Is the Blind Side Tackle Worth It?: An Analysis of the Salary Allocation of the NFL Offensive Line

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Abstract

The importance of the left tackle position in comparison to the other offensive line positions in the National Football League (NFL) has been widely debated amongst sports commentators, as the left tackle is traditionally the second highest paid player on a football team behind the quarterback; yet, this debate lacks empirical findings. This paper aims to quantify the impact of the individual offensive linemen on the chance of winning a game on a game-by-game basis and then compare the impact of the left tackle to the other offensive line positions. Using a conditional logistic regression and the marginal effects from that regression, the results do not dispute the NFL's current trend in spending more on the left tackle in comparison to the other offensive line positions. The results show that optimal spending for the left tackle could extend to 15.976 percent of the salary cap. Thus, the possibility remains that the optimal spending for the left tackle can range up to fifteen percent of the salary cap, seven percentage points above the next highest optimal offensive lineman spending.

I. Introduction

The professional sports industry provides a unique opportunity to study labor economics and compensation through its extensive performance and salary data. Performance statistics can measure a player's contribution to the team's success, measured in wins, and those statistics can be seen vis-à-vis the compensation of that player. In particular, the NFL presents a particularly distinctive opportunity to study labor economics in that the league functions under a hard salary cap and features players of markedly different functions.

Before delving into the intricacies of the salary and performance of different positions in the NFL, a discussion of the sport, the league, and the various positions is necessary for understanding the implications of this paper's findings. The National Football League (NFL) appears to be the strongest of the US professional sports. It leads the professional sports market in revenue, with $9.5 billion in league revenue for the 2012 season, thus trumping the MLB (Major League Baseball), the second highest-earning league, of $7.7 billion for the same season. For comparison, for the 2010-2011 season, the NBA (National Basketball Association) and the NHL (National Hockey Leauge) earned $4.3 billion and $3.0 billion in league revenue respectively. In addition, the NFL leads the U.S. professional sports market in average per game attendance and in average team value. Average per game attendance for the NFL 2012 season was 67,413, compared to the second-highest MLB average game attendance of 29,950, and with an average NFL team value of $1.04 billion, compared to the second-highest MLB average team value of $605 million. However, it is important to note that the NFL has 32 teams while the MLB, NHL, and NBA each have 30 teams. In addition, the NFL only plays a 16 game season while the MLB is a 162 game season and the NBA and NHL are both 82 game seasons. In summary, according to Goldberg (2007),"The National Football League (NFL) has the highest per-game attendance, in any sport, in the world…For tickets to NFL games, there is limited supply and high demand".

The 1993 Collective Bargaining Agreement (CBA) instituted the hard salary cap, under which players' salaries were negotiated, to begin in the 1994 season.

Under the hard salary cap, teams are not allowed to spend above the salary cap without strong penalties. Therefore, each team must allocate their salaries underneath this cap. The salary cap institution began because of the 1993 season when player salaries reached nearly 70% of that season's DGR (Defined Gross Revenues), thus exceeding the 67% rule that would trigger the salary cap the following season. Under the current agreement, players are guaranteed 58% of the actual DGR.

Defined Gross Revenues is a percentage of a team's income during a League Year that is allocated for player expenditures. DGR includes all gate receipts, income from luxury box and premium seating, revenue from NFL radio and broadcast rights, and revenue from the sale of any right to receive revenue from a source within the DGR definition (Heller 2000). From DGR, the salary cap is calculated under various mathematical equations. Taken from Heller (2000), the most simple equations for calculating the Salary Cap are:

1. (Projected DGR * CBA Percentage) = Players Share of DGR
2. Players Share – Projected League-wide Benefits = Amount for Player Salaries
3. Amount for Player Salaries/Number of Teams = Unadjusted Salary Cap per Team
4. Projected League-wide Benefits/Number of Teams = Equal Allocation per Team for Benefits

The salary cap, as a percentage, is set between 63%-64% of DGR, and cannot exceed 70% of projected DGR. In 1994, the salary cap was $34.6 million per team and, by 2009, the cap was $112.1 million per team (NFL Communications). Table 1 shows the year-by-year salary cap. An important caveat in player salaries and bonuses is that signing bonuses can be paid to players up front but will be divided over the length of the contract, while the base salary of a player can vary from year to year. The most important aspect of the salary cap, for this paper, is that the salary cap is a "hard" cap in which exceeding this cap incurs steep penalties.

Other leagues, such as Major League Baseball (MLB), function under a soft salary cap where teams do not have to strictly allocate their salaries under one cap; rather, teams have the freedom to pay players according to their ability to so.

Therefore, the allocation of salary cannot be equally compared across teams as the total salary amounts can differ greatly. On the other hand, NFL teams can only operate within the salary cap and must allocate their limited salary cap to the positions deemed as most important. Thus, how an NFL team distributes its salary can be equally compared to the distribution of another NFL team as each team must spend under the same given amount. In the NFL, therefore, all teams are allocated the same amount of scarce resources, which is the hard salary cap for players, and the result of this allocation can be seen in the number of wins and losses per team. A point of interest for this paper will be how an NFL team allocates scarce salary resources on the offensive line positions, and then how that salary converts to a

Table 1

Year-by-Year Salary Cap, 1994-2009

Year	Maximum Team Salary (in millions)
1994	$34.608
1995	$37.1
1996	$40.753
1997	$41.454
1998	$53.388
1999	$57.288
2000	$62.172
2001	$67.405
2002	$71.101
2003	$75.007
2004	$80.582
2005	$85.5
2006	$102
2007	$109
2008	$116
2009	$123

NOTE. – Taken from *NFL Communications*

player's magnitude of the success of the team. Therefore, this paper focuses only on the NFL seasons after the salary cap was instituted in 1994. Due to incomplete salary data for the 1994 season and the 2000 season, in addition to the unavailable salary information for the 2010 and 2011 seasons, these seasons are disregarded in this paper; thus, the paper covers the seasons between 1995 and 2009, excluding 2000.

In addition, the NFL contains players of definitively different functions. For example, players are divided as either offensive or defensive players, not both, as in baseball and basketball, and the offensive and defensive positions are further divided into different and distinct positions. Therefore, this distinctly measured result of performance as a result of resource allocation proves an intriguing and measureable natural experiment in the allocation of scarce resources. In addition, the differentiation of NFL positions affords the ability to measure a single player's contribution without much overlap of player functions. NFL players cannot be equally compared across all positions. A quarterback's success may be measured by touchdowns thrown while a defensive player's success may be measured in sacks. Additionally, measures of the same component may be measured differently depending on position. For example, an interception is a positive component for a defensive player but a negative component for a quarterback. Thus, because player functions are more specialized in football, meaning there are few two-way players in terms of offense and defense in contrast to other major team sports where every player is a two-way player, the NFL provides a unique platform for evaluating the effectiveness of the allocation of salary to different positions. Because of these different positions, this paper focuses on comparing the salary allocation of the offensive line positions, as the offensive line positions are most closely related in function while maintaining distinctive and unique functions from one another, as explained below.

The offensive line consists of five players: Center (C), left guard and right guard (LG and RG, respectively), and left tackle and right tackle (LT and RT, respectively). The center, who snaps the ball back to the quarterback, lines up in the center of the line of scrimmage, as named. The left guard is to the left of the center, and the left tackle, the position of interest in this paper, is to the left of the left guard. The same applies for the right guard and right tackle positions. Figure 1 shows a detailed picture the football positions and alignment, with the star indicating the left tackle position.

Figure 1
National Football League Positions

A football team's offensive line is responsible for two main aspects of the football game. The first, and arguably the most important, is to protect the quarterback and give him time to make a decision when dropping back to throw. Here, offensive linemen are an integral part of a football team's passing game, measured in yards passing. The second is to block for those running the ball, namely the running backs. Offensive linemen do not usually handle the ball, except for fumbles, and thus are not considered "skill players" nor receive the majority of sports commentators' or academics' attention.

Ultimately, this paper focuses on the salary allocation within the offensive line, with particular attention on the impact of the blind side tackle position, typically the left tackle position unless the quarterback is left-handed, in which case the blind side tackle is the right tackle position, in comparison to the other offensive line positions. The blind side tackle position is usually the most valued offensive line position and the second highest-paid position on an NFL football team after the quarterback. As explained by CBS Sports' Senior NFL Columnist, Clark Judge, the left tackle position is often considered the second most important position on a football team, after the quarterback, because, for right-handed quarterbacks, the left tackle is responsible for making sure the quarterback does not get hit from behind, also known as the “blind side”. The left tackle position is usually occupied by the most skilled offensive lineman. Thus, while the other offensive line positions are also responsible for blocking and guarding the quarterback, the left tackle is considered the highest offensive line position because the position protects the quarterback’s most vulnerable side. This stress on the importance of the left tackle has led to a larger salary allocation to the left tackle than to the other offensive line positions, as seen in Table 2 and Table 3. The left tackle is consistently the highest paid offensive line position, with an average across seasons of 3.5% of the salary cap spent on the starting left tackle while the other offensive line positions are paid, on average, between 1.8% and 2.4% of the salary cap. Ultimately, the left tackle, a position that usually lacks the recognition of skill positions such as the quarterback or wide receiver, is, salary-wise, the second most important player on an NFL football team.

While there is no argument against the left tackle usually being the second highest paid player on an NFL football team, there has been debate on whether this high paying position is well deserved, with sports commentators arguing both sides. For example, CBS Sports’ Senior NFL Columnist, Clark Judge (2012), when asking the question on the second most important player in football, answers, “Yep, give me the left tackle because not only is he the guy who protects the quarterback's

Table 2

Descriptive Statistics of the Percentage of Salary Cap Spent on the Starting Offensive Positions, 1995-2009 (Excluding 2000)

	Mean	Minimum	Maximum
Offensive Line			
Left Tackle	.0353892 (.0236051)	.0024199	.1129569
Left Guard	.0208408 (.018338)	.0027532	.1307655
Center	.0222868 (.0157048)	.0031798	.0997109
Right Tackle	.0240923 (.019586)	.0028355	.1313569
Right Guard	.0181588 (.014607)	.0027533	.0860886
Quarterback	.0504435 (.0369003)	.0029105	.204792
Remaining Five Skilled Positions	.1176367 (.038714)	.0273221	.2544579

NOTE. – Standard errors are listed in parentheses.

