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NFL Salary Cap Allocation: Matching Theory with Observed Behavior

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Abstract

Using a representative agent optimization model, we assess the degree to which average team salary cap shares devoted to offense and defense in the National Football League (NFL) are consistent with the shares predicted by a constrained optimization model. Results from a balanced fixed-effects panel for all thirty-two NFL teams over a 13-year period (2002-2009 and 2012-2016) indicate that the model is effective at matching the salary cap allocation between offense and defense, and closely matches the ratio of offensive to defensive cap shares that we see in practice. Overall, the model fits well with observed NFL managerial oversight in this respect.

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1. Introduction

Since its inception in 1993, the National Football League's (NFL) salary cap has represented one of the purest forms of constrained optimization in professional sports: teams are presented with a hard ceiling on total player payroll and must choose how to allocate spending on players to maximize wins. While the nature of the sport essentially compels teams to devote a minimum number of roster spots, and therefore salary cap dollars, to specific positions, teams do have a relatively high degree of flexibility in deciding how much payroll to allocate across positions. For example, based on data from Over The Cap, in 2013, both the Oakland Raiders and the New York Giants had two active quarterbacks on their rosters, but the Raiders devoted only $1.15 million, or less than 1% of their salary cap to the position compared to $22 million, or 17% of the cap, for the Giants. While each team is certainly faced with its own unique set of circumstances each year, what can we say about the optimality of these vastly different outcomes?

Our aim in this paper is to formally model one of the constrained optimization problems facing an NFL General Manager (GM) – how to best allocate scarce salary cap funds to maximize wins - and to use this model to derive closed-form solutions of the salary cap allocation across offensive and defensive positional groupings. We thus develop a representative agent framework in which a GM produces wins by using salary cap allocations as inputs into a standard production function, subject to the constraint that the sum of all positional spending cannot exceed that year's league-mandated cap. We find that the theoretical optimal salary cap shares are just functions of the production function's parameters. Upon estimation of said parameters, we then obtain numerical estimates of the optimal salary cap share for both offense and defense and then compare the model's predicted optimal shares to actual observed team cap allocations to ascertain how well the theoretical model 'fits the facts' of the real-world.

Other researchers have addressed the question of how NFL front office executives should best allocate scarce salary cap funds. Mulholland (2016), using data from 2011 – 2015, runs numerous regressions across three different models to estimate the optimal salary cap allocation across 19 different positions. The author finds that in addition to devoting a large amount of the salary cap (up to 15%) to the position of quarterback (QB), teams should also devote significant funds to guard (G), defensive tackle (DT), and free safety (FS). Winsberg (2015) uses data from 2006-2013 to estimate a regression of team performance on several control variables, including positional compensation, and finds that spending more than the league average on the offensive line (OL) reduces team success and that spending more on both the OL and QB lead to poorer overall offensive performance.

Along a different line, Froelich (2013) uses a conditional logit model to examine how the share of the NFL salary cap devoted to the left tackle position affects a team's likelihood of winning and finds that the optimal share of the salary cap devoted to this position could be as high as 15%. Ness (2010) utilizes a similar methodology and finds that the share of the salary cap devoted to defensive players has no effect on the probability of winning an NFL game, but increasing the share of the cap going to defensive starters does increase team wins.

Finally, other studies of salary allocation have focused on the impact of salary dispersion on player and team performance. Einolf (2004), uses data envelope analysis and finds that NFL franchises experienced efficiency gains once the salary cap was introduced in 1994. Borghesi (2008) uses data from 1994-2004 and finds that team success in the NFL depends positively on both the actual and perceived fairness of the distribution of player salaries. Mondello and Maxcy (2009) also find a positive relationship between salary dispersion and team success in the NFL, as well as a positive relationship between team performance and total payroll. Similar papers have focused on other North American team sports. Simmons and Berri (2011), for example, find that pay dispersion increases both team and individual success in the National Basketball Association, while Breunig et al. (2014) show that wage disparity reduces team success in Major League Baseball.

This paper presents an original contribution to this previous work in that predicted salary cap allocations are based on a micro-founded representative agent model capturing a key decision facing NFL front office executives. We also use thirteen years' worth of data and reconcile the model's prediction with observed front-office behavior. The hope is that this study can provide a better understanding of one of the many decisions facing front-office executives in the NFL. The rest of this paper proceeds as follows: Section 2 presents the theoretical model and analytically solves for the optimal salary-cap shares. Section 3 presents the data and the estimation technique whereby the numerical values of the model's predicted optimal shares can be calculated. Section 4 provides estimation results and discussion, and Section 5 outlines various robustness checks to our empirical specifications. Section 6 gives concluding remarks.

