the regressions are specified, I believe this variable is picking up an "underdog effect". Those who attended smaller or lesser known football institutions see a positive impact on their pay.

The *franchise/transition player* is a dummy variable that equals one if the player is designated as a franchise or transition player as defined in section 3.1.1 and zero otherwise. By definition, a player who receives one of these designations is highly paid and therefore, the strong positive 71% impact on salary is expected. It is interesting to note that there were no franchise or transition designations on any quarterbacks or running backs during the time period of this study. These designations are not typically used on these positions. When a team wants to keep a quarterback or running back, it usually compensates them accordingly and keeps them under contract to preclude negotiations with other teams.

The results for receivers who are allowed to become free agents and for receivers who are allowed to become free agents AND switch teams are very different from those we have seen thus far. The variable *free agent* is a dummy variable that equals one if the eligible player is allowed to become a "free agent," meaning he is NOT under contract and is free to negotiate with many teams. We see that a receiver who is allowed to become a free agent sees a 33% reduction in his salary. Essentially, allowing him to become a "free agent" is like a downgrade from his current team. It does not consider the receiver essential to the team. Otherwise, the team would give him a contract and not allow him to become a free agent. However, we see a positive and significant 33% return for a free agent receiver that switches teams. The variable *free agent who switched teams* is defined earlier in the chapter. Referring back to the human capital accumulation argument given earlier in the chapter, the skill positions of quarterback and running back accumulate more specific human capital than a position like receiver. The more general human capital accumulated by a receiver is more easily transferable to another team. When a free agent receiver switches teams, he is worth less to his current team than he is to the new team and he is paid a substantial premium for the new fit. Therefore, the large, positive result for a free agent receiver who switches teams reinforces the earlier hypothesis.

6.4 Regression Model and OLS Results for Offensive Linemen

The main jobs of the offensive lineman are to protect the quarterback on passing plays and block for the running back on running plays. There are three types of offensive lineman: centers, guards and tackles. While each is used differently, their main jobs are the same. Strength, agility and football intelligence are important for the offensive lineman. Although the offensive lineman is a member of the offense, his job is mainly a defensive one. Therefore, unlike with the other offensive positions, there are few well defined individual performance measures for the lineman.

Table 6.7 contains the descriptive statistics for the variables used in the final parsimonious regression model for free agent linemen. Appendix A defines all of the variables attempted in alternative specifications of the linemen regression model.

Table 6.7
Descriptive Statistics of Free Agent Offensive Linemen

VARIABLE	MEAN	STD DEVIATION
Log of total salary (t)	13.984	0.751
Dummy for offensive tackle	0.350	0.478
Attended BCS eligible school	0.792	0.406
Height	76.364	1.560
Year (t)	1999.019	0.807
Player who switched teams	0.240	0.428
Released (t)	0.081	0.273
Free Agent (t)	0.267	0.443
Franchise/Transition player	0.013	0.115
Games played (t-1)	13.895	3.818
Games started (t-1)	11.253	6.108
Not drafted	0.167	0.374
Drafted as a Junior	0.022	0.145
Experience (t)	6.960	2.890
Experience squared (t)	56.765	49.469
Free agent who switched teams	0.156	0.364
Draft number in first round	3.116	7.331
Draft number (recoded)	169.065	106.285
Super Bowl winner (t -1)	0.040	0.197
Selected to Pro Bowl (t -1)	0.116	0.321
Average salary of offensive lineman	985764.871	274102.757
Team sacks allowed	24.663	21.367
Population of MSA	1094521.976	1821708.206
N = 371		

The final specification of the regression model for free agent linemen is:

$$(6.5)\quad \ln(Salary_i) = \alpha_0 + \alpha_1\,\textit{Offensive Tackle} + \alpha_2\,\textit{Attended BCS Eligible School} + \alpha_3\,\textit{Height} + \alpha_4\,\textit{Not Drafted} + \alpha_5\,\textit{Drafted as a Junior} + \alpha_6\,\textit{Year} + \alpha_7\,\textit{Free Agent} + \alpha_8\,\textit{Population of MSA} + \alpha_9\,\textit{Released} + \alpha_{10}\,\textit{Franchise/Transition Player} + \alpha_{11}\,\textit{Player who Switched Teams} + \alpha_{12}\,\textit{Games Played} + \alpha_{13}\,\textit{Games Started} + \alpha_{14}\,\textit{Super Bowl Winner} + \alpha_{15}\,\textit{Average Salary of Offensive Lineman} + \alpha_{16}\,\textit{Experience} + \alpha_{17}\,\textit{Experience Squared} + \alpha_{18}\,\textit{Free Agent who Switched Teams} + \alpha_{19}\,\textit{Draft Number} + \alpha_{20}\,\textit{Draft Number in First Round} + \alpha_{21}\,\textit{Selected to Pro Bowl (t-1)} + \alpha_{22}\,\textit{Team Sacks Allowed} + \varepsilon_i.$$

The results of the OLS regression for free agent linemen are contained in Table 6.8. Many additional variables were attempted in various alternative specifications of the linemen model.

The dependent variable is the *natural logarithm of total salary*, which is the player's base salary plus prorated bonuses. The independent variables are *Offensive Tackle, Attended BCS eligible school, Height, Not drafted, Drafted as a junior, Year, Free Agent, Population of MSA, Released, Franchise/Transition player, Player who switched teams, Games played, Games started, Super Bowl winner, Average salary of offensive lineman, Experience, Experience squared, Free Agent who switched teams, Draft number, Draft number in first round, Selected to Pro Bowl (t-1) and Team sacks allowed.*

Table 6.8
Results of the OLS Estimation for Free Agent Offensive Linemen

Variable	Estimated Coefficient	Standard Error	t statistic	Pr > |t|
(Constant)	-104.032	68.854	-1.511	0.132
Dummy for offensive tackle	0.166**	0.062	2.666	0.008
Attended BCS eligible school	-0.137*	0.066	-2.084	0.038
Height	-0.032	0.018	-1.776	0.077
Year (t)	0.060	0.034	1.731	0.084
Player who switched teams	-0.370**	0.130	-2.845	0.005
Released (t)	-0.443**	0.132	-3.350	0.001
Free Agent (t)	-0.319**	0.080	-3.961	< 0.001
Franchise/Transition player	0.508*	0.208	2.440	0.015
Games played (t-1)	-0.031**	0.008	-3.892	< 0.001
Games started (t-1)	0.068**	0.005	13.115	< 0.001
Not drafted	0.227*	0.098	2.318	0.021
Drafted as a Junior	0.349*	0.171	2.036	0.043
Experience (t)	0.119**	0.045	2.631	0.009
Experience squared (t)	-0.006*	0.003	-2.286	0.023
Free agent who switched teams	0.404**	0.161	2.515	0.012
Draft number in first round	0.010*	0.004	2.304	0.022
Draft number (recoded)	0.001**	0.000	3.244	0.001
Super Bowl winner (t -1)	0.257*	0.133	1.940	0.053
Selected to Pro Bowl (t -1)	0.182*	0.081	2.244	0.025
Average salary of offensive lineman	< 0.001**	0.000	4.180	< 0.001
Team sacks allowed	-0.002	0.001	-1.665	0.097
Population of MSA	< 0.001	0.001	1.883	0.060
Adjusted R^2 = 0.634 N = 371	F = 30.180	Dependent Variable = LNTOTSAL		
* significant at 5% level ** significant at 1% level				

Overall, the results for the offensive linemen vary significantly from those of the previously discussed offensive positions. The performance measures used for these defensive- minded offensive players are very different from the individual performance measured presented thus far. The performance measures for the offensive linemen are more team oriented due to the nature of the position and the lack of data on individual performance for this position.

The only position thus far where there is a significant pay difference for different sub-positions is among the offensive linemen. There is a significant 16% return to being an offensive tackle. The tackle protects the very vulnerable outside of the offensive line.

Therefore, one could posit that an offensive tackle needs to be more agile and keen in reading defensive plays and is paid more as a result. According to the Weisman (2006), the average salary of an offensive tackle is on par with that of quarterbacks and running backs at over three million dollars. It is the left tackle, in particular, that protects the blind side of the quarterback and therefore is usually the most skilled of the tackles (Lewis, 2006; Weisman, 2006).

While there are substantial differences between the coefficients in the regression model for free agent offensive linemen and that of receivers, there are also many similarities. One could argue that offensive lineman, like receiver, is a relatively "less skilled" offensive position than quarterback or running back. He generally accumulates less specific human capital and more general human capital relative to the skilled positions. Additionally, the offensive lineman is more dependent on other positions, mainly his other offensive linemen, while the "skill positions" can be more independent players.

If offensive linemen accumulate largely general human capital then we should see similar results for offensive linemen and receivers regarding free agency status. Indeed, we do see that these "less skilled" positions have similar returns to free agency status. An offensive lineman who is allowed to become a free agent sees a 32% reduction in salary; a receiver in this category sees a 33% reduction. Being allowed to become a "free agent" means he is being downgraded by his current team. The team no longer considers this player essential. Therefore, at least initially, it does not offer him a contract and allows him to negotiate with other teams.

Similar again to the results for receivers, we see a positive 40% return for a free agent lineman that switches teams. The more general human capital accumulated by a lineman is more easily transferable to another team. This result indicates that although his current team does not value him enough to re-sign him, other teams do. Another team pays a substantial premium to get him. The dummy variables, *franchise/transition player*, *player who switched teams* and r*eleased* have the expected results which are very similar to those of the receivers and therefore are not discussed any further in this section.

Games played and g*ames started* are significant and have the expected results. However, the coefficients on these two variables are more than double those reported in the salary model for receivers. The larger effects on linemen are explained by the lack of individual performance measures included in their salary equation. *Experience* and *experience squared* are significant and have the expected signs. The coefficient estimates are similar to those in the receivers model. However, the breakeven point after which the negative impact of experience dominates occurs later for offensive linemen, not until almost ten years into their careers. The mean of the *experience* variable is about seven years. Therefore most offensive linemen see positive returns to experience for their entire careers.

Offensive linemen face some of the usual effects of the draft, and they face unique returns from the draft. For example, linemen who were not drafted see an unexpected 23% increase in salary compared to their drafted counterparts, all else equal. We see in the next section that linebackers see a similar positive return to not being drafted. The variable *draft number in the first round* is significant for the first time in this study in the salary equation for offensive linemen. The variable is recoded to reflect a positive relationship between draft number and expectations for a player. A lineman who is drafted in the first round sees a 1% increase for each higher position in that round; an offensive lineman drafted 1st sees a 30% higher salary than an offensive lineman who is drafted in the 30th position in the first round, all else equal. We find the expected positive and significant returns for *draft number* and *drafted as a junior.* Taking these results together, we see that being drafted late is worse than not being drafted, for offensive linemen that make the team. Basically, teams knew who the player was (he was drafted), they were just not that impressed and drafted the player late. On the other hand, the un-drafted player who made the squad and performs similarly to the late drafted lineman, is a pleasant surprise. This result is analogous to that of the players coming from non-BCS eligible schools in the quarterback and receiver equations.

