Optimizing the Allocation of Funds of an NFL Team under the Salary Cap, while Considering Player Talent

Jason Mulholland and Shane T. Jensen

jmul@wharton.upenn.edu; stjensen@wharton.upenn.edu

Department of Statistics, The Wharton School, University of Pennsylvania

463 Huntsman Hall

3730 Walnut Street

Philadelphia, PA 19104

ABSTRACT

Every NFL team faces the complex decision of choosing how to allocate salaries to each position while being limited by the salary cap. In this paper, we use regression strategies to focus on identifying what positions are worth greater investment under the assumption that players are paid in an efficient market. Using a combination of many univariate regression models, we identify that the positions at which it is worth investing in elite players are quarterback, guard, defensive tackle, and free safety. Additionally, we consider the possibility that markets are not actually efficient through separate regressions and detect that the optimal way to take advantage of inefficiency is through skilled drafting to find players who can provide significant win contributions early in their careers (since they are being paid the relatively low salaries of rookie contracts).
KEYWORDS: National Football League, linear regression, resource allocation, salary cap

INTRODUCTION

The focus on analytics has been increasing across all major sports leagues in the United States since the early 2000s (Fry and Ohlmann, 2012). However, in the NFL, this growth has been slowest, possibly due to the vast financial success that the NFL is experiencing which leads to hesitance to change. As analytics is now beginning to take a stronger hold in the NFL (as seen by the Next Gen Stats program started by the league), salary cap management appears as one of the key applications of statistical analysis to NFL team decision-making.

Unlike some other professional sports leagues, the NFL has a strict salary cap, meaning that teams cannot pay a luxury tax to gain permission to have a higher player salary total. This creates a classic allocation of a scarce resource decision, a topic on which there has been vast literature in the past. Radner (1972) discusses allocation of a scarce resource in situations of uncertainty, and Borghesi (2008) applies this issue specifically to the NFL salary cap. Radner (1972) used an economic model for an allocation problem of a scarce raw material to many enterprises. This study assigned an output function to each enterprise and attempted to maximize the expectation of total output with respect to the constraint of the scarce resource. Meanwhile, Borghesi (2008) used regression to identify what NFL players were overpaid relative to performance and identify the impact of this overpayment on their team performance.

When NFL executives make decisions on what players to sign, they are aware of past performance and measurables, but do not know how players will perform in the future. Therefore, decisions must be made without knowledge of the player's true value moving forward. Literature in this area indicates that players who are paid relatively less can earn large salary increases with increased performance, while those already with high pay will not earn much more with increased performance (Leeds and Kowalewski, 2001).

Motivated by this uncertainty of performance, there has been some literature on how to optimize salary structure of an NFL team in order to increase player performance. Mondello and Maxcy (2009) find that giving a player an increased salary with incentive bonuses for performance in a mostly uniform salary structure (one with little dispersion) will result in increased on-field performance. Meanwhile, Jane, San, and Ou (2009) find that a uniform salary structure is optimal for team performance in the professional baseball league in Taiwan, as well.

However, Quinn, Geier, and Berkovitz (2007) identify that teams in the NFL do not have a uniform salary structure, but more of a "superstar" salary structure, with some players earning far higher salaries than their teammates. They discuss that this comes from the fact that NFL owners and managers have convex utility curves against wins, so gaining a small amount of extra talent on their roster is believed to have a large impact on utility. While these findings are relevant, the paper concludes by stating, "Moreover, while there may be some rather difficult-to-detect strategies in cap allocation across players to enhance winning, teasing them out of the available data remains elusive" (Quinn, Geier, and Berkovitz, 2007, p. 15).

Winsberg (2015) began to attempt to discover some of these cap allocation strategies to maximize wins. This thesis focused only on a few position groups and concluded that paying offensive lineman and quarterbacks more than the league average leads to decreased team performance.

One of our contributions is to consider all position groups. Once all position groups are considered, it will be possible to identify an optimal percentage breakdown of the salary cap by position group. For example, we will calculate that teams that spend x% of the salary cap on quarterbacks, y% of the salary cap on right tackles, etc. will be expected to win the most games.

