Resource Optimization Under Asymmetric Spillovers in the NFL

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Abstract

This paper studies resource optimization under asymmetric spillovers, which occur when one position's unobserved true quality disproportionately affects other positions' observed performances. Because the NFL has vast public data, we use it as a laboratory for our study. Specifically, we estimate a production function equilibrium model of team performance by mapping salary cap spending into expected wins. To account for asymmetric spillovers between quarterbacks and their teammates, we use game-level variation to identify quarterbacks' marginal productivity, calibrate the model, and calculate optimal positional allocations. We find that most positions were paid near their model-implied optima with a few significant deviations.

Keywords: NFL, Production Functions, Resource Optimization, Spillover Effects

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1 Introduction

How do we value an individual's contribution to a team? Individual performance matters for final output, but so does each individual's influence on their colleagues, especially when the team consists of individuals across different positions. As such, correctly identifying the marginal productivity of each position independently of other positions is a crucial challenge for decision-makers, such as firm owners, when allocating resources toward these positions. Decision-makers who correctly identify each position's marginal productivity can choose efficient allocations, while those who do not risk misvaluing certain positions. The challenge steepens when spillover effects across positions are asymmetric; that is, when the observable performances of many positions depend disproportionately on the true quality of an ex-ante known critical position.

For example, CEOs and managers of corporations can raise or depress the performances of entire divisions through their decisions and leadership. Behind the scenes, "glue employees" (Levy 2025) purposefully boost their colleagues in ways that do not show up in the glue employees' own performance measures. In scientific laboratories, a principal investigator can affect the performance of junior scientists. Even a critical machine in a factory can asymmetrically influence the performances of workers and other, non-critical machines. Within these environments, accurately determining the magnitude of the asymmetric spillovers is crucial for understanding how decision-makers actually allocate resources, how they should do so if the allocations are suboptimal, and whether allocations are in accordance with marginal productivities.

It is important to clarify that our definition of spillovers is not the same as the definition of complementarities, which have been studied in such papers as Herkenhoff, Lise, Menzio, and Phillips (2024), along with many other papers. We define a spillover as occurring when the observable performance of one position depends on the unobservable true quality of at least one other position. As such, it is a specific type of measurement error in the positional inputs of a team's production function. In contrast, a complementarity occurs when the production function itself is such that an increase in one position's performance affects for at least one other position the relationship between the other position's performance and its contribution to the final output. Assuming the production function has continuous second-order partial derivatives, all complementarities must be symmetric. Spillovers, however, need not be symmetric.

A challenge in providing an empirical application of production function-based resource optimization under critical position-driven asymmetric spillovers is that the data required to do so, such as internal firm data containing firm outputs along with positional performance measures, are often private. Therefore, professional team sports provide an ideal environment to study this phenomenon. Compared to most industries, performance data are public, and objectives are transparent (Palacios-Huerta 2025). Teams act as decision-makers, constrained by league rules resembling regulatory frameworks, and they allocate resources across a diverse set of positions that each play a specialized on-field role while maximizing a well-defined objective function.

The National Football League (NFL), in which teams are multi-billion dollar enterprises,[1] is a particularly clean setting for multiple reasons. First, each team faces the same hard salary cap and floor,[2] which ensures that owners cannot maximize profits at the expense of wins by spending less on players (Coates, Ivanov, & Parshakov 2024). Second, teams operate on relatively short time horizons (Clark 2020), making single-season win maximization a good model of team behavior. Third, quarterbacks, who play the NFL's critical position, exert a greater influence over their teammates than the other way around (Groysberg, Hecht, & Naik 2019). Finally, there has been a shift in quarterbacks' valuation over the duration of our sample in the form of a "quarterback salary explosion," per former NFL agent Joel Corry (2024). When Kirk Cousins became a rare starting quarterback to reach free agency in his prime, the Minnesota Vikings signed him to a three-year, $84 million contract. Although Cousins was not considered elite, this contract was the then-richest in league history. We show using difference in differences that since then, expensive contracts for veteran quarterbacks have grown significantly faster than the cap.