We see with the other positions that a player's individual performance has a strong impact on his pay. Unfortunately, there are not clear individual performance measures for the offensive linemen. Therefore, team effects are included and found to play a significant role in salary determination for offensive linemen. The dummy variable *Super Bowl winner* equals one if the offensive lineman's team was the Super Bowl winner in the prior season and zero otherwise. There is a 26% return to being an offensive lineman on the Super Bowl winning team. The *average salary of an offensive lineman* is the yearly average salary of a free agent offensive lineman on each team in the current season. This variable is included to see if teams view good offensive linemen as complements and are therefore willing to pay a premium to assemble a strong offensive line. Consistent with the literature finding complementarity in the production process in hockey, I find that NFL teams view offensive linemen as complements. The salary of an offensive lineman increases 1% for each additional $1000 increase in the average salary of offensive linemen on his team.

The most important job of the offensive line is to protect the marquee player, the quarterback, on passing plays. Although I cannot isolate the amount of sacks allowed by an individual offensive lineman, I do have information on the number of sacks allowed by the team in the prior year. The variable *team sacks allowed* shows a significant 0.2% reduction in the salary of an offensive lineman for each additional sack allowed by his line in the previous season. This means an offensive lineman sees a 5% pay decrease for every 25 additional sacks allowed by his line. This is additional evidence that good offensive linemen are viewed as complements. A good offensive lineman is paid more on a team with a good offensive line, all else equal.

When an offensive lineman is selected to play in the Pro Bowl, he is considered a superstar offensive lineman and can expect an increase in salary the following season. An offensive lineman who was selected to the Pro Bowl receives 18% more than his counterpart who was not selected to the Pro Bowl.   The variable *attended BCS eligible school*, defined earlier, has the expected 14% reduction in salary. The way the regressions are specified, this variable is picking up an "underdog effect". Those who attended smaller or lesser known football institutions see a positive impact on their pay.

Height is significant and surprisingly negative for an offensive lineman. A taller offensive lineman sees a 3% reduction in salary for each additional inch. The mean height of a lineman is over six feet four inches. It is fair to say that none of the lineman would be considered short by average standards for the population. The negative result might indicate that a relatively low center of gravity is an advantage for a lineman.

Another surprising result is the significance of the *population of MSA* variable. There is a 1% premium paid for each 1000 additional people in the MSA. This variable is only significant for two positions: the offensive linemen and the defensive linemen. With the strict revenue sharing in the league it is surprising to find that a large market team would pay a player more. Linemen on both sides of the ball are probably the least known players on the team to fans. Perhaps the large local fan base leads to some unseen or difficult to quantify benefits for the team. However, if this is true it is surprising that this variable is significant only for the offensive and defensive linemen.

6.5 Regression Model and OLS Results for Linebackers

The linebacker is a defensive player whose main job is to prevent the advance of the football. He tries to pressure the quarterback on passing plays and stop the run on running plays. Strength, agility and football intelligence are important for the linebacker. There are several standard measures of individual performance measures for linebackers but fewer than we have for the skill positions.

Table 6.9 contains the descriptive statistics for the variables used in the final parsimonious regression model for free agent linebackers. Appendix A defines all of the variables attempted in alternative specifications of the linebackers regression model.

Table 6.9
Descriptive Statistics of Free Agent Linebackers

VARIABLE	MEAN	STD DEVIATION
Log of total salary (t)	13.829	0.764
Degree	0.362	0.482
Weight	243.341	9.078
Height	73.913	1.348
Not drafted	0.127	0.333
Switched Teams	0.294	0.456
Year (t)	1998.975	0.815
Free Agent (t)	0.272	0.448
Released (t)	0.138	0.345
Franchise/Transition Player (t)	0.004	0.060
Games played (t-1)	14.478	3.120
Games started (t-1)	9.873	6.562
Sacks (t-1)	2.109	2.717
Opponent Points Allowed	324.580	62.787
Experience (t)	6.656	2.371
Experience squared (t)	49.902	37.169
Free agent who switched teams	0.149	0.356
Round drafted (recoded)	8.746	3.815
Total Pro Bowl selections to t-2	0.609	1.472
Selected to Pro Bowl (t-1)	0.120	0.325
N = 276		

The final specification of the regression model for free agent linemen is:

$$(6.6)\quad \ln(Salary_i) = \alpha_0 + \alpha_1\,Degree + \alpha_2\,Weight + \alpha_3\,Height + \alpha_4\,Not\ Drafted + \alpha_5\,Switched\ Teams + \alpha_6\,Year + \alpha_7\,Free\ Agent + \alpha_8\,Opponent\ Points\ Allowed + \alpha_9\,Released + \alpha_{10}\,Franchise/Transition\ Player + \alpha_{11}\,Sacks + \alpha_{12}\,Games\ Played + \alpha_{13}\,Games\ Started + \alpha_{14}\,Experience + \alpha_{15}\,Experience\ Squared + \alpha_{16}\,Free\ Agent\ who\ Switched\ Teams + \alpha_{17}\,Round\ Drafted + \alpha_{18}\,Total\ Pro\ Bowl\ Selections\ (t\text{-}2) + \alpha_{19}\,Selected\ to\ Pro\ Bowl\ (t\text{-}1) + \varepsilon_i.$$

The results of the OLS regression for free agent linebackers are contained in Table 6.10. Many additional variables were attempted in various alternative specifications of the linebackers model.

The dependent variable is the *natural logarithm of total salary,* which is the player's base salary plus prorated bonuses. The independent variables are *Degree, Weight, Height, Not drafted, Player who switched teams, Year,, Free Agent, Opponent points allowed, Released, Franchise/Transition player, Sacks, Games played, Games* *started, Experience, Experience squared, Free Agent who switched teams, Round drafted, Total Pro Bowl Selections (t-2) and Selected to the Pro Bowl (t-1).*

Many of the variables found to significantly affect the salary of linebackers have been defined and discussed in previous sections. In order to avoid redundancy, I limit my discussions to those variables with surprising results or interesting trends that have not been discussed in previous sections.

Table 6.10
Results of the OLS Estimation for Free Agent Linebackers

Variable	Estimated Coefficient	Standard Error	t statistic	Pr > |t|
Constant	-189.469**	62.212	-3.046	0.003
Degree	-0.085	0.054	-1.582	0.115
Weight	0.005	0.003	1.417	0.158
Height	-0.041	0.022	-1.875	0.062
Not drafted	0.318**	0.122	2.611	0.010
Switched Teams	-0.370**	0.114	-3.242	0.001
Year (t)	0.102**	0.031	3.289	0.001
Free Agent (t)	-0.255**	0.080	-3.186	0.002
Released (t)	-0.398**	0.113	-3.517	0.001
Franchise/Transition Player (t)	0.941*	0.427	2.206	0.028
Games played (t-1)	-0.026**	0.009	-3.021	0.003
Games started (t-1)	0.055**	0.005	11.260	< 0.001
Sacks (t-1)	0.055**	0.011	4.793	< 0.001
Opponent Points Allowed	0.001	0.001	1.236	0.218
Experience (t)	0.082	0.063	1.306	0.193
Experience squared (t)	-0.006	0.004	-1.522	0.129
Free agent who switched teams	0.324*	0.144	2.252	0.025
Round drafted (recoded)	0.038**	0.012	3.285	0.001
Total Pro Bowl selections to t-2	0.067**	0.023	2.894	0.004
Selected to Pro Bowl (t-1)	0.198*	0.093	2.132	0.034

Adjusted R^2 = 0.712 N = 276 F = 36.769 Dependent Variable = LNTOTSAL
* significant at 5% level ** significant at 1% level

The salary equation for linebackers is the first that has the variable d*egree* in the final specification. *Degree* is a dummy variable that equals one if a player has a college degree and zero if he does not. This variable was tested for every position but was close to significant only for linebackers. However, the coefficient estimate is in the wrong direction. Conventional wisdom and economic theory indicate that there is a positive relationship between education (or having a degree) and pay. It is possible that a negative relationship could exist if indeed the player split his time between studying and football but, it is unlikely that we would see this relationship still exist after a player has at least four years tenure in the league.

Height has a significant negative effect and *not drafted* has a significant positive effect on the salary of a linebacker. Both of these relationships are the opposite of what is expected but ironically, they are the same unexpected results that we see for offensive linemen.

The results for the player status variables for linebackers (*released, switched teams, free agent, franchise/transition player and free agent who switched teams*) are strikingly similar to the results for these variables in the offensive linemen and receivers equations. The results for *games played* and g*ames started* for linebackers also mirror the results for offensive linemen and receivers. Unlike the results for receivers and offensive linemen but similar to results for quarterbacks and running backs, experience does not have a significant effect on the pay of linebackers.

The individual performance statistics for linebackers are *sacks* and *interceptions*. *Sacks* is a discrete variable measuring the number of times a player "sacked" or tackled the quarterback for a loss of yardage. *Interceptions* is a discrete variable measuring the number of times a player intercepted a pass. Typically a linebacker will have more sacks than interceptions but the ratio will vary depending on whether he plays inside or outside linebacker. The *interceptions* variable had no significant effect on the pay of a linebacker and was deleted from the final regression equation. In contrast, the number of sacks a linebacker has is an important determinant of his salary. A linebacker receives a 5.5% return for each additional sack. This result reinforces previous findings that individual player performance has a strong impact on his pay in the NFL.

After recoding, the round in which a linebacker was drafted exhibits the expected positive relationship. A linebacker experiences a 4% increase in pay for each higher round drafted compared to another player. This means that a linebacker drafted in the 1st round earns 20% more than a linebacker drafted in the 5th round, all else equal.

Linebacker is the first position for which both lifetime Pro Bowl selections and being selected to the most recent Pro Bowl affect a player's salary. We find the expected positive relationships for both Pro Bowl variables. The magnitude on the coefficients is also as we would expect with the most recent selection (s*elected to Pro Bowl (t-1)*) being triple the magnitude of the lifetime Pro Bowl selections (t*otal Pro Bowl Selections to (t-2)*). Theory predicts that a player's recent performance should have a stronger impact on his pay than distant performance. The incentive clauses and lack of guaranteed contracts in the NFL allow players to capitalize on their good performance and they allow teams to penalize players with poor performance.

6.6 Regression Model and OLS Results for Cornerbacks

The cornerback is a defensive player whose main job is to cover wide receivers and prevent them from receiving and advancing the football. Strength, speed, agility and football intelligence are important for the cornerback. There are several standard measures of individual performance for cornerbacks but fewer than we have for the skill positions.

Table 6.11 contains the descriptive statistics for the variables used in the final parsimonious regression model for free agent cornerbacks. Appendix A defines all of the variables attempted in alternative specifications of the cornerbacks regression model.