2. Theoretical Model

The win percentage W in season t for team j is produced using a Cobb-Douglas production technology (CDPT) of the following form,

$$W_{jt} = A_{jt} \prod_{i=1}^{n} X_{ijt}^{\alpha_{ij}}, \tag{1}$$

where A_{jt} is a measure of total factor productivity for position i on team j in year t, and X_{ijt} is team $j's$ share of its salary cap spent on position i in year t. The exponent α_{ijt} is the win elasticity of X_{ijt}. We use Cobb-Douglas as the functional form of the production function due to its tractability and leave the application of more general production functions (e.g., CES) to future research.[1] Note that although we do include a 't' subscript in our equations for exposition, the analysis in this paper is not intertemporal in nature; this we also leave to future research.

We assume that team management chooses $X_{ijt} \forall\ i$ to maximize (1) subject to the following salary cap constraint,

$$\sum_{i=1}^{n} X_{ijt} + \frac{Distance\ from\ Cap_{jt}}{Salary\ Cap_t} + \frac{Specialists_{jt}}{Salary\ Cap_t} = 1, \tag{2}$$

Where $Distance\ from\ Cap_{jt}$ is the amount of salary cap in year t minus the amount of payroll devoted to players on the actual final roster for team j in year t, and $Specialists_{jt}$ is the amount

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[1] Even though the maximization problem outlined in this section is not a utility maximization problem, the math of solving for the optimal shares is identical. In other words, our problem is exactly like maximizing a Cobb-Douglas utility function subject to a simple, linear resource constraint. In this case, it is unnecessary to assume that the sum of the coefficients in the Cobb-Douglas function sum to a value between 0 and 1 (which would guarantee concavity of the production function in a profit maximization or cost minimization problem). For more on this, see Chapter 5 (pp. 85-88) of *Intermediate Microeconomics with Calculus* (Varian, 2014).

spent on the punter and place kicker (and in some instances, the long snapper) in year t by team j. Equation (2) is therefore a binding equality constraint that takes into consideration the reality that most NFL teams rarely exhaust their full salary cap on players currently on their roster. Previously, we treated both 'distance' and 'specialists' as choice variables and found the model predicted an optimal salary cap share for both 'distance' and 'specialists' of 0%. We therefore opt for this framework to indirectly account for the fact that teams must devote salary cap dollars to kickers, punters, and long-snappers and that, given the dynamics associated with dead money, incentive structures, etc., teams almost never devote all their salary cap dollars to players currently on their rosters. It is also important to note that the salary cap allocations across positions are not fully reset each year – a decision to sign a player or extend another's contract can have salary implications for years to come. Player contracts can and often are renegotiated in any given year to alter the salary cap charge in that year.

The resulting optimal input shares from solving the simple constrained maximization problem are thus defined as,

$$X^*_{ijt} = \frac{\alpha_{ijt}}{\sum_{i=1}^{n}\alpha_{ijt}}\left[1 - \frac{Distance\ from\ Cap_{jt}}{Salary\ Cap_t} - \frac{Specialists_{jt}}{Salary\ Cap_t}\right]\ \forall\ i. \tag{3}$$

We estimate the parameters of interest in (3) to obtain the model's predicted optimal salary cap allocations for offense and defense.[2] We understand there are likely other objective functions considered by team management but focus on the production of wins in this paper and derive the optimal input shares within a constrained CDPT framework. We compare these predicted optimal shares to the actual positional shares observed in the NFL over our sample period.

3. Data and Estimation

Most of our data is from the collection assembled by Rodney Fort at the University of Michigan, who compiled various data from the USA Today NFL Salaries Database and other sources. Our salary data for 2012 through 2016 are compiled from The Wall Street Journal (2012) and overthecap.com (2013-2016). Owing to missing data for 2010 and 2011, we utilize a strongly balanced panel spanning 2002-2009 and 2012-2013. We selected 2002 as the first year so we have a consistent count of 32 repeated teams for each year (in 2002, the Houston Texans joined the NFL replacing the late Houston Oilers who left Houston in 1999 to become the Tennessee Titans). Despite the lack of data for 2010 and 2011, our methodology prevents us from using 2010 because there was no salary cap in place. Where applicable, we have also cross-checked the data to that posted on NFL.com, especially for win percentages.