Table 3

Mean and Standard Deviation of the Percentage of the Salary Cap Spent on the Starting Offensive Positions by Year, Seasons 1995-2009 (Excluding 2000)

	Offensive Line Positions						
	Left Tackle	Left Guard	Center	Right Tackle	Right Guard	Quarter-back	Remaining Five Skilled Positions
1995	.0359521 (.0205813)	.0189824 (.0167776)	.0236038 (.0142958)	.0257 (.0178457)	.0190277 (.0124447)	.0648718 (.031053)	.1231634 (.0372418)
1996	.0363004 (.0215064)	.024968 (.0193326)	.0232333 (.013286)	.026368 (.017371)	.0171298 (.0110942)	.0609805 (.0392104)	.1202291 (.0354533)
1997	.0333411 (.0213821)	.0224794 (.0179417)	.0239837 (.0179601)	.0256898 (.0191877)	.0192551 (.0156771)	.0557289 (.0385075)	.1159586 (.0359701)
1998	.0387274 (.0182093)	.024227 (.0167992)	.0222506 (.0155621)	.0223387 (.0146912)	.0184486 (.0122612)	.0492636 (.0369573)	.1226344 (.0360913)
1999	.0372575 (.0194782)	.0190767 (.01365)	.0213566 (.0104172)	.020223 (.0183533)	.0205467 (.0162744)	.0408388 (.0317179)	.109712 (.0392952)
2001	.0321262 (.026171)	.0175985 (.0126301)	.0206558 (.0165797)	.0185044 (.015621)	.021498 (.0184261)	.0399321 (.0342224)	.118901 (.0356591)
2002	.0279852 (.018962)	.0146448 (.0142292)	.0228502 (.0172545)	.0247992 (.0175752)	.0153179 (.0121755)	.0460815 (.0359152)	.1086955 (.038219)
2003	.036196 (.0265998)	.0186519 (.0223283)	.0227455 (.0156034)	.024843 (.0206338)	.0213787 (.0193646)	.0501834 (.0417829)	.1191624 (.0388748)
2004	.0353912 (.0261668)	.0156491 (.0141487)	.0196882 (.0153423)	.0277774 (.0297715)	.0166748 (.0144904)	.0428111 (.0303696)	.1162085 (.0485426)
2005	.036247 (.0258908)	.0182919 (.0168134)	.0227821 (.0163989)	.0248426 (.0189171)	.0168741 (.0142558)	.052996 (.0344656)	.1110942 (.0392882)
2006	.038667 (.0274625)	.0245132 (.0247665)	.0227592 (.0203379)	.0229424 (.0217031)	.0203581 (.016091)	.0526791 (.038887)	.1276286 (.0390309)
2007	.0315092 (.021078)	.0239973 (.0188857)	.0239822 (.0140748)	.0201316 (.0160883)	.0165758 (.0122189)	.0398278 (.0329307)	.1082715 (.0348302)
2008	.0353271 (.0235939)	.0240273 (.0192872)	.0197884 (.0139451)	.0283657 (.0182754)	.0145696 (.0117527)	.0452302 (.0371719)	.1208898 (.0335015)
2009	.0387394 (.0280931)	.0235502 (.018584)	.0229909 (.0156599)	.0214915 (.0153892)	.0163941 (.013142)	.0704389 (.0391886)	.1232197 (.0414399)

NOTE. – Standard errors are listed in parentheses.

back, he's the guy who must hold off opponents' best pass rushers, too…So let's talk about five left tackles who could determine what happens to your favorite quarterbacks and, therefore, determine what happens to your favorite football teams". Therefore, because the left tackle has a direct effect on the safety of the quarterback, the most important position in football, he is thus the second most important player. On the other hand, Yahoo! Sports' Expert, Jason Cole (2012), argues the diminishing importance of the left tackle, citing the lack of left tackle first-round picks appearing in Super Bowl champions over the past eleven years and the less time quarterbacks now spend in the pocket as evidence. Despite the back-and-forth banter between sports commentators on the left tackle's importance, there has been a lack of literature on the topic.

Ultimately, the combination of player specialization and a hard salary cap make the NFL an interesting platform to investigate how teams allocate resources to their offensive line under the salary cap. The main question in the development of this paper is: Is the left tackle worth the money? Thus this paper aims to measure if the impact of the left tackle on a team's winning percentage is justified in the position's higher salary. The hypothesis is that offensive line positions contribute positively to the success of a team and, if NFL teams are already effectively allocating salaries within the salary cap, that the left tackle is paid higher because that position produces statistically significantly higher effects in a team's success than the other offensive line positions.

II. Literature Review

Current literature on professional sports, not just the NFL, has revealed a list of factors affecting the outcome of professional sporting games. Concerning the teams themselves, Borghesi (2007) found that compensation equity, meaning relatively equal salaries, amongst players in the NFL is significant in determining team performance. Specifically, teams with high player equity are relatively more proficient than those with high player inequity. Furthermore, Borghesi posits that "franchises taking a superstar-approach to personnel decisions perform worse on average, most likely because of the dissatisfaction generated among relatively low-paid teammates" (Borghesi, 2007). Therefore, the salary equity amongst players will be a significant factor in contributing to a team's success, and will be included in the regressions. In addressing the salary cap, both Lee (2009) and Larsen et al. (2006) found in two separate papers that the 1994 NFL salary cap generated greater competitiveness within the league. Because teams are now more competitive under the salary cap, the slight differences in salary allocation should prove interesting in determining a team's success or failure.

In addition to player salaries, Hadley et al. (2000) found that, in the NFL specifically, higher quality coaching can lead to three to four additional wins in the sixteen-game NFL season. Ultimately, coaching can have a substantial positive or negative effect on the outcome of a season. Furthermore, Scully (1994) found a positive correlation between a coach's success, as measured through winning record, and a coach's tenure. Thus, coaching tenure can be used as an effective instrument for measuring coaching success, and the tenure of the head coach will be included in the regressions. Due to the focus on the offensive line, I would have ideally liked to include the tenure of the offensive coordinator as well as the offensive line coach; however, that information is not readily available and thus could not be included in my regression.

In predicting NFL outcomes, which is essentially the backbone of this paper, there has been substantial literature. Boulier and Steckler (2003) evaluated the forecasts of power scores in comparison to the forecast of the betting market and of the opinions of the sports editor of *The New York Times*. Their findings conclude that the betting market was the best predictor of actual NFL game outcomes, followed by the power scores and then by the sports editor of *The New York Times*. In addition, Harville (1980) developed a mixed linear model to predict the outcomes of NFL games based on differences in scores from past games, taking into account home-field advantage and differences in yearly characteristic performance. Included in Harville's model was the differentiation in predicting outcomes for regular season games and for postseason games, as well as preseason games. Most recently, Duke graduate Eric Ness (2010) wrote his senior Economics thesis on the question of whether higher quality defense was a predictor of winning on a game-by-game basis, and found significant results that when teams at the salary cap play teams under the salary cap, increasing the proportion of payroll for defensive players increased the chances of winning. However, this result did not hold true when both teams playing were below the salary cap nor when both teams were at the salary cap. These findings, although not directly applicable in evaluating factors to account for in this paper's regressions, prove useful in the structure of their analysis and in their empirical specification.

Finally, focusing on specific positions, Arkes (2011) found that, in comparing the rushing game to the passing game, having a first-half passing yard advantage significantly increases the probability of winning, while having a first-half rushing yard advantage does not. Focusing on the passing game is important for both the offense and the defense. Therefore, according to Arkes findings, the passing game, which includes the quarterback and the receivers, should be more predictive of winning than other offensive players. Entangled in the passing game and playing important roles are the offensive linemen, specifically in their role in guarding the quarterback and allowing for more time in the pocket. However, Arkes's findings lack the prediction of success from the specific offensive line players. Therefore, Arkes's findings simply prove the importance and relevance of the offensive line in the passing game, and thus their subsequent contribution to the outcome of a game as a win or a loss.

As noted, there has been a lack of extensive literature on the impact of offensive line positions on a team's success. However, Alamar and Weinstein-Gould (2008) determined the impact of offensive linemen on the passing game in the NFL through measuring how effective a lineman was in creating time in the pocket (TIP). Then, in measuring TIP, Alamar and Weinstein-Gould calculated the probability of a completed pass given a failure on the offensive line. Therefore, Alamar and Weinstein-Gould could then evaluate the impact of an individual lineman in substitution into the offensive line through calculating the team's completion percentage. Thus, Alamar and Weinstein-Gould's work provides a framework for evaluating individual linemen and their effect on the passing game. A further implication of these findings is more pointed and specific salary negotiations for offensive linemen as the magnitude of an individual player's impact can be measured. While the model in Alamar and Weinstein-Gould's paper differs greatly from the model used in this paper, their paper provides a strong background and point of reference for calculating the impact of offensive line players individually. Therefore, while Alamar and Weinstein-Gould measured the impact of a specific offensive lineman in the passing game through measuring TIP, my paper plans to expand this view by looking at the impact of a specific offensive lineman in the whole offensive game, not just the passing game, and measuring the impact of that offensive lineman through game outcome.

The lack of literature on the impact of the left tackle in football largely stems from two main obstacles. The first obstacle is that the perceived impact and importance of the left tackle is, on the whole, a new phenomenon; therefore, there has been a limited time frame to examine the position more closely. The second obstacle is the lack of available data on the individual performances of the left tackle and offensive linemen as a whole. While FootballOutsiders.com provides an "adjusted line yards" measure of NFL offensive lines, this measure, in addition to the limited other measures, such as sack rate, evaluates the offensive line as a whole, and thus the data of the impact of individual linemen and positions is not readily available (Alamar and Weinstein-Gould, 2008).