Table 6.11
Descriptive Statistics of Free Agent Cornerbacks

VARIABLE	MEAN	STD DEVIATION
Log of total salary (t)	13.991	0.853
Weight	189.899	11.163
Attended BCS eligible school	0.815	0.390
Not drafted	0.051	0.220
Year (t)	1999.000	0.817
Free Agent (t)	0.270	0.445
Traded (t)	0.0170	0.129
Released (t)	0.135	0.343
Player who switched teams	0.343	0.476
Games played (t-1)	14.258	3.209
Games started (t-1)	9.680	6.384
Interceptions (t-1)	2.242	2.119
Sacks (t-1)	0.486	0.858
Free agent who switched teams	0.174	0.380
Drafted in first round	0.264	0.442
Selected to Pro Bowl (t-1)	0.112	0.317
N = 178		

The final specification of the regression model for free agent cornerbacks is:

$$(6.7)\quad \ln(Salary_i) = \alpha_0 + \alpha_1\, Weight + \alpha_2\, Attended\ BCS\ Eligible\ School + \alpha_3\, Not\ Drafted + \alpha_4\, Year + \alpha_5\, Free\ Agent + \alpha_6\, Traded + \alpha_7\, Released + \alpha_8\, Player\ who\ Switched\ Teams + \alpha_9\, Games\ Played + \alpha_{10}\, Games\ Started + \alpha_{11}\, Interceptions + \alpha_{12}\, Sacks + \alpha_{13}\, Free\ Agent\ who\ Switched\ Teams + \alpha_{14}\, Drafted\ in\ First\ Round + \alpha_{15}\, Selected\ to\ Pro\ Bowl\ (t\text{-}1) + \varepsilon_i.$$

The results of the OLS regression for free agent cornerbacks are presented in Table 6.12.

The dependent variable is the *natural logarithm of total salary*, which is the player's base salary plus prorated bonuses. The independent variables are *Weight,* *Attended BCS eligible school, Year, Free Agent, Traded, Released, Player who switched teams, Games played, Games started, Interceptions, Sacks, Free Agent who switched teams, Drafted in first round and Selected to the Pro Bowl (t-1).*

Many of the variables found to significantly affect the salary of cornerbacks have been defined and discussed in previous sections. In order to avoid redundancy, I limit my discussions to those variables with surprising results, interesting trends, or those which have not been discussed in previous sections.

Table 6.12
Results of the OLS Estimation for Free Agent Cornerbacks

Variable	Estimated Coefficient	Standard Error	t statistic	Pr > |t|
Constant	-132.647	81.536	-1.627	0.106
Weight	0.014**	0.003	4.371	< 0.001
Attended BCS eligible school	-0.219**	0.088	-2.491	0.014
Not drafted	-0.603**	0.155	-3.882	< 0.001
Year (t)	0.072	0.041	1.768	0.079
Free Agent (t)	-0.416**	0.122	-3.401	0.001
Traded (t)	-0.544	0.314	-1.733	0.085
Released (t)	-0.619**	0.188	-3.299	0.001
Player who switched teams	-0.260	0.190	-1.369	0.173
Games played (t-1)	-0.040**	0.012	-3.256	0.001
Games started (t-1)	0.056**	0.007	8.224	< 0.001
Interceptions (t-1)	0.038*	0.019	2.038	0.043
Sacks (t-1)	-0.060	0.039	-1.529	0.129
Free agent who switched teams	0.277	0.231	1.200	0.232
Drafted in first round	0.246**	0.082	3.010	0.003
Selected to Pro Bowl (t-1)	0.319**	0.115	2.761	0.006

Adjusted R^2 = 0.747 N = 178 F = 35.838 Dependent Variable = LNTOTSAL
* significant at 5% level ** significant at 1% level

Cornerbacks are the first position for which a player's weight affects his salary. Later we see a similar relationship exists for safeties. There is a positive 1% return for each additional pound on a cornerback. The mean weight of a cornerback is just under 190 pounds which is relatively thin for an NFL player. Additional weight on a cornerback is more than likely from additional muscle which translates into additional strength and perhaps better tackling. Weight is a proxy for strength in this salary equation; the stronger the cornerback, the better he can tackle and the more he is paid all else equal.

Many of the variables in the salary equation for cornerbacks have the expected relationships that we have seen in prior positional salary equations. The variables *attended BCS eligible school, not drafted, free agent, released, games played, games started, and selected to Pro Bowl (t-1)* have the expected sign and significance as discussed in previous sections and therefore need no further discussion.

The variable *traded* has a large and surprisingly negative 62% return. Less than 2% of the cornerbacks in the study were traded. It is also possible that the receiving team(s) was salary cap constrained, needed a cornerback and traded for a particular cornerback knowing that they could pay him less. In any case, it is very difficult to decipher what is driving this surprising result given the available data.

The variables *player who switched teams* and *free agent who switched teams* have the expected signs and coefficient estimates within the ranges established in earlier sections but, neither of them is significant. This insignificance is unexpected because we have seen a similar relationship between these variables for all but the "skill positions".

As predicted, individual performance plays a role in salary determination for cornerbacks[54]. A corner sees a 4% return for each additional interception he makes. The variable *sacks* was also included but the coefficient is insignificant. Due to the nature of

[54] There was no data readily available for tackles for the years of this study. I do have data on tackles for later years and will use it to extend the study in the future.

the position, we would expect that interceptions would play a larger role in salary determination than sacks as cornerbacks have more interceptions than sacks.

As we have seen for every other position, draft position plays a role in salary determination for free agent cornerbacks. Corners who are drafted in the first round receive a 25% premium compared to a corner that was not drafted in the first round holding all else constant. *Drafted in the first round* is also significant for defensive linemen and safeties. Additionally, the coefficient estimate is nearly the same for all three positions. It is surprising that there is still such a large return to be being drafted in the first round so many years after the draft occurred. I believe that the consistent and long lasting effect of the draft is due to the fact that there are so few individual performance measures for these defensive players. If I had data on tackles or some other accurate individual performance measures for these positions, the draft effect may not be so large.

6.7 Regression Model and OLS Results for Defensive Linemen

The defensive lineman's main job is to disrupt offensive plays. He pressures the quarterback, stops runs and does anything he can to negate the forward progress of the offense. Strength, endurance, agility and football intelligence are important for the defensive lineman. There are only a couple standard measures of individual performance for defensive linemen.

Table 6.13 contains the descriptive statistics for the variables used in the final parsimonious regression model for free agent defensive linemen. Appendix A defines all of the variables attempted in alternative specifications of the defensive linemen regression model.

Table 6.13
Descriptive Statistics of Free Agent Defensive Linemen

VARIABLE	MEAN	STD DEVIATION
Log of total salary (t)	14.046	0.768
Dummy for defensive tackle	0.439	0.497
Attended BCS eligible school	0.801	0.400
Win percentage (t-1)	0.505	0.209
Year (t)	1999.017	0.819
Player who switched teams	0.243	0.430
Released (t)	0.066	0.249
Free Agent (t)	0.271	0.445
Games played (t-1)	13.798	4.014
Games started (t-1)	10.080	6.541
Sacks (t-1)	4.203	3.851
Opponent points allowed	326.884	69.599
Experience (t)	6.525	2.322
Experience squared (t)	47.950	36.825
Free agent who switched teams	0.166	0.372
Drafted in first round	0.287	0.453
Round drafted (recoded)	9.459	3.999
Total Probowl selections to t-2	0.577	1.645
Selected to Pro Bowl (t-1)	0.088	0.284
Playoff team (t-1)	0.274	0.446
Population of MSA	1121312.133	1868069.809
N = 362		

The final specification of the salary model for free agent defensive linemen is:

$$(6.8)\quad \ln(Salary_i) = \alpha_0 + \alpha_1\, Defensive\ Tackle + \alpha_2\, Attended\ BCS\ eligible\ school + \alpha_3\, Free\ Agent + \alpha_4\, Year + \alpha_5\, Released + \alpha_6\, Player\ who\ Switched\ Teams + \alpha_7\, Games\ Played + \alpha_8\, Games\ Started + \alpha_9\, Sacks + \alpha_{10}\, Drafted\ in\ First\ Round + \alpha_{11}\, Round\ Drafted + \alpha_{12}\, Opponent\ Points\ Allowed + \alpha_{13}\, Win\ Percentage + \alpha_{14}\, Experience + \alpha_{15}\, Experience\ Squared + \alpha_{16}\, Free\ Agent\ who\ Switched\ Teams + \alpha_{17}\, Playoff\ Team + \alpha_{18}\, Total\ Pro\ Bowl\ Selections\ (t\text{-}2) + \alpha_{19}\, Selected\ to\ Pro\ Bowl\ (t\text{-}1) + \alpha_{20}\, Population\ of\ MSA + \varepsilon_i.$$

The results of the OLS regression for free agent defensive linemen are contained in Table 6.14.

The dependent variable is the *natural logarithm of total salary*, which is the player's base salary plus prorated bonuses. The independent variables are *Defensive*

Tackle, Attended BCS eligible school, Free Agent, Year, Released, Player who switched teams, Games played, Games started, Sacks, Drafted in first round, Round drafted, Oppoent Points Allowed, Win Percentage, Experience, Experience squared, Free Agent who switched teams, Playoff team, Total Pro Bowl Selections (t-2, Selected to the Pro Bowl (t-1) and Population of MSA.

As with the last few positions, many of the variables that significantly affect the salary of defensive linemen have been defined and discussed in previous sections. In order to avoid redundancy, I limit my discussions to those variables with surprising results, interesting trends, or those that have not been discussed in previous sections.

Table 6.14
Results of the OLS Estimation for Free Agent Defensive Linemen

Variable	**Estimated Coefficient**	**Standard Error**	**t statistic**	**Pr > |t|**
(Constant)	-213.020**	65.432	-3.256	0.001
Dummy for defensive tackle	0.162**	0.059	2.748	0.006
Attended BCS eligible school	-0.214**	0.071	-3.022	0.003
Experience (t)	0.078	0.066	1.185	0.237
Free Agent (t)	-0.377**	0.091	-4.154	< 0.001
Year (t)	0.113**	0.033	3.448	0.001
Released (t)	-0.540**	0.131	-4.138	< 0.001
Player who switched teams	-0.336**	0.122	-2.763	0.006
Games played (t-1)	-0.020*	0.009	-2.224	0.027
Games started (t-1)	0.040**	0.006	7.006	< 0.001
Sacks (t-1)	0.025**	0.010	2.643	0.009
Selected to Pro Bowl (t-1)	0.277**	0.112	2.466	0.014
Experience squared (t)	-0.006	0.005	-1.389	0.166
Free agent who switched teams	0.364*	0.156	2.339	0.020
Drafted in first round	0.227**	0.075	3.028	0.003
Round drafted (recoded)	0.028**	0.008	3.360	0.001
Total Pro Bowl selections to t-2	0.051*	0.026	2.003	0.046
Opponent points allowed	0.002**	0.001	3.956	< 0.001
Win percentage (t-1)	0.682**	0.202	3.369	0.001
Playoff team (t-1)	-0.233**	0.088	-2.641	0.009
Population of MSA	< 0.001	< 0.001	-1.761	0.079
Adjusted R^2 = 0.585 N = 362 F = 26.468 Dependent Variable = LNTOTSAL				
* significant at 5% level ** significant at 1% level				

Defensive linemen are split into two sub-positions: defensive ends and defensive tackles. The defensive linemen attempt to maintain their original formation while preventing the advance of the ball. Defensive tackles are usually strongest of the defensive players and the best tacklers on the team. Defensive tackles are more skilled at stopping the run while, defensive ends are smaller, faster, more skilled pass rushers. The positive coefficient on the dummy variable for defensive tackles indicates that they are paid 16% more than defensive ends, all else equal. This result is similar to that for offensive linemen, where the offensive tackles are paid a premium.