It will then be possible to further extend our approach to add the dimension of talent level of the players. Not only will this identify what salary cap allocations have led teams to the most success in the past, but it will provide the ability to identify the marginal talent (or win contribution) that can be added by investing more money at any given position, making it possible to identify which positions are worth an added investment to achieve the greatest increase in talent (or expected wins). Therefore, when presented with limited salary cap room remaining and multiple positions to fill, a team will know which positions are worth the investment of those final dollars.

With a full consideration of all position groups and player talent levels, the goal of this analysis is to identify the best possible salary cap allocation, in which a team will maximize talent (win contribution) per marginal cost at every position in order to maximize a team's expected wins.

Based on past results, there was an indication that a more uniform salary structure would be found to be optimal rather than that which currently exists in the NFL. While, in general, it seems that teams with the best quarterbacks are those that win the most, Winsberg (2015) indicated that it is not optimal in terms of team performance to have a highly paid quarterback. However, once taking talent (win contribution) into consideration, an allocation strategy that is relatively far from uniform and does pay high salary to quarterbacks is found to be optimal.

It is noteworthy that the optimal allocation strategies that we identify in this paper assume that players are paid efficiently, which is not the case in reality. Thus, we will also separately analyze how specific players win contributions compare to their salaries to identify uncompensated win contributions (win contributions beyond what would be expected at their given salary). Teams that are able to pay players low salaries and get many uncompensated wins tend to be the best teams. Past success of this formula can be seen by the dominance of the Seattle Seahawks in 2013 and 2014, who earned many uncompensated wins with quarterback Russell Wilson on his rookie contract, earning under $1 million each year, while they also had very few players earning "superstar" salaries. In 2014, only 2 Seahawks players earned more than $8 million ("Seattle Seahawks 2014 Salary Cap," 2015).

Overall, there are three questions to answer. First, in general, what positions should a team invest money in to maximize expected wins? Second, what is the best way to measure talent (or win contribution) of players at every position? And, finally, how do different players at different positions compare, in terms of additional marginal talent (win contribution) from additional investment.

With these three pieces of information, teams would have the ability to identify the available players with the highest expected talent (or win contribution) through prediction models. Then, by considering their talent level and position, the team will be able to identify the additional marginal win contribution that will be gained by spending on one player over another and the salary that would be efficient for that player's win contribution.

This analysis addresses this allocation problem with an optimal solution that can be the overall goal for a team when making each individual decision, as well as insights to assist in each individual decision. The methodology used in this analysis is applicable to any sports league with a strict salary cap.

DATA AND METHODOLOGY

This analysis requires data on NFL player salaries, NFL team performance and NFL player talent/performance. Salary data for the 2011 through 2015 seasons was obtained from spotrac.com. Though this only provides 160 team-seasons (32 teams over 5 years), there is a benefit to having a data set that is focused on the most recent past because team strategy continually evolves in the NFL. Focusing on the most recent past will provide a solution more applicable to future seasons in the NFL. For team performance, data on team wins was obtained from NFL.com. Meanwhile, data to measure player talent/performance was gathered from Pro-Football-Reference.com (AV, Approximate Value). Approximate value is Pro Football Reference's "attempt to put a single number on each player-season since 1950" to measure player value ("Football glossary and football statistics glossary," 2000-2016).

In order to perform this analysis, we first need to identify each player's win contribution each season. We used a multivariate regression that predicts team wins from the total AV that the team had from each position.

$$Wins \sim \alpha_{norm} + \sum_{i=1}^{19} \left(\beta_i * AV_{position\ i}\right)$$

Each player's win contribution for any given year can be calculated by multiplying the AV the player obtained that year by the β_i for the player's position. Additionally, a team's win contribution from any position can be calculated as the total AV from that position multiplied by the position's β_i.

Now, knowing the win contribution each team gained from each position, it is possible to model salary versus win contribution. We use a combination of three linear regression strategies (univariate, multivariate, and sequential multivariate) to identify these relationships.