Ultimately, there has been a multitude of findings on factors that affect a team's performance and, in turn, how those factors play a part in predicting the probability of winning an NFL game. Although Ness examined the significance of defense compared to the significance of offense, there lacks deeper findings on which positions on the offensive line are most significant in predicting NFL wins on a game-to-game basis. In this lack of literature also exists a lack of findings on if the left tackle position is more impactful than the other offensive line positions. This paper aims to measure the relationship of player salary with player quality in offensive line positions, calculated by a player's impact on game outcome, and then evaluate the impact of the left tackle position in comparison to the other offensive line positions.

III. Theoretical Framework

The theory of interest is to measure the impact of the left tackle in a team's probability of winning in comparison to the impact of the other offensive line positions. While the significance of the left tackle position has been highly debated by sports commentators, the argument lacks literature and empirical findings. Therefore, there is little guidance and previously established theory on how to measure an individual position's impact on the chance of winning for an NFL game. Ideally, I would have liked to use a measure of performance for the quality of the left tackle that is independent of the performance of the other offensive linemen. Potential candidate measures of left tackle performance include sacks allowed, yards passing, and yards rushed. However, these measures evaluate the performance of the offensive line as a whole, not of individual linemen. Therefore, these measures are not suitable to measure the performance of the left tackle as they are confounded and influenced by the performance of the other offensive linemen.

While not avoiding the problems associated in the influence of other players when measuring the individual performance of a player, there is a recently developed measure to quantify the overall performance of a quarterback, called the Total Quarterback Rating (Total QBR). The Total Quarterback Rating is measured on a scale of 1 to 100, with 100 as the best rating, and, as described by ESPN's Dean Oliver (2011), is "a statistical measure that incorporates the contexts and details of those throws and what they mean for wins. It's built from the team level down to the quarterback, where we understand first what each play means to the team, then give credit to the quarterback for what happened on that play based on what he contributed." While not a perfect measure of isolated quarterback performance, the QBR is positively correlated with quarterback salary. Given the salary data and the Total QBR listings for the 2008 and 2009 seasons, a picture of the relationship between salary and player performance, as indicated by the Total QBR, can be seen in Table 4, visually illustrated in Figure 2. While ideally the Total QBR statistics would cover my entire time frame of data, a lack of Total QBR statistics prior to 2008 and lack of salary data past 2009 result in only having the 2008 and 2009 seasons included in the above regression. Despite only having data for two seasons, the relationship between player salary and player performance is not perfectly

Table 4

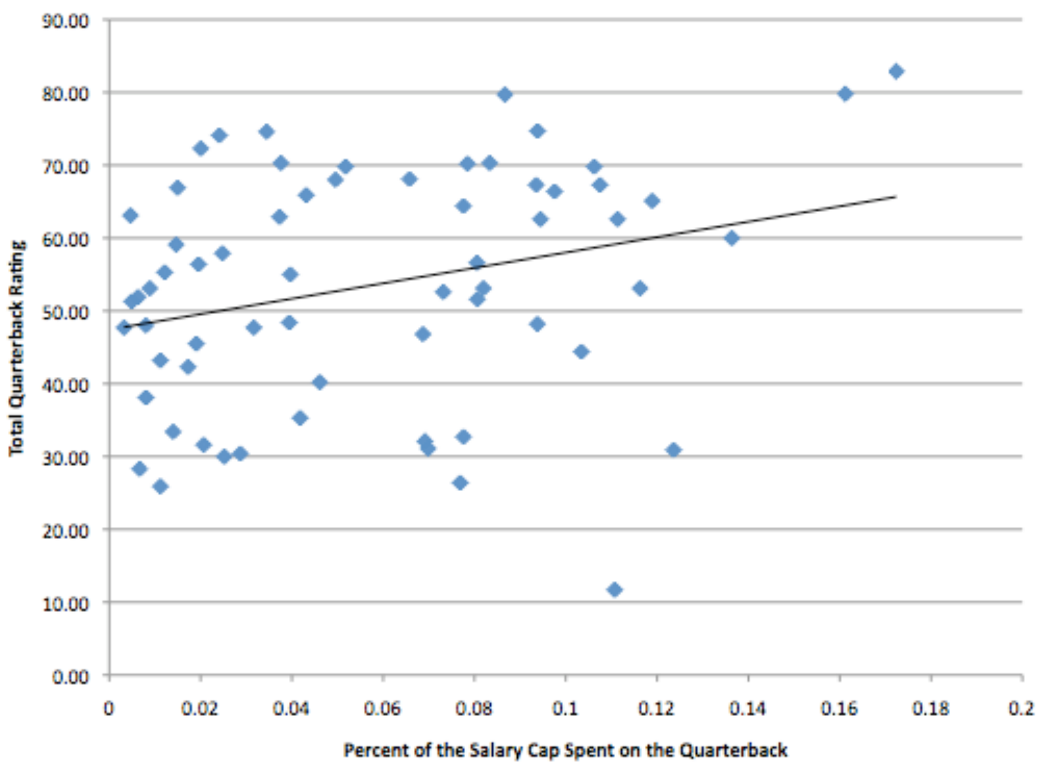
Correlation and Regression Statistics of Percent of the Cap Spent on the Quarterback and Total Quarterback Rating for the NFL's Starting Quarterbacks, 2008-2009

Correlation Statistics		
Correlation	0.2973	
Regression Statistics	Coefficient	T-statistic
Percent of the Cap Spent on the Quarterback	117.6427 (46.49897)	2.53**
Adjusted R-squared	0.0746	
Number of Observations	68	
**Significant at the 0.05 level		

NOTE. – Standard errors are listed in parentheses.

Figure 2

Relationship between Quarterback Salary and Quarterback Performance, 2008-2009



correlated but there is a strong and positive correlation at 0.2973 and reasonable Adjusted R-squared value of 0.0746 when regressing Quarterback Salary on Total

QBR that explains this relationship. Furthermore, the Total QBR portrays the ability to assess an NFL player at the individual level, in this case the quarterback, and thus measure an individual player's performance. Therefore, while no measure of an individual lineman's performance exists today, the Total QBR demonstrates that there is the possibility to do so.

In light of the correlation between quarterback performance and quarterback salary, I will use the salaries of the offensive linemen as a measure of performance. The null hypothesis is that player salary and player quality are highly correlated and therefore, given the importance of the left tackle position, the impact of the share of salary allocated to the left tackle position should have a greater positive impact on a team's chances of winning than the share of the cap allocated to any other offensive line position. This hypothesis stems from the assumption that NFL teams are effectively allocating their salary resources under the salary cap, and that the left tackle receives a higher salary than the other offensive line positions because that position has a higher impact on a team's chance of winning than the other offensive line positions.

IV. Data

The data for this paper comes from a variety of sources with various important caveats and possible limitations. As data sets for various NFL statistics are not readily available, the largest "ready-to-use" data set comes from the work of Eric Ness, a 2010 graduate of Duke's Trinity School of Arts and Sciences. This data contains the games played from the 1995-2009 seasons, including injuries of the offense, defense, and special teams, game result, and, for each team, average rushing per game allowed, average passing per game allowed, turnovers forced, points allowed, average passing per game, average rushing per game, turnovers, points scored, coaching tenure, if the team made the playoffs for that season, and if the team made the playoffs the previous year. In terms of spending, the data set also includes the percent of the cap spent on defense, the percent of the spending spent on defense, the standard deviation of the spending on defense, and the percent of the defensive allocation spent on defensive starters. The same data is also included for the offense. Ness located salary data and a set of rosters for each season and team from *USA Today's* online salary database and through sports economist Rodney Fort's personal website (www.rodneyfort.com), and a second set of player rosters, complete with each player's position, the number of games they played and the number of games they started, was obtained from *Sport Reference LLC's* website *pro-football-reference.com*. The 1994 and 2001 seasons were excluded due to incomplete sets of salary data.

For my addition to the data set, I obtained roster information and salary data from two different sources. Like Ness, the roster data of the starting offensive linemen and the specific offensive line positions comes from *Sport Reference LLC's* website *pro-football-reference.com.* Salary data was accessed through sports economist Rodney Fort's personal website (www.rodneyfort.com). I used the prorated salary data per player. Prorating the signing bonus over the player's contract is in conjunction with the salary cap, as, even though the signing bonus is usually paid in full the first year, it is considered, for the salary cap, to be prorated throughout the length of the contract. For example, if a team signed a five-year contract with a $10 million bonus with a player, the player would likely receive the full $10 million the first year, but it would only count into a team's salary as $2 million each year, and not the full $10 million at once. Therefore, this prorated salary will be use to capture the salary of a player without great fluctuations between years for one player. However, it is important to note that the two sources of rosters do not always match up exactly. For the importance of this data, there are cases where salary data is missing for one or more of the starting offensive positions per season per team. When this occurs, the team is dropped from the data set for that season. Given the number of observations, dropping one or two teams per season, on average, should not affect the data nor the results; however, it is an important caveat to note that there may be an omitted variable bias in the data due to these missing observations.