Similar to the other positions discussed, individual performance plays an important role in salary determination for defensive linemen. A defensive lineman earns a 2.5% increase in salary for each additional sack he obtains. Team performance also proves important for the salary of the defensive lineman. *Opponent points allowed* is the total number of points other teams scored against the defensive lineman's team in the previous season. A defense which allows relatively fewer points is generally considered a good defense. A defensive lineman sees a 0.2% increase in salary for each additional point allowed by his team. This means that a defensive lineman earns less playing on a team that had a relatively strong defense in the previous season. This result is the opposite of what one would expect. Additionally, a defensive lineman playing on a team that made the playoffs in the previous season sees a 23% reduction is his salary, all else equal. Both of these results are difficult to explain given the limitations of the data available. There is no way to know when a player his signed his current contract and therefore no way to know if he was signed in an effort to improve a weak defense or whether his team chose to spend its resources on a high scoring offense.

Another interesting result for defensive linemen, especially considering the lack of many individual performance measures, is the insignificance of the *experience* and *experience squared* variables.

6.8 Regression Model and OLS Results for Safeties

The safety is a defensive player whose main job is to cover the pass and impede the forward progress of the ball. The safety is also called on at times to block the run and rush the quarterback. A safety is expected to be a strong tackler; many times, he is the "last defense" on the field. Strength, speed, agility and football intelligence are important for the safety.

Table 6.15 contains the descriptive statistics for the variables used in the final parsimonious regression model for free agent safeties.

Table 6.15
Descriptive Statistics of Free Agent Safeties

VARIABLE	MEAN	STD DEVIATION
Log of total salary (t)	13.768	0.676
Weight	202.801	9.598
Height	71.854	1.486
Year (t)	1998.971	0.822
Player who switched teams	0.251	0.435
Released (t)	0.105	0.308
Free Agent (t)	0.339	0.475
Games played (t-1)	14.532	2.961
Games started (t-1)	10.602	6.426
Interceptions (t-1)	1.865	1.856
Sacks (t-1)	0.643	1.037
Not drafted	0.222	0.417
Drafted as a Junior	0.058	0.235
Experience (t)	6.673	2.461
Experience squared (t)	50.544	39.292
Free agent who switched teams	0.170	0.376
Drafted in first round	0.135	0.342
Draft number (recoded)	179.462	116.969
Selected to Pro Bowl (t -1)	0.105	0.308
Total Pro Bowl selections to t -2	0.696	1.557
Playoff Team (t-1)	24.663	21.367
Population of MSA	1016219.877	1627872.332
N =171		

The final specification of the salary model for free agent safeties is:

$$(6.9)\quad \ln(Salary_i) = \alpha_0 + \alpha_1\, Weight + \alpha_2\, Height + \alpha_3\, Year + \alpha_4\, Player\ who\ Switched\ Teams + \alpha 5\, Released + \alpha_6\, Free\ Agent + \alpha_7\, Games\ Played + \alpha_8\, Games\ Started + \alpha_9\, Interceptions + \alpha_{10}\, Sacks + \alpha_{11}\, Not\ Drafted + \alpha_{12}\, Drafted\ as\ a\ Junior + \alpha_{13}\, Experience + \alpha_{14}\, Experience\ Squared + \alpha_{15}\, Free\ Agent\ who\ Switched\ Teams + \alpha_{16}\, Drafted\ in\ First\ Round + \alpha_{17}\, Draft\ Number + \alpha_{18}\, Selected\ to\ Pro\ Bowl\ (t\text{-}1) + \alpha_{19}\, Total\ Pro\ Bowl\ Selections\ (t\text{-}2) + \alpha_{20}\, Playoff\ Team + \alpha_{21}\, Population\ of\ MSA + \varepsilon_i.$$

The results of the OLS regression for free agent safeties are contained in Table 6.16. Many additional variables were attempted in various alternative specifications of the safeties model. See Appendix A for the list and definitions of these variables.

The dependent variable is the *natural logarithm of total salary*, which is the player's base salary plus prorated bonuses. The independent variables are *Weight, Height, Year, Player who switched teams, Released, Free Agent, Games played, Games* *started, Interceptions, Sacks, Not drafted, Drafted as a Junior, Experience, Experience squared, Free Agent who switched teams, Drafted in first round, Draft number, Selected to the Pro Bowl (t-1), Total Pro Bowl Selections (t-2), Playoff Team, and Population of MSA.*

All of the variables that significantly affect the salary of safeties have been defined and discussed in previous sections. To avoid redundancy, discussion of these variables is not repeated. The table of results is presented for completeness.

Table 6.16
Results of the OLS Estimation for Free Agent Safeties

Variable	**Estimated Coefficient**	**Standard Error**	**t statistic**	**Pr > |t|**
(Constant)	-206.254**	71.877	-2.870	0.005
Weight	0.007	0.004	1.891	0.061
Height	-0.031	0.025	-1.245	0.215
Year (t)	0.110**	0.036	3.059	0.003
Player who switched teams	-0.433**	0.167	-2.594	0.010
Released (t)	-0.357**	0.144	-2.478	0.014
Free Agent (t)	-0.424**	0.089	-4.769	0.000
Games played (t-1)	-0.020	0.011	-1.750	0.082
Games started (t-1)	0.048**	0.006	7.936	< 0.001
Interceptions (t-1)	0.023	0.019	1.215	0.226
Sacks (t-1)	0.066*	0.032	2.062	0.041
Not drafted	-0.239	0.134	-1.782	0.077
Drafted as a Junior	-0.214	0.133	-1.606	0.110
Experience (t)	0.202**	0.073	2.788	0.006
Experience squared (t)	-0.015**	0.005	-3.340	0.001
Free agent who switched teams	0.737**	0.195	3.786	< 0.001
Drafted in first round	0.236*	0.118	2.005	0.047
Draft number (recoded)	-0.001	0.001	-1.393	0.166
Selected to Pro Bowl (t -1)	0.249*	0.109	2.271	0.025
Total Pro Bowl selections to t -2	0.097**	0.027	3.549	0.001
Playoff Team (t-1)	0.147*	0.068	2.175	0.031
Population of MSA	< 0.001	< 0.001	1.584	0.115
Adjusted R^2 = 0.688 N = 171	F = 18.890	Dependent Variable = LNTOTSAL		
* significant at 5% level ** significant at 1% level				

6.9 Summary of Positional Regression Models

This section summarizes the main results of the previous sections. It helps the reader easily compare and contrast the results by variable group across positions. Interesting trends in the results are highlighted but the discussion is kept brief as the results have been discussed in length in previous sections.

Table 6.17
Summary of Player Status Across Position

Variable	QB	RB	WR	OL	LB	CB	DL	S
Released	-0.602*	NS	-0.421*	-0.443*	-0.398*	-0.619*	-0.504*	-0.357*
Free Agent	NS	NS	-0.325*	-0.319*	-0.255*	-0.416*	-0.377*	-0.424*
Free Agent who switched teams	-0.476*	-0.543*	0.326*	0.404*	0.324*	0.277	0.364	0.737*

* significant at 10%
Dependent Variable = LNTOTSAL NS = Not significant and not included in final regression

Table 6.17 presents the summary of player status across the positions. When a player is released there is a definite, large, negative effect on his salary. The variable r*eleased* is negative and significant for seven of the eight positions. NFL teams release players that they do not want or players whose salaries need to be re-negotiated (with more favorable terms for the team) as discussed in previous sections.

The results for the variables *free agent* and *free agent who switched teams* are arguably the most interesting of the paper. When a team allows a player's contract to expire and that player becomes a free agent, it is generally considered a negative. Hence, six of the eight positions see a salary reduction when allowed to become free agents. When a player is a free agent who switches teams, the results are also interesting. For quarterbacks and backs, the two positions where team-specific human capital accumulation is likely to be greatest, free agents who switch teams see drastic reductions in their salaries. The results are mixed for the other six positions where general human capital accumulation is likely to be more important.

Table 6.18
Summary of Experience Across Position

Variable	QB	RB	WR	OL	LB	CB	DL	S
Games Played	0.040[55]*	-0.049*	-0.012	-0.031*	-0.026*	-0.040*	-0.020*	-0.020
Games Started	NS[56]	0.021*	0.029*	0.068*	0.055*	0.056*	0.040*	0.048*
Experience	NS	NS	0.094*	0.119*	0.082*	NS	0.078	0.202*
Experience Squared	NS	NS	-0.007*	-0.006*	-0.006	NS	-0.006	-0.015*

* significant at 10%
Dependent Variable = LNTOTSAL NS = Not significant and not included in final regression

Experience, both tenure and hands-on, is an important component of pay in any profession. Table 6.18 above shows that the relationship is no different for the professional football player. *Games started* is positive and significant for all seven positions. The coefficient also tends to be larger for the positions with fewer individual performance measures and smaller for those positions with more individual performance measures (RB & WR). The variable g*ames played* is negative and significant for five out of the seven positions.

[55] *Games played* for the quarterback regression is interpreted differently in the quarterback model since g*ames started* is not also included in the model. As described in previous sections, g*ames played* picks up the return to a marginal player entering a game when it is included in the same model with g*ames started*. However, in the quarterback model g*ames played* is included in the model without g*ames started*. In this context, the variable is picking up the fact that quarterbacks gain valuable experience when they enter a game and carry out a play, regardless of whether or not they started the game.

[56] The variable g*ames started* was not included in the quarterback regression. Instead, the variable s*tarter* was included for quarterbacks to account for the returns to being a starting quarterback as opposed to a second or third string quarterback.

The relationship for years of experience is not as strong as that of playing experience. *Experience* and e*xperience squared* are significant in half of the positions. The experience relationship is concave for all of those positions. As these players gain more experience they see a positive effect on salary but the effect is increasing at a decreasing rate.

