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A QUANTITATIVE ANALYSIS OF THE USE AND EFFICACY OF THE FRANCHISE TAG IN THE NATIONAL FOOTBALL LEAGUE

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ABSTRACT

This thesis examines the use of the franchise tag in the National Football League (NFL), the effects of its use on player salary, and what factors make its use on a specific player more likely. The franchise tag is a designation that teams in the NFL can apply to a player whose contract is expiring which binds that player to the team on a guaranteed one-year contract. Use of the franchise tag has become more frequent in recent years, as has the stigma of being designated a team’s franchise player. With recent developments and research regarding concussions and head trauma in the NFL, more players would rather have long-term contracts than run the risk of getting seriously hurt while playing on a one-year deal. A literature review on the subject shows that there has been virtually no research done on the impacts of the franchise tag, and this thesis aims to begin to fill that void. OLS and treatment model regressions are conducted to analyze the effects of the franchise tag on player salary, and probit analysis is used to determine what factors make the tag’s use more likely. Results show that there are some factors not captured by statistics but captured by the treatment regression model which are inherent in players more likely to be tagged. Among positions where multiple players have been given the franchise tag from the years 2005 to 2009, the data shows that the franchise tag has had a mostly negative impact on player salary. Probit analyses also show that better performance and starting more games make a player more likely to be tagged, and that more years of NFL experience make a player less likely to be tagged. The data, however, is not always very significant due to relatively few instances of players actually being given the tag and playing the following season under it during the time period studied.

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Chapter 1

Introduction

The Thesis

This thesis aims to look at the effects of the franchise tag in the National Football League (NFL) on player salary, and determine what factors make a player more likely to be tagged.

What is the Franchise Tag?

The franchise tag is a designation that any team in the NFL can apply to any potential free agent (a player on that team whose current contract has expired) in any given year. Teams can only designate one franchise player each year, and are not obligated to use the franchise tag at all. While a more thorough definition of the franchise tag will be discussed in the next section, it is basically a one-year guaranteed contract for a player, with a salary equal to the greater of the following two quantities: the average salary of the top-five earning players at the tagged player's position over the past five seasons, or 120% of the tagged player's salary from last season. However, over the years studied in this thesis, the first quantity considered only takes the salaries of the top five earning players at a given position over *just the previous season*. This means that salaries associated with the franchise tag were relatively higher during the seasons studied in this thesis than they would be today.

Why Study the Franchise Tag?

While the franchise tag came into existence with the advent of NFL free agency in 1993, virtually no research can be found regarding its use or effects. Searching through various academic databases reveals plenty of papers studying other pertinent topics in the NFL, but none that study any aspect of the franchise tag. This dearth of study regarding the franchise tag could be partly due to the recent rise in notoriety that the tag has received. Indeed, the tag has been increasingly used in recent years, after rarely being used at all in its early days of existence. A certain stigma has also become associated with the franchise tag in recent years, as players who receive the tag dislike playing under a one-year contract. Given recent research about the prevalence and detrimental effects of concussions and head trauma in the NFL, and how violent the sport is in general, most players would rather have a long-term contract in case they were to suffer any serious injury. And though not all the money in a long-term contract is guaranteed should a player get injured, the guaranteed money over the life of these contracts would likely be more than the guaranteed, one-year tag for top players.

Since there have been virtually no studies done on the franchise tag at this point, it is difficult to tell if the franchise tag has achieved one its intended effects: to keep the salaries of top players down so that teams can maneuver under the salary cap to build a competitive roster. Thus, my study aims to find what effect the franchise tag has had on the salaries of top players. I also use the large set of data that I have collected for my research to observe other aspects of the franchise tag's use. Specifically, I examine what characteristics make a player more likely to be given the franchise tag.

Layout of the Thesis

The rest of this paper is organized into five different chapters. Chapter two will go into more detail on the theoretical framework of my topic, and review literature that is related to my study. In this section I will give a more thorough definition of the franchise tag, discuss literature on salary determination and the effects of free agency and salary caps, and discuss some viewpoints from contemporary media sources on the franchise tag.

Chapter three will discuss my data and the methods that I used to analyze it. I will go into detail on my data collection techniques, including a description of all variables and types of data I used, how I organized my data, and where my data came from. Also, I will discuss the methods I used to analyze my data: mainly, running standard OLS regressions, treatment model regressions, and probit analyses in STATA.

Chapter four is a description of my findings. I will present the results of my regressions and analysis, and determine whether or not my initial beliefs were accurate. I will also discuss interesting trends found in the data, the limitations of my study, and future areas of study to look into. Finally, chapter six concludes and summarizes my research.

Chapter 2

Literature Review and Theoretical Framework

Definition

The franchise tag is a designation that teams in the National Football League (NFL) can apply to one player in any given year. The tag is applied to a potential free agent (a player whose current contract has expired), and the same player can only be given a franchise tag three times (Sando, 2012). While a team is not required to designate a franchise player (in fact, many teams opt not to every year), the teams that do must be willing to adhere to the salary guidelines prescribed by the definition of the tag. There are two versions of the franchise tag that a player can receive: an exclusive tag, or a non-exclusive tag. A player who receives the exclusive version of the tag is not free to sign with another club. The exclusive player is offered a guaranteed, one-year contract worth the greater of the following two quantities:

- The average of the top five salaries at that player's position over the past five seasons, or
- 120% of the exclusive player's previous year's salary.

A non-exclusive player gets a contract worth the greater of the same two quantities as the exclusive player, however, a non-exclusive player is allowed to bargain with other NFL teams for a new contract. If a non-exclusive player is offered a contract by another team, the player's current team has two options: they can decide to match the offer, or they can choose not to match and receive two first-round draft choices (Alder, n.d.). The purpose of the franchise tag is to help restrict player movement from smaller-market to larger-market teams, and to allow a general manager to retain a star player at a "reasonable" price, so that they can acquire other players without exceeding the league's salary cap.

An important note to make is that the way that the franchise tag is calculated has changed in recent years. Since the NFL's most recent collective bargaining agreement was ratified in 2011, the tag is calculated as I described above. However, during the years I studied, the tag was calculated as the average of the top five salaries at a player's position over only the past season. This led to relatively higher tag numbers than the current method of calculation leads to, as the older method doesn't take into account the lower salaries from previous seasons.

Literature Review

The use of the franchise tag in the NFL is a relatively recent and understudied development. While the tag was initially conceived in the early 1990's, there is very little research on its use. A search through many published and working economic research papers related to the National Football League that can be found in online databases turned up zero papers that were directly related to the use and effects of the franchise tag. This dearth of research is surprising, yet not impossible to explain; though the franchise tag was created in 1993 with the advent of free agency in the NFL, its use has become increasingly more frequent and controversial in recent years. However, there does exist plenty of economic research on other factors affecting salary allocation and determination in the NFL.

One of the most relevant studies in this case is a 2001 paper by Michael Leeds and Sandra Kowalewski on “The Effect of the Salary Cap and Free Agency on the Compensation of Skill Position Players.” Aiming to find out what effects the 1993 creation of free agency had on the compensation of NFL players, Leeds and Kowalewski point out many important considerations that a study of NFL salary determination must consider. Most importantly, Leeds and Kowalewski note that, “More than the other major sports, in football one cannot compare the performance of two players at different positions (Leeds and Kowalewski, 2001, p. 244).” Whereas in other sports such as baseball and basketball there exist measures (batting average, rebounds, points scored) that can be used to capture the effectiveness of mostly all the players, football is very different. Quarterbacks are judged on different statistics than running backs (passing yards are very important for a quarterback, while they mean virtually nothing for a running back), and both are judged on very different statistics than defensive players. Since it is so difficult to compare players across positions in football, Leeds and Kowalewski ran separate regressions for each position they analyzed (Leeds and Kowalewski, 2001).

Leeds and Kowalewski also bring up an important consideration regarding skill and non-skill position players in the NFL. They chose to only consider the skill positions − quarterback, running back, wide receiver, tight end − in their study since, “because the players at these positions handle the ball more frequently than players at other positions, they have more direct performance measures than other players, allowing us to establish better tests of the impact of personal performance" (Leeds and Kowalewski, 2001, p. 245). It is much harder, they argue, to find reliable statistics to measure the performance of offensive linemen and defensive players. Though it may seem that interceptions can measure a defensive player's ability, for instance, it may actually be the case that the best defensive backs have very few interceptions because quarterbacks rarely choose to throw to the player they are covering. Ultimately, Leeds and Kowalewski found that players who were relatively underpaid (in the bottom 25 percent of salaries at their position) could increase their salaries by improving in the key statistical measures for their position. It was found that these relatively underpaid players had higher salary returns to performance than their higher-paid counterparts (Leeds and Kowalewski, 2001).

Samuel Allen and Julianne Treme push the analysis of salary determination even further by examining payoffs to media exposure among NFL wide receivers. Allen and Treme argue that there are other reasons a player can become a superstar than just traditional performance statistics. They measured how often wide receivers were mentioned in newspapers leading up to the NFL Draft, and found that a higher degree of publicity (controlling for similar measureable statistics) had a significant impact on a player's draft position and first year salary. Allen and Treme also noted that playing for a more reputable college program also had an effect on players' draft position (Allen and Treme 2011). This emphasis on higher salaries being correlated with attending more prestigious college programs can potentially relate to the movement-restricting purpose of the franchise tag. The tag allows smaller market teams to hold on to players who may want to run to larger markets to gain higher publicity and the payoffs that come with it.

Lawrence Kahn examined race as a determinant of NFL salaries, in another example of an unorthodox variable determining the salaries of players. Kahn found that, while controlling for other performance measures, the difference between the salaries of white players and non-white players was only 4%− not large enough to be considered significant. An important takeaway from Kahn's study is his decision of which measures to use to capture player performance, and how he compartmentalized his regressions by position. Kahn assigned a variable to each player's salary, year their current contract was signed, duration of their current contract, years of NFL experience, draft position, number of games played, number of games started, number of times on injured reserve, number of days on injured reserve, number of Pro Bowls (NFL All-Star games) they were selected to, and the winning percentage of their team the previous season. Kahn also used dummy variables to show if each player was a starter in the most recent year examined, and if they graduated college. Lastly, Kahn ran separate regressions for each position, recognizing that different positions perform different functions (Kahn, 1992).

Michael Conlin (1999) discusses the effects of long negotiations on player contract value and subsequent player performance. Conlin found that while entering into longer salary negotiations often leads to a player obtaining a more lucrative contract, it also impacts the player's ability to get onto the field and succeed early on in that contract. This is because if negotiations drag on for a while, the player may miss a significant amount of practice and training time. With the complexity of many NFL systems, and the challenges that come with adapting to a new team and environment, missing this time can prove to be a significant barrier to performing well right away. Because of this, Conlin finds that long negotiations for a more lucrative contract are usually only worthwhile for very high-ability players, as their skill level can help offset any time missed while negotiating (Conlin, 1999).

While Conlin's study focuses on negotiations of rookie players who were just drafted, it translates well to research on the impacts of the franchise tag. Oftentimes (as will be discussed later on), players are unhappy with receiving the franchise tag, and threaten to "hold-out"− refusing to play or practice at all until a new contract is negotiated. Conlin also touches on injury and health concerns as a reason why players sometimes choose not to engage in long contract negotiations, and just try to get a contract signed as soon as possible. This sentiment relates directly to current concerns with concussions and head trauma associated with the NFL, and the lack of fully-guaranteed NFL contracts.

Tina Heubeck and Jochen Scheuer (2002) examine incentive contracts in German soccer, the NBA, and the NFL. Heubeck and Scheuer compare incentive contracts in these team sports to what would be expected in the classical agent-principal model. In the study, it is noted that about 65-75% of NFL players have either individual incentives (winning awards, surpassing certain statistical marks, playing a certain number of games) or team incentives (winning a certain number of games, winning the Super Bowl) as a part of their contract, however, these incentives only comprise around 5% of any player's total salary (Heubeck and Scheuer, 2002). Incentivized play due to contract status is something that relates in many ways to the use of the franchise tag. While the franchise tag as an incentive must be examined differently than smaller incentives written into contracts, the fact that a player is playing on a one-year contract is an incentive in itself for that player to perform well; the better a player performs under the franchise tag, the larger a contract they can reasonably expect to secure for the next season and for seasons into the future.