Although Ness includes injury data for offensive, defensive, and specialty team players, grouped together respectively, I include injury data for the positions of interest, namely the LT, LG, C, RG, RT, and QB. For injury data, the most comprehensive list comes from John Troan of *JT-SW.com,* where, for each week of

Table 5
Minimum Salary and Minimum Salary as a Percentage of the Salary Cap, Seasons 1995-2009 (Excluding 2000)

Year	Minimum Salary (in nominal dollars)	Minimum Salary as a Percentage of the Salary Cap
1995	118600	.0031968
1996	167200	.0041028
1997	136000	.0032807
1998	157700	.0030102
1999	180000	.003142
2001	209000	.0031007
2002	231500	.0032559
2003	211647	.0028217
2004	243416	.0030207
2005	240250	.0028099
2006	277420	.0027198
2007	365160	.0033501
2008	334250	.0028815
2009	297647	.0024199
Average	201159.3 (76955.4)	.0029982 (.0004788)

NOTE. – Standard errors are listed in parentheses.

play, a player's chance of playing is listed as "probable", "questionable", "doubtful", or "out". In designating which players to include as injured, I use Ness's method of using only those players listed as "doubtful" or "out" as those as injured for each game. When one of these positions is designated as "doubtful" or "out" and thus presumably was replaced with a non-starter that game, their salary is replaced with the minimum salary of the starting offensive line positions for that season. Table 5 portrays the minimum salary and the minimum salary as a percentage of the salary cap per season.

Finally, a last concern for the data is that there are variables that I would have liked to include that do not have complete information available for the time frame of interest, from 1995 to 2009. For example, head coach's salary, offensive line coach's salary, and offensive line coach's tenure are unavailable variables. Thus, this data may suffer from omitted variable bias due to the omission of those desired variables. However, I believe this omission to be of minimum importance.

V. Empirical Specification

The empirical framework for this paper is based upon a conditional logit model, which will be used to measure the impact of the different offensive lineman positions on game outcome by predicting the outcome of a single game using the differences in characteristics between teams. A conditional logistic model calculates the probability of an outcome with the data in matched pairs where only the relative differences between the data are of importance. Thus, in the case of this paper, only the relative difference between team characteristics will be of note.

The conditional logistic model is specified as:

$$P(\text{Team A}) = \exp(X_A\beta) / (\exp(X_A\beta) + \exp(X_B\beta))$$

rewritten as:

$$P(\text{Team A}) = 1 / (1 + e^{\wedge}((X_B - X_A)\beta))$$

where P(Team A) is the probability of Team A winning against Team B and where X_A and X_B are vectors of variables specific to each of the two teams.

The conditional logit model is advantageous for this paper as it determines the probability of an outcome in a setting where the data are matched in pairs, in this case X_A and X_B, and only the relative difference in their characteristics are significant. In simpler terms, the model will be predicting the outcome of each game by using the differences of the vectors of factors between the two teams playing each other.

Many factors were considered to be included in the final regression, as shown in the Table 6; however, the variables included in the final regression can be seen in Table 8. For reference, the final results also include a raw regression of the result on just the salaries and squared salaries of the center, left guard, left tackle, right guard, right tackle, quarterback, and skilled positions, with no other control variables, as seen in Table 9. A further discussion of why each variable was either chosen or rejected from the final regression is below.

The dependent variable is the result of the game between Team A and Team B, labeled a 1 if Team A wins, a 0 if Team A loses, and 0.5 if, by rare chance, Team A and Team B tie. This dependent variable was chosen amongst other possible dependent variables, such as points per game, yards passing per game, and yards rushed per game, because, at the end of the game, the most important factor in determining a team's success is the scoreboard with who won and who lost. Therefore, the dependent variable for this paper is the outcome of a game, determined as a win, loss, or tie.

As there are no readily available statistics for individual offensive linemen, the independent variable of interest is the salary of left tackle as a percentage of the salary cap in comparison to the salaries of the other offensive linemen as a percentage of the salary cap. From this regression, the results of interest are the marginal effects on the chance of winning when the salary of the different offensive line positions is increased.

The rosters of each team are divided into the left tackle, left guard, center, right guard, and right tackle, and only the primary starters are included. The only other player specifically and individually included in the analysis is the quarterback, due to the widely accepted notion of how important the quarterback is to a football team's offense. Offensive skill positions, including the tight ends, running backs, and wide receivers, are grouped into their own category. Individual defensive positions, and special teams, such as kickers and punters, will be disregarded in this analysis, unless they are designated as offensive starters. However, the defensive and special teams players are controlled for through the inclusion of the variable of the percentage of the salary cap spent; therefore, this variable includes the amount of money spent on the defensive and special teams in addition to how much of the total salary cap was spent. The percentage of the salary cap spent is the variable chosen to use as it encompasses both the amount spent on defense and the amount of the cap spent in general; therefore, the inclusion of the this variable means that the coefficients of the individual offensive salary variables show the affect of the reallocation of salary spending away from defense, special teams, and reserves on a team's probability of winning a game holding constant the level of spending on all other offensive positions. As such, the coefficient could be either positive or negative. In addition, it is also a very significant variable. The other variable of consideration was percentage of the cap spent on defensive starters; however, in the final regression, the percentage of the cap spent on defensive starters was only significant at the 0.01 level, with a p-value of 0.008, while percentage of the cap spent was significant at the 0.001 level, with a p-value of 0.001. Therefore, the percentage of the cap spent was chosen as a better indicator. The reasoning behind only looking at starters is to determine where a team's true salary cap allocation lies and, then, how a team performs when a starter does not play, as taken from NFL injury reports. A measure of a team's spending preferences is calculated by taking the total salary per season for each starting player of the specified positions and dividing that salary by the salary cap for that season. Therefore, salaries can be compared as percentages of the salary cap across years. Total salary includes the actual base salary and portion of bonuses the player received that year. If a player does not play in a game, their salary is replaced with the minimum salary for that season, as aforementioned. In addition, if the quarterback is left-handed the salaries of the left guard and the right guard and the salaries of the left tackle and right tackle are switched, as the importance in the left tackle is seen in the ability of that position to cover a quarterback's blind side, which, for left-handed quarterbacks, is the right side. Finally, a squared variable of the percent of the salary cap spent on the offensive players is added to the regression under the assumption that there may lie a unique maximum under which paying one player too much begins to erode the quality of the other players, as the NFL functions under a hard salary cap and teams cannot exceed that given cap. A regression is run on these preferences and the outcome of the games on a game-by-game basis.

First, the regression was run with the dependent variable as game result and the independent variables as those listed in Table 6. The results from the first regression can be seen in Table 7**.** Note that the results are reported with and without team fixed effects, with the results from the team effects shown in the Appendix. The results with team effects are denoted by (1) and the results without team effects are denoted by (2) in the table. Ultimately, the only variables that proved significant in the initial regression were home turf, points allowed per game, points per game, and playoffs made, all significant at the 0.001 level, and special team injuries, significant at the 0.05 level. No other variables were significant at the

0.01 level.

For this paper, the variables of interest are the salary variables of the offensive line; however, in this initial regression, those salary variables were insignificant.

Table 6
Summary of the List of the Variables Considered for the Final Regression

Variables		
Team-specific	Game-specific	Player-specific
General Coaching Tenure Playoffs Made *Defense* Rushing Allowed Passing Allowed Turnovers Forced Points Allowed Standard Deviation of Salary *Offense* Passing Per Game Rushing Per Game Turnovers Per Game Points Per Game Standard Deviation of Salary Percent of the salary cap spent (total) Time Fixed Effects Team Fixed Effects	Offensive Injuries Defensive Injuries Special Teams Injuries Home Turf Advantage	*Percent Salary Cap Spent on:* Center Left Guard Left Tackle Right Guard Right Tackle Quarterback Skilled Positions *Percent Salary Cap Spent Squared on:* Center Left Guard Left Tackle Right Guard Right Tackle Quarterback Skilled Positions *Tenure of:* Center Left Guard Left Tackle Right Guard Right Tackle Quarterback Skilled Positions Left-handed QB

Table 7

Initial Regression Coefficients and Standard Deviations Including All Salary Variables and Control Variables, with Team Fixed Effects (1) and Without (2)

Salary Variables	(1)	(2)	**Control Variables**	(1)	(2)
Offensive Line Salary:			***Injuries***:		
Center	6.883448	3.326718	Offensive	-.0514906	-.0544472
	(7.017919)	(6.522183)		(.0359434)	(.0352578)
Left Guard	7.434359	6.281942	Defensive	-.037231	-.0415548
	(5.119402)	(4.684225)		(.0337184)	(.0330582)
Left Tackle	1.094195	.587367	Special Teams	.4690491**	.4281994**
	(5.189973)	(4.696476)		(.2071743)	(.193935)
Right Guard	-.486579	2.815897	***Tenure***:		
	(7.362906)	(6.999257)			
Right Tackle	2.608288	1.747414	Center	.0018791	.0024293
	(4.683733)	(4.409056)		(.0124607)	(.0112401)
Quarterback	4.540223	2.896624	Left Guard	-.0162575	-.0101129
	(2.918433)	(2.682565)		(.0120415)	(.0106324)
Skilled Positions	-3.136997	-2.977202	Left Tackle	-.0035618	-.0001736
	(4.456338)	(4.205254)		(.0120269)	(.0109498)
			Right Guard	-.0123351	-.0128573
				(.0131702)	(.0118542)
			Right Tackle	-.0148346	-.0106474
				(.0128506)	(.0118153)
Offensive Line Salary Squared:			Quarterback	-.0028809	-.0014408
				(.0096652)	(.0087405)
Center	-111.871	-64.4648	Skilled Positions	.0003613	-.0014336
	(97.73939)	(91.1946)		(.0060153)	(.0053225)
Left Guard	-90.87185	-73.7541	***Defensive Measures***		
	(56.07723)	(51.81012)			
Left Tackle	-16.70339	-13.75405	Rushing Allowed	-.00234	-.0025799
	(58.14775)	(52.1354)		(.0023512)	(.0021392)
Right Guard	-38.83843	-75.09814	Passing Allowed	.0000634	-.0002829
	(114.4371)	(108.6746)		(.0019593)	(.001792)
Right Tackle	-42.18668	-22.26831	Turnovers Forced	.0091321	.0078651
	(53.10794)	(50.23075)		(.0063561)	(.0059872)
Quarterback	-28.8952	-17.73826	***Offensive Measures***		
	(21.21755)	(19.56523)			
Skilled Positions	10.90214	9.451523	Rushing Per Game	.0018011	.002747
	(17.12228)	(16.14718)		(.0023452)	(.002148)
			Passing Per Game	.0009454	.0011529
				(.0016987)	(.0015953)
			Turnovers Per Game	-.0059508	-.0070454
				(.0066171)	(.0060983)
			Points Allowed	-.0074091***	-.0067376***
				(.0011379)	(.0010382)
			Points Per Game	.0051837***	.0053608***
Standard Deviation	1.54e-08	6.35e-08		(.0010068)	(.0009666)
of Offense	(7.73e-08)	(7.19e-08)	Left-handed QB	-.0675823	-.1247768
				(.1669806)	(.138777)
Standard Deviation	6.16e-09	1.91e-08	Home Turf	.5023155***	.4692467***
of Defense	(8.51e-08)	(8.04e-08)		(.0504305)	(.0459151)
			Coaching Tenure	-.0024635	-.0006721
Percent of Salary Cap	-.071359	-.276992		(.0077828)	(.0067411)
Spent (Total)	(.4676404)	(.4402461)	Playoffs Made	.3811997***	.3859672***
				(.0924062)	(.0888627)
Number of Observations		5738	Pseudo R-squared	0.2163 (1)	0.2110 (2)

*significant at 0.1 level **significant at the 0.05 level ***significant at the 0.01 level

NOTE. – Standard errors are listed in parentheses.