Table 6.19
Summary of Draft Effects Across Position

Variable	QB	RB	WR	OL	LB	CB	DL	S
Not Drafted	-0.946*	-0.285*	-0.126	0.227*	0.318*	-0.603*	NS	-0.239
Drafted as a Junior	0.327*	NS	0.077	0.349*	NS	NS	NS	-0.214
Draft Number	-0.001*	NS	0.006*	0.001*	NS	NS	NS	-0.001
Drafted in 1st Round	NS	0.146*	-0.007*	NS	NS	0.246*	0.227*	0.236*
Round Drafted	NS	NS	-0.159*	NS	0.038*	NS	0.028*	NS

* significant at 10%
Dependent Variable = LNTOTSAL NS = Not significant and not included in final regression

Table 6.19 shows that the overall effect of the draft on salary is mixed. When backs and quarterbacks are not drafted, there is a significant, negative impact on their salaries. No clear pattern exists for undrafted players in other positions. *Drafted as a junior* is significant only for quarterbacks and offensive lineman (two of the highest paid positions on the team). *Drafted in the first round* is positive and significant for four of the eight positions, three of those four are defensive positions with few individual performance measures. With the exception of quarterbacks and wide receivers, generally players who are drafted earlier (those perceived to be better players) see a positive impact on pay[57] even after being in the league for at least four years.

[57]After recoding as described in footnote 54.

Table 6.20
Summary of Pro Bowl Effects Across Position

Variable	QB	RB	WR	OL	LB	CB	DL	S
Total Pro Bowl selections (t-2)	0.121*	0.061*	0.065*	NS	0.067*	NS	0.051*	0.097*
Selected to Pro Bowl (t-1)	NS	NS	NS	0.182*	0.198*	0.319*	0.277*	0.249*

* significant at 10%
Dependent Variable = LNTOTSAL NS = Not significant and not included in final regression

Glancing at Table 6.20, it is obvious that there is an increase in salary from being selected to a Pro Bowl. The positive and significant relationship exists for all positions. The coefficient on being selected to the prior year's Pro Bowl is always larger than that of the lifetime Pro Bowl selections indicating that recent performance has a stronger impact on pay than past performance. Additionally, the impact of being selected to a Pro Bowl(s) is stronger for those positions with fewer individual performance measures (OL, LB, CB, DL, and S). The existence of the positive relationship between Pro Bowl selections and salary, holding performance constant, indicates that these Pro Bowl variables may be proxies for other important aspects of a good player such as leadership and/or football intelligence.

The variable for having attended a BCS eligible school was negative and significant for five out of the eight positions. As discussed in previous sections, I believe this variable is picking up an "under dog" or pleasant surprise. For example, suppose there are two quarterbacks who look similar on paper and have a similar performance record but one attended a BCS eligible school and the other did not. Higher expectations were probably placed upon the quarterback from the BCS eligible school relative to those placed on his counterpart from the non-BCS eligible school. The results show that when the non-BCS player performs above expectations he is rewarded with a higher salary than his BCS counterpart.

Individual performance also plays an important role in salary determination for all positions[58]. Although the applicable individual performance statistic(s) varies across positions, the positive relationship is the same. As expected, individual performance plays an important role in salary determination in the NFL. Those players who perform at a higher level are compensated accordingly.

[58] With the exception of offensive lineman. There was no individual performance data readily available for offensive lineman for the period of my study. I am certain that if the data was available, the same positive relationship would exist for the offensive lineman's salary and his individual performance.

CHAPTER 7 QUANTILE REGRESSION RESULTS

The previous chapter explores the first step in this study of salary determination in the NFL. OLS regressions highlight the relevant market factors that combine to determine salaries for each position in the NFL. The goal of this chapter is to explore the bargaining aspect of McLaughlin's theoretical model as related to the NFL. Quantile regression (QR) is the method used to investigate the effects of bargaining strength on salary in the NFL.

This chapter is organized into three sections. The first section provides a background and brief literature review of quantile regression. The second section contains a detailed description of the specifics of the QR technique. The final section briefly describes the proper techniques for discussion and presentation of QR results. This section also deals with QR specific to this study and contains the QR results for salary determination in the NFL.

7.1 Background of Quantile Regression

The idea of median regression goes back to the 18th century when a Jesuit priest, Fr. Boscovich, went to London for computational help to solve his method of median regression (Koenker, 2000). Median regression minimizes the sum of absolute residuals. Computationally, even up until more recent years, this regression posed a huge challenge. In the 1970s, when computing technology combined with new, algorithmic developments such as linear programming, median regression modeling became more practical (Hao & Naiman, 2007). With today's computer capabilities and the powerful software packages available, fitting a median regression model is not a problem (Hao & Naiman, 2007; Koenker, 2000).

The median is a specific quantile that describes the central location of a distribution. Non-central positions of a distribution are described by specific terms such as quartile, quintile, decile and percentile. A quantile is a general notion that can denote any position of a distribution such that the *p*th quantile represents the value of the response below which the proportion of the population is *p*. In the literature, conditional quantiles are denoted as $Q_y (p|X)$ where $p \in [0,1]$ denotes the quantiles. For example when $p = 0.80$, $Q_y (0.80|X)$ is the 80^{th} percentile of the distribution of *y* conditional on the values of X. In other words, 80% of the population lies below the 80^{th} quantile or said another way, 80% of the values of *y* are less than or equal to the specified function of X (Cade and Noon, 2003; Hao and Naiman, 2007).

Quantile regression was introduced by Koenker and Bassett (1978) as an extension of the linear model for estimating rates of change across the entire distribution of the dependent variable. Ordinary least squares (OLS) regression is based upon the **mean** of the conditional distribution of the dependent variable. This approach implicitly assumes the possible differences in the impact of the exogenous variables along the conditional distribution are not important and are thus, ignored. Unlike OLS, quantile regression models specify changes in the conditional quantile and any quantile can be used. Therefore, QR allows researchers to use the additional information and extend the estimation to allow for a full characterization of the conditional distribution of the dependent variable (Martins and Pereira, 2004).

In contrast to OLS, researchers can use any or many quantiles for QR and therefore model and study any predetermined position of the distribution. This powerful and flexible technique allows economists and other social scientists to tailor their work for their specific interests. They can study the sickest of the sick, the richest of the rich, the smallest of the small babies, the smartest of the smart children and the weakest of the poor achievers.

For obvious reasons the volume of research using this technique is large and rapidly advancing. Much work using QR has been carried out in labor economics. Chamberlain (1994) and Buchinsky (1994) carried out some of the earliest empirical work using QR to study the distribution of wages. Chamberlain focused specifically on the returns to schooling and the union relative wage effect. Buchinsky examined changes in the US wage structure during the period of 1963-1987. Buchinsky (1998) looks at changes in the female wage distribution in the US. Koenker & Bilias (2001) apply QR methods to duration data while re-examining data from Pennsylvania Reemployment Bonus Experiments. The literature also extends to labor markets beyond the United States, including Germany, Portugal (Machado and Mata, 2005) and Spain (Garcia, Hernandez and Lopez-Nicolas, 2001), to name just a few.

The QR technique[59] has allowed researchers to better understand the returns to schooling (Arias, Hallock & Sosa-Escudero, 2001; Eide and Showalter, 1998 and Hartog, Pereira & Vieira, 2001), peer effects and reductions in class size (Levin, 2001). As Koenker and Hallock (2001) put it, there is rapidly expanding empirical quantile

---

[59] For an excellent introduction to and application of quantile regression see the book *Quantile Regression* by Hao and Naiman (2007).

regression literature in economics that, taken as a whole, makes a persuasive case for the value of "going beyond models for the conditional mean" in empirical economics (p 151)." The applications of this powerful method extend far beyond economics. The QR approach is used as a more powerful approach to investigation in Ecology (Cade & Noon, 2003), Sociology, Biology, Medicine and beyond.

7.2 Specifics of the Quantile Regression Model and Technique

Following Martins and Pereira (2004) in a wage equation setting, we can write the quantile regression model as:

$$(7.1) \qquad \ln w_i = x_i\beta_\theta + \mu_{\theta i} \quad \text{with } \mathrm{Quant}_\theta (\ln w_i|x_i) = x_i\beta_\theta$$

where x_i is the vector of exogenous variables and β_θ is the vector of parameters. Quant_θ $(\ln w|x)$ denotes the θth conditional quantile of ln w given x. The θth regression quantile, $0 < \theta < 1$, is defined as a solution to the problem of minimizing $\beta \in R^k$

$$\left\{\sum_{i=ln\, w_i \geq x_i\beta} \theta |\, ln\, w_i - x_i\beta_\theta| \;+ \sum_{i=ln\, w_i < x_i\beta} (1-\theta)\, |ln\, w_i - x_i\beta_\theta|\right\}$$

This is usually written as:

$$(7.2) \qquad \min \beta \in R^k \qquad \sum_i \rho_\theta\, (\ln w_i - \, x_i\, \beta_\theta),$$

where $\rho_\theta(\varepsilon)$ is the check function defined as $\rho_\theta(\varepsilon) = \theta\varepsilon$ if $\varepsilon \geq 0$ or $\rho_\theta(\varepsilon) = (\theta - 1)\varepsilon$ if $\varepsilon < 0$. This problem does not have an explicit form but can be solved by linear programming methods. The QR models in this study are solved using the STATA software package.

The least absolute deviation (LAD) estimator of β is a particular case within this framework. It is obtained by setting $\theta = 0.5$ to get the median regression. The first decile is obtained by setting $\theta = 0.1$ and so on. As θ is increased from zero to one, we trace the whole distribution of y, conditional on x.

Deciles are used in this study, increasing θ from zero to one in 0.1 increments. This allows for a sufficient number of points to characterize the entire salary distribution, conditional on the independent variables. Like in the OLS regressions in the previous chapter, these QR estimations are carried out for each of the eight positions using the same independent variables as those in the OLS regressions.

The quantile regressions are performed using the *bsqreg* command in the STATA software package. This results in quantile regression with bootstrapped standard errors. Bootstrapping proposed by Efron (1982) provides a method to obtain standard errors without limiting assumptions. Bootstrapping is based on the idea that the sample is a close approximation to the population. With bootstrapping the sampling experiment is replicated. However, this re-sampling adds a random element to the experiment. To minimize the randomness, many replications are carried out to obtain the bootstrapped standard errors (Rogers, 1992). The standard errors obtained by the bootstrap technique are only approximations however, the accuracy of the approximation increases with the number of replications (Gould, 1992).

7.3 Quantile Regression Results

The use of QR to extend the linear regression model beyond the conditional mean and fully characterize the conditional distribution of the dependent variable results in many additional estimates to report. For example, if an OLS regression with ten independent variables is analyzed using QR with quintiles, the number of estimates that need to be reported will increase five-fold. Under QR with deciles, the number of estimates will increase ten-fold and so on. Therefore, it is reasonable and even preferable to present the results of QR studies graphically as opposed to a tabular format.

However, it is important that the presentation and the discussion of the results of the QR technique are consistent and hold up to standard statistical testing. The graphs must contain confidence intervals for the QR estimates. Additionally, the discussion of the results must address whether the QR estimates are statistically, significantly different from one another. Without the confidence intervals or significance testing we cannot conclude that the QR estimates are different from the OLS estimate for a particular variable. Therefore, any results lacking the confidence intervals and significance testing are questionable.