Another important issue in the NFL that relates to the use of the franchise tag is the concept of a salary cap. A salary cap is an upper limit that the total salaries of any team cannot exceed without incurring some type of penalty. The penalty could potentially include fines or loss of draft picks. A certain amount of each player's base salary counts toward the cap each year; many incentive-based bonuses and signing bonuses don't count toward a team's cap limit.

One main reason for having a salary cap in the NFL, as pointed out by Barriger et al. (2004) is that, "Theoretically, a salary cap would narrow the spread among teams in total player salaries, prevent an overzealous owner from monopolizing playing talent and, presumably, improve competitive balance" (Barriger et al., 2004, p. 2). However, Barriger et al. actually found, "neither an improvement in competitive balance over time nor a discernible change in competitive balance after the NFL instituted a salary cap before the start of the 1994 season" (Barriger et al., 2004, p. 3). Possible reasons given for this lack of change in competitive balance are the effects of free agency, revenue sharing, and creative contracts that defer payments and work around the cap. This begs the question of whether teams that use the franchise tag effectively to stay under the cap and sign more players are more successful than those that do not.

Finally, Richard Borghesi (2007) claims that with the presence of a salary cap in the NFL, "team management is forced to abide by a fixed salary budget and therefore must formulate a distribution scheme that retains the best talent while simultaneously ensuring that players feel fairly compensated" (Borghesi, 2007, p. 537). Borghesi goes on to determine whether teams (and offensive/defensive units) are more successful when salaries are dispersed among few superstar players and many lower-level or role players, or when salaries are more evenly distributed among a team of similarly skilled players. He also makes sure to differentiate between players who are justified in receiving a high salary based on statistical performance, and those who are not justified. Ultimately, Borghesi found that even when teams paid superstar players high salaries that were justified, teams and units were more successful when pay was relatively less dispersed among all positions, and that the presence of superstar players could actually be disruptive (Borghesi, 2007).

Current Thoughts and Media Opinion

The use of the franchise tag has become much more prevalent in the NFL in recent years. Twenty-one players were given the franchise designation before the 2012 season, up from only seven in 2007. Players, however, have begun to bristle at the prospect of being designated a “franchise” player. Most players would rather have the security of a long-term contract rather than a one-year deal, especially given the glut of research and news that has recently come out regarding the dangers of concussions and head trauma in the NFL. Because of resentment toward receiving the tag, some franchise-tagged players actually threaten to “hold out”− meaning they refuse to practice or play until a new contract is negotiated. The franchise tag is an attractive tool for general managers to use, though, as they can guarantee having a player on their roster for just one season, rather than giving a longer contract and taking a hit against the cap in future seasons.

One common reason a team may tag a player, writes Schuyler Velasco (2012), is if that player has had some character issues or has a great deal of injury risk associated with them. The tag thus allows the player to prove himself on a one-year deal, and lets the owner keep that risky player without committing to them for the long term just yet. Another reason players may be tagged, which Velasco touches on, is to buy management more time to sign that player to a contract. In this case, rather than letting an important player walk away and have the opportunity to negotiate contracts with other teams, the tag binds that player to their original team for another year. This allows the two sides more time to come to agreement on a long-term deal, and pushes back the threat of the player leaving for one more year (Velasco, 2012).

Many players' attitudes toward receiving the tag are illustrated by the examples given by Nate Caminata. Caminata wrote that Detroit Lions defensive tackle Cliff Avril publicly chafed at the idea of being his team's franchise player last year. Caminata also quoted an agent who said that, "Players have been," complaining, "about (the franchise tag) since it first came into being, and it's just a part of the game the last 20 years" (Caminata, 2012). However, Caminata then goes on to juxtapose these feelings of resentment with how general managers and owners feel about the franchise tag. Many owners, according to Caminata, "suggested that the marker has been good for the game and for the fans, and that it will probably never disappear" (Caminata, 2012).

Albert Breer (2012) of NFL.com shares one agent's stinging thoughts on the franchise tag: "They should call it the prison tag. It locks the player in, keeps him in jail contractually, doesn't allow him to test what his true market is, or seek what his compensation should be. It's take it or leave it" (Breer, 2012). However, Breer is quick to add of the tag, that, “It's not always a bad thing for players. It can create framework for deals, leverage a negotiation, or get a young, unproven player a quick buck. But it can also create contempt” (Breer, 2012). A big reason for that contempt is the recent decision in the NFL’s last collective bargaining agreement to calculate the franchise tag differently. Rather than the average of the top five salaries at a player’s position over the last season, the franchise number is now calculated as the average of the top five salaries at a player’s position over the last *five* years. This has led to a twenty percent decrease in the franchise number for some positions, and made the franchise tag even more attractive for teams to use.

While the years that I study are based on the old calculations for the franchise tag, the change in the way that the franchise tag is now calculated has led to different types of players being tagged. When the tag was relatively more expensive, it was a bigger commitment for a team to tag a player. As a result of this, the types of players who were given the tag under the old collective bargaining agreement were players who were going to get a big contract anyway. This sentiment was especially true in 2011, when teams feared a 2012 lockout and so were wary of committing long-term to their star free agents. Indeed, 71% of players who were given the franchise tag in 2011 were then signed to long-term deals before the season. Breer argues that since the franchise tag is now relatively cheaper, it is a great tool for management to use on players who may have had a flash-in-the-pan type year, or players at positions where skill has been known to decline quickly. By using the tag in this way, teams are able to avoid long-term commitments to players who may still be very good (an example given is 31-year-old Patriots wide receiver Wes Welker), but could decline in skill rapidly over the life of a longer contract. It also prevents teams from overpaying for a young or out-of-nowhere player who had an incredibly successful year which they are unlikely to repeat (Breer, 2012). Ultimately, the state of the franchise tag today may be summed up by a quote near the end of Nate Caminata's article: "Once regarded as a badge of excellence, the franchise designation now largely is about as dreaded as the scarlet letter" (Caminata, 2012).

Hypothesis

Taking both the intended effects of the franchise tag and the current literature surrounding its use into account, I believe I will find that franchise tagged players during the period studied earned lower salaries than would be expected if they were not tagged. I also believe I will find that higher-performing players were more likely to be tagged.

Chapter 3

Data and Methods

Data Collection

In collecting my data, I borrowed and built on techniques from many of the studies I mentioned in my literature review. I separated all player records by position, as Leeds and Kowalewski's research suggested (Leeds and Kowalewski, 2001). In this way, I could make sure that each player was judged on the statistical measures most relevant to their specific position. This was also necessary because players at different positions have different calculated salaries for the franchise tag, so this separation allowed players to be compared against the salaries of other players at their position. A challenge in recording my data like this came in measuring the performance of "non-skill" players, such as offensive linemen and defensive players. To better evaluate the performance of these players, I included data on whether or not these players made the Pro Bowl in a given season (the NFL all-star game), how many games these players played in and started, and how many years these players had been in the league. I also used a statistical measure called "approximate value" which was developed by Doug Drinen of pro-football-reference.com. According to Drinen, approximate value is, "an attempt to put a single number on the seasonal value of a player at any position from any year" (Drinen, 2008). Thus, approximate value (or AV) is an infinitely useful metric in helping me compare the values of various players at various positions, and in determining the value of non-skill position players. AV is based on a players performance in a wide range of categories relevant to their positions. While I will discuss AV a little more when describing why I decided to use certain statistics and measures, a full description of how AV is calculated for each position is attached as an appendix.

Although I originally intended on including the winning percentage of each player’s team for a given year, similar to what Lawrence Kahn did in his study, I opted not to go this route (Kahn, 1992). While including winning percentage or the total number of points that each player’s team scored and allowed in a given year would be interesting, I ultimately left these variables out due to their heavy dependence on the performance of so many other players. With 11 players on the field for a team at any given time, and an active roster of 53 players available to contribute to any given game, football is an incredibly team-oriented rather than individual-oriented sport. This makes it harder to attribute the success of a team to one player when compared to basketball (with only 5 players on the court at a time, one star can have a huge impact) or baseball (where most of the action on a play involves just one player from each team, the pitcher and the batter).

Description of Salary Data

My data on players’ salaries comes primarily from *USA Today*’s NFL salary database. According to *USA Today*, the data is based on their research, information from NFL player agents, and information from NFL Players Association research documents

(USA Today, 2012). I also used Excel files of the *USA Today* salary data that were put together by University of Michigan sports economics professor Rodney Fort (Fort, 2012).

The salary data for each player has five different categories: base salary, signing bonus, other bonus, total salary, and cap value. An explanation for each category is given by *USA Today* as follows:

- Base Salary: "The base salary is the value according to his," (each player's), "contract; however, contracts are not guaranteed and he may not have received the entire amount."
- Total Salary: "The amount he" (each player) "received in base salary and bonuses combined."
- Signing Bonus: "Signing bonuses are listed in entirety only for the year the contract was signed. As a result, a player's total salary can fluctuate extensively from one year to the next."
- Other Bonus: Bonuses for a player in a given season which are separate from their signing bonus.
- Cap Value: "Represents the player's pro-rated signing bonus, plus salary and other bonuses for the season (*USA Today*, 2012)."

Given that it pro-rates the player's one-time signing bonus, which can be substantial, I believe cap value to be the most useful measure of a player's salary to use for my research. Players who play under the franchise tag also receive no signing or other type of bonus, so using cap value helps take this difference into account by apportioning the bonuses of other players for a given season.

Description of Measures by Position

Skill Players

Skill players consist of quarterbacks, running backs (halfbacks and fullbacks), wide receivers, and tight ends. Since these players handle the ball very often, many of the traditional statistical measures do a good job capturing their value. Though I separated each player based on their position, all offensive players were measured by the same group of statistics[1]. I did this to best capture the true value of each player. For instance, though quarterbacks traditionally demonstrate their value simply by passing, there are some quarterbacks for whom rushing and scrambling is also an integral part of their skill set. Likewise, though the main job of a running back is to accumulate rushing yards and rushing touchdowns, some running backs are also quite adept at catching the ball. Thus, I compiled the following traditional statistical measures to evaluate all offensive players: completions, pass attempts, passing yards, passing touchdowns, interceptions thrown, rushing attempts, rushing yards, rushing touchdowns, receptions, receiving yards, and receiving touchdowns.

The following parameters were included to measure the value of each player's NFL experience, and to try and better value each player whose full contribution might not have been captured by standard statistics: games played, games started, years in the NFL, approximate value, and whether or not that player was selected for the Pro Bowl in a given season. Games played helps to capture a player's ability to stay healthy, and games

[1] The exception to this is the tight end position. Since no tight ends threw any passes during the period I studied, all passing measures were omitted when analyzing the position.

started helps to separate players of lesser caliber from players of higher caliber; while NFL teams can carry 53 active players on their roster for each game, only 22 of those players actually “start” in each game. The players a team decides to start are usually that team’s best players.

Years in the NFL helps to value players based on their longevity. Even if a player might not seem to put up good primary statistics, he is likely valuable to his team in some capacity (leadership, blocking, depth) if that team decides to keep him on their roster year after year. There are a limited number of spots on NFL rosters, and if a player wasn’t valuable to his team at all, NFL coaches and general managers wouldn’t waste a precious roster spot on that player. Players at different positions also peak at different ages, and start to wear down after different periods of time (running backs usually have much shorter careers than quarterbacks because of how often they get hit). Years in the NFL also helps to capture these phenomena.

Whether or not a player was selected for the Pro Bowl also helps to measure the popularity and perception of that player’s skill compared to other players at his position. For each position, there are no more than a handful of players selected to participate in the Pro Bowl in any year. Thus, if a player was selected for the Pro Bowl it means that NFL fans and coaches believed he was one of the best and/or most exciting players at his position that season.