The raw data was by player and position for each team in a given year. Associated with each player was a "cap value," which USA Today defines as "the player's pro-rated signing bonus, plus salary and other bonuses for the season." Where necessary, we aggregated the cap value to the position level on each team for each year which yielded 9 categories across offense and defense including offensive line, tight end, running back, wide receiver, quarterback, linebacker, safety, cornerback, and defensive line. From there, we aggregated to offense and defense as aggregate categories. The data also includes a "specialists" category which is comprised of the punter, place-kicker, and (in some cases) long-snapper but we are unable to

[2] For more on this derivation, see footnote (1) above as well as pages 85-88 of Chapter 5 in *Intermediate Microeconomics with Calculus* (Varian, 2014).

separately consider each position due to data limitations across years and positions. All players besides kickers, punters, and long-snappers who would only play on special teams are counted with their roster positions on offense or defense.

As noted in equation (2), we augment the maximization problem to account for both spending on "specialists" (kickers, punters, and long-snappers), and the distance from the salary cap ("distance"), which is a measure of the amount of the cap leftover (typically due to dead money and under spending in a given year) after accounting for spending on those offensive players, defensive players, and specialists on that year's current roster. The distance variable is negatively correlated with winning percentages – the pairwise correlation coefficient is -.3058 and is significant at the 1% level - indicating that having a smaller distance from the cap is associated with higher winning percentages. This is of course unsurprising, as having a smaller 'distance from cap' implies the team is devoting more cap space to players currently on the roster.

Some summary statistics about positional spending are presented in Table (1), including cap value, winning percentage, and the aggregate spending values on each major category as a share of the salary cap. The mean offense and defense share values are 42.75% and 40.30%, respectively. For specialists and distance, these values are 2.45% and 14.51%.[3]

3.1 Estimation Technique

Taking the natural log of (1) yields the following expression for team j in year t,

$$\ln(W_{jt}) = \ln(A_{jt}) + \sum_{i=1}^{n} \alpha_{ijt} \ln(X_{ijt}), \tag{4}$$

which we transform and estimate in our empirical specifications.

3.2 Fixed Effects Regression

Rewriting equation (4) and including the normally distributed error term, ϵ_{jt}, we obtain the following functional form,

$$\ln(\mathrm{W_{jt}}) = \ln(\mathrm{A_{jt}}) + \alpha_1 \ln(\mathrm{X_{1jt}}) + \cdots + \alpha_n \ln(\mathrm{X}_{njt}) + \epsilon_{jt}. \tag{5}$$

To include team and year fixed effects, we define $\ln(A_{jt})$ as,

$$\ln(A_{jt}) = \beta_j + \delta_t, \tag{6}$$

where β_j and δ_t capture unobserved team and year heterogeneity, respectively. Note that we drop the j and t notation because the fixed effects panel regression only produces point estimates associated with each share. Of course, it is possible that the win elasticities of each share vary

[3] We also calculated summary statistics for each positional category as a share of the cap value and found that the largest percentage of the cap value is typically spent on the offensive line at 15.34% and the smallest is on the tight end (3.85%). These statistics and other results are available upon request.

over j and t, but we have a limited number of observations and, short of imposing some random variation in the parameter estimation process, cannot feasibly obtain said estimates.

Even though the total number of wins in a season is constrained across the league, it is still important to control for year fixed effects. The year specific term, δ_t, is not meant to predict wins nor is it meant to function as an explanatory variable, instead it captures year-specific changes in the NFL that impact the entire league. Using year fixed effects to capture unobserved year-specific effects which may impact the cross-section is standard practice in econometric analysis. The fixed effects regression model is thus written as,

$$\ln\left(\mathrm{W_{jt}}\right) = \beta_j + \delta_t + \alpha_1 \ln(\mathrm{X_{1jt}}) + \cdots + \alpha_n \ln(\mathrm{X}_{njt}) + \epsilon_{jt}. \tag{7}$$

We estimate equation (7) using simple OLS techniques with team-clustered robust standard errors. The coefficient estimates of α_i obtained from the estimation process are then used to calculate the estimated optimal shares, $\widehat{\mathrm{X}}_i$, using equation (3). Recall that estimating equation (7) yields single coefficient estimates on each α for the entire sample, hence we do not obtain estimated optimal shares by team/year but by position or category for all teams/years. Per equation (3), the predicted optimal shares are then adjusted with a weighting that takes into consideration the distance from the cap and the amount spent on specialists. Given the nature of the data and estimation process, we use the average distance share of 0.1451 and the average amount spent on specialists, 0.0245, such that the adjustment factor is 0.8304. Instead of implementing an adjustment factor that varies by team and year, we opted for an average adjustment factor for the sake of simplicity and because the estimation results have already exploited the variation in the panel data. After applying this adjustment, the predicted optimal shares are compared at the team/year level to the observed shares to offer insight into the differences between observed spending shares and the predicted optimal shares under the assumptions and limitations of the above theoretical model.