Many times the interpretation of the QR results is logically difficult. In this study, the interpretation nicely falls out of the modeling. The two step empirical model employed uses OLS first to investigate the market forces at work in determining salaries. Step two employs QR to investigate the bargaining aspect of the model. Therefore we can interpret players in the first decile as those with unusually low salaries conditional on all of the independent variables. These are the players with little or no outside bargaining power. [60] The players in the highest decile (90%) have unusually high salaries conditional on the independent variables. These are the players with a very high degree of outside bargaining power.

---

[60] Outside bargaining power is referring to any bargaining power other than that from superior performance.

In order to discover any bargaining aspects of model, quantile regression is run on each of the eight positional models presented in Chapter 6. As discussed in Section 7.2 standard errors are obtained using the bootstrapping method. Deciles are used in the QR method to obtain a sufficient number of points to characterize the entire salary distribution conditional on the independent variables.

Unfortunately, there are few variables (by position) with any significant variation across deciles. Graphs and discussions for the variables with statistically, significant differences across deciles are presented below.

The return to *games played* has statistically, significant variation across deciles in the quantile regressions for offensive linemen and linebackers. The graphs for both quantile regressions are presented below in Figure 7.1 and Figure 7.2.

Figure 7.1
QR Estimates for Games Played for Offensive Linemen

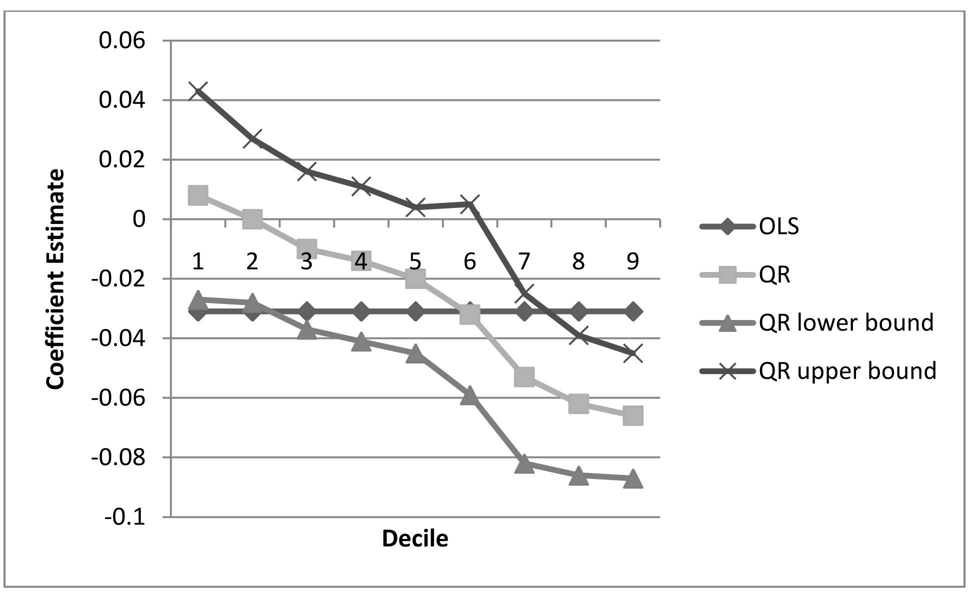
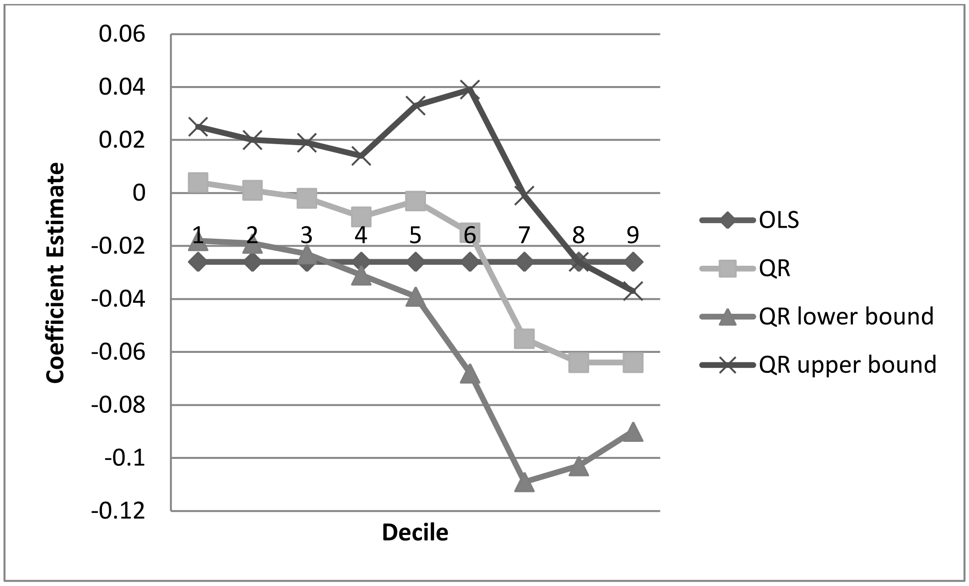


Figure 7.2
QR Estimates for Games Played for Linebackers



There is a downward trend in the return to *games played* for both positions. The return is slightly positive in the 1st decile and decreases across the distribution. Since we control for starting, the *games played* variable is picking up the effect of playing but not starting a game. Those in this category are many times the marginal players. They see some playing time but not as much as a starter, they are substitutes. The QR results show that offensive linemen and linebackers with a high degree of outside bargaining strength (those in the higher quantiles) are significantly penalized when they are relegated to the substitute role. They are un-performing relative to the expectations placed upon them.

The return to *games started* has statistically, significant variation across deciles in the quantile regressions for offensive linemen and safeties. The graphs for both quantile regressions are presented below in Figure 7.3 and Figure 7.4.

Figure 7.3
QR Estimates for Games Started for Offensive Linemen

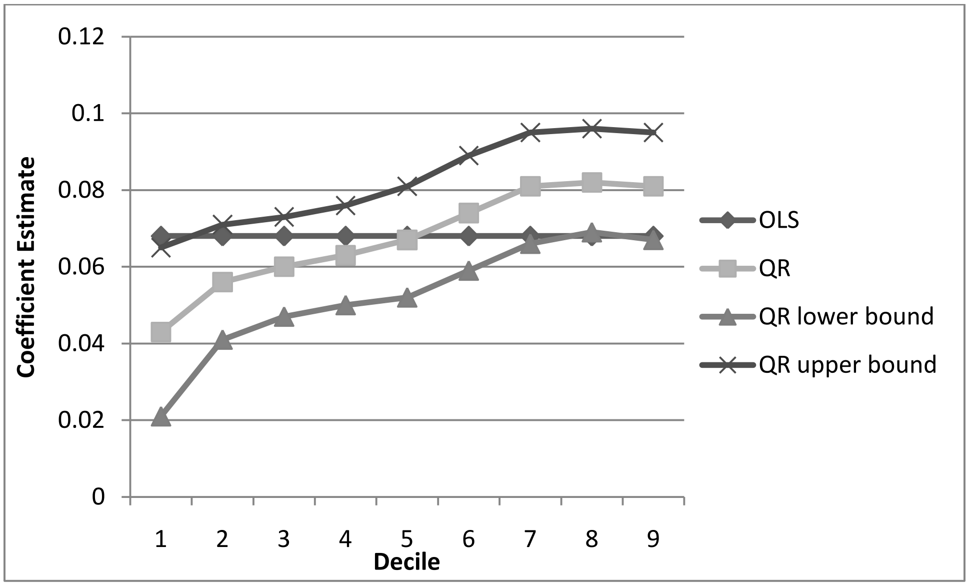
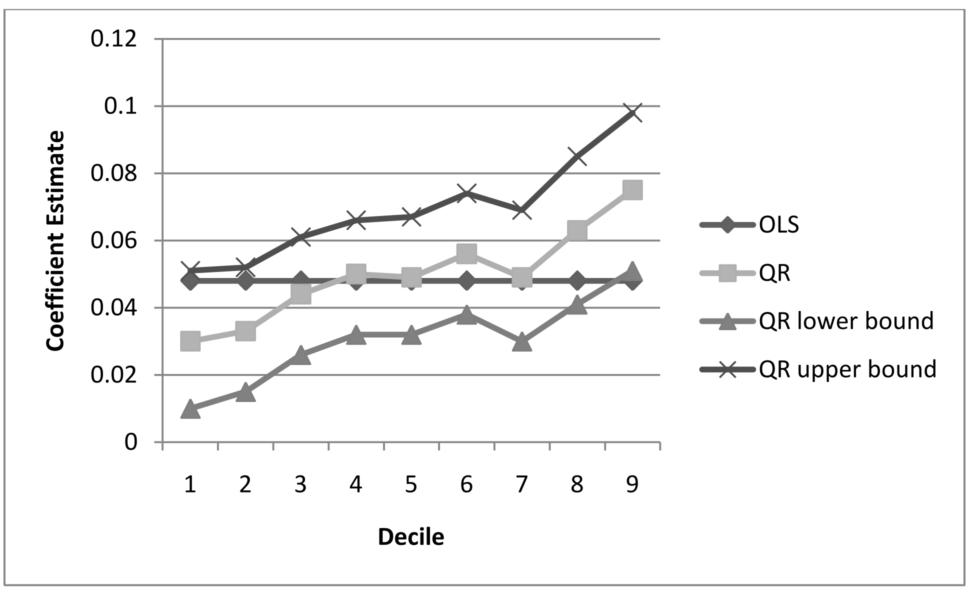


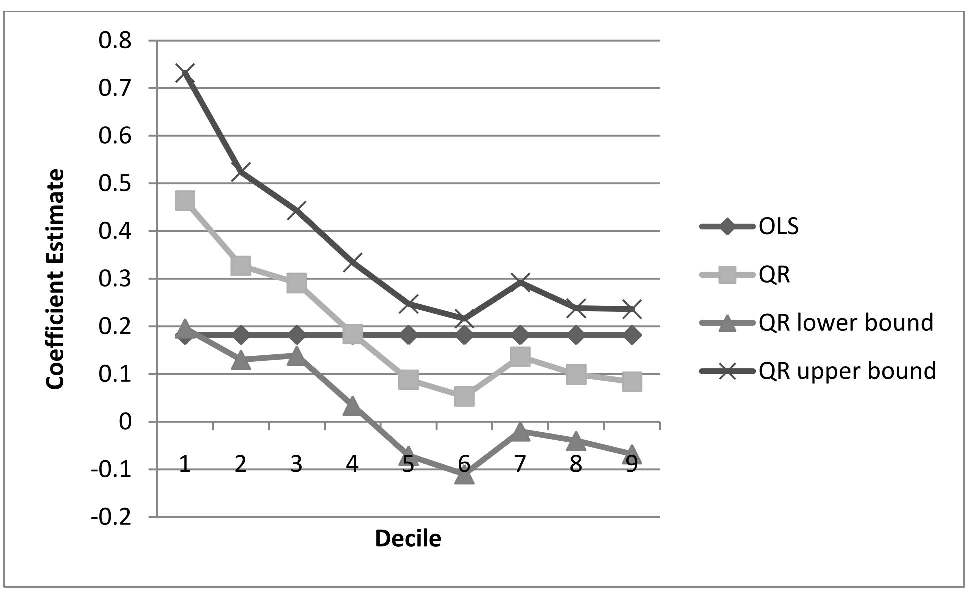
Figure 7.4
QR Estimates for Games Started for Safeties



There is an upward trend in the return to games started across the distribution for offensive linemen and safeties. Players with a high degree of outside bargaining strength receive a higher return for starting a game than those with relatively less outside bargaining strength, all else equal. Offensive linemen and safeties in the higher deciles are able to use their bargaining strength to magnify the positive impact of starting on salary.