For the univariate model, we create a separate univariate regression for each position: $Win\ Contribution_{position\ i} \sim \alpha_{i,uni} + \beta_{i,uni} * \log(salary_{position\ i})$. Then, a team's projected wins can be obtained through a combination of the 19 univariate regressions:

$$Projected\ Wins_{uni} = \alpha_{norm} + \sum_{i=1}^{19} \left(\alpha_{i,uni} + \beta_{i,uni} * \log(salary_{position\ i})\right)$$

For the multivariate model, meanwhile, we create one multivariate regression:

$$Model\ Wins \sim \alpha_{i,multi} + \sum_{i=1}^{19} \left(\beta_{i,multi} * \log(salary_{position\ i})\ \right)$$

Where “model wins” is defined as:

$$Model\ Wins = \alpha_{norm} + \sum_{i=1}^{19}\left(Win\ Contribution_{position\ i}\right)$$

Then, from this model, a team’s projected wins is calculated as:

$$Projected\ Wins_{multi} = \alpha_{i,multi} + \sum_{i=1}^{19}\left(\beta_{i,multi} * \log(salary_{position\ i})\right)$$

Finally, for the sequential model, we begin with the univariate model with the highest $\beta_{i,uni}$ and sequentially add each position in the ordering of the size of the $\beta_{i,uni}$ while holding each previous resulting $\beta_{i,seq}$ constant (forming a multivariate model). Thus, for step j of the sequential:

$$\sum_{i=1}^{j}\left(Win\ Contribution_{position\ i}\right) - \sum_{i=1}^{j-1}\left(\beta_{i,seq} * \log\left(salary_{position\ i}\right)\right) \sim \alpha_{j,seq} + \beta_{j,seq} * \log\left(salary_{position\ j}\right)$$

Once all 19 $\beta_{i,seq}$ are calculated, a team’s projected wins from this model is calculated similarly to in the multivariate model:

$$Projected\ Wins_{seq} = \alpha_{norm} + \alpha_{19,seq} + \sum_{i=1}^{19}\left(\beta_{i,seq} * \log(salary_{position\ i})\right)$$

It is important to note the degree to which each of these modeling strategies preserves the association between salaries at one position with win contribution from the same position. The multivariate model, which estimates a regression of all win contributions from all salaries, does not maintain this association. This allows for the potential to find relationships between pay at different positions, but with 19 covariates and a sample size of only 160 team-seasons, there is a high likelihood of overfitting. The sequential model then attempts to fit a multivariate model while maintaining the within position associations to a certain extent, which again allows for potential relationships between positions, but will still have a high likelihood of overfitting, though to a lesser extent than the original multivariate. The univariate, meanwhile, completely preserves the association between salaries and win contribution at each position and, with only one covariate in each regression, will not be overfitting the data. As a result, the correlation between projected wins from the univariate and the actual in-sample wins is lowest, but would likely do the best job predicting the future due to a lack of overfitting. Additionally, the maintenance of the association within each position likely leads the univariate model's optimal allocation to be the best possible team allocation, assuming efficient pay.

Once we have the formula for projected wins from each model, linear programming can be used to identify the salary allocation that optimizes projected wins given the salary cap. With known value contributions per investment at each position, linear programming allocates scarce funds to these investments to optimize the overall value (Asher 1962). Beginning with the rookie minimum salary for the number of players a team must have at each position, we allocate each additional dollar to the position that has the highest current marginal benefit (the highest partial derivative with respect to salary). Thus, this method will create a breakdown of how much should be paid to each position to create maximal projected wins under each model.

While our procedure will produce the optimal allocation of salary by position assuming efficient pay, we must also consider the fact that pay is not truly efficient. Therefore, we also created a univariate regression of $\log(salary)$ versus win contribution by player for each position. Thus, a player's expected win contribution can be calculated as the implied win contribution for the player's salary from the regression log-curve for the player's position. Then, a player's uncompensated win contribution can be observed as actual win contribution minus expected win contribution for the player's salary. It is then optimal for teams to attempt to sign players that they expect to have a positive uncompensated win contribution (will be above the regression log-curve for their position and salary).

RESULTS

Allocation Model Results

The optimal allocation strategy identified by each model can be seen both in dollar terms and in percentage of the salary cap terms in **Table 1**. As previously stated, due to the preservation of the association between salaries and win contribution at each position, the univariate likely produces the best result.

The univariate result confirms the commonly held belief throughout the league that it is worth paying for an elite quarterback with a high salary. However, it does not suggest the common strategy that left tackle and edge pass rusher (defensive end or outside linebacker depending on the scheme) should be next highest paid. Instead, relative to what top players at each position get paid currently in the league, the model suggests paying for top tier players at guard, defensive tackle, and free safety.

The optimal allocation from the univariate model pays relatively low salary to running backs, which has been a trend throughout the league in recent years.