4. Results and Discussion

We estimated two specifications of equation (7) at the aggregate level and the results are displayed in Table (2). Models (1) and (2) are different from Models (3) and (4) in that the former use team-clustered robust standard errors while the latter use the standard fixed effects panel standard errors. Although the standard errors on the estimates vary across the models as a result of these specification differences, it's clear that spending more money on offense and defense is positively related to winning percentage. We also tested the returns to scale to winning percentage within each model with respect to the sum of the coefficient estimates and did not find evidence supporting decreasing or constant returns to scale but rather the evidence points towards increasing returns to scale. This could imply that annual increases in the salary cap tend to be greater than anticipated, so that there is a relative advantage to exhausting as much of the cap as possible, which would be consistent with our finding that having a greater 'distance' from the cap is associated with reduced team success. We tested for returns to scale because if the model results demonstrated constant returns to scale, then the optimal predicted shares would coincide with the parameter estimates.

Using equation (3) and the estimates in Table (2), we calculate the predicted optimal shares for offense and defense. For example, to obtain the model's theoretical optimal share for offense using Model (1), we sum across Model (1)'s coefficient estimates in Table (2) (.5878 for offense and .5524 for defense) and divide this sum (1.1402) into the coefficient for offense. We then scale the resulting value of .515 by the adjustment factor of .8304. This process leads to a predicted optimal share for offense of 42.82% in Models (1) and (3) and 42.81% in Models (2) and (4). For defense the corresponding shares are 40.22% and 40.23%. Recall that the mean observed spending shares on offense and defense are 42.75% and 40.30%. Despite the better statistical fit of Models (1) and (3) relative to Models (2) and (4) respectively, our results and discussion are based on the results of Models (2) and (4) because of their econometric structure and appeal to statistical and econometric intuition by using team and year fixed-effects instead of only team fixed-effects. The remaining analysis and fundamental results do not significantly change when we instead use the results of Models (1) and (3) to complete the analysis and discussion. In short, despite the different standard errors, the statistical significance of the coefficient estimates, and the corresponding optimal shares are identical in Models (2) and (4).[4]

These results show that the theoretical framework does an excellent job of matching aggregate salary cap allocations. The model slightly over-predicts spending on offense and under-predicts spending on defense, but both by fractions of a percent. Even more impressive is that the model very accurately matches the *ratio* of offensive to defensive cap shares. The ratio of the predicted optimal share on offense to that on defense is 1.065, compared to 1.061 over the actual sample. This is a remarkably close match to observed behavior and shows that once distance from the cap and spending on specialists are accounted for, the model's prescription on how to divide up the remaining cap space across offense and defense is very much in line with what front office executives are doing.[5] But, based on the statistical fit of each model, it's possible that the spending strategy implemented by managers has a severely limited impact on the winning (or losing) percentage of a given team in a given year.

5. Robustness Checks

To test the sensitivity of our results to the chosen "win" outcome, we replaced actual win percentage for a given team in a given year with Pythagorean Wins, which is the ratio of the square of points scored by team i in year t divided by the square of points scored by team i in year t plus the square of points allowed by team i in year t. Across the entire sample, actual win percentage is correlated with Pythagorean Wins at the 87% level, which makes sense given that a higher Pythagorean Wins value is associated with an increased likelihood of winning a given game. Based on the above analysis, we re-estimated the empirical framework replacing actual

[4] For more on when it is appropriate to use clustered standard errors, see Cameron and Miller (2015) and Abadie, et al. (2017).