Therefore, in order to obtain significance with some of the salary variables, I subsequently parsed through the initial regression to determine which variables were necessary to the regression and which variables could and should be left out. First, I looked at the variables that may be eroding from the significance of the salary variables. I eliminated the variables of points per game, points allowed per game, and playoffs made, as those variables are so strong and so indicative of the outcome of a game that they may be picking up some of the effects wanted to be seen in the salary variables. Logically, the teams who score the most points and allow the least points will be the teams who will most likely win a game, and those teams that make the playoffs win more games. Home turf, the only other variable significant at the 0.001 level of the first two initial regressions, was still included as a control variable in the final regression as home turf advantage is not directly indicative of a team's offensive or defensive performance nor does it have a direct impact of game outcome. In addition, the backbone of this paper is the theory that player salary is an indicator of player performance, as shown through a team's wins and losses. Other measures of a team's offensive performance other than salary may be detracting from the significance of those salary variables. Therefore, the team-specific measures of the offense (passing per game, rushing per game, turnovers per game) were removed from the regression. The same concept was applied for the defense, as team-specific measure of the defense other than the salary, as measured through the variable of total salary cap spent, would detract from the significance of the total salary cap spent variable. Therefore, the team-specific measures of the defense (passing allowed, rushing allowed, turnovers forced) were removed from the regression. Furthermore, the tenure of the center, left guard, left tackle, right guard, right tackle, quarterback, and skilled players were eliminated from the regression, as the tenure of a player may affect that player's performance, either positively or negatively, thus detracting from the influence and significance of the salary variables.

Time fixed effects were excluded due to the nature of the regression where only the differences in teams matter. Therefore, the difference in time fixed effects is zero for every regression and thus cannot provide any significant results.

After eliminating the aforementioned variables, I then ran the regression of result as the dependent variable on the independent variables: percentage of the salary cap spent on the center, left guard, left tackle, right guard, right tackle, quarterback, and skilled positions, the squared percentages of the salary cap spent on the center, left guard, left tackle, right guard, right tackle, quarterback, and skilled positions, offensive injuries, defensive injuries, special teams injuries, home turf advantage, coaching tenure, left-handed QB, standard deviation of spending on the offense, standard deviation of spending on the defense, and percent of the salary cap spent (total). This regression was run both with and without team fixed effects. The results showed that the percentage of salary cap spent on the center, left guard, right tackle, and quarterback, the percentage of the salary cap spent squared on the left guard, right tackle, and quarterback, offensive injuries, defensive injuries, special injuries, left-handed QB, and home turf were significant at the 0.1 level at least in the regression with team fixed effects. In addition, the percentage of the salary cap spent on the left guard, right guard, and quarterback, the percentage of the salary cap spent squared on the left guard, offensive injuries, defensive injuries, coaching left-handed QB, and home turf were significant at the 0.1 level at least in the regression without team fixed effects.

After conducting a Wald test to determine if any additional variables were insignificant to the regression and thus could be eliminated, the standard deviation of the offensive salary and the standard deviation of the defensive salary were eliminated, with p-values of 0.326 and 0.799 in the regression with team fixed effects and 0.198 and 0.220 in the regression without team fixed effects, respectively, and with Wald test results of a chi2 value of 1.02 and a p-value of 0.6010 for the regression with team fixed effects and a chi2 value of 3.04 and a p-value of 0.2192 for the regression without team fixed effects. Thus, these two variables were safely removed from the regression. The final variables included in the regression are shown in Table 8.

Table 9 shows the final regression results, including the marginal effects from the regression. The marginal effects are of interest because they provide an easier interpretation of the coefficients from the final regression. An interpretation of the marginal effects will be discussed below. Table 10 shows regression results with the only independent variables as the percentage of the salary cap spent on the individual offensive players and the percentage of the salary cap spent squared on the individual offensive players. Thus, Table 10 shows the raw regressions of just the variables of interest while Table 9 shows the final regressions of the variables of interest, namely the salary variables of the starting offensive players, and of the control variables.

Table 8

Summary of the List of the Variables Included the Final Regression

Variables		
Team-specific	Game-specific	Player-specific
General:	Offensive Injuries	*Percent Salary Cap Spent on:*
Coaching Tenure	Defensive Injuries	
	Special Injuries	Center
Percent of the salary cap spent (total)	Home Turf Advantage	Left Guard
		Left Tackle
		Right Guard
Team Fixed Effects		Right Tackle
		Quarterback
		Skilled Positions
		Percent Salary Cap Spent Squared on:
		Center
		Left Guard
		Left Tackle
		Right Guard
		Right Tackle
		Quarterback
		Skilled Positions

The regressions in Table 9 and Table 10 are subdivided into a regression that does include team fixed effects (1) and a regression that does not include team fixed effects (2). The reasoning behind including these two regressions is that, while including team fixed effects is important to account for market correction and unique caveats to each team that are not necessarily picked up through the data,

Table 9

Final Regression Coefficients, Marginal Effects, and Standard Deviations Including Interest and Control Variables, with Team Fixed Effects (1) and Without (2)

	(1)		(2)	
	Coefficient	Marginal Effect	Coefficient	Marginal Effect
***Offensive Line Salary**:*				
Center	9.454149*	.9593162*	6.426168	.8869135
	(5.446138)	(.56367)	(5.030229)	(.67666)
Left Guard	12.2203***	1.239998**	10.86935***	1.500143**
	(4.225725)	(.52226)	(3.818202)	(.58865)
Left Tackle	4.754378	.4824286	3.259315	.4498374
	(4.38573)	(.42952)	(3.901749)	(.52373)
Right Guard	8.365954	.8488966	10.71579**	1.47895**
	(5.653099)	(.59639)	(5.261049)	(.75032)
Right Tackle	6.334658	.6427802	1.738202	.2398995
	(3.907318)	(.4267)	(3.624291)	(.49939)
Quarterback	9.808302***	.9952523***	7.236119***	.9986997**
	(2.558388)	(.38622)	(2.362749)	(.3991)
Skilled Positions	-3.309331	-.3357992	-.0356427	-.0049193
	(3.826275)	(.44967)	(3.520695)	(.48654)
***Offensive Line Salary Squared**:*				
Center	-61.79523	-6.270386	9.201698	1.269981
	(80.50273)	(8.05645)	(74.5225)	(10.342)
Left Guard	-153.016***	-15.52659**	-128.3113***	-17.70901**
	(49.78064)	(6.33274)	(45.77985)	(7.0542)
Left Tackle	-41.15721	-4.176238	-10.20087	-1.407882
	(50.293)	(4.91453)	(44.2362)	(6.03845)
Right Guard	-79.43445	-8.060245	-109.6061	-15.12739
	(88.10962)	(9.06246)	(82.93823)	(11.55)
Right Tackle	-96.53256**	-9.795196*	-35.54211	-4.905378
	(47.21571)	(5.40104)	(44.1902)	(6.12607)
Quarterback	-51.10417***	-5.18556**	-17.39188	-2.400357
	(18.94346)	(2.41555)	(17.45741)	(2.4852)
Skilled Positions	23.91666	2.426833	5.31655	.7337686
	(14.75908)	(1.95286)	(13.52118)	(1.96047)
Control Variables				
Offensive Injuries	-.0647322**	-.0065684*	-.0741226**	-.0102301**
	(.0318469)	(.00395)	(.0305027)	(.00499)
Defensive Injuries	-.0727108**	-.007378*	-.0843529**	-.011642**
	(.0300289)	(.00382)	(.0288194)	(.00484)
Special Team Injuries	.3642965**	.0366933*	.2796168	.0387265
	(.1825454)	(.021)	(.1722861)	(.02536)
Coaching Tenure	.009742	.0009885	.0182729***	.002522***
	(.0065309)	(.00068)	(.0056595)	(.00089)
Home Turf	.3688648***	.0375116***	.3503961***	.0484024***
	(.0438648)	(.01173)	(.0392561)	(.01184)
Left-handed QB	.4747964***	.0411218**	.2797085**	.0355498**
	(.1410109)	(.01518)	(.1188144)	(.01589)
Percent of Salary Cap Spent	.8750772***	.0887944***	.5921293**	.0817233***
	(.2738645)	(.02479)	(.25849)	(.0287)
Number of Observations		5776	Pseudo R2 0.0913 (1) 0.0583(2)	
*significant at 0.1 level **significant at the 0.05 level ***significant at the 0.01 level				

NOTE. – Standard errors are listed in parentheses.