Approximate value, which I described briefly above, is a metric which attempts to fully encompass a player’s value and performance in a given season. In the words of its creator, Doug Drinen:

> "AV is not meant to be a be-all end-all metric. Football stat lines just do not come close to capturing all the contributions of a player the way they do in baseball and basketball. If one player is a 16 and another is a 14, we can't be very confident that the 16AV player actually had a better season than the 14AV player. But I am pretty confident that the collection of all players with 16AV played better, as an entire group, than the collection of all players with 14AV" (Drinen, 2008).

Though I have separated my player data by position (as the salary a player receives when given the franchise tag is dependent on which position they play), approximate value allows me some leeway to compare the value and returns of players at different positions to their salary. The total description of how a player's approximate value is determined is included as an appendix.

Offensive Linemen

Measuring the quality of offensive linemen using traditional statistics is almost impossible. There are few widely used, trustworthy statistics that measure an offensive lineman's abilities; it's hard to determine just how well or poorly he blocked on a run, how responsible he was for giving up a sack or preventing one, or how many defensive linemen he knocked over (and whether or not that even helped a play). Thus, the variables that I used to measure offensive linemen were those that represented how much playing time they earned (games played in and games started), their years of experience in the league, and their approximate value as determined by pro-football-reference.com. Among offensive lineman especially in my OLS regressions, I really counted on approximate value as a good way to differentiate players whose skill was otherwise hard to determine. I also used a binary variable to show whether or not each offensive lineman was selected for the Pro Bowl in each given year, which, again, would mean they were thought to be among the best at their position.

Defensive Players

The defensive players I analyzed were broken into three initial sub-groupings: defensive linemen, linebackers, and defensive backs. From there, I broke defensive linemen and defensive backs down further as the franchise tag salary number differentiates between positions in these groupings; there is a different number among linemen for defensive ends and defensive tackles, and among defensive backs the number is different for cornerbacks and for safeties. The traditional statistical measures that I compiled to evaluate defensive players are: solo tackles, combined tackles, sacks, safeties, passes defended, interceptions, interceptions returned for touchdowns, total interception return yards, fumbles forced, fumbles recovered, and fumbles returned for touchdowns. Combined tackles is simply the addition of tackles the player made completely by themselves (solo tackles), and tackles that the player helped another player out on (assisted tackles).

Certainly, some of these traditional statistics apply more to certain categories of defensive players than others − for instance, cornerbacks are more likely to defend passes than defensive ends, who are more likely to accrue high sack totals − however, they all help to show a particular player’s value. A defensive end who can bat a couple of passes down at the line of scrimmage, or even intercept one, is more valuable than one who cannot, all else held equal. Similarly, defensive backs who can force fumbles or get sacks will stand out among their peers.

As mentioned in my literature review, traditional statistics may not be the best indicator of defensive player performance. For example, a very good cornerback might total few interceptions or passes defended during a season because the opponent will be afraid to throw to the player he is covering. Thus, for defensive players I again use the following parameters that I have used for the previous positions discussed to supplement traditional statistics: games played, games started, years of experience in the NFL, whether or not they made the Pro Bowl in a given year, and approximate value.

Kickers

Even though kickers and punters are grouped together by the franchise tag, and thus receive the same salary if they are designated a team’s franchise player, they are measured by different statistics. Because of this, I grouped them separately. The traditional statistics I compiled to measure kickers are: total field goals made, field goal percentage, extra points made, extra point percentage, and the number of punts a kicker may have attempted. I again used the non-traditional parameters that I already discussed for previous positions (games played in, Pro Bowl, experience, etc.), to value kickers.

Punters

The traditional statistics I gathered for punters are: number of punts, total yardage of those punts, net yardage of those punts (punt yardage minus return yardage and touchback yards), longest punt, number of punts blocked, number of punts downed inside the opponent's 20 yard line, number of touchbacks, number of punts fair caught, and number of punt return touchdowns allowed. Along with those traditional statistics, I also evaluated punters on all of the non-traditional parameters I have previously discussed (games played in, Pro Bowls selected to, etc.).

Data Sources

My data came primarily from four sources. Statistics for offensive players and kickers came from www.pro-football-reference.com (Pro-Football Reference, 2012). I also got all of my data on Pro Bowl appearances, games played in and started, player age and NFL experience, and approximate value from pro-football-reference. Statistics for punters and all defensive players came from NFL.com (NFL, 2012). Lastly, as discussed earlier, all salary data was taken from *USA Today*'s salary reports and spreadsheets put together by Rodney Fort (Fort, 2012; *USA Today*, 2012).

Information on which players actually received and played under the franchise tag in each season was harder to come by. I was able to find *USA Today* and Yahoo! articles from each season, published directly after the deadline for teams to designate a franchise player, listing the players that had been tagged that off-season (Weisman, 2006; *USA Today* 2006, 2007, 2008; Aldrks, 2009). Then, I went through each tagged player's transaction history to see which players signed long-term contracts or were traded (and subsequently signed a long-term contract) before the season. By eliminating those players who ended up signing long-term contracts from my initial list of tagged players, I was able to come up with a list of players who played each season under the one-year franchise tender. I included a binary variable to distinguish those players who played under the franchise tag in a given season from those who did not.

Methods of Analysis

Initial Regressions

My first method of analysis was to run standard OLS regressions using all of the different independent variables I had collected data for and described above (salary, passing yards, approximate value, etc.) to see what effect playing under the franchise tag had on a player's pay. To conduct these regressions I used the data analysis and statistical software package STATA. After running these regressions, I was able to obtain the coefficient associated with the franchise tag's effect on salary, and the significance of that effect.

Treatment Regression Model

After the results of my initial regressions (discussed in the next section), I also decided to conduct analysis using the treatment regression model to help determine why certain players were tagged, and to control for the likelihood of a player getting tagged.

The treatment regression model essentially adds a variable representing the likelihood of a player getting tagged into my regressions. This helped to correct a bias that I believed was present in my initial regressions, which assumed that all players analyzed were equally likely to be given the franchise tag. Running regressions using this model also gave me the results of a probit analysis for each position, which showed the effects of different variables representing a player's performance and experience on the likelihood of that player being tagged. I used STATA to run these regressions using a revised set of variables (games played in, games started, years of NFL experience, approximate value, and whether or not a player made the Pro Bowl) that I collected data for.

Chapter 4

Results and Discussion

Standard Regressions

My general finding when running standard OLS regressions was that playing under the franchise tag added to a player's Cap Value salary (roughly base salary plus pro-rated bonuses) for a given season at every position that I analyzed. My results are shown in Table 4-1, where the column "coefficient for franchise tag's effect on salary" shows the effect that playing under the franchise tag had on the salary of a player at each position, all other variables held equal. Though the amount of the effect that playing under the tag added to a player's salary varied among positions, the coefficient associated with the franchise tag was positive in each instance. For example, the results in Table 4-1 imply that being tagged as a defensive end added almost 5.5 million dollars to a player's salary:

Table 4-1. Standard OLS Regression Summary

Position	Coefficient for Franchise Tag's Effect on Salary	Standard Error	t	P>t	R Squared
Cornerback	5628671***	669906.6	8.4	0	0.4687
Defensive End	5472879***	805637	6.79	0	0.5323
Defensive Tackle	2190596	1470039	1.49	0.137	0.4597

Kicker	1150995***	410516.8	2.8	0.006	0.2301
Linebacker	5252973***	657095.7	7.99	0	0.4881
Offensive Line	4082200***	1050875	3.88	0	0.4267
Punter	1688914***	456404.6	3.7	0	0.464
Quarterback	1392339	2858358	0.49	0.626	0.4843
Running Back	4446717***	697662.5	6.37	0	0.517
Safety	5057508***	1067803	4.74	0	0.3832
Tight End	2715563***	617435.4	4.4	0	0.5065
Wide Receiver	6532651***	1492722	4.38	0	0.5029

***significant at .01 level

The positive values for the effect of the franchise tag on salary were not what I initially anticipated, and seemed intuitively wrong. After all, my hypothesis, and what would be expected, was that the franchise tag would have a negative effect on the salaries of top players. In an attempt to bring those values back in line with what would be expected, I ran the regressions again excluding rookies and players who had less than four years of NFL experience. Generally speaking, these players either do not or cannot get designated a team's franchise player. Their inclusion also might skew salary numbers, as they are not in their peak earning years, and may be bringing salary numbers down by earning significantly less than players receiving the franchise tag. While the effect on salary associated with playing under the franchise tag did decrease at all positions except defensive tackle, it was still positive in every case, though insignificant for defensive tackles and quarterbacks. As shown in table 4-2, in the case of defensive ends for example, the coefficient associated with the tag decreased to about 4.7 million:

Table 4-2. OLS Results for Players With at Least Four Years of Experience

Position	**Coefficient for Franchise Tag's Effect on Salary**	**Standard Error**	**t**	**P>t**	**R Squared**
Cornerback	4971815***	879279.8	5.65	0	0.4053
Defensive End	4671359***	1010799	4.62	0	0.4655
Defensive Tackle	2363106	1948511	1.21	0.226	0.3787
Kicker	788227.3	403817.7	1.95	0.054	0.082
Linebacker	4348889***	807874.4	5.38	0	0.4685
Offensive Line	3353649***	1238463	2.71	0.007	0.3515
Punter	1602854***	492413.9	3.26	0.002	0.3675
Quarterback	136972.6	3302001	0.04	0.967	0.4988
Running Back	3329247***	811404.1	4.1	0	0.6083
Safety	4422046***	1453177	3.04	0.003	0.3082
Tight End	2345334***	727756.2	3.22	0.001	0.517
Wide Receiver	6033358***	1833413	3.29	0.001	0.4395

***significant at .01 level

One reason for these numbers being so positive and volatile could be due to very few points of observation. Though approximately 44 players were given the franchise tag during the five year period I studied[2], only 29 players actually played a full season under the tag. The rest of the players either worked out new long-term contracts with their teams before the season began, or were traded and worked out new contracts with their new teams.

The results are even more skewed when the breakdown of players who played under the tag by position is considered. While there were a handful of players at certain

[2] 36 players were given the tag from 2006-2009, however, I could not find how many players were actually given the tag in 2005, only that 8 players played under the one-year franchise tender.

positions who played a season under the tag (defensive ends and cornerbacks in particular), there were some positions where only one player did this. From 2005 to 2009 there was only one quarterback and one punter who played a full season under the franchise tag. For instance, Table 4-3 shows the distribution of the “Tag” variable among all the Safeties that I had statistical data for. Only one out of 666 total Safeties (0.15% of the total dataset) actually played under the franchise tag:

Table 4-3. Distribution of the Binary Franchise Tag Variable among Safeties

Tag	**Freq.**	**Percent**	**Cum.**
0	665	99.85	99.85
1	1	0.15	100
Total	666	100	

Thus, I decided to exclude some positions from my analysis.[3] I was then left with the following positions to analyze: cornerback, defensive end, linebacker, offensive line, running back, and tight end.

While the results of my initial regressions were mostly significant, the highly positive coefficients associated with the franchise tag were very unexpected. While unexpected results are not necessarily a bad thing, these results still did not convince me that the franchise tag had really raised the salaries of “star” players. These initial regressions also did not control for what makes players more likely to be franchise

[3] I kept only positions where more than one player had played under the franchise tag during the period I studied. The exception to this was with kickers, who proved hard to analyze using the treatment regression model due to singularity issues.

tagged; basically, for what makes these players “star” players. Certainly, not all players are equally likely to be tagged. The franchise tag from 2005-2009 was an expensive investment for teams, and they likely wouldn’t use it on just anyone; it would be much more likely for a team to use the tag on a good player than on a bad player. Therefore, there was a large bias in the initial OLS regressions that were conducted, as they assumed that all players were equally as likely to be tagged.

Treatment Regression Model

The use of a treatment regression model helped solve a problem that was inherent in my initial regressions. The model essentially adds a variable which is the likelihood of a player playing under the franchise tag. Standard OLS regressions assumed that salary was a dependent variable which was determined by a player’s measurable statistics. However, it is likely that beyond measurable statistics there exists another determinant of salary, and whether or not a player is likely to receive the franchise tag; I believe this has something to do with the player’s estimated innate abilities and potential.