These developments raise two fundamental questions. First, we ask how a representative NFL team should allocate its salary cap across 53 players playing 18 positions (see Figure 6 of Appendix C for a diagram of the positions), given the coexistence of rookie and veteran contracts.[3] Then, we ask how much quarterback performance contributes to team wins, after accounting for the asymmetric spillovers of quarterbacks on their teammates. We answer both questions through a series of complementary analyses on data from 2011 to 2024. In our first analysis, we estimate a baseline season-level production function model of team success, which relates wins to cap spending across positions and contract types. While we frame this model in terms of the NFL, it can be applied to resource optimization in general. The model lets us estimate each position's "importance" (how strongly player performance affects wins) and "cost effectiveness" (how well spending translates to performance), and from these estimates derive model-implied win-maximizing allocations for the representative team. However, we find that the optimal quarterback allocations are overly modest, which reflects the difficulty of quantifying the magnitude of the asymmetric spillovers of quarterbacks on their teammates, particularly on offense.

To address this challenge, we first use game-level data to show that asymmetric spillovers exist. We find that injuries to quarterbacks, which induce a largely exogenous change in quarterback quality (Gregory-Smith 2021), have a significantly greater effect on offensive skill position (i.e.

[1]At the start of the 2025 season, the average team was valued at over $5.25 billion, the highest-valued Dallas Cowboys were worth $13 billion, and $125.5 billion in television deals in 2022 and 2023 helped make every team profitable (Teitelbaum 2025). The salary cap was $279.2 million, $23.8 million higher than in 2024 (Patra 2025). In addition, the highest-paid player on an annual basis, Dallas Cowboys quarterback Dak Prescott, had a 2025 cap hit of $50.5 million, which was 18.1% of his team's cap and part of a four-year $240 million contract (Bergman 2024).

[2]Per Robinson (2025), each team must spend at least 89% of the cap every four-year period, and the NFL must spend 95% of the cap every year. Any team that fails to comply must pay the difference to its players.

[3]Since 2011, the NFL has had a separate rookie contract scale, in which salaries are suppressed, for players in their first four to five years in the league. Any contract signed after a player's rookie contract is a veteran contract. We model two budget constraints per team: one for players on rookie contracts and one for those on veteran contracts.

running backs, wide receivers, and tight ends) performance than the other way around. Then we turn to game-level variation in the usage of quarterbacks to identify their marginal win productivity more cleanly. When teams replace their starting quarterback for reasons such as injuries, the resulting change in win probability provides a quasi-experiment of how much quarterback performance contributes to wins. Our estimates indicate that moving from a replacement-level to an elite quarterback added roughly 3.5 wins per season, which was the difference between finishing in the bottom vs. top 10 out of 32 teams. We then use these estimates to calibrate the season-level model, adjusting the quarterback coefficient upward to reflect quarterbacks' true contribution to wins. In the calibrated model, quarterbacks receive a significantly larger optimal allocation. Also, even though the model is not estimated with teams' choice data, actual allocations in the aggregate are very close to the model's predictions, as the mean absolute difference from the optimal portfolio across positions is only 1.4% points. Still, deviations emerge: left tackles, tight ends on rookie contracts, and kickers on veteran contracts received significantly higher spending than the model suggests. In Section 7, we provide football intuition for these deviations.

Finally, we analyze the evolution of the quarterback market before and after 2018, which is the year that marked a sharp acceleration in veteran quarterback pay. By doing so, we provide a case study of a critical position's value changing over time, as well as an industry updating its valuation of that position. We first show that after 2018, quarterbacks on rookie contracts were significantly underallocated. Because the dollar value of rookie contracts is based on draft position as opposed to NFL performance,[4] this result is synonymous with quarterbacks having been underdrafted, on the order of the representative team taking a quarterback every four years with the 25th vs. the 7th pick. We also show that the post-2018 market "explosion" has been concentrated among expensive veterans, whose salaries have grown significantly faster than the cap itself. Specifically, post