Table 10

Raw Regression Coefficients, Marginal Effects, and Standard Deviations of All Interest Variables, with Team Fixed Effects (1) and Without (2)

	(1)		(2)	
	Coefficient	Marginal	Coefficient	Marginal
***Offensive Line Salary**:*				
Center	5.706157	.92142	6.298979	1.200173
	(5.095093)	(.79721)	(4.73924)	(.87025)
Left Guard	12.30865***	1.987579***	11.19765***	2.133539***
	(3.985693)	(.69073)	(3.645354)	(.70694)
Left Tackle	4.68648	.7567644	3.86835	.7370546
	(3.931241)	(.60855)	(3.552884)	(.65612)
Right Guard	10.07683*	1.627188*	12.93055***	2.463718***
	(5.373021)	(.85953)	(4.997824)	(.93482)
Right Tackle	5.910536	.9544228	1.034023	.1970172
	(3.670359)	(.59893)	(3.422292)	(.65039)
Quarterback	11.87402***	1.917396***	9.402187***	1.791442***
	(2.376386)	(.46773)	(2.193155)	(.44869)
Skilled Positions	-2.292168	-.3701352	1.264897	.2410067
	(3.55626)	(.62062)	(3.313093)	(.60924)
***Offensive Line Salary Squared**:*				
Center	-17.34063	-2.800134	-1.674908	-.319128
	(75.95524)	(12.179)	(70.6034)	(13.443)
Left Guard	-136.9302***	-22.11125***	-115.6671***	-22.03858***
	(47.53204)	(8.18499)	(44.09375)	(8.50159)
Left Tackle	-20.9076	-3.376122	-5.924256	-1.128776
	(44.45268)	(7.04514)	(40.02539)	(7.59246)
Right Guard	-91.31695	-14.7457	-139.8303*	-26.64251*
	(84.43365)	(13.538)	(79.3656)	(14.921)
Right Tackle	-49.03735	-7.918463	-9.141587	-1.741789
	(43.6613)	(7.12245)	(41.23921)	(7.85091)
Quarterback	-62.79252***	-10.13962***	-30.82178*	-5.872616*
	(17.67665)	(3.16702)	(16.26495)	(3.12837)
Skilled Positions	18.85584	3.044808	.0801898	.0152789
	(13.70848)	(2.57701)	(12.72757)	(2.42637)
Number of Observations		6106	Pseudo R2 0.0602(1)	0.0261(2)
*significant at 0.1 level **significant at the 0.05 level ***significant at the 0.01 level				

NOTE. – Standard errors are listed in parentheses.

these team fixed effects may be eroding from the effects of the salary data on game outcome. Therefore, both regressions with and without team fixed effects are included for reference. The results for the team fixed effects can be found in the Appendix. An important note is that Arizona is used as a basis for the team fixed effects; thus, the individual team fixed effects are in comparison to those of Arizona.

VI. Conclusion

Ultimately, the results from the final regression in Table 9, both with team fixed effects in column one and without team fixed effects in column two, are interesting and somewhat suspect. Before delving into a discussion of the regression results, an explanation of the results is necessary. The theory is that, since the left tackle is traditionally the highest paid offensive lineman on an NFL team, the optimal percentage of the salary cap allocated to the left tackle should be higher than the other offensive line positions. The theory continues that if teams are already optimizing their salary cap appropriately, then the marginal effects when evaluated at the percent of the salary cap and the percent of the salary cap squared values should be zero.

Essentially, the results of interest are those on the salary data, as shown in Table 9, and the marginal effects of increasing that salary. For example, in the regression with team fixed effects in Table 9, column two, the interpretation for the results of the center is that the coefficient of the marginal effect is the change in the chance of winning when, all other salary allocations being equal, a team adds an extra percentage point of the salary cap to the center position and away from the omitted positions—namely, the defensive positions, special teams positions, and the offensive non-starters. Therefore, when a team is at the salary cap, for every one percentage point more of the salary cap spent on the center, the chances of winning a game increase by 0.95 percentage points.

However, to properly interpret the salary coefficients, the percent of the salary cap spent squared variables must also be included in the interpretation. Unfortunately, adding these variables makes the results hard to interpret as, using the same example of the results from the center in the second column of Table 9, when the percent of the salary cap spent on the center increases, the chances of winning increase through the positive coefficient on the percent of the salary cap spent variable but also decrease through the negative value of the percent of the salary cap spent squared variable. Therefore, in order to interpret the results of the salary variables at the margin for each position and holding all other variables equal, I took the regression equation utilized in column one and column three of Table 9:

$$\text{Result} = \beta_1 * \text{Percent of Salary Cap} + \beta_2 * (\text{Percent of Salary Cap})^2$$

and used the partial derivative of that equation:

$$\partial \text{Result} / \partial \text{Percent of Salary Cap} = \beta_1 + 2 * \beta_2 * (\text{Percent of Salary Cap})$$

where Percent of Salary Cap is the percent of the salary cap spent on the position and $ß_1$ and $ß_1$ are the coefficients of the salary and the salary squared variables for that particular position, respectively, to evaluate where the marginal effect equals zero and thus at what percentage of the salary cap is the team optimizing their salary allocation. The theory behind evaluating the marginal effect of the percentage of the salary cap variable at zero is that if teams are properly allocating their salary, then the point at which the marginal effects for the left tackle equals zero, and thus the marginal effects go from positive to negative, should be at a higher percentage of the salary cap in comparison to the other offensive line positions. Accordingly, I evaluated where the marginal effect equals zero for each position using the partial derivative equation above and the coefficients for percent of the salary cap and percent of the salary cap spent squared variables for each position from column one and column three in Table 9. The results can be seen in Table 11.

According to the results in Table 11, the optimal spending for the left guard is between 3.990 percent, as seen in the regression with fixed effects, and 4.236 percent, as seen in the regression without fixed effects, of the salary cap. Similar numbers can be seen for the right guard, as the optimal salary is between 4.888 percent and 5.266 percent of the salary cap. The optimal spending on the left tackle, on the other hand, has a larger disparity in numbers, as it is between 5.776 percent, a number right on par with the spending of the other offensive line positions and in between the bounds of the left tackle's positional counterpart, the right tackle, which has optimal spending between 2.445 percent and 6.198 percent, and 15.976

Table 11

The Percentage of the Salary Cap at which the Marginal Effect for Each Position Equals Zero Evaluated Using the Coefficients From Column One and Column Three in Table 9, with Team Fixed Effects (1) and Without (2)

	(1)	(2)
	Percentage of the salary cap at which the marginal effect equals zero	Percentage of the salary cap at which the marginal effect equals zero
Offensive Line		
Center	0.07650	-0.34918
Left Guard	0.03990	0.04236
Left Tackle	0.05776	0.15976
Right Guard	0.05266	0.04888
Right Tackle	0.06198	0.02445
Quarterback	0.09596	0.20803
Skilled Positions	-0.06918	-0.00335

percent, a number that is seven percentage points higher than the upper bound of the highest position, the center, at 7.650 percent. In addition, the salary of the quarterback is the highest, with the percentage of the salary cap between 9.596 percent and 20.803 percent. These results for the quarterback are in accordance with the theory that the quarterback is the most important player on a football team's offensive line and thus receives, on average, the highest portion of the salary. Ultimately, the results in Table 11 do not dispute the NFL's current trend in spending more on the left tackle in comparison to the other offensive line positions as, while the regression with fixed effects in column one places the left tackle as exactly in the middle of the other offensive line position in terms of the optimal percent of the salary spent on that position, the results in the second column from the regression show that optimal spending for the left tackle could extend to 15.976 percent of the salary cap. However, given the descriptive statistics in Table 2 and Table 3 on how much of the teams are currently spending on average of the different offensive line positions, I would venture that the optimal spending on the left tackle is closer to 5.776 than 15.976 percent of the salary cap as the average percent of the salary cap spent on the left tackle is 3.539, with the highest being 11.296 percent.

However, some of the results in the Table 11 do prove suspect—namely, the marginal effects of the center and of the skilled positions. For the center, the results from the regression with fixed effects, denoted in the first column of Table 11, seem reasonable, with an optimal level of spending at 7.650 percent of the salary cap; on the other hand, the results from the regression without fixed effects, denoted in the second column, seem very unreasonable, as the result is an optimal level of spending on the center that is negative at -0.34918. A similar situation occurs with the offensive skilled positions, as in both regressions the results are negative, with -6.918 and -0.335 percent of the salary cap as optimal spending with and without team fixed effects, respectively. The reason for these negative numbers can be attributed to the lack of significance of the figures, as seen in the columns one and three in Table 9, and the possibility of the variables picking up effects not controlled for in the regression, especially in the second set of regressions that is run without team fixed effects.

Ultimately, despite the uncertainty of the negative figures, the results of the marginal effects show, firstly, that the left tackle may be paid more on average in the NFL because the point at which the marginal effect is zero for the left tackle is, in fact, higher than the other offensive linemen in column two of Table 11. However, this number must also be looked at in context of the other number presented in column one of Table 11 that puts the left tackle as the third highest paid offensive line position. Therefore, while column two shows the possibility of the left tackle having a higher optimal salary in comparison to the other offensive linemen, column one in Table 11 shows that the optimum salary of the left tackle is the third, not first, highest of the offensive linemen. Thus, the possibility remains that the left tackle may have the highest optimum salary, as shown in column two, but this statement is not definitive as column one shows the possibility of the left tackle to be in par with the other offensive linemen in terms of optimum salary.

Secondly, the center position shows to be deserving of the second highest salary on the offensive line at a high of 7.650 percent of the salary cap and low of -34.918, while the right tackle follows closely behind with a high of 6.198 percent of the salary cap and a low of 2.445. The theory behind the relative importance of these positions in comparison to the other offensive line positions is sound. The center is responsible for snapping the ball to the quarterback, a critical role in beginning each offensive play; thus, the high optimal percentage of the salary cap for this position is intuitive. The right tackle plays the position of the left tackle except on the opposite side; hence, the right tackle will need a similar skill set to protect the quarterback, even though the right tackle is not protecting the quarterback's blind side.