Put in other terms, consider the effect of attending college on an individual’s expected future earnings. While it seems clear that attending college has a positive effect on future salary, it’s not necessarily the case that this effect is entirely attributed to a college education. Perhaps some individuals are just inherently smarter than others and would have earned a high salary regardless of whether they attended college or not. This “inherent smartness” is directly related the abilities and characteristics of NFL players that I use the treatment regression model to account for.

The treatment model works in two steps. First, a probit model is formed to determine the probability of a player playing under the franchise tag, and also show the effect of other independent variables (statistics, experience, games started) on whether or not a player receives and plays under the franchise tag. The second step incorporates the probability of a player playing under the franchise tag as an additional variable into the regressions on player salary.

Initially, the formula I used for salary determination could be simplified to the formula in Equation 1 below, where salary is just determined by all of the statistical measures I used (represented as βX_i) and whatever random error/noise is present (ε_i). βX_i is simply a condensed version of all of the measures and variables I decided to include (for example, $\beta X_i = \beta_1$PassingYards + β_2ApproximateValue + β_3ProBowl + β_4Tag……).

Equation 1 - Simplified OLS Example Formula

$$Salary_i = \beta X_i + \varepsilon_i$$

However, using the treatment regression model allows me to separate a player's likelihood of getting tagged from the error/noise term, so that it can be accounted for when determining the effects of the franchise tag on salary. This likelihood is represented as α_i in Equation 2, which is the inverse Mills ratio[4] of the probit analysis conducted in the first step of the treatment regression.

Equation 2 - Treatment Regression Model Example Formula

$$Salary_i = \beta X_i + \alpha_i + \varepsilon_i$$

[4]The inverse Mills ratio is the ratio of the probability density function to the cumulative density function of a distribution. It allows conversion of a probit model to a variable that can be used in OLS regressions.

For the treatment regressions that I ran, I limited the independent variables used to games played, games started, years of experience, approximate value, and the binary marker for whether or not that player was selected for the Pro Bowl. I did this because approximate value is highly dependent on many of the individual statistical measures that I recorded for each player, and I believe that approximate value gives each measure its proper weight.

I also followed the convention I established in my OLS regressions of limiting my analysis to players with at least four years of NFL experience. The exception to this was with offensive linemen, where issues with singularity forced me to use all offensive linemen in order to get results in STATA. Table 4-4 shows the results of my treatment regression analysis for the franchise tag's effect on salary, where the column "coefficient for franchise tag's effect on salary" shows the effect that playing under the franchise tag had on the salary of a player at each position, all else held equal:

Table 4-4. Treatment Regression Model Results Summary

Position	**Coefficient for Franchise Tag's Effect on Salary**	**Standard Error**	**z**	**P>z**
Cornerback	-786266.6	3896635	-0.2	0.84
Defensive End	1310446	5222636	0.25	0.802
Linebacker	-3332895	3057030	-1.09	0.276
Offensive Line	-9279416	6053471	-1.53	0.125
Running Back	1828054	2194075	0.83	0.405
Tight End	-1.01E+07*	6005729	-1.68	0.093

*significant at 0.10 level

Effects of the Franchise Tag

After examining the results in Table 4-4, the effects of the franchise tag on player salary remain unclear. Though the coefficient representing the franchise tag's effect on salary is significant at 0.10 level for tight ends, it is insignificant at every other position. However, though most of these coefficients are insignificant, I still believe it is important and telling that they all either turned negative or became much less positive than they were for each position in my initial OLS regressions. I believe that even though the results do not say with certainty or significance exactly how much the franchise tag altered player salary at each position, the large drop in each coefficient does say something: that my initial OLS results were biased, and that the franchise tag seems to have reduced the salary of most top players to some extent.

While the tag appears to have decreased the salaries of top cornerbacks, kickers, linebackers, offensive linemen, and tight ends that received and played under it from 2005-2009, the results show that it raised salaries for top defensive ends and running backs. These results can be interpreted in different ways. Certainly, it seems that the franchise tag actually increased the salary of some players compared to what their actual performance would dictate they should be paid. This could be due to the fact that these players were already among the highest paid players at their position, so the franchise tag actually increased their salary to 120% of what they made the previous season. It could also be attributed to teams using the franchise tag as a holding marker for players; perhaps teams applied the franchise tag to these players not because they were stars, but because they wanted to get one more year to look at their performance before deciding whether or not these players were actually worthy of a long-term investment.

For most positions, though, the results of my treatment regressions show that the franchise tag lowered the salaries of top players who play a season under the one year contract, all else held equal. This is consistent with my initial hypothesis, and with the supposed purpose of the tag. For example, the results show that a general manager could have saved about 3.3 million dollars during the years studied by applying the franchise tag to his star linebacker.[5] In theory, this saving would have allowed the general manager to allocate that money to other players he previously would not have been able to sign to build a more competitive team.

While the overall effects of the franchise tag in every situation may be unclear, it seems likely that "a certain type of player" gets tagged. Based on the difference between the results from my initial OLS regressions (which all showed highly positive returns to salary from playing under the tag), and the results from the controlled treatment regressions (which showed negative returns to salary from playing under the franchise tag for most positions), there is another variable involved in determining who gets tagged outside of measurable statistics and experience. Whether that other variable is a general manager's opinion of a specific player's innate ability or potential, or something else, is unclear; however, it is clear that there is some type of outside determinant or "noise" involved in determining who gets tagged that was not captured by standard OLS regressions.

[5] The results imply that applying the franchise tag to a linebacker would reduce his salary by 3.3 million dollars compared to what his statistics and experience would dictate he should earn. In reality, on the open market, it's hard to say what that linebacker would earn. Depending on how other teams valued and bid on this player, the general manager could end up saving less or more than 3.3 million dollars.

Factors Contributing to Playing Under the Tag

The results of my probit analyses are shown in Tables 4-5 through 4-10. The "coefficient for effect on likelihood of being tagged" column shows the effect that an increase in each independent variable listed had on the likelihood of a player at that position being given the franchise tag. Similar to the results in Table 4-4, the results for my probit analyses are mostly insignificant. This is, again, due to having very few franchise tagged players at each position in my data. I still believe, however, that the trends in the signs of the coefficients obtained can provide some useful data for an exploratory discussion of why some players at different positions are more likely to get franchise tagged than others.

Table 4-5. Probit Results for Cornerbacks

Variable	**Coefficient for Effect on Likelihood of Being Tagged**	**Standard Error**	**z**	**P>z**
G (Games Played In)	-0.2873297	0.2680283	-1.07	0.284
GS (Games Started)	0.2331493	0.2462373	0.95	0.344
Yrs (Years of NFL Experience)	-0.2234327*	0.1417949	-1.58	0.115
AV (Approximate Value)	0.0682892	0.1527486	0.45	0.655
ProBowl (Binary Marker for Pro Bowl)	0.4748127	1.088463	0.44	0.663
Constant	-0.4106898	1.194502	-0.34	0.731

*significant at roughly 0.10 level

The results of the probit analyses of which factors contribute to a player getting and playing under the franchise tag vary by position. This could be due to the fact that different weight is put on different characteristics for players at different positions. For instance, the age where players are in their prime and start to decline varies by position. Being selected as a Pro Bowler also could carry different weight at different positions; it may be easier to make the Pro Bowl at certain positions that carry more players on the roster, or if many players at a certain position were hurt and could not play in the Pro Bowl.

Table 4-6. Probit Results for Defensive Ends

Variable	**Coefficient for Effect on Likelihood of Being Tagged**	**Standard Error**	**z**	**P>z**
G (Games Played In)	-0.0295713	0.1097806	-0.27	0.788
GS (Games Started)	0.0008593	0.0767537	0.01	0.991
Yrs (Years of NFL Experience)	-0.1231718	0.1172196	-1.05	0.293
AV (Approximate Value)	0.1403316	0.1227857	1.14	0.253
ProBowl (Binary Marker for Pro Bowl)	-0.2512324	0.9230497	-0.27	0.785
Constant	-1.992762	1.509633	-1.32	0.187

The three most consistent trends across all positions examined were: more games started being correlated with a higher likelihood of playing under the franchise tag, a higher approximate value being correlated with a higher likelihood of playing under the franchise tag, and more years of NFL experience being correlated with a lower likelihood of playing under the franchise tag. Starting more games and having a higher approximate value make sense in predicting a higher likelihood of being tagged. Both measures reflect a player’s abilities, and players with high totals of approximate value and games started are likely very good players.

Table 4-7. Probit Results for Linebackers

Variable	**Coefficient for Effect on Likelihood of Being Tagged**	**Standard Error**	**z**	**P>z**
G (Games Played In)	-0.1243512	0.3129742	-0.4	0.691
GS (Games Started)	0.3445327	0.2941071	1.17	0.241
Yrs (Years of NFL Experience)	-0.4665477*	0.2847107	-1.64	0.101
AV (Approximate Value)	-0.242135	0.1905837	-1.27	0.204
ProBowl (Binary Marker for Pro Bowl)	1.651785*	1.035403	1.6	0.111
Constant	-1.368486	2.55705	-0.54	0.593

*significant at roughly 0.10 level

The negative correlation between years of experience and being tagged can also be explained. The above analyses looked at players with *at least* three years of NFL experience. Playing football in the National Football League takes a toll on players' bodies, often very quickly. According to a study by the NFL management council, the average career of an NFL player who makes a team's opening-day roster as a rookie is only six years long. If a player doesn't make an opening-day roster as a rookie, his average career is then only 3.5 years long (NFL Communications, 2011). Thus, the cutoff mark for players that I analyzed is nearing the average career length for most NFL players. Especially at some positions, players lose value and ability very quickly as they increase in age and seasons played. The negative correlation between years of experience and being tagged can probably be interpreted as teams' expectations that players' abilities are deteriorating as they accrue more wear and tear on their bodies.

Table 4-8. Probit Results for Offensive Linemen

Variable	Coefficient for Effect on Likelihood of Being Tagged	Standard Error	z	P>z
G (Games Played In)	-2.930904	422.6104	-0.01	0.994
GS (Games Started)	2.940908	422.6103	0.01	0.994.
Yrs (Years of NFL Experience)	-0.035349	0.0853445	-0.41	0.679
AV (Approximate Value)	0.0197933	0.1096823	0.18	0.857
ProBowl (Binary Marker for Pro Bowl)	0.5542945	0.7660655	0.72	0.469
Constant	-3.042793	1.524061	-2.00	0.046

The results of these probit analyses suggest a couple of things. First of all, it's possible that perhaps being selected to the Pro Bowl isn't as indicative of player skill as previously thought. Especially when compared to games started and approximate value, selection to the Pro Bowl is not a consistent predictor of a player's likelihood to play under the tag. This might be due to the "superstar" impact of players, which goes beyond what they do on the field. Selection for the Pro Bowl is in part determined by fan voting, and perhaps teams would rather keep these players happy, and give them long-term contracts to keep their fans happy, than franchise tag these players and cause contempt.

Table 4-9. Probit Results for Running Backs

Variable	Coefficient for Effect on Likelihood of Being Tagged	Standard Error	z	P>z
G (Games Played In)	0.1140906	0.3399171	0.34	0.737
GS (Games Started)	-0.203319	0.1935204	-1.05	0.293

Yrs (Years of NFL Experience)	-0.3135231	0.2983644	-1.05	0.293
AV (Approximate Value)	0.190899**	0.0974417	1.96	0.05
ProBowl (Binary Marker for Pro Bowl)	1.886533	2.171185	0.87	0.385
Constant	-3.061002	5.382665	-0.57	0.57

**significant at .05 level

Also, it is interesting to see the negative link between years of experience and being tagged. With all of the recent innovations in equipment and rule changes to protect players and improve safety, football remains a very violent sport. Players' bodies wear down every year at different rates, and they increasingly become less and less valuable to their teams. This could be why teams are less likely to invest guaranteed money in older players (even for just one season), when they could sign them to less risky contracts − contracts that may be longer in duration, but guarantee less money so that players can be cut loose easier if they slip in production.