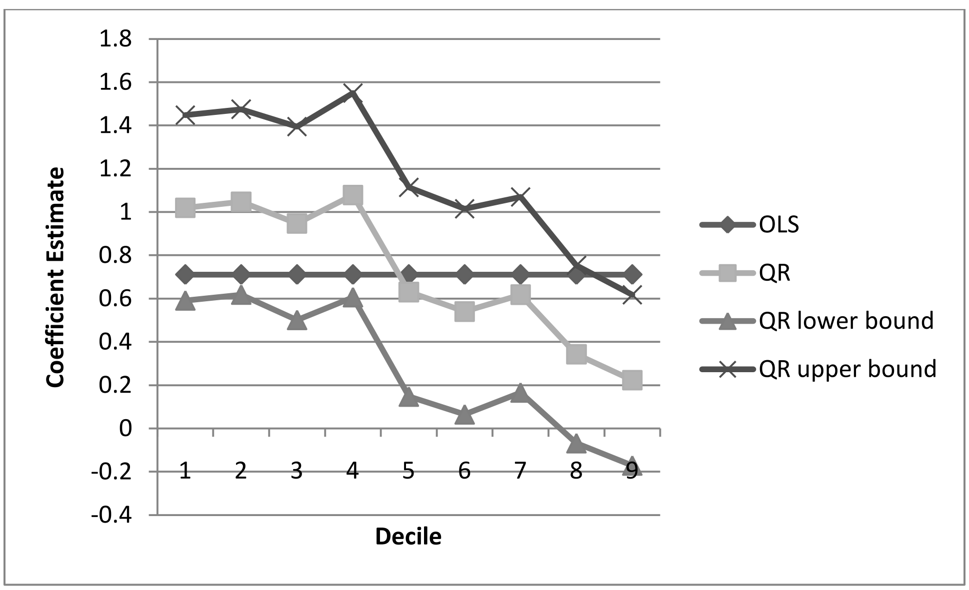
Figure 7.5 shows the return to being selected to the *prior year's Pro Bowl* has a downward trend for offensive linemen. When a lineman with relatively less outside bargaining strength was selected to the prior year's Pro Bowl he sees a larger return than his counterpart with more bargaining strength. The players in the lower deciles who were selected to the Pro Bowl probably exceeded expectations and are compensated accordingly.

Figure 7.5
QR Estimates for Prior Year Pro Bowl Selection for Offensive Linemen



The return to the being named a *Franchise player*, plotted in Figure 7.6, decreases across the conditional distribution for receivers. By definition, a player must be paid within a certain (high) range once he is given the franchise/transition designation.[61] Therefore, it makes sense that players with less outside bargaining strength would see a greater return to this designation. Although the return is positive across the entire conditional distribution, the designation is worth more to a receiver with less outside bargaining power.

Figure 7.6
QR Estimates for Franchise Player for Receivers



None of the coefficient estimates for quarterbacks, backs, cornerbacks, or defensive linemen were statistically, significantly different across deciles. In other

[61] See footnote 20 for a detailed definition of these designations and the pay that accompanies them.

words, there is no evidence for differences in bargaining strength leading to differences in salary for these positions. One would expect the greatest impact from bargaining strength to come at the marquee positions of quarterback and back, I find no evidence to support this.

In general, the results of the quantile regressions provide little evidence to support McLaughlin's rent-sharing model. This means that outside bargaining power, not bargaining power that comes from superior performance, has very little impact on salary determination in the NFL. The salaries of offensive linemen are most impacted by differences in bargaining strength. This may be driven by the lack of individual performance measures included in the salary model for offensive linemen.

It is possible and very likely the case that outside bargaining power has a role in determining salaries but not in a way that can be tested with this data. Perhaps more outside bargaining power leads to more guaranteed money or longer contracts. These ideas will be expanded on in the next chapter.

CHAPTER 8 CONCLUSIONS AND IDEAS FOR FUTURE RESEARCH

This paper investigates salary determination in the National Football League (NFL). In the NFL, the heterogeneity of teams and players results in thin labor markets. In such an environment, the neoclassical model, used by most researchers in sports economics, is too simple. McLaughlin's (1994) rent sharing model appears to be a better fit for the structure of the NFL.

In this study a two step process is employed to investigate whether the rent-sharing model is more applicable to salary determination in the league. In the first step, a comprehensive model of salary determination, using many unique variables, is constructed and tested for each position. These models examine the market determinants of salary by position. This is the only study of its kind to investigate salary determination at a disaggregated level for all non-kicking positions in the NFL.

Salaries in the league are found to depend on individual performance, teammate performance, outside measures of performance (Pro Bowl selections), player status regarding free agency, tenure, and hands on experience. Past measures of future expectations (the draft) are found to have mixed effects on salary even for veteran players. The positional regression models constructed will be invaluable for future research of this type.

In the second step, quantile regression is employed to examine the bargaining aspects at work in salary determination in the NFL. The positional quantile regressions showed little variation across the conditional salary distribution. There was weak, at best, evidence for differences in bargaining strength leading to differences in salary. Half of the positional regressions had no variables with any coefficient estimates that were statistically significantly different across deciles. Only offensive linemen, the one position with no individual performance measures in the model, have more than one variable with estimates that were statistically significantly different across deciles.

In general, the results of the quantile regressions provide little evidence to support McLaughlin's rent-sharing model. This means that outside bargaining power, not bargaining power that comes from superior performance, has very little impact on salary determination in the NFL. Although little support is found for the rent-sharing model, this study lays the framework and presents the argument for further investigation.

It is likely that outside bargaining power plays a role (perhaps even a strong one) in determining salaries but, not in a way that can be tested with this data. More bargaining power is likely to earn a player more guaranteed money or a longer contract. There is a trend in the league towards more guaranteed money for good players. An enlightening extension of this work would be to test the ratio of guaranteed money to contract value.

Expanding the time period of the study would be an interesting extension. The addition of contract length and contract expiration could prove interesting. An accurate measure of salary cap room on the player's team along with the number of available free agents at his position would improve the existing literature. Many players in the league have also been getting negative press for poor and/or illegal behavior; it would be interesting to see if negative press translates into decreased salary. This study presents a comprehensive empirical model for salary determination in the NFL provides a useful framework for any future studies of salary in sports.

BIBLIOGRAPHY

Arias, Omar, Hallock, Kevin F., & Sosa-Escudero, Walter. "Individual Heterogeneity in the Returns to Schooling: Instrumental Variables Quantile Regression Using Twins Data." *Empirical Economics*, 26, 2001, 7-40.

Badenhausen, Kurt. "The World's Highest-Paid Athletes 2009." 2009. [Online] Available: http://www.forbes.com/2009/08/10/tiger-woods-schumacher-business-sports-top-earning-athletes.html?partner=contextstory.

Badenhausen, Kurt; Ozanian, Michael K., & Settimi, Christina. "Recession Tackles NFL Team Values." 2009. [Online] Available: http://www.forbes.com/2009/09/02/nfl-pro-football-business-sportsmoney-football-values-09-values.html.

Bahr, Kevin M. "The Business of Sports and Small Market Viability: The Green Bay Packers and the Milwaukee Brewers." 2001. [Online] Available: http://www.uwsp.edu/business/CWERB/1stQtr01/SpecialReportQtr1_01.htm.

Blass, Asher A. "Does the Baseball Labor Market Contradict the Human Capital Model of Investment?" *Review of Economics and Statistics*, 71, 1992, 261-268.

Borjas, George. "Assimilation and Changes in Cohort Quality Revisited: What Happened to Immigrant Earnings in the 1980s?" *Journal of Labor Economics*, 13, 1995, 201-245.

Brooks, David E. "NFL Salary Cap and Minimum Salary Scale." 2005. [Online] Available: http://www.vertgame.com/sal_cap.html.

Buchinsky, Moshe. "Recent Advances in Quantile Regression Models: A Practical Guide for Empirical Research." *Journal of Human Resources*, 33, 1988, 88-126.

___________. "Changes in the US Wage Structure 1963-1987: Application of Quantile Regression." *Econometrica*, 62, 1994, 405-458.

___________. "The Dynamics of Changes in the Female Wage Distribution in the USA: A Quantile Regression Approach." *Journal of Applied Econometrics*, 13, 1998, 1-30.

Buhai, Sebastian. "Quantile Regression: Overview and Selected Applications." 2004. [Online] Available: http://www.tinbergen.nl/~buhai/papers/others/quantile_regressions.pdf.

Cade, Brian S. & Noon, Barry R. "A Gentle Introduction to Quantile Regression for Ecologists." *Frontiers in Ecology and the Environment*, 8, 2003, 412-420.

Chamberlin, Gary. "Quantile Regression, Censoring and the Structure of Wages." In Christopher Sim (ed.), *Advances in Econometrics*, Cambridge: Cambridge University Press, 1994, 171-209.

Chiswick, Barry. "Is the New Immigration Less Skilled than the Old?" *Journal of Labor Economics*, 4, 1986, 168-192.

Economist. "In a League of Its Own." April, 27, 2006. [Online] Available: http://www.economist.com/displaystory.cfm?story_id=6859210.

Efron, Bradley. "The Jackknife, the Bootstrap, and Other Resampling Plans". *Society of Industrial and Applied Mathematics CBMS-NSF Monographs*, 38, 1982.

Eide, Eric & Showalter, Mark H. "The Effect of School Quality on Student Performance: A Quantile Regression Approach." *Economics Letters*, 58, 1998, 345-350.

ESPN The Magazine. May 10, 2004, 103.

Fleming, David. "Today's NFL is Like High School: You Get Four Years to Beat the System-Or You Get Left Behind." *ESPN The Magazine*, September 15, 2003, 85-88.

Friedberg, Rachel M. "You Can't Take It With You? Immigrant Assimilation and the Portability of Human Capital." *Journal of Labor Economics*, 18, 2000, 221-251.

Garcia, Jaume, Hernandez, Pedro J., & Lopez-Nicolas, Angel. "How Wide is the Gap? An Investigation of Gender Wage Differences Using Quantile Regression." *Empirical Economics*, 26, 2001, 149-167.

Gould, William. "Quantile Regression with Bootstrapped Standard Errors," *Stata Technical Bulletin*, STB-9, 1992, 19-21.

Hao, Lingxin & Naiman, Daniel Q. *Quantile Regression*, London: Sage Publications, 2007.