Ultimately, however, this approach sets up a situation where there is a unique, one-size fits all optimum for maximizing a team's chances of winning through the allocation of the salary cap. In practice, I suspect that there are multiple approaches to optimizing a team's salary cap and, thus, these alternate approaches are left out in the results of finding the optimum salary in Table 11. As such, the disparity between the optimum salary for a given position in Table 11, such as the ten point difference between column one and column two for the quarterback, may be showing that there is more than one optimum salary allocation for the offensive positions.

In addition to evaluating the point of optimal spending for different offensive positions, I also wanted to evaluate how teams are currently allocating their salary cap. Using the equation:

$$\frac{\exp(ß_1 * \text{Percent of Salary Cap} + ß_2 * (\text{Percent of Salary Cap})^2)}{1 + \exp(ß_1 * \text{Percent of Salary Cap} + ß_2 * (\text{Percent of Salary Cap})^2)}$$

I calculated the marginal effect of adding an extra percentage point of the salary cap to a certain position, where Percent of Salary Cap is the percent of the salary cap spent on the position and $ß_1$ and $ß_1$ are the coefficients of the salary and the salary squared variables, respectively, in the final regression, denoted as the first and third columns in Table 9. The result of this equation is the marginal effect of an extra percentage point of the salary cap allocated to the offensive position at that percent of the salary cap, holding all other offensive salaries and control variables equal, on the chances of winning a game. First, I evaluated the NFL as a whole by using the average percentage of the salary cap allocated to each position, as denoted in Table 2, as the Percent of the Salary Cap variable, and those results can be seen in Table 12.

Using the center position as an example, the interpretation for the results in Table 12 is that at the average percentage of the salary cap allocated to the center, in this case .0222868, as denoted in Table 2, the marginal effect in adding an extra

Table 12

Marginal Effects of Adding an Extra Percentage Point of the Salary Cap to Each Offensive Position Evaluated Using the Coefficients from Table 9 and the League Average from Table 2, with Team Fixed Effects (1) and Without (2)

	(1)	(2)
	Marginal Effect of Adding an Extra Percentage Point of the Salary Cap	Marginal Effect of Adding an Extra Percentage Point of the Salary Cap
Offensive Line		
Center	.602019	.584186
Left Guard	.606636	.597025
Left Tackle	.566757	.558737
Right Guard	.571641	.589931
Right Tackle	.534883	.512045
Quarterback	.698781	.677118
Skilled Positions	.466514	.539875

percentage point of the salary cap to that position is an increase in the chances of winning by 0.602019 percentage points, in the regression with fixed effects, denoted as column one in Table 12. The regression without fixed effects, denoted as column two in Table 12, shows that the marginal effect of adding an extra percentage point of the salary cap to the center results in a 0.584186 percentage point increase in the chances of winning. Similar situations are seen with the other offensive line positions and with the quarterback and skilled positions, as the marginal effects of adding an extra percentage point of the salary cap to each position is between 0.466514 percentage points and 0.698781, with the greatest difference between the results from the regression with fixed effects and the regression without fixed effects within one position being 0.073361, as is the case with the skilled positions.

Theoretically, if teams are allocating their resources properly and game result is the only outcome affecting the allocation of the salary cap, the marginal effect of adding an extra percentage point to a position should be the same across positions and should be zero. In the case that the marginal effect is above zero, as is the case with all the offensive positions, the possibility remains to allocate a larger portion of the salary cap to each of those positions and still see a positive marginal effect and thus an increase in the chance of winning. To the extent that the variables are not zero and not the same, two possibilities exist. The first is that teams may not be fully aware of the marginal value of particular positions. As is the case with all the results in Table 12, a positive marginal effect means that, at the current average salary allocation, teams could add an extra percentage point of the salary to all the starting offensive positions and see positive results; thus, teams are, on average, under spending on their starting offensive players. The second is that there are other objectives of salary allocation that may not go hand in hand with winning. Thus, a team's goal in the allocation of the salary cap may not only be to increase their chances of winning each game; rather, other motivations, such as optimizing profit or bringing more publicity to the team, may affect a team's salary allocation. Therefore, on the margins, profits are not equal to a team's chance of winning, and the salary cap is not exclusively optimized for game result.

A similar interpretation is used for the control variables. For the injuries, for each player that is injured offensively or defensively, the chances of winning decrease by 0.0065 percentage points and 0.0073 percentage points, respectively, significant at the 0.1 level. The puzzling result for injuries is that for each injury on the special teams, the chances of winning actually increases by 0.037 percentage points, significant at the 0.1 level, which, intuitively, does not make sense, as one would believe that each special teams injury would decrease the chances of winning; however, there is the possibility that, when measured on a per game basis, the injury of a special teams player may allow a better offensive player, such as a starting receiver, to step in for that game. While having a starting offensive player also start on the special team may not be optimal for a season strategy as that player is further prone for injury, on a per game basis having a starting offensive player also start on the special team due to an injury on the special team may actually increase a team's chances of winning. To check this belief, I ran a regression of the season winning percentage on the variables used in the final regression, shown in Table 8, both with and without team fixed effects. In the regression with team fixed effects, the coefficient on special teams injuries is -0.00835692, with a p-value of 0.515. In the regression without team fixed effects, the coefficient on special teams injuries is -0.0164914, with a p-value of 0.238. While the special teams injuries does not prove significant when using the season winning percentage as the dependent variable, the sign of the special teams injuries is negative, thus showing that injuries of special teams starters do negatively affect a team's chances of winning when looking at those chances in terms of the entire season.

For coaching tenure, for each additional year a head coach has coached in the NFL, the chances of winning increase by 0.00099 percentage points; however, coaching tenure is not a significant variable here. For percent of the salary cap spent (total), for every one percentage point increase in the percent of the salary cap spent (total), the chances of winning a game increase by 0.089 percentage points, significant at the 0.01 level. Both of these variables make intuitive sense as a coach's quality should increase in the years of experience of that coach, thus increasing a team's chances of winning, and a higher percent of the salary cap used should result in higher quality players, again increasing a team's chances of winning. For the handiness of a quarterback, if a quarterback is left-handed, the chances of winning a game increase by 0.041 percentage points, significant at the 0.05 level. However, there were only 28 instances, out of a possible 448 (32 teams * 14 seasons), of starting left-handed quarterbacks, including the careers of well-distinguished quarterbacks such as Michael Vick and Boomer Esiason. Therefore, the magnitude and significance of the left-handed quarterback variable may also be attributed to the small sample of left-handed quarterbacks during the time period and to the high quality of that selection of quarterbacks. Finally, for home turf advantage, if a team is playing on its own turf, the chances of winning a game increase by 0.038 percentage points, significant at the 0.01 level. Ultimately, the results and interpretations of the control variables make logical sense.

However, with a Pseudo R-squared value of 0.0913 in the regression with team fixed effects and of 0.0583 in the regression without team fixed effects, as seen in Table 9, there are clearly other factors that play a large role in determining the probability of a team winning other than their allocation of the salary cap to the different offensive positions. Despite the other factors missing from this regression, looking solely at the impact of individual salaries on a team's performance, defined by a win, loss, or tie, the conclusion is that the blind side tackle position, denoted as the left tackle in my paper, could have positive marginal effects on the chances of winning a game up to fifteen percent of a team's total salary cap. Although the likelihood of a left tackle generating positive marginal effects at fifteen percent of the salary cap without negatively detracting from the allocations of the other players under the salary cap seems unlikely, especially given that the average percent of the salary cap spent on the left tackle is .0353892 percentage points, I cannot dispute, given the results, that the left tackle is overpaid in comparison to the other offensive line positions. Ultimately, the left tackle *may* be worth it. Therefore, to some degree, NFL teams are allocating the salary cap toward optimizing game result with respect to the salaries of the starting offensive players.

Further implications and insights of this research would be to expand upon the results by dividing the time period selected (1995-2009) and looking at the marginal effects of the left tackle over time, as sports commentators such as ESPN's senior writer, David Fleming (2013), have been citing the demise of the left tackle's importance over the recent years. Fleming states, "The left tackle, once considered an essential building block for every franchise, has seen its importance erode in this era of read-option spread offenses." Therefore, the left tackle may have been a more critical player to a team's success in earlier years but has seen a demise in that importance as the game of football has evolved. Thus, the results from this paper may be showing a possible higher optimal salary for the left tackle than for other offensive line positions due to the larger impact and higher importance of the left tackle in the past that may not hold in today's football game. However, to briefly examine this phenomenon, I calculated the correlation between the percentage of the salary cap allotted to the left tackle and a team's winning percentage, both at the game-by-game and season level, on a year-by-year basis, with the results seen in Table 13. Plotted, these preliminary results show evidence that, over the time period, the importance of the left tackle increased and subsequently decreased in

Table 13

Correlation between Percent of the Salary Spent on the Left Tackle and Chances of Winning, both at the Game-by-Game and Season Level, by Year

	Correlation between Percent of the Salary Spent on the Left Tackle and:	
Year	Game Result	Season Winning Percentage
1995	0.0650	0.2346
1996	-0.0560	-0.2415
1997	-0.0173	-0.0639
1998	0.0688	0.1657
1999	0.0133	0.0418
2001	0.1140	0.2678
2002	0.0591	0.1628
2003	0.0955	0.2430
2004	0.0638	0.1673
2005	0.0073	0.0302
2006	0.0240	0.0247
2007	0.0738	0.1834
2008	-0.0452	-0.1416
2009	0.0706	0.1772

the most recent years, as shown in Figure 3 and Figure 4. A polynomial model best fit the plotted correlations, with an R-squared value of 0.10019 for the scatter plot of the correlation between season winning percentage and the percent of the salary cap spent on the left tackle, and of 0.13371 for the scatter plot of the correlation between game result and percentage of the salary cap spent on the left tackle. Ultimately, while the results in Table 11 show the possibility of the optimal salary of the left tackle being above the optimal salary of the other offensive linemen, these results may be indicative of the past trends of the importance of the left tackle position, and those trends may not completely be representative of the importance of the left tackle today, as shown in the decrease in correlation between a team's chances of winning and the percent of the salary cap spent on the left tackle at both the game-by-game and the season level, as seen in Table 13 and Figures 3 and 4.