Table 4-10. Probit Results for Tight Ends

Variable	**Coefficient for Effect on Likelihood of Being Tagged**	**Standard Error**	**z**	**P>z**
G (Games Played In)	-0.060091	0.127519	-0.47	0.637
GS (Games Started)	0.0754107	0.111614	0.68	0.499
Yrs (Years of NFL Experience)	-0.4595064	0.4052919	-1.13	0.257
AV (Approximate Value)	0.0745012	0.1609837	0.46	0.644
ProBowl (Binary Marker for Pro Bowl)	-4.83472	845.2683	-0.01	0.995
Constant	-0.1553366	2.10315	-0.07	0.941

Finally, it's intriguing that rates at which an additional year of experience takes away from a players likelihood to play under the franchise tag vary by position. This seems to imply that players at certain positions with very negative coefficients for experience (linebackers, running backs, tight ends) lose value faster than players with coefficients closer to zero (cornerbacks, defensive ends, offensive linemen). This is likely due to the amount of vicious hits that running backs and tight ends are subject to as ball-handlers, and the amount of big collisions that the linebackers trying to tackle them are a part of.

Limitations and Future Research

The clearest limitation to my research was the sample size of players who played under the franchise tag from 2005-2009. Having only 29 such players as data points led to data sets where there were only three or four tagged players out of 700 or 800 total players at a position. This scarcity of tagged players manifests itself in mostly insignificant P values for my treatment regressions, and is a big reason why any conclusions about the effects of the franchise tag must be made carefully and thoughtfully, and cannot be proclaimed defiantly. The main way I dealt with this problem was to limit my regressions to players who had at least four years of NFL experience; this helped to eliminate hundreds of younger players from my analysis, none of whom had been tagged or were likely candidates to be tagged.

Another limitation of my study can be attributed to the fact that all available NFL salary data is somewhat incomplete. Many players who were signed later in the season as free agents did not have official salary numbers in the data compiled by *USA Today* and Rodney Fort; however, none of these players were franchise tagged. Also, in compiling data from different sources (different statistics from different websites, salary data from different sources, data on years of experience and pro bowl appearances from yet another website, etc.), it is possible that a handful of players were left out of my analysis due to different naming by different sources. For instance, if one player was referred to as Steve Smith by one source, Stephen Smith in another, and Steve M. Smith (CAR) in a third, they might have been left out when statistical and salary data were merged. Though I believe I caught nearly all of these instances, and know with 100% certainty that no franchise tagged players were left out, a couple of players could have been left out from my position-by-position analysis. Unless these players were extreme statistical outliers, though, the effect of their inclusion would likely be very small.

My research is also highly dependent on which statistics one values for each position, and how exactly one chooses to manipulate the data. For instance, if sacks and passes defended were included for defensive ends, and the analysis is limited to only players with *five* or more years of NFL experience, results show a negative coefficient for the effect of the franchise tag on salary. The data can manipulated in similar ways for different positions by including or excluding different statistics and measures of experience, or by limiting the data to different sets of players. I personally chose to limit my data as little as possible, and be as objective in my selection of independent variables as possible. Because of this, I chose to include approximate value alone in my treatment regressions instead of many individual statistics for players. I trusted that approximate value gave the important statistical measures for each position their appropriate weight, and that I would be better off not picking and choosing which statistics to include again by themselves.

One interesting area to look at further is how franchise tagged players are paid compared to players of similar skill during that players tagged season, and also how franchise tagged players' skill varies before, after, and during the year that they are tagged. The former could be done by determining the approximate value of each franchise tagged player, and then running a regression of salary on the franchise tag for all players who had the same or slightly different approximate values during that season. The latter would simply involve examining the players statistics before, during, and after the year they played under the franchise tag, and noting any major discrepancies. Looking more into these areas could provide insight as to how players typically perform under the franchise tag compared to how they perform otherwise, and whether or not the franchise tag is paying players a similar amount to the average salary for their skill level in a given season.

Also, a more comprehensive probit analysis to determine what factors lead to a player getting tagged could be completed. In my analysis, I only considered players who actually played a full season under the franchise tag in order to examine the tag's effect on salary. By including all players who were given the franchise tag in a given year (including all those who worked out long-term contracts before the season), there would be almost twice as many data points to examine.

Chapter 5

Conclusion

My analysis shows that the franchise tag has had a somewhat ambiguous, though mostly negative, effect on the salaries of top players in the National Football League. For four of the six positions where more than one player played under the franchise tag from 2005 through 2009[6], treatment regression analysis showed a negative effect on player salary associated with playing under the franchise tag. Probit analyses of factors contributing to playing under the franchise tag also showed some correlation between being tagged and having more games started, a higher approximate value, and fewer years of NFL experience. My results, however, are mostly exploratory due to the insignificant amount of players who actually played under the franchise tag in the years that I studied. This small sample size led to largely insignificant coefficients in my treatment regressions and probit analyses. Even though they were largely insignificant, however, I still believe the signs of each coefficient, and the magnitude of change in each coefficient from their values initially obtained by OLS, reveal useful data in analyzing the franchise tag and determining its effects.

The results of my analysis are mostly in line with my hypothesis that the franchise tag has kept down the salaries of top players who have received it. The results of the probit analyses are also in line with my expectations that more skilled and more

[6]This excludes kickers due to econometric issues explained earlier.

successful players are more likely to get the tag. I also found that my initial OLS regressions were biased, as they didn't take into account that certain players were more likely to be tagged than others.

The key to most future research on the franchise tag lies in being able to examine more data points for tagged players. When salary data comes out for years up to 2012 (a record 19 players were tagged in 2012), there will be a bigger pool of tagged players to examine. A more thorough probit analysis could use all players who were tagged, and not just those who actually played under the tag, to determine factors leading to a player being tagged with more significance. Future studies could also take time into account, and measure how each player's contract and performance changed in the years before, during, and after they were tagged.

Appendix A

Approximate Value Derivation

What follows is a more thorough definition of the approximate value metric that I relied on heavily in my study. The following calculations and descriptions are taken from a post by Neil Paine on pro-football-reference.com describing how Doug Drinen calculated each player's approximate value:

"

Offense

'Every team gets this many points to divvy up among its offensive players:
team_offense_points = 100 * (team offensive points per drive) / (league average offensive points per drive),
where
offensive points per drive = (7*(rushTD+passTD) + 3*FG) / (rushTD + passTD + turnovers + punts + FGA)

Offensive line

As a unit, the offensive line for a given team will share this many points:
team_points_for_o_line = 5 / 11 * team_offense_points'
...
'For each offensive lineman (and fullback and tight end), we define:
individual_points = [(games played) + 5*(games started)*(pos_multiplier)] * (all_pro_multiplier),
where pos_multiplier = 1.2 for tackles, 1.0 for guards and centers, 0.3 for fullbacks, and 0.2 for tight ends,
and all_pro_multiplier = 1.9 for first-team AP all-pro, 1.6 for second-team AP all-pro, and 1.3 for a pro bowler who was not first- or second-team all-pro. [NOTE: all_pro_multiplier is for tackles, guards, and centers only, not fullbacks or tight ends.]
Finally, each individual player receives this many points:
approx_value = (individual_points) / (sum of individual_points for all players on team) * (team_points_for_o_line)

Skill-position players

Since we know the entire offensive unit will get *team_offense_points*, and we gave *team_points_for_o_line* of those to the line, we have:
team_points_for_skill_positions = team_offense_points - team_points_for_o_line
Now we split that up into two pieces:
team_points_for_rushers = team_points_for_skill_positions * (.22) * [(team_rsh_yards / team_total_yards) / .37]'
...
'Now every individual player gets the following share:
approx_value = (rushing yards) / (team rushing yards) * team_points_for_rushers

Finally, we give a small bonus (or impose a small penalty) to running backs who had 200 or more carries and whose yards per carry average was much higher or lower than the league average:
bonus = .75 * [(yards per rush) - (league yards per rush by RBs)], if the player's yards per rush is better than league average.
penalty = 2 * [(yards per rush) - (league yards per rush by RBs)], if the player's yards per rush is worse than league average.
Note that quarterbacks, wide receivers, and anyone else who compiles rushing yards is eligible to get approximate value points at this stage.
Now onto the passers and receivers....
team_points_for_passers = (team_points_for_skill_positions - team_points_for_rushers) * .26. (see part II for an explanation of the .26.)
So that leaves:
team_points_for_receivers = (team_points_for_skill_positions - team_points_for_rushers) * .74.
Anyone who had a receiving yard gets this many AV points:
approx_value = (receiving yards) / (team receiving yards) * team_points_for_receivers
(Eventually, I might want to work in a touchdown bonus here, but for now there isn't one.)
And similarly for passers.
approx_value = (passing yards) / (team passing yards) * team_points_for_passers
And, as with rushers, we add an efficiency adjustment here:
bonus = .5 * [(Adjusted yards per attempt) - (League average adjusted yards per attempt)], if the player's AYPA was better than league average.
penalty = 2 * [(Adjusted yards per attempt) - (League average adjusted yards per attempt)], if the player's AYPA was worse than league average.'

Defense

'**team_defense_points** = 100 * [(1 + 2 M - M^2) / (2 M)],
where M = (team defensive points allowed per drive) / (league average defensive points allowed per drive)
team_points_for_front_7 = (2/3) * team_defense_points
team_points_for_secondary = (1/3) * team_defense_points'
...
'Now, for all defensive players, we compute:
individual_points = [(games played) + 5*(games started) + sacks + 4*(fumble recoveries) + 4*(interceptions) + 5*(defensive TDs) + (tkl_constant)*(tackles)] + (all_pro_bonus),
where
tkl_constant = 0 if the year is before 1994, and otherwise, tkl_constant = .6 if the player is a defensive lineman, .3 if the player is a linebacker, and 0 of the player is a defensive back.
all_pro_bonus = (all_pro_level)*(year_multiplier),
where
all_pro_level = 1.5 for first-team all-pro, 1.0 for second-team all-pro, and 0.5 for pro bowler
year_multiplier = (year_constant) * (number_of_games_multiplier),
where year_constant = 40 for the pre-sack years (1970--1981) and 80 for the post-sack years (1982--present), and

number_of_games_multiplier = (number of games played by each team in that season) / 16'
...
'Now, each front-seven player gets:
approx_value = [(individual_points) / (sum of individual_points for all front-seven players on the team)] * team_points_for_front_7
and each defensive back gets:
approx_value = [(individual_points) / (sum of individual_points for all defensive backs on the team)] * team_points_for_secondary

Returns

Every player gets one point of approx_value for each kick or punt return TD.'

" (Paine, 2010).