[5] In unreported results (which are available upon request), we also used the model to predict optimal cap allocations across nine disaggregated position groupings. We found that the model accurately matched positional salary cap allocations for six of the nine positions (QB, RB, WR, OL, TE, and S), but was inaccurate for the other three (LB, DL, and CB). While the performance of the model as it pertains to the offensive side of the ball is encouraging, its ability to match observed behavior for disaggregated defensive allocations – particularly for linebacker and cornerback - calls for further investigation. As mentioned above, it is possible that breaking these defensive categories into more disaggregated groupings could help. Or perhaps a more general production function, such as CES, may provide a better fit with observed behavior. We leave these endeavors to future research.

wins with Pythagorean Wins, and the results were largely unchanged as the predicted shares were similar, and the statistical results were substantively the same.[6]

Finally, even though we include a year fixed-effect term in our model to capture league-wide changes that affect all teams in a given cross-section, we also completed the above analysis on shorter panels to account for various on-field NFL rule changes, off-field changes (such as the implementation of the rookie salary scale in 2012), and for evolutions in offensive and defensive strategies. To this end, we calculated the optimal shares based on estimation results from (A) 2002-2009 and 2012-2016, and (B) 2002-2005, 2006-2009, and 2012-2016.[7]

6. Conclusion

We developed a representative agent optimization model using CDPT to derive theoretical optimal NFL salary cap allocations and to analyze the extent to which observed NFL salary cap allocations from 2002-2009 and from 2012-2016 are consistent with the model's predictions. The results indicate that the model is quite effective at matching observed salary cap allocation between offense and defense, and almost perfectly matches the ratio of offensive cap allocation to defensive cap allocation that we see in the real world of 1.06.

Our aim was to test whether a straight-forward model of constrained optimization could capture observed decision making by NFL front office executives pertaining to salary cap allocation. The fact that the behavior of these decision makers is so consistent with a theoretical model of constrained optimization utilizing such a tractable production function provides evidence both for the rationality of front office executives and for the theoretical framework we have used to capture their behavior. Future research possibilities are numerous, including the incorporation of a different form of the production function, or the utilization of dynamic analysis to take account of the inter-temporal nature of NFL salary cap decisions.

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[6] These results are available upon request.

[7] Although the results are not presented here, we found that the full panel is better at capturing the variation in spending across teams and years, as well as predicting optimal shares closer to the actual money spent on offense and defense. In yet other unreported results, we controlled for position quality by including data for Pro-Bowl selections by position and team and year. While controlling for quality makes intuitive sense, the results were worse than the simple results presented above. These results are available upon request.

7. Tables

Table 1 – Aggregate Summary Statistics

Variable		Mean	Std. Dev.	Minimum	Maximum	Obs.
Cap Value (millions)	Overall	111.00	25.50	71.10	155.00	416
Win Percentage	Overall	0.50	0.19	-	1.00	416
	Between		0.10	0.32	0.76	32
	Within		0.16	0.10	0.91	13
Offense Spending / Cap	Overall	0.43	0.07	0.14	0.65	416
	Between		0.03	0.35	0.49	32
	Within		0.07	0.12	0.68	13
Defense Spending / Cap	Overall	0.40	0.07	0.22	0.61	416
	Between		0.03	0.34	0.46	32
	Within		0.07	0.19	0.57	13
Specialists / Cap	Overall	0.02	0.01	0.00	0.09	416
	Between		0.00	0.02	0.04	32
	Within		0.01	0.00	0.08	13
Distance / Cap	Overall	0.15	0.09	(0.09)	0.59	416
	Between		0.04	0.05	0.22	32
	Within		0.08	(0.03)	0.56	13

Table 2 – Estimation Results

	Model (1)	Model (2)	Model (3)	Model (4)
Offense Spending / Cap	0.59***	0.65***	0.59***	0.65***
	(0.14)	(0.14)	(0.12)	(0.13)
Defense Spending / Cap	0.55***	0.61***	0.55***	0.61***
	(0.10)	(0.10)	(0.12)	(0.13)
Observations	415	415	415	415
Fixed Effects				
Team	Yes	Yes	Yes	Yes
Year	No	Yes	No	Yes
Adjusted R-Squared	0.09	0.07	0.01	-0.01
R-Squared				
Within	0.09	0.10	0.09	0.10
Between	0.21	0.21	0.21	0.21
Overall	0.11	0.12	0.11	0.12
AIC	407.6	426.4	409.6	428.4
BIC	415.7	482.8	421.7	488.8

Note(s):

* p<0.10, ** p<0.05, and *** p<0.01.

Models (1) and (2) use team-clustered robust standard errors.

Models (3) and (4) use the typical fixed effects panel standard errors

The base year across all models is 2002.

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