Figure 3
Scatter Plot of the Correlation between Season Winning Percentage and Percent of the Salary Cap Spent on the Left Tackle, by Year

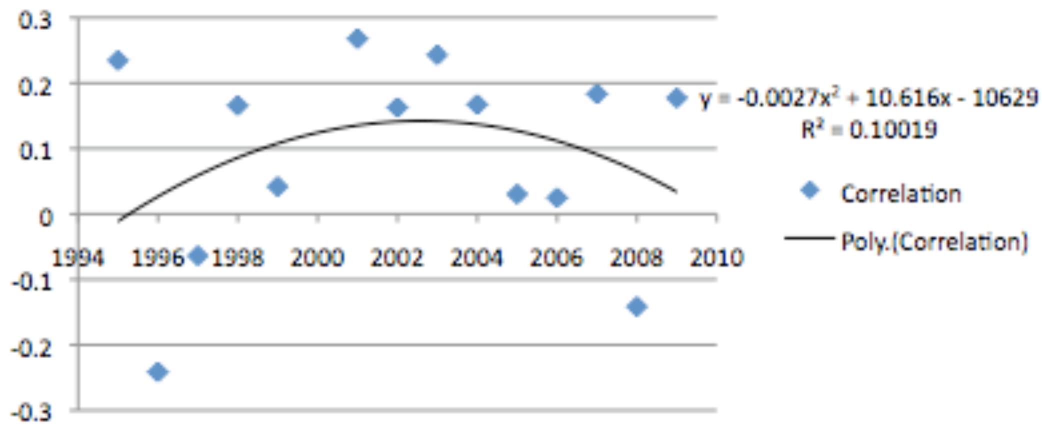
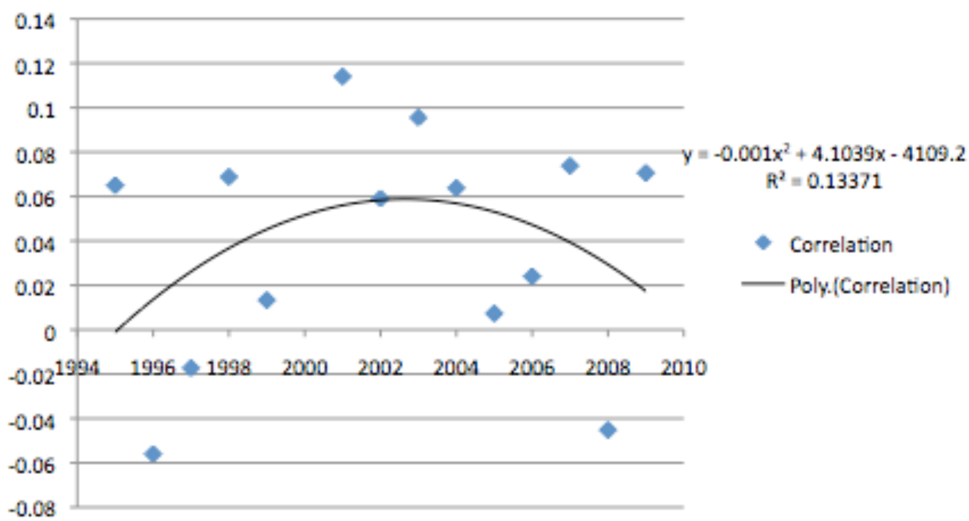


Figure 4
Scatter Plot of the Correlation between Game Result and Percent of the Salary Cap Spent on the Left Tackle, by Year



In conclusion, the final results do not dispute the NFL's current trend in spending more on the left tackle in comparison to the other offensive line positions. The results show that optimal spending for the left tackle could extend from 5.776 to 15.976 percent of the salary cap. Thus, the possibility remains that the optimal spending for the left tackle can range up to fifteen percent of the salary cap, seven percentage points above the next highest optimal offensive lineman spending. In addition, on average, teams could afford to allocate more of their salary to the starting offensive players in general, as the positive marginal effects show that allocating one more percentage point to each position would result in an increase in the probability of a team winning. However, optimizing the probability of winning may not be the only objective in salary allocation and thus the results show that, on average, teams are not optimizing their salary allocation. [1]

[1] For further information or inquiry, contact me at kellyannfroe@gmail.com. This July I will be moving to Austin, TX to begin on the Payment Operations Team at Facebook.

Appendix

Team Fixed Effects Coefficient and Standard Deviation Results for the Initial Regression Denoted as Regression (1) in Table 7

Team	Coefficient	**Team**	Coefficient
Atlanta	-.0294356 (.2270652)	Minnesota	-.0912735 (.2330497)
Baltimore	-.2024593 (.2480898)	New England	.2298793 (.2436872)
Buffalo	.0776888 (.2182424)	New Orleans	-.1979942 (.2132725)
Carolina	-.2571416 (.2342165)	New York Giants	-.504495* (.2689812)
Chicago	.0836497 (.2472381)	New York Jets	-.4031587 (.2752219)
Cincinnati	.0670741 (.2301318)	Oakland	-.0273177 (.2298201)
Cleveland	-.109011 (.2665614)	Philadelphia	-.1933614 (.2217137)
Dallas	-.0056386 (.2296768)	Pittsburgh	-.1833371 (.2363834)
Denver	.2005281 (.2498645)	San Diego	-.1039662 (.222636)
Detroit	-.3108465 (.2277845)	San Francisco	.0636496 (.2804722)
Green Bay	-.2150878 (.2465636)	Seattle	-.2821983 (.2285043)
Houston	-.1741446 (.299689)	St. Louis	.0521297 (.2324101)
Indianapolis	.0777397 (.2450045)	Tampa Bay	-.3205956 (.2233621)
Jacksonville	-.1084629 (.239962)	Tennessee	.0948016 (.2446963)
Kansas City	-.0234637 (.2396817)	Washington	-.0737685 (.2115561)
Miami	-.1126593 (.2185973)		
Note: All team fixed effects are in comparison to Arizona, as Arizona is the base team			
*significant at 0.1 level **significant at the 0.05 level ***significant at the 0.01 level			

NOTE. – Standard errors are listed in parentheses.

Team Fixed Effects Coefficient and Standard Deviation Results for the Final Regression Denoted as Regression (1) in Table 9

Team	Coefficient	**Team**	Coefficient
Atlanta	-.019953 (.1937191)	Minnesota	.3224552 (.2023114)
Baltimore	.4665503** (.2093541)	New England	1.066329*** (.2118687)
Buffalo	.4468118** (.1872258)	New Orleans	-.1713607 (.1891446)
Carolina	.3250736* (.1977682)	New York Giants	-.2281116 (.242237)
Chicago	.5249421** (.212715)	New York Jets	-.1369245 (.244154)
Cincinnati	-.0989324 (.1978903)	Oakland	-.0540077 (.1957417)
Cleveland	-.3465121 (.2404841)	Philadelphia	.4578968** (.1897022)
Dallas	.4652069** (.1988094)	Pittsburgh	.6074109*** (.2020407)
Denver	.8366898*** (.2049703)	San Diego	.2907999 (.1953721)
Detroit	-.6297467** (.2035178)	San Francisco	.3388651 (.2399575)
Green Bay	.7556135*** (.2082104)	Seattle	.2244882 (.1861304)
Houston	-.5144484* (.2711367)	St. Louis	.0288832 (.1930483)
Indianapolis	.570484*** (.2045582)	Tampa Bay	.2144816 (.1920408)
Jacksonville	.4083333** (.2072429)	Tennessee	.306119 (.2085647)
Kansas City	.1892902 (.1985722)	Washington	.0735295 (.1819026)
Miami	.4394274** (.1902961)		
Note: All team fixed effects are in comparison to Arizona, as Arizona is the base team			
*significant at 0.1 level **significant at the 0.05 level ***significant at the 0.01 level			

NOTE. – Standard errors are listed in parentheses.

Team Fixed Effects Coefficient and Standard Deviation Results for the Raw Regression Denoted as Regression (1) in Table 10

Team	Coefficient	**Team**	Coefficient
Atlanta	.3385629* (.1770679)	Minnesota	.4894046*** (.1865546)
Baltimore	.5581261*** (.192937)	New England	1.190534*** (.1965611)
Buffalo	.5580162*** (.1750709)	New Orleans	-.0584237 (.1772206)
Carolina	.4281166** (.1807181)	New York Giants	.2685901 (.2192726)
Chicago	.4147613** (.1880185)	New York Jets	.48268** (.2240932)
Cincinnati	-.0256571 (.1824348)	Oakland	.0693423 (.1798081)
Cleveland	-.1941587 (.2288685)	Philadelphia	.5958786*** (.1741868)
Dallas	.6623923*** (.1838648)	Pittsburgh	.7476672*** (.1881389)
Denver	.9715278*** (.1930937)	San Diego	.546699*** (.1807768)
Detroit	-.3634156* (.1868107)	San Francisco	.8271651*** (.2199223)
Green Bay	.7323897*** (.1937003)	Seattle	.3426737** (.1703794)
Houston	-.0325794 (.24306)	St. Louis	.1401151 (.1832105)
Indianapolis	.7600901*** (.1917801)	Tampa Bay	.311446* (.1779255)
Jacksonville	.7250725*** (.1924329)	Tennessee	.4139426** (.1961112)
Kansas City	.4196523** (.1851278)	Washington	.3429075** (.1689452)
Miami	.6379636*** (.1768761)		

Note: All team fixed effects are in comparison to Arizona, as Arizona is the base team

*significant at 0.1 level **significant at the 0.05 level ***significant at the 0.01 level

NOTE. – Standard errors are listed in parentheses.

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John Troan of JT-SW.com