Appendix B

Full Regression Results

Cornerback OLS Regression on Cap Value

Variable	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Tag	5628671	669906.6	8.4	0	4313718	6943623
AV	5382.447	54515.91	0.1	0.921	-101626.3	112391.2
CombinedTackles	-14577.1	16822.39	-0.87	0.386	-47597.61	18443.38
SoloTackles	21721.7	19606.09	1.11	0.268	-16762.9	60206.3
Sck	-150536	111286.4	-1.35	0.177	-368979.3	67906.63
SFTY	1346727	1481417	0.91	0.364	-1561131	4254584
Pdef	32683.12	16361.27	2	0.046	567.7501	64798.5
INT	-1714.08	65487.23	-0.03	0.979	-130258.3	126830.1
INTTDs	138439.1	193074.4	0.72	0.474	-240544.7	517422.8
INTYds	-2395.35	2800.386	-0.86	0.393	-7892.2	3101.5
FF	52938.65	71011.49	0.75	0.456	-86449.07	192326.4
FumRec	-78256.8	98729.39	-0.79	0.428	-272051.7	115538.1
FumTD	-129904	273460.8	-0.48	0.635	-666677.3	406869.3
Yrs	216044.4	17518.5	12.33	0	181657.5	250431.3
G	-61060.4	16706.42	-3.65	0	-93853.26	-28267.5
GS	91389.6	24568.08	3.72	0	43165.17	139614
ProBowl	1454278	400006.5	3.64	0	669109.9	2239447
_cons	747447.8	183541.3	4.07	0	387176.5	1107719

Cornerback OLS Regression on Cap Value Where Players Have Four Years or More Experience

Variable	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Tag	4971815	879279.8	5.65	0	3242016	6701613

AV	8132.609	114978	0.07	0.944	-218063	234327.7
CombinedTackles	-21769.5	30801.99	-0.71	0.48	-82365.9	38826.99
SoloTackles	39560.35	35327.72	1.12	0.264	-29939.5	109060.2
Sck	-246755	183041.3	-1.35	0.179	-606851	113339.9
SFTY	1284058	1921385	0.67	0.504	-2495863	5063979
Pdef	61404.08	32633.74	1.88	0.061	-2795.95	125604.1
INT	33096.63	118940	0.28	0.781	-200893	267086.2
INTTDs	-129572	351305	-0.37	0.712	-820691	561547
INTYds	-4099.51	5608.27	-0.73	0.465	-15132.6	6933.589
FF	98752.77	123025.3	0.8	0.423	-143274	340779.2
FumRec	42859.62	185352.2	0.23	0.817	-321782	407501.2
FumTD	-932843	535319	-1.74	0.082	-1985971	120284.9
Yrs	57703.93	45800.75	1.26	0.209	-32399.4	147807.3
G	-155729	35810.7	-4.35	0	-226180	-85279.4
GS	132848.3	48612.7	2.73	0.007	37213.01	228483.6
ProBowl	1247231	731721.1	1.7	0.089	-192277	2686738
_cons	2318922	476770.4	4.86	0	1380976	3256868

Defensive End OLS Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	5472879	805637	6.79	0	3891065	7054693
AV	131251.9	64382.91	2.04	0.042	4840.385	257663.5
CombinedTackles	-23968.3	16540.29	-1.45	0.148	-56444.09	8507.422
SoloTackles	4833.477	22149.13	0.22	0.827	-38654.85	48321.81
Sck	50079.13	33891.95	1.48	0.14	-16465.45	116623.7
SFTY	675827.1	394750.7	1.71	0.087	-99239.49	1450894
Pdef	-50797.2	102967.4	-0.49	0.622	-252966.8	151372.5
INT	976333.1	491780.9	1.99	0.048	10754.26	1941912

INTTDs	1560422	608563.7	2.56	0.011	365548.2	2755297
INTYds	-56350.3	16001.5	-3.52	0	-87768.12	-24932.4
FF	200154	68524.42	2.92	0.004	65610.85	334697.1
FumRec	-37161.5	89520.12	-0.42	0.678	-212928.3	138605.3
FumTD	-25294.2	332008.2	-0.08	0.939	-677170.2	626581.8
Yrs	271281.2	20735.34	13.08	0	230568.8	311993.7
G	-56082.1	21638.91	-2.59	0.01	-98568.63	-13595.5
GS	88949.35	25981.73	3.42	0.001	37935.96	139962.7
ProBowl	1172235	436526	2.69	0.007	315145.2	2029324
_cons	766295.2	234939.2	3.26	0.001	305007.8	1227583

Defensive End OLS Regression on Cap Value Where Players Have Four Years or More Experience

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	4671359	1010799	4.62	0	2682440	6660278
AV	331949.2	102331.8	3.24	0.001	130593.9	533304.4
CombinedTackles	-12798.3	26541.84	-0.48	0.63	-65023.94	39427.26
SoloTackles	-18685.6	35676.79	-0.52	0.601	-88885.73	51514.61
Sck	95258.46	56288.1	1.69	0.092	-15498	206014.9
SFTY	480005.2	594008.3	0.81	0.42	-688807.6	1648818
Pdef	262080.3	185531.6	1.41	0.159	-102984.7	627145.4
INT	-299333	817007.5	-0.37	0.714	-1906935	1308268
INTTDs	2030599	1067858	1.9	0.058	-70594.3	4131793
INTYds	-94323.3	28319.13	-3.33	0.001	-150046.1	-38600.6
FF	390357.3	113409.2	3.44	0.001	167205.3	613509.3
FumRec	-40688.4	154530.5	-0.26	0.792	-344753.6	263376.9
FumTD	-594479	715916.4	-0.83	0.407	-2003167	814208.9
Yrs	87043.92	49646.68	1.75	0.081	-10644.42	184732.3
G	-176483	44153.12	-4	0	-263361.6	-89604
GS	54960.59	46483.96	1.18	0.238	-36504.54	146425.7

ProBowl	146915.2	669619.2	0.22	0.826	-1170675	1464505
_cons	3098601	646729.8	4.79	0	1826050	4371152

Defensive Tackle OLS Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	2190596	1470039	1.49	0.137	-696610.7	5077803
AV	-27476	65850.79	-0.42	0.677	-156809.2	101857.2
CombinedTackles	38398.81	15185.16	2.53	0.012	8574.635	68222.98
SoloTackles	-34366.5	20593.4	-1.67	0.096	-74812.67	6079.635
Sck	94985.48	40724.18	2.33	0.02	15001.79	174969.2
SFTY	-936613	519321.6	-1.8	0.072	-1956579	83352.19
Pdef	103277.3	123097.4	0.84	0.402	-138490.3	345044.9
INT	-139693	447235.5	-0.31	0.755	-1018079	738692.5
INTTDs	784763	1009074	0.78	0.437	-1197093	2766619
INTYds	-5307.7	19934.07	-0.27	0.79	-44458.89	33843.49
FF	10145.05	106904.8	0.09	0.924	-199819.6	220109.7
FumRec	115094.3	101048.3	1.14	0.255	-83368	313556.7
FumTD	-615703	429617.7	-1.43	0.152	-1459487	228081.1
Yrs	165633.7	17705.2	9.36	0	130860.1	200407.3
G	-44234.9	18434.25	-2.4	0.017	-80440.42	-8029.43
GS	76569.15	24789.59	3.09	0.002	27881.54	125256.8
ProBowl	2118965	425547.6	4.98	0	1283175	2954755
_cons	513786.3	180647.4	2.84	0.005	158988.6	868583.9

Defensive Tackle OLS Regression on Cap Value Where Players Have Four Years or More Experience

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	2363106	1948511	1.21	0.226	-1473904	6200116
AV	-171403	110669.5	-1.55	0.123	-389334	46527.09
CombinedTackles	29346.54	26377.81	1.11	0.267	-22596.7	81289.75
SoloTackles	-23778.2	35903.27	-0.66	0.508	-94479	46922.53
Sck	187514.5	70353.01	2.67	0.008	48975.25	326053.7
SFTY	-1408353	994974.7	-1.42	0.158	-3367658	550952.8
Pdef	829256.5	279552.1	2.97	0.003	278762.2	1379751
INT	-1885873	900854.8	-2.09	0.037	-3659837	-111908
INTTDs	372912.6	2467682	0.15	0.88	-4486451	5232276
INTYds	-31008.3	58982.47	-0.53	0.6	-147157	85140.03
FF	-70807.2	187403.8	-0.38	0.706	-439843	298228.6
FumRec	197026	174699.9	1.13	0.26	-146993	541045.3
FumTD	-1156835	770677.2	-1.5	0.135	-2674454	360783.3
Yrs	68286.28	39158.64	1.74	0.082	-8824.96	145397.5
G	-78144.6	38071.96	-2.05	0.041	-153116	-3173.21
GS	158008.5	41975.95	3.76	0	75349.41	240667.6
ProBowl	3012991	669802.9	4.5	0	1694015	4331968
_cons	1502515	498624.8	3.01	0.003	520622	2484407

Kicker OLS Regression on Cap Value

Variable	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Tag	1150995	410516.8	2.8	0.006	340225.7	1961764
G	28996.58	34606.31	0.84	0.403	-39350.76	97343.92
TotalFGM	7779.86	14543.99	0.53	0.593	-20944.47	36504.19
FG	219024.9	563803.6	0.39	0.698	-894485.1	1332535
XPM	-3701.38	5971.989	-0.62	0.536	-15496.03	8093.281
XP	284514.1	557096.8	0.51	0.61	-815750	1384778
Punts	-3858.62	6938.415	-0.56	0.579	-17561.96	9844.727
Yrs	48581.82	10411.99	4.67	0	28018.18	69145.46
ProBowl	-218350	248355.9	-0.88	0.381	-708851.9	272152
_cons	-18527.5	569469.1	-0.03	0.974	-1143227	1106172

Kicker OLS Regression on Cap Value Where Players Have Four Years or More Experience

Variable	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
Tag	788227.3	403817.7	1.95	0.054	-12380.5	1588835
G	31707.99	42946.15	0.74	0.462	-53436.9	116852.9
TotalFGM	8917.825	17936.57	0.5	0.62	-26643.2	44478.82
FG	-313605	906957.9	-0.35	0.73	-2111737	1484528
XPM	-274.697	7396.162	-0.04	0.97	-14938.3	14388.91
XP	-1237067	3788039	-0.33	0.745	-8747222	6273089
Punts	-60355	114055	-0.53	0.598	-286480	165770.1
Yrs	-10880	13888.04	-0.78	0.435	-38414.4	16654.43
ProBowl	-60058	355278.9	-0.17	0.866	-764433	644317.1
_cons	2489628	3851393	0.65	0.519	-5146133	1.01E+07

Linebacker OLS Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	5252973	657095.7	7.99	0	3963663	6542284
AV	45789.33	36704.53	1.25	0.212	-26229.9	117808.6
CombinedTackles	-12781	6655.316	-1.92	0.055	-25839.66	277.5887
SoloTackles	19456.59	8882.392	2.19	0.029	2028.142	36885.04
Sck	61744.28	23839.07	2.59	0.01	14968.81	108519.7
SFTY	-578878	331131.9	-1.75	0.081	-1228604	70847.14
Pdef	30922.97	31257.88	0.99	0.323	-30409.2	92255.14
INT	-30683.2	113474	-0.27	0.787	-253334.4	191968
INTTDs	-153399	240350.3	-0.64	0.523	-624998.3	318201
INTYds	390.8032	4359.547	0.09	0.929	-8163.216	8944.823
FF	-101588	45880.47	-2.21	0.027	-191611.2	-11563.8
FumRec	17815.48	62784.34	0.28	0.777	-105375.9	141006.8
FumTD	-130873	225216.9	-0.58	0.561	-572779.1	311032.8
Yrs	227153.2	13263.15	17.13	0	201129.1	253177.3
G	-57423	11866.37	-4.84	0	-80706.39	-34139.5
GS	78999.72	18468.25	4.28	0	42762.52	115236.9
ProBowl	697368.9	250722	2.78	0.006	205418.5	1189319
_cons	599542.9	145162.7	4.13	0	314714.2	884371.6

Linebacker OLS Regression on Cap Value Where Players Have Four Years or More Experience

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	4348889	807874.4	5.38	0	2761482	5936297
AV	79178.5	59665.9	1.33	0.185	-38060.1	196417.1
CombinedTackles	-16885.2	11472.3	-1.47	0.142	-39427.4	5656.905
SoloTackles	32400.38	15358.7	2.11	0.035	2221.792	62578.97

Sck	77593.08	42027.3	1.85	0.065	-4987.15	160173.3
SFTY	-1350042	520127.2	-2.6	0.01	-2372050	-328035
Pdef	34789.51	53516.89	0.65	0.516	-70366.8	139945.8
INT	61331.87	193525.2	0.32	0.751	-318929	441593
INTTDs	161027.5	498673.3	0.32	0.747	-818825	1140880
INTYds	-789.682	8177.125	-0.1	0.923	-16857.1	15277.7
FF	-110484	78223.57	-1.41	0.158	-264187	43218.68
FumRec	1223.407	110375	0.01	0.991	-215655	218101.4
FumTD	-356491	386453.8	-0.92	0.357	-1115841	402859.4
Yrs	110933.6	30596.44	3.63	0	50814.09	171053.1
G	-116556	21936.3	-5.31	0	-159659	-73453.2
GS	101902.4	30931.43	3.29	0.001	41124.63	162680.1
ProBowl	1010809	410101.3	2.46	0.014	204993.6	1816625
_cons	1561334	340987	4.58	0	891322.4	2231346