Harris, Nick. "Premier League Footballers Not the Richest on the Planet – Revealed." 2010. [Online] Available: http://www.telegraph.co.uk/sport/football/leagues/premierleague/7527796/Premier-League-footballers-not-the-richest-on-the-planet-revealed.html.

Hartog, Joop, Pereira, Pedro T., & Vieira, Jose A. C. "Changing Returns to Education in Portugal during the 1980s and Early 1990s: OLS and Quantile Regression Estimators." *Applied Economics*, 33, 2001, 1021-1037.

Idson, Todd L. & Kahane, Leo H. "Team Effects on Compensation: An Application to Salary Determination in the National Hockey League." *Economic Inquiry,* 38, 2000, 345-357.

Kahn, Lawrence M. "The Effects of Race on Professional Football Player's Compensation." *Industrial and Labor Relations Review,* 45, 1992, 295-310.

King, Bill. "Passion That Can't Be Counted Puts Billions of Dollars in Play." In *Street and Smith Sports Business Journal,* 5, 2003, 148-149.

Koenker, Roger. "Quantile Regression." Prepared for Stephen Fienberg and Jay Kadane (eds.) *International Encyclopedia of the Social Sciences,* version October 25, 2000.

Koenker, Roger & Bilias, Yannis. "Quantile Regression for Duration Data: A Reappraisal of the Pennsylvania Reemployment Bonus Experiment." *Empirical Economics,* 26, 2001, 199-220.

Koenker, Roger & Bassett, Gilbert Jr. "Regresion Quantiles." *Econometrica*, 46, 1978, 33-50.

Koenker, Roger & Hallock, Kevin F. "Quantile Regression." *Journal of Economic Perspectives*, 15, 2001, 143-156.

Kowalewski, Sandra & Leeds, Michael A. "The Impact of the Salary Cap and Free Agency on the Structure and Distribution of Salaries in the NFL." In John Fizel, Elizabeth Gustafson, and Lawrence Hadley (eds.) *Sports Economics: Current Research,* Westport: Praeger, 1999, 213-226.

Krautmann, Anthony C. "What's Wrong with Scully-Estimates of a Player's Marginal Revenue Product." *Economic Inquiry,* 37, 1999, 369-381.

Leeds, Michael A. & Kowalewski, Sandra. "Winner Take All in the NFL: The Effect of the Salary Cap and Free Agency on the Compensation of Skill Position Players in the NFL." *Journal of Sports Economics*, 2, 2001, 244-256.

Leggett, Theodore. "Goodell Positive on NFL Progress." 2009. [ONLINE] Available: http://news.bbc.co.uk/2/hi/business/8327293.stm.

Levin, Jesse. "For Whom the Reductions Count: A Quantile Regression Anaylsis of Class Size and Peer Effects on Scholastic Achievement." *Empirical Economics*, 26, 2001, 221-246.

Lewis, Michael. *The Blind Side: Evolution of a Game*, New York: W.W. Norton & Company, 2006.

Machado, Jose A. F. & Mata, Jose. "Counterfactual Decomposition of Changes in Wage Distributions Using Quantile Regression." Journal of Applied Econometrics, 20, 2005, 445-465.

Martins, Pedro S. & Pereira, Pedro T. "Does Education Reduce Wage Inequality? Quantile Regression Evidence from 16 Countries." *Labour Economics*, 11, 2004, 355-371.

McLaughlin, Kenneth J. "Rent Sharing in an Equilibrium Model of Matching and Turnover." *Journal of Labor Economics*, 12, 1994, 499-523.

Mirabile, McDonald P. "The Drafting and Compensation of College Quarterbacks: Salary Determinants and Evidence of Discrimination in the NFL." Unpublished, 2004.

NFL Press Release "NFL Free Agency Questions & Answers." [Online] Available: http://www.packers.com/news/releases/1999/02/02-11.html.

NFL Press Release "NFL Free Agency Questions & Answers." [Online] Available: http://www.packers.com/news/releases/2000/02/02-09c.html.

NFLPA. "Collective Bargaining Agreement Between the NFL Management Council and the NFL Players Association." 1998. [Online] Available: http://www.nflpa.org/Shared/CBAPrinter.asp.

NFLPA. "Collective Bargaining Agreement Between the NFL Management Council and the NFL Players Association." 2006. [Online] Available: http://images.nflplayers.com/mediaResources/files/PDFs/General/NFL%20COLLECTIVE%20BARGAINING%20AGREEMENT%202006%20-%202012.pdf.

NFLPA. "Minimum Salaries." 2003. [Online] Available: http://www.nflpa.org/Media/main.asp?subPage=Minimum+Salaries.

NFLPA. "The State of the Game: A Current Look at the Success of the League." 2010. [Online] Available: http://www.nflplayers.com/Articles/CBA-News/The-State-of-the-Game-A-Current-Look-at-the-Success-of-the-League/.

NFLPA. "The State of the Game: A Historical Perspective." 2010. [Online] Available: http://www.nflplayers.com/Articles/CBA-News/The-State-of-the-Game-A-Historical-Perspective/

Richards, Donald G. & Guell, Robert C. "Baseball Success and Structure of Salaries." *Applied Economic Letters*, 5, 1996, 291-296.

Ritter, Jeff, :NFL Player Salaries: Is the NFL Salary Cap a Sham?" 2008. [Online] Available: http://blogs.payscale.com/content/2008/05/nfl-player-sala.html.

Roberts, Brendan (ed.). The Sporting News Pro Football Register, St. Louis: The Sporting News, 1998 & 1999.

Roberts, Brendan & Walton, David (eds.). The Sporting News Pro Football Register, St. Louis: The Sporting News, 2000.

Rogers, William. "Quantile Regression Standard Errors," *Stata Technical Bulletin*, STB-9, 1992, 16-19.

Roy, A.D. "Some Thoughts on the Distribution of Earnings." *Oxford Economic Papers*, 3, 1951, 135-146.

Staudohar, Paul D. "Salary Caps in Professional Team Sports." *Compensation and Working Conditions*, Spring 1998, 3-11.

Scully, Gerald. "Pay and Performance in Major League Baseball." *American Economic Review*, 64, 1974, 915-30.

________. *The Business of Major League Baseball*, Chicago: University of Chicago Press, 1989, 151- 170.

Sullivan, George. *Football Rules Illustrated*, New York: Simon & Schuster, 1981, 7-80.

Vrooman, John. "The Baseball Players' Labor Market Reconsidered." *Southern Economic Journal*, 63, 1996, 339-360.

Weisman, Larry. "Expect NFL Salary Cap to Keep Going Through the Roof." 2006. [Online] Available: http://www.usatoday.com/sports/football/nfl/2006-07-07-salary-report_x.htm.

Williams, Jack F. "The Coming Revenue Revolution in Sports." 2006. [Online] Available: http://www.willamette.edu/wucl/pdf/review/42-4/williams.pdf.

Zimbalist, Andrew. *Baseball and Billions*. New York: Basic Books, 1992, 75- 104.

APPENDICES

Appendix A: Definition of Variables Used In All Positional Equations[62]

BOWL CHAMPIONSHIP SERIES (BCS): A dummy variable that equals one if the player came from a college football program that is eligible for the Bowl Championship Series (BCS).

TOP25: A dummy variable that equals one if his college was ranked in the BCS top 25 at the conclusion of the season in the year the player was drafted.

 # IN 1ST ROUND: Captures the effects of being drafted in the first round. The variable equals zero if the player was not drafted in the first round. There are thirty one teams and each has a draft pick in the first round therefore the variable equals 31 if the player was the first draft choice in the first round and equals one if the player was the last draft choice in the first round. The range of this variable is zero to thirty-one and is constructed in this way to keep a positive sign on any positive effects of being drafted early in the first round.

ROUND: The round in which the player was drafted. The highest draft round in my data set was 11 so any players that were not drafted were assigned a value of 12 for this variable.

DRAFT#: The overall draft position. The highest draft position in my data set was 285 so any players that were not drafted were assigned a value of 286 for this variable.

NONDRAFT: A dummy variable that equals one if a player was not drafted and zero otherwise.

TOTAL PROBOWLS: The total number of Probowls that a player was selected into up to year t-2.

PRIOR YEAR PROBOWL: A dummy variable which equals one if a player was selected to the Probowl in the prior year, t-1.

---

[62] All of these variables were not used in the same equation. I am including them so that the reader is aware that many different specifications have been attempted.

CAP: measures the extent to which each particular team is constrained by the salary cap in the relevant year. This variable will be the amount that the player's team is over or under the salary cap on a particular date in the season.

PROFIT: The profit reported to the NFL by each team in the previous year.

GAMES PLAYED: The number of regular season games the player participated in the previous season**.**

GAMES STARTED: The number of regular season games the player started in the previous season.

EXPERIENCE: The total number of years a player has been in the NFL.

EXPERIENCE^2 : The square of the total number of years a player has been in the NFL. This variable is included to capture non-linearity in the returns to experience.

HEIGHT: The player's height measured in inches.

WEIGHT: The player's weight measured in pounds.

DEGREE: A dummy variable which equals one if a player has a degree from college and zero otherwise.

MAJOR LEAGUE BASEBALL: A dummy variable which equals one if a player was drafted by MLB.

#SUPERBOWLS: The number of Superbowls a player has participated in. (Slightly modified for certain positions)

SWITCH: A dummy variable which equals one if a player has switched teams from the previous season and zero otherwise.

STADIUM: A dummy variable which equals one if the player's team plays in stadium which was built in or after 1995 and zero otherwise.

JUNIOR: A dummy variable which equals one if a player entered the NFL prior to their senior year in college and zero otherwise.

LUXURY SUITES: The number of luxury suites in the team's stadium. The variable is included because most luxury suite revenue is not subject to the revenue sharing in the League. It could be a measure of the team's financial success and/or affect the demand for a player.

Appendix B: Definition of Variables Specific to the Quarterback Equation

YARDS: The total number of yards the player had in the previous season.
ATTEMPTS: The number of passing attempts the player had in the previous season.
COMPLETIONS: The number of passes completed in the previous season.
RUSHING TOUCHDOWNS: The number of rushing touchdowns the player had in the previous season.
TOUCHDOWNS: The total number of touchdowns by the player in the previous season.
PASSING YARDS: The total yards passing by the player in the previous season.
TOP 10: A dummy variable which equals 1 if the quarterback is in the top 10 in rating points for the season. A quarterback's rating is a summary statistic calculated by the NFL which is a weighted average of completion percentage, passing yards, interceptions and touchdowns. In order to include a quarterback in this category, he will also have to have completed at least 100 passing attempts in the previous year.[63] This avoids inclusion of quarterbacks with limited attempts and very high ratings. This variable accounts for superstar effects at the quarterback position; those with many attempts and the highest ratings and are also likely to be pro bowl selections.
YARDS PER ATTEMPT: Equals the total yards passing divided by the number of attempts. This is a measure of quarterback efficiency.

[63] I also constructed this variable with the number of attempts greater than 200, 250 and 300.