However, the low salary for left tackles is the opposite of the trend in the league. Left tackles are among the highest paid players in the NFL, but this model suggests that they are often not worth the investment. While many left tackles are being paid high salaries, not all of them deserve this because of lackluster performance. Thus, due to the fact that many left tackles with high salaries actually do not have a high win contribution, the expected marginal win contribution from paying a higher salary to left tackles is lower than that of other positions, though there are some talented left tackles that would be exceptions to this rule.

The multivariate and sequential models both indicate low pay for left tackles, as well. However, the positions for which these models indicate higher pay are somewhat different: these models do not indicate as high pay for guard or defensive tackle as compared to the univariate model. These models suggest paying for top tier wide receivers, free safeties, and strong safeties, while also suggesting a relatively high salary for running backs (as compared to what most running backs are currently paid in the league). The issue of not maintaining the association of win contribution and salary within each position can be seen in the fact that these models suggest paying the rookie minimum to several positions: fullback (sequential model), tight ends (both models), center (both models), defensive end (multivariate model), and kicker (both models), with the multivariate even suggesting not having a fullback. In reality, it does not seem like a justifiable plan to start undrafted rookies at this many positions without any depth (backup players) behind them in order to finance large investments in other positions. This issue is also evident in the unreasonably high salaries suggested for long snappers by these models.

Evaluation of Team Allocations

Separately, our models can be used to observe what teams were expected to have the highest number of compensated wins based on their salary allocation each year. **Table 2** displays the team that was projected the highest compensated win total each year with their actual record (and a "+" to indicate reaching the Super Bowl and a "++" to indicate winning the Super Bowl) and **Table 3** does the same for the team that was projected the lowest compensated win total each year. For the most part, teams with the best allocations did have successful seasons and teams with the worst allocations did not, but it is important to note that these were teams projected the most/least compensated wins, not actual wins.

It is interesting to notice that the only team agreed as the best allocation in one year across all three models is the 2013 New Orleans Saints. When considering their allocation, the six highest cap hits are a quarterback (Drew Brees), two guards (Jahri Evans and Ben Grubbs), two wide receivers (Marques Colston and Lance Moore), and a free safety (Malcolm Jenkins). And, a strong safety (Roman Harper) had the eighth highest cap hit on the team. Thus, the Saints were focusing their allocation primarily on the optimal positions from each of these three models and were able to win eleven games in the regular season before being eliminated from the playoffs in the divisional round by the eventual Super Bowl champion (the Seahawks).

Uncompensated Wins

While the 2013 New Orleans Saints were the only best team predicted by all models in terms of compensated wins, the 2013 Seattle Seahawks that eliminated the Saints and won the Super Bowl had the highest uncompensated wins of any team-season in the sample. In terms of compensated wins, the Seahawks were expected to win less than half of their games that year. However, with impressive production from many players (Russell Wilson, Richard Sherman, Bobby Wagner, Golden Tate, Doug Baldwin, Malcolm Smith, K.J. Wright, Byron Maxwell, Walter Thurmond, J.R. Sweezy, etc.) who were all on rookie contracts with cap hits under $1 million, the Seahawks were able to achieve more uncompensated wins than any other team in the league from 2011 to 2015 (see **Table 7** for 2011 to 2015 average uncompensated wins).

Figure 1 shows the regression log-curve for the relationship between player salary and player win contribution (i.e. each point is one player-season, like Russell Wilson-2013). The expected win contribution for a player is the y-coordinate of the red log-curve for their position at the x-coordinate of the player's salary. The player's uncompensated win contribution is their actual win contribution minus their expected win contribution. As noted earlier, it is optimal for teams to attempt to sign players that they believe will be above the line (i.e. their actual win contribution will be greater than the expected win contribution for their salary or, equivalently, their uncompensated win contribution will be greater than zero.

It is important to pay attention to differences in scale when observing **Figure 1**. For example, the top of the y-axis of the quarterback plot is a win contribution of six, while all of the other y-axes only reach two or less. While win contribution does extremely favor quarterbacks, it is logical that this is the case as the quarterback has the highest impact on the quality of a team, as he possesses the ball every offensive play.