Offensive Line OLS Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	4082200	1050875	3.88	0	2020780	6143620
G	-65165.7	10693.97	-6.09	0	-86143.21	-44188.2
GS	85443.92	13717.01	6.23	0	58536.33	112351.5
Yrs	205532.9	12165.15	16.9	0	181669.5	229396.4
AV	82703.61	31081.01	2.66	0.008	21734.42	143672.8
ProBowl	1691651	200070.2	8.46	0	1299189	2084113
_cons	557290.8	117039.5	4.76	0	327703.5	786878

Offensive Line OLS Regression on Cap Value Where Players Have Four Years or More Experience

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	3353649	1238463	2.71	0.007	921996.9	5785302
G	-123847	19579.31	-6.33	0	-162290	-85404
GS	136077.3	21408.72	6.36	0	94042.46	178112.1
Yrs	52771.62	27196.85	1.94	0.053	-627.854	106171.1
AV	102847.9	47099.28	2.18	0.029	10371.09	195324.6
ProBowl	1544594	286178.4	5.4	0	982699.1	2106489
_cons	1986214	304267.7	6.53	0	1388801	2583626

Punter OLS Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	1688914	456404.6	3.7	0	786404.9	2591422
Punts	-38677.9	14394.53	-2.69	0.008	-67142.1	-10213.7
Yds	94.9783	537.5569	0.18	0.86	-968.0035	1157.96
Lng	3656.421	7677.858	0.48	0.635	-11526.02	18838.86
NetYds	975.3194	614.6038	1.59	0.115	-240.0173	2190.656
Blk	27932.76	68475.48	0.41	0.684	-107472.8	163338.3
IN20	10158.95	8390.885	1.21	0.228	-6433.446	26751.35
TB	11580.99	16633.67	0.7	0.487	-21310.95	44472.92
FC	-7139.15	9800.042	-0.73	0.468	-26518.05	12239.76
TD	216136.2	70084.63	3.08	0.002	77548.62	354723.7
G	-1044.23	19669.4	-0.05	0.958	-39939.1	37850.65
Yrs	61120.92	8141.832	7.51	0	45021	77220.83
ProBowl	-39767.8	174056.3	-0.23	0.82	-383952.2	304416.6
_cons	-103561	457053.9	-0.23	0.821	-1007353	800231.9

Punter OLS Regression on Cap Value Where Players Have Four Years or More Experience

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	1602854	492413.9	3.26	0.002	622333	2583376
Punts	-28248.8	18835.54	-1.5	0.138	-65755.2	9257.533
Yds	27.11571	720.4653	0.04	0.97	-1407.51	1461.745
Lng	22223.47	10987.94	2.02	0.047	343.6783	44103.26
NetYds	925.6393	833.0455	1.11	0.27	-733.166	2584.445
Blk	-83267.8	94600.72	-0.88	0.381	-271642	105106.3
IN20	6071.933	12192.54	0.5	0.62	-18206.5	30350.37
TB	13454.7	21673.54	0.62	0.537	-29702.8	56612.22
FC	-18186.7	14117.07	-1.29	0.202	-46297.4	9923.967
TD	171580.4	97611.18	1.76	0.083	-22788.3	365949.1
G	-12264.8	26307.03	-0.47	0.642	-64648.8	40119.19
Yrs	41815.42	13883.48	3.01	0.004	14169.87	69460.97
ProBowl	-109539	214784.1	-0.51	0.612	-537228	318151.3
_cons	-997072	686741	-1.45	0.151	-2364548	370404.5

Quarterback OLS Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	1392339	2858358	0.49	0.626	-4228276	7012953
Completions	16536.77	15957.06	1.04	0.301	-14840.85	47914.39
PassAttempts	-5636.92	11002.21	-0.51	0.609	-27271.43	15997.59
PassYards	-428.165	1312.101	-0.33	0.744	-3008.251	2151.922
PassTD	95551.98	61741.39	1.55	0.123	-25854.98	216958.9
Int	36929.41	57956.81	0.64	0.524	-77035.64	150894.5
RushAttempts	-39577.1	27763.17	-1.43	0.155	-94170.05	15015.76

RushYards	5955.08	3799.635	1.57	0.118	-1516.443	13426.6
RushTD	-181776	185271.4	-0.98	0.327	-546089.9	182537.6
Receptions	278249.6	284517.3	0.98	0.329	-281219.2	837718.5
ReceivingYards	-29558.5	35694.66	-0.83	0.408	-99747.68	40630.76
ReceivingTD	-2691118	3119290	-0.86	0.389	-8824823	3442587
G	-85418.2	58021.43	-1.47	0.142	-199510.3	28673.93
GS	233309.4	135998.5	1.72	0.087	-34115.17	500733.9
Yrs	174430.1	36866.37	4.73	0	101936.8	246923.3
AV	-7899.34	140054.6	-0.06	0.955	-283299.8	267501.1
ProBowl	1458684	640240.1	2.28	0.023	199729.7	2717639
_cons	626352.4	318497	1.97	0.05	66.68166	1252638

Quarterback OLS Regression on Cap Value Where Players Have Four Years or More Experience

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	136972.6	3302001	0.04	0.967	-6377215	6651161
Completions	29679.67	23497.65	1.26	0.208	-16676.5	76035.84
PassAttempts	-12885.6	17128.73	-0.75	0.453	-46677.1	20906.01
PassYards	-660.517	1847.979	-0.36	0.721	-4306.21	2985.176
PassTD	120269.7	87327.67	1.38	0.17	-52010.4	292549.7
Int	53623.99	87977.7	0.61	0.543	-119938	227186.4
RushAttempts	-70819.4	44055.61	-1.61	0.11	-157732	16093.54
RushYards	12593.62	5963.426	2.11	0.036	828.9684	24358.26
RushTD	285627.3	295155.2	0.97	0.334	-296655	867909.6
Receptions	46596.81	690132.9	0.07	0.946	-1314897	1408091
ReceivingYards	29423.4	82940.75	0.35	0.723	-134202	193048.9
ReceivingTD	0	(omitted)				
G	-98888.6	91994.97	-1.07	0.284	-280376	82599.1

GS	305841.5	218133.1	1.4	0.163	-124492	736174.5
Yrs	55307.78	69437.01	0.8	0.427	-81677.6	192293.1
AV	-57315.6	216267.5	-0.27	0.791	-483968	369337
ProBowl	1656653	905748.1	1.83	0.069	-130206	3443513
_cons	1384268	674505.2	2.05	0.042	53604.18	2714932

Running Back OLS Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	4446717	697662.5	6.37	0	3076938	5816496
Completions	-570232	678686.5	-0.84	0.401	-1902754	762289.3
PassAttempts	648552.3	227623.1	2.85	0.005	201640.9	1095464
PassYards	32508.64	32016.41	1.02	0.31	-30351.85	95369.12
PassTD	460340.9	595550.7	0.77	0.44	-708953.3	1629635
Int	11408.52	713145.2	0.02	0.987	-1388769	1411586
RushAttempts	14945.31	3028.161	4.94	0	8999.871	20890.75
RushYards	-1704.64	831.4553	-2.05	0.041	-3337.107	-72.1765
RushTD	-18912.7	22017.6	-0.86	0.391	-62141.7	24316.27
Receptions	9471.066	11826.9	0.8	0.424	-13749.67	32691.8
ReceivingYards	-1116.6	1465.269	-0.76	0.446	-3993.486	1760.281
ReceivingTD	171603.3	64339.18	2.67	0.008	45280.81	297925.7
G	-48755.2	11822.4	-4.12	0	-71967.11	-25543.3
GS	37983.42	12587.58	3.02	0.003	13269.18	62697.65
Yrs	160629.6	14430.2	11.13	0	132297.6	188961.6
AV	751.0152	46940.82	0.02	0.987	-91411.79	92913.82
ProBowl	-112206	231651.6	-0.48	0.628	-567027.4	342614.5
_cons	461430.2	138250.6	3.34	0.001	189991.3	732869.1

Running Back OLS Regression on Cap Value Where Players Have Four Years or More Experience

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	3329247	811404.1	4.1	0	1732395	4926099
Completions	-2061139	1066373	-1.93	0.054	-4159773	37495.12
PassAttempts	1409310	355104.1	3.97	0	710460.8	2108158
PassYards	-63196.7	60393.33	-1.05	0.296	-182052	55657.98
PassTD	1905786	1177700	1.62	0.107	-411940	4223512
Int	-858056	967861.6	-0.89	0.376	-2762818	1046706
RushAttempts	25549.41	5131.14	4.98	0	15451.27	35647.54
RushYards	-3792.58	1439.661	-2.63	0.009	-6625.85	-959.314
RushTD	-35382.2	34615.94	-1.02	0.308	-103507	32742.38
Receptions	-7999.47	21702.26	-0.37	0.713	-50709.8	34710.8
ReceivingYards	927.6806	2648.943	0.35	0.726	-4285.47	6140.829
ReceivingTD	181786.8	109245.4	1.66	0.097	-33209.3	396783
G	-70185.3	21237.03	-3.3	0.001	-111980	-28390.6
GS	62071.03	20678.57	3	0.003	21375.39	102766.7
Yrs	75391.57	31339.23	2.41	0.017	13715.63	137067.5
AV	42916.02	80366.79	0.53	0.594	-115247	201078.7
ProBowl	507114.2	370477.3	1.37	0.172	-221989	1236218
_cons	916640.6	325138.1	2.82	0.005	276765.4	1556516

Safety OLS Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	5057508	1067803	4.74	0	2960736	7154280
AV	80883.92	44915.8	1.8	0.072	-7314.178	169082
CombTackles	-27931.6	8810.721	-3.17	0.002	-45232.6	-10630.6
SoloTackles	34375.18	11089.28	3.1	0.002	12599.92	56150.45
Sck	6618.35	56369.21	0.12	0.907	-104070	117306.7
SFTY	293566.8	487552.8	0.6	0.547	-663807.3	1250941
Pdef	32979.94	21288.83	1.55	0.122	-8823.485	74783.36
INT	-12237.9	70577.02	-0.17	0.862	-150825.1	126349.4
INTTDs	-86721	195712.6	-0.44	0.658	-471028.5	297586.4
INTYds	-3571.58	2512.957	-1.42	0.156	-8506.102	1362.943
FF	-58443.1	49485.48	-1.18	0.238	-155614.3	38728.16
FumRec	-52314.6	67646.99	-0.77	0.44	-185148.4	80519.13
FumTD	170464.8	270735.5	0.63	0.529	-361160	702089.6
Yrs	153999	14216.51	10.83	0	126083	181914.9
G	-32957	13096.03	-2.52	0.012	-58672.76	-7241.22
GS	31520.35	21275.06	1.48	0.139	-10256.03	73296.73
ProBowl	961581.9	239435.1	4.02	0	491419.6	1431744
_cons	569584.3	153359.4	3.71	0	268442.9	870725.7

Safety OLS Regression on Cap Value Where Players Have Four Years or More Experience

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	4422046	1453177	3.04	0.003	1560395	7283697
AV	123962	82349.64	1.51	0.133	-38204	286128
CombTackles	-28378.4	17735.5	-1.6	0.111	-63303.8	6546.994