Accordingly, when observing the highest uncompensated win contributions, quarterbacks dominate the chart. **Table 4** shows the top ten cumulative uncompensated win contributions over the 2011 through 2015 seasons, while **Table 5** shows the top ten average uncompensated win contributions per season. With the exception of Richard Sherman, who is only on the cumulative chart and not the average chart, every player in the top ten is a quarterback. Also, unsurprisingly, seven of the ten quarterbacks on the average uncompensated win contribution chart are players who were mostly on their rookie contract in this five year span.

The same pattern is also evident when excluding quarterbacks. **Table 6** shows the top ten non-quarterbacks in average uncompensated wins per season. Again, every player in this chart was on their rookie contract for at least part of the sample of 2011 to 2015 and, interestingly, every player is a defensive player. This is likely due to the fact that the quarterback dominates a team's win contribution from its offense, while there is no single position dominating defensive win contribution.

These results indicate that to achieve high uncompensated wins, teams must be skilled in selecting the best players in the NFL Draft because with the exception of top tier quarterbacks, it is these recently drafted players with low rookie salaries that contribute the most uncompensated wins. It is generally accepted that the reason that the Seahawks have had sustained success for the past several years is that they have succeeded in finding successful players in the NFL Draft. This is evident in **Table 7**, as the Seahawks have by far the highest average uncompensated wins of any team from 2011 to 2015.

Also, it is noteworthy that the top teams in uncompensated wins per season in **Table 7** are, in fact, the teams that have been the best teams over the sample from 2011 to 2015. In this five year sample, a team's average uncompensated wins per season has a correlation of 0.72 with actual team wins per season. Therefore, not only is drafting well the key to increasing uncompensated wins, but it is also the key to leading a team to the top of the league standings.

MODEL PROJECTIONS FOR THE 2016 NFL SEASON

The models developed in this analysis can also be used to project forward to the 2016 season based on the current team salary cap allocations. The projections from each model for compensated wins using team salary cap allocations (as of April 11, 2016) can be seen in **Table 8**. Note that these allocations are not the final allocations for the 2016 season, as the 2016 NFL Draft has not yet occurred and there are some free agents still to be signed.

Interestingly, the two teams with the highest average projection for compensated wins are the Tampa Bay Buccaneers and the Oakland Raiders. These teams both signed elite guards this offseason to high paying contracts with the two highest 2016 cap hits at the position (J.R. Sweezy and Kelechi Osemele, respectively) and Tampa Bay has the defensive tackle with the second highest 2016 cap hit in the NFL (Gerald McCoy).

Meanwhile, the Carolina Panthers (defending NFC champions) are projected the fewest compensated wins for 2016 based on the April 11, 2016 allocation. This is because the Panthers are paying low salaries at key positions in the models, such as guard and defensive tackle, because the Panthers have starters at these positions playing on low rookie contract salaries (guards, Trai Turner and Andrew Norwell, and defensive tackles, Kawann Short and Star Lotulelei). Therefore, while the Panthers are projected very few compensated wins, they should be expected to achieve many uncompensated wins, especially from those four players and quarterback Cam Newton (these five players, alone, contributed 4.4 uncompensated wins in the 2015 season).

To obtain an overall win projection, we can take these average compensated win projections and add on each teams uncompensated wins from 2015. These win projections can be seen in **Table 9**. However, we must note that this is not a perfect system, as players will have large changes in uncompensated win contribution if they have a large change in their salary cap hit (i.e. Russell Wilson's uncompensated wins will be far lower in 2016 than it has been in the past due to his far higher cap hit). Therefore, it is likely that the Seahawks are over-projected with their 14.0 win projection, as Russell Wilson should not be expected to continue to average 4.0 uncompensated wins after the end of his rookie contract. Meanwhile, the Eagles have traded away some of the players brought in during the Chip Kelly era, so likely will not match their -4.5 uncompensated wins from 2015, though they do still have starting quarterback Sam Bradford who has averaged an uncompensated win contribution of -1.3 for the 2011 through 2015 seasons, including zero seasons with a positive uncompensated win contribution. Nevertheless, the Eagles are still likely under-projected at 1.4 wins.

SUMMARY AND DISCUSSION

In this paper we have presented an optimization of salary cap allocations for NFL teams based on several different regression strategies. These strategies include a combination of univariate regression models, a multivariate regression model, and a sequentially-created multivariate regression model based on our univariate model results. As discussed, it is likely that the univariate model provides the most optimal solution due to the fact that it completely maintains the association between salary paid to each position and the win contribution gained from the given position.

In addition to paying for a relatively expensive quarterback, the univariate model suggests it is optimal to pay for elite players at guard, defensive tackle, and free safety, rather than at left tackle or edge pass rusher (defensive end or outside linebacker), as is commonly believed. The univariate model also supports the current trend throughout the league of paying lower salaries to running backs. On the other hand, the multivariate and sequential models still have a relatively high salary for running backs, while suggesting paying for expensive players at wide receiver, free safety, and strong safety.

A shortcoming of our modeling approaches are that they assume that every team will achieve the same win contribution return from investment at each given position as another team with an equal investment (i.e. every player is paid exactly efficiently according to their win contribution), which is not actually the case. Therefore, we also created univariate models by player at each position to consider which players produce more or less than the win contribution that would be expected from their salary. Thus, we can observe what teams are getting a higher return than expected (i.e. more uncompensated win contribution) from the players that they are paying.

Through these models, we identified that the Seattle Seahawks (especially Russell Wilson) achieved the highest uncompensated wins from 2011 to 2015. This is due to the fact that the Seahawks were able to make many successful draft picks and have productive players paying on low rookie-contract salaries. Additionally, we find that a team's uncompensated win total is extremely highly correlated with the team's actual win total. This implies that the key for teams to be among the premier organizations is to draft players who will achieve high win contributions while still playing on their rookie contracts (which last four years, typically).

Overall, we believe that if a team focuses their salary allocation towards the positions with a higher optimal salary in our univariate model (unless they have players on their rookie contracts at those positions) and is able to draft players who can quickly make an impact in the league, that team will be expected to win the most games. Optimally, a team can create prediction models for player win contributions, use those projections to observe the expected efficient salary for each player, and attempt to sign players whose salary implied by the existing free agent market is lower than what was determined to be their expected efficient salary. If a team is able to sign many players for salaries below efficient value, they will achieve many uncompensated wins and then have the salary cap space to invest more money in key positions where a high return of compensated wins is expected, and thus achieve maximal expected wins.

REFERENCES

Asher, D. T. "A Linear Programming Model for the Allocation of R and D Efforts." *IRE Transactions on Engineering Management* 9, no. 4 (1962): 154-57. Accessed October 13, 2015. http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=5007697&tag=1

Borghesi, Richard. "Allocation of scarce resources: Insight from the NFL salary cap." *Journal of Economics and Business* 60 (2008): 536-550. Accessed September 5, 2015. http://proxy.library.upenn.edu:2187/econlit/docview/56736582/A8BACC7F7F64B95PQ/1?accountid=14707.

"Football glossary and football statistics glossary." Pro Football Reference, 2000-2016. http://www.pro-football-reference.com/about/glossary.htm

Fry, Michael J. and Jeffrey W. Ohlmann. "Introduction to the Special Issue on Analytics in Sports, Part I: General Sports Applications." *Interfaces* 42, no. 2 (2012): 105-108. http://dx.doi.org/10.1287/inte.1120.0633

Jane, Wen-Jhan, Gee San, and Yi-Pey Ou. "The Causality between Salary Structures and Team Performance: A Panel Analysis in a Professional Baseball League." *International Journal of Sport Finance* 4, no. 2 (2009): 136-150. http://search.proquest.com/docview/56947197?accountid=14707.

Leeds, Michael A. and Sandra Kowalewski. "Winner Take All in the NFL: The Effect of the Salary Cap and Free Agency on the Compensation of Skill Position Players." *Journal of Sports Economics* 2, no. 3 (2001): 244-256. Accessed September 15, 2015. http://search.proquest.com/docview/56979075?accountid=14707.

Mondello, Mike and Joel Maxcy. "The impact of salary dispersion and performance bonuses in NFL organizations." *Management Decision* 47, no. 1 (2009): 110-123. http://dx.doi.org/10.1108/00251740910929731.

Quinn, Kevin G., Melissa Geier, and Anne Berkovitz. "Superstars and Journeymen: An Analysis of National Football Team's Allocation of the Salary Cap across Rosters, 2000-2005." *International Assocation of Sports Economists*, IASE/NAASE Working Paper Series, Paper No. 07-22 (2007). Accessed September 5, 2015. http://college.holycross.edu/RePEc/spe/Quinn_NFLJourneymen.pdf.

Radner, Roy. “Allocation of a scarce resource under uncertainty: an example of a team.” In *Decision and Organization*, edited by C. B. McGuire and R. Radner, 217-236. Amsterdam: North-Holland Publishing Company, 1972.

"Seattle Seahawks 2014 Salary Cap." Spotrac. 2015. Accessed November 3, 2015. http://www.spotrac.com/nfl/seattle-seahawks/cap/2014/.

Winsberg, Max. “Player Compensation and Team Performance: Salary Cap Allocation Strategies across the NFL.” Thesis, Claremont McKenna College, 2015.

TABLES

Table 1: Optimal Allocation by Model

Position	Univariate	Multivariate	Sequential	Univariate	Multivariate	Sequential
QB	19,828,242	15,539,040	16,367,155	15.0%	12.3%	13.0%
RB	1,884,935	9,056,926	8,406,588	1.4%	7.2%	6.7%
FB	621,705	0	450,000	0.5%	0.0%	0.4%
WR	12,778,616	35,839,937	36,598,777	9.6%	28.4%	29.0%
TE	1,533,146	900,000	900,000	1.2%	0.7%	0.7%
LT	1,611,491	1,281,189	910,446	1.2%	1.0%	0.7%
G	24,377,649	12,184,242	15,103,967	18.4%	9.7%	12.0%
C	2,360,067	450,000	450,000	1.8%	0.4%	0.4%
RT	1,731,446	4,477,051	4,461,128	1.3%	3.5%	3.5%
DE	12,130,718	900,000	1,888,870	9.2%	0.7%	1.5%
DT	23,327,368	11,060,828	14,918,580	17.6%	8.8%	11.8%
ILB	7,512,065	2,290,458	1,364,241	5.7%	1.8%	1.1%
OLB	13,941,756	13,247,327	15,772,658	10.5%	10.5%	12.5%
CB	16,399,689	3,968,279	3,190,855	12.4%	3.1%	2.5%
FS	10,004,127	27,558,291	18,895,962	7.6%	21.8%	15.0%
SS	2,152,741	10,349,867	9,486,501	1.6%	8.2%	7.5%
K	1,323,776	450,000	450,000	1.0%	0.4%	0.4%
P	1,300,463	1,172,000	1,783,565	1.0%	0.9%	1.4%
LS	450,000	4,544,565	3,870,707	0.3%	3.6%	3.1%

Table 2: Best Team Allocations

Year	Univariate	Multivariate	Sequential
2011	PIT (12-4)	NO (13-3)	GB (15-1)
2012	DET (4-12)	SF+ (11-4-1)	BAL++ (10-6)
2013	NO (11-5)	NO (11-5)	NO (11-5)
2014	CIN (10-5-1)	MIA (8-8)	MIA (8-8)
2015	CIN (12-4)	SD (4-12)	CIN (12-4)

Table 3: Worst Team Allocations

Year	Univariate	Multivariate	Sequential
2011	STL (2-14)	STL (2-14)	STL (2-14)
2012	NYG (9-7)	KC (2-14)	KC (2-14)
2013	OAK (4-12)	OAK (4-12)	OAK (4-12)
2014	OAK (3-13)	JAX (3-13)	JAX (3-13)
2015	OAK (7-9)	CHI (6-10)	CHI (6-10)

Table 4: Top Total Uncomp. Win Cont.		
Ranking	**Name**	**Total 2011-2015 Uncompensated Win Contribution**
1	Russell Wilson	15.8
2	Cam Newton	12.3
3	Tom Brady	10.4
4	Aaron Rodgers	9.9
5	Andy Dalton	9.2
6	Drew Brees	8.6
7	Matt Ryan	6.7
8	Richard Sherman	6.0
9	Alex Smith (QB)	5.9
10	Ryan Tannehill	5.7

Table 5: Top Avg. Uncomp. Win Cont.

Ranking	Name	Uncompensated Win Contribution per Season
1	Russell Wilson	4.0
2	Cam Newton	2.5
3	Tom Brady	2.1
4	Teddy Bridgewater	2.0
5	Aaron Rodgers	2.0
6	Andy Dalton	1.8
7	Drew Brees	1.7
8	Jameis Winston	1.7
9	Derek Carr	1.6
10	Ryan Tannehill	1.4

Table 6: Top Non-QB Avg. Uncomp.

Ranking	Name	Uncompensated Win Contribution per Season
1	Richard Sherman	1.2
2	J.J. Watt	1.0
3	Patrick Peterson	0.9
4	Marcus Peters	0.8
5	Justin Houston	0.8
6	Aaron Donald	0.8
7	Luke Kuechly	0.8
8	Bobby Wagner	0.8
9	Von Miller	0.8
10	Lavonte David	0.7

Table 7: Team Rankings of Average Uncompensated Wins per Season

Ranking	Team	Uncompensated Wins per Season	Ranking	Team	Uncompensated Wins per Season
1	SEA	5.7	17	DET	-0.5
2	NE	3.6	18	IND	-0.6
3	SF	1.9	19	PIT	-0.6
4	DEN	1.8	20	MIN	-1.0
5	GB	1.5	21	TB	-1.0
6	CAR	1.3	22	ARI	-1.1
7	CIN	1.3	23	NYJ	-1.2
8	NO	1.2	24	SD	-1.3
9	HOU	1.0	25	NYG	-1.3
10	ATL	0.9	26	KC	-1.4
11	BAL	0.7	27	PHI	-1.4
12	MIA	0.3	28	TEN	-1.6
13	CHI	0.3	29	WAS	-1.7
14	DAL	-0.1	30	BUF	-1.8
15	CLE	-0.1	31	STL	-2.2
16	OAK	-0.2	32	JAC	-2.6

Table 8: 2016 Projected Compensated Wins by Model (Sorted by Avg)

Rank	Team	Uni	Multi	Seq	Avg
1	TB	8.7	9.7	9.5	9.3
2	OAK	8.5	9.5	9.4	9.1
3	DAL	8.3	9.5	9.2	9.0
4	SD	8.4	9.4	9.1	9.0
5	DET	8.3	9.3	9.0	8.9
6	BAL	8.1	9.3	8.9	8.8
7	TEN	8.1	9.1	8.9	8.7
8	PIT	8.3	9.1	8.7	8.7
9	CIN	8.7	8.4	8.7	8.6
10	CHI	8.0	8.9	8.8	8.6
11	KC	8.3	8.7	8.6	8.5
12	MIN	8.4	8.7	8.5	8.5
13	SEA	8.0	8.9	8.5	8.5
14	NE	8.3	8.4	8.3	8.3
15	HOU	8.6	8.1	8.3	8.3
16	BUF	8.0	8.5	8.2	8.2

Rank	Team	Uni	Multi	Seq	Avg
17	IND	8.0	8.2	8.1	8.1
18	JAC	7.8	8.1	8.1	8.0
19	NO	7.9	8.2	7.8	7.9
20	WAS	8.0	7.7	7.9	7.9
21	CLE	7.8	7.7	7.9	7.8
22	ATL	7.9	7.5	8.0	7.8
23	SF	8.0	7.8	7.5	7.8
24	GB	8.1	7.5	7.6	7.7
25	MIA	7.6	7.5	7.7	7.6
26	ARI	8.3	7.0	7.4	7.6
27	STL	6.7	7.3	8.3	7.4
28	DEN	7.1	7.0	7.3	7.1
29	NYJ	7.2	7.1	7.0	7.1
30	NYG	7.8	4.7	5.5	6.0
31	PHI	7.6	5.1	5.1	5.9
32	CAR	7.3	4.1	4.2	5.2

Table 9: 2016 Projected Wins (Average Projected 2016 Compensated Wins Plus 2015 Uncompensated Wins)

Ranking	Team	Wins	Ranking	Team	Wins
1	SEA	14.0	17	ATL	8.0
2	NE	13.1	18	DEN	7.9
3	CIN	11.8	19	IND	7.8
4	OAK	11.5	20	NO	7.4
5	ARI	10.0	21	NYJ	7.2
6	CHI	9.6	22	JAC	6.9
7	KC	9.5	23	GB	6.7
8	HOU	9.3	24	SD	6.7
9	TB	9.1	25	BAL	6.5
10	BUF	9.1	26	SF	6.1
11	MIN	8.8	27	NYG	5.7
12	CAR	8.8	28	WAS	5.2
13	PIT	8.6	29	STL	5.0
14	DET	8.4	30	CLE	4.9
15	TEN	8.3	31	DAL	4.5
16	MIA	8.0	32	PHI	1.4

FIGURES

Figure 1: Player-Position Regression Log-Curves