SoloTackles	40257.38	22730.13	1.77	0.078	-4503.65	85018.41
Sck	-6412.45	100482	-0.06	0.949	-204285	191460.4
SFTY	-14566.4	1475555	-0.01	0.992	-2920284	2891152
Pdef	-8238.96	41171.32	-0.2	0.842	-89315.1	72837.16
INT	104704.6	139657.3	0.75	0.454	-170314	379723
INTTDs	175943.5	419865.2	0.42	0.676	-650871	1002758
INTYds	-7471.14	5136.907	-1.45	0.147	-17586.9	2644.645
FF	-113037	105079.9	-1.08	0.283	-319964	93890.37
FumRec	-83079.2	136385.6	-0.61	0.543	-351655	185496.5
FumTD	123302.9	567507.5	0.22	0.828	-994254	1240860
Yrs	13378.58	36337.55	0.37	0.713	-58178.7	84935.85
G	-111194	28543.85	-3.9	0	-167404	-54984.2
GS	64559.9	40748.8	1.58	0.114	-15684.2	144804
ProBowl	1286748	425765.7	3.02	0.003	448314.3	2125182
_cons	2078845	399237.8	5.21	0	1292651	2865039

Tight End OLS Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	2715563	617435.4	4.4	0	1502427	3928698
RushAttempts	351599.8	151341	2.32	0.021	54245.31	648954.2
RushYards	-9210.77	26481.38	-0.35	0.728	-61241.31	42819.78
RushTD	-921443	908645.5	-1.01	0.311	-2706747	863861.8
Receptions	23024.67	10172.93	2.26	0.024	3036.938	43012.41
ReceivingYards	-1022.69	1070.802	-0.96	0.34	-3126.598	1081.221
ReceivingTD	-2095.06	30870.82	-0.07	0.946	-62749.97	58559.86
G	-37297.1	11513.98	-3.24	0.001	-59919.72	-14674.4
GS	48421.83	11739.36	4.12	0	25356.37	71487.29
Yrs	131230.3	12303.98	10.67	0	107055.4	155405.1

AV	45820.31	50564.66	0.91	0.365	-53529	145169.6
ProBowl	981549.4	227232.2	4.32	0	535084.2	1428015
_cons	368220.4	142074.6	2.59	0.01	89072.71	647368.1

Tight End OLS Regression on Cap Value Where Players Have Four Years or More Experience

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	2345334	727756.2	3.22	0.001	911729	3778940
RushAttempts	372971.5	231816.6	1.61	0.109	-83683.49	829626.5
RushYards	-45657.2	44501.15	-1.03	0.306	-133319.9	42005.53
RushTD	0	(omitted)				
Receptions	9509.001	16735.45	0.57	0.57	-23458.11	42476.12
ReceivingYards	147.3797	1788.276	0.08	0.934	-3375.341	3670.1
ReceivingTD	-9609.61	53334.13	-0.18	0.857	-114672.4	95453.18
G	-55316.9	18936.21	-2.92	0.004	-92619.25	-18014.5
GS	81295.97	18317.23	4.44	0	45212.91	117379
Yrs	75398.38	28584.14	2.64	0.009	19090.55	131706.2
AV	93209.49	83424.82	1.12	0.265	-71128.86	257547.8
ProBowl	706008.4	354412.5	1.99	0.047	7852.112	1404165
_cons	771814.5	304992	2.53	0.012	171011.4	1372618

Wide Receiver OLS Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	6532651	1492722	4.38	0	3602393	9462909
Completions	153570.8	577920.2	0.27	0.791	-980903.8	1288045
PassAttempts	-268830	269917.4	-1	0.32	-798686.1	261025.5
PassYards	-4764.79	19539.85	-0.24	0.807	-43122.09	33592.5
PassTD	-587461	1038080	-0.57	0.572	-2625243	1450320

Int	-380108	688002.5	-0.55	0.581	-1730677	970461.3
RushAttempts	-5364.92	21068.6	-0.25	0.799	-46723.2	35993.36
RushYards	2879.453	4697.682	0.61	0.54	-6342.236	12101.14
RushTD	-418445	321030.3	-1.3	0.193	-1048637	211747
Receptions	2251.164	8430.139	0.27	0.79	-14297.45	18799.78
ReceivingYards	1493.48	846.7515	1.76	0.078	-168.7179	3155.679
ReceivingTD	66878.44	32944.97	2.03	0.043	2206.492	131550.4
G	-50618.1	14781.31	-3.42	0.001	-79634.22	-21601.9
GS	128094.7	19803.87	6.47	0	89219.08	166970.2
Yrs	197754.9	17096.88	11.57	0	164193.2	231316.6
AV	-137615	53565.81	-2.57	0.01	-242766.1	-32463.5
ProBowl	1080208	256614.5	4.21	0	576465.9	1583950
_cons	521880.3	163093.2	3.2	0.001	201723.5	842037.2

Wide Receiver OLS Regression on Cap Value Where Players Have Four Years or More Experience

Variable	**Coef.**	**Std. Err.**	**t**	**P>t**	**[95% Conf.**	**Interval]**
Tag	6033358	1833413	3.29	0.001	2426461	9640254
Completions	172618	1374914	0.13	0.9	-2532268	2877505
PassAttempts	-212397	491416.9	-0.43	0.666	-1179168	754373.8
PassYards	-37875.9	78222.81	-0.48	0.629	-191765	116012.8
PassTD	3703650	5441166	0.68	0.497	-7000826	1.44E+07
Int	-340306	1265541	-0.27	0.788	-2830020	2149409
RushAttempts	-264563	106477.9	-2.48	0.013	-474039	-55087.8
RushYards	24785.64	11921.64	2.08	0.038	1332.032	48239.24
RushTD	-982503	595962.3	-1.65	0.1	-2154947	189941
Receptions	8514.963	13703.35	0.62	0.535	-18443.8	35473.75

ReceivingYards	1402.418	1450.716	0.97	0.334	-1451.59	4256.43
ReceivingTD	105207.5	51509.76	2.04	0.042	3871.743	206543.3
G	-95918.2	31290.82	-3.07	0.002	-157477	-34359.4
GS	196772.4	35729.71	5.51	0	126480.9	267064
Yrs	86391.86	37673.51	2.29	0.022	12276.29	160507.4
AV	-169630	90503.64	-1.87	0.062	-347678	8419.496
ProBowl	1062474	414172.2	2.57	0.011	247667.9	1877280
_cons	1419252	433861.9	3.27	0.001	565710.2	2272794

Cornerback Treatment Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
G	-150403	35749.91	-4.21	0	-220471.8	-80334.7
GS	184142.4	45139.16	4.08	0	95671.26	272613.5
Yrs	22829.96	50344.75	0.45	0.65	-75843.95	121503.9
AV	100806	113092.6	0.89	0.373	-120851.5	322463.4
ProBowl	1196841	753575.6	1.59	0.112	-280140.4	2673822
Tag	-786267	3896635	-0.2	0.84	-8423530	6850997
_cons	2620482	525690.3	4.98	0	1590148	3650816

Defensive End Treatment Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
G	-213329	44324.89	-4.81	0	-300204.3	-126454
GS	25685.72	45482.96	0.56	0.572	-63459.24	114830.7
Yrs	78028.82	53491.56	1.46	0.145	-26812.71	182870.4
AV	406786.2	109682.6	3.71	0	191812.2	621760.2
ProBowl	1108608	666351.2	1.66	0.096	-197416.3	2414633
Tag	1310446	5222636	0.25	0.802	-8925733	1.15E+07

_cons	3436714	692741.9	4.96	0	2078965	4794463

Linebacker Treatment Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
G	-104452	23533.68	-4.44	0	-150577.4	-58327.1
GS	160982	29472.22	5.46	0	103217.5	218746.5
Yrs	86308.4	33882	2.55	0.011	19900.91	152715.9
AV	65384.44	59933.31	1.09	0.275	-52082.69	182851.6
ProBowl	1506277	446822.3	3.37	0.001	630521.2	2382032
Tag	-3332895	3057030	-1.09	0.276	-9324565	2658774
_cons	1628896	372631.8	4.37	0	898550.9	2359241

Offensive Line Treatment Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
G	-66204.25	11263.5	-5.88	0	-88280.32	-44128.19
GS	84335.73	14443.79	5.84	0	56026.43	112645.1
Yrs	204236.6	12815.25	15.94	0	179119.2	229354
AV	91043.7	32918.96	2.77	0.006	26523.72	155563.7
ProBowl	1770202	213435.1	8.29	0	1351877	2188527
Tag	-9279416	6053471	-1.53	0.125	-2.11e+07	2585170
_cons	563782.4	123202.7	4.58	0	322309.6	805255.1

Running Back Treatment Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
G	-100456	22493.32	-4.47	0	-144541.8	-56369.58
GS	114927.8	20698.9	5.55	0	74358.73	155496.9
Yrs	41532.21	34236.59	1.21	0.225	-25570.28	108634.7
AV	238553.4	32629.04	7.31	0	174601.7	302505.2

ProBowl	-253620	384205.7	-0.66	0.509	-1006649	499409.4
Tag	1828054	2194075	0.83	0.405	-2472253	6128362
_cons	1426432	353988.6	4.03	0	732626.7	2120237

Tight End Treatment Regression on Cap Value

Variable	**Coef.**	**Std. Err.**	**z**	**P>z**	**[95% Conf.**	**Interval]**
G	-67851	27421.46	-2.47	0.013	-121596.1	-14106
GS	92862.83	25414.85	3.65	0	43050.64	142675
Yrs	37667.43	44183.3	0.85	0.394	-48930.26	124265.1
AV	188351.9	63462.73	2.97	0.003	63967.21	312736.5
ProBowl	401554.4	534773.4	0.75	0.453	-646582.2	1449691
Tag	-1.01E+07	6005729	-1.68	0.093	-2.19E+07	1682636
_cons	1151257	468772.1	2.46	0.014	232480.5	2070033

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ACADEMIC VITA

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Education

The Pennsylvania State University, Schreyer Honors College — University Park, PA

College of the Liberal Arts — Graduation: May 2013

Major: B.S. in Economics

Minor: Information Sciences and Technology

Honors and Awards

- Rosenberg Undergraduate Scholarship in Economics — *Fall 2012*
- Phi Beta Kappa National Honor Society — *May 2012–Present*
- First Place – Penn State Civic Public Speaking Competition hosted by The New York Times and Pearson Publishing — *December 2011*
- Academic Excellence Scholarship — *August 2009–Present*
- National Merit Scholarship — *August 2009–Present*

Association Memberships/Activities

Phi Chi Theta Professional Business Fraternity
Pledge Class President — *Spring 2010 – Present*

- Collaborated with professional, philanthropic and social chairs to coordinate pledge class events, fundraisers, and information sessions with businesses
- Participated in philanthropic activities including Penn State's Dance Marathon (THON), helping raise over $80,000 toward the fight against pediatric cancer in 2013

Professional Experience

Verizon Wireless — Trevose, PA
Sales Operations Intern — *Summer 2012*

- Assisted with the implementation of two new company initiatives at strategy sessions during the summer: Resource Central (a new database/system for logging employee time and creating schedules), and Verizon Wireless' new Share Everything plans for consumers

- Created an Excel-based report to help the company track and update small-to-medium business deals
- Attended meetings with company's regional operations, marketing, finance, and sales teams
- Studied the various controls in the business to reduce costs; helped to ensure that unnecessary costs related to returns, discounting, etc., were managed and kept to a minimum to maximize revenues and efficiency

Collaborative Privacy Practices Research Project — University Park, PA
Research Assistant — *Fall 2010 – Spring 2012*

- Conducted grant-funded research on collaborative privacy practices in the healthcare field alongside professors
- Contributed to survey preparation and qualitative research; wrote a literature review
- Murphy, A.R., Reddy, M.C., Xu, H., and Ringel, B. Exploring Collaborative Privacy Practices. *CHI 2011 Workshop on Networked Privacy*.

Bleacher Report — www.bleacherreport.com
Featured Columnist — *Spring 2012*

- Featured baseball columnist for the United States' third most visited sports media site
- Wrote 32 articles that totaled over 80,000 reads and generated more than 260 comments

Pinemere Camp — Stroudsburg, PA
Counselor/Adventure Specialist — *Summers 2009–2011*

- Selected for and completed Cornerstone leadership program for third-year camp counselors; learned to assume larger leadership role and was responsible for planning large, camp-wide programs
- Supervised and was a role model for 8th and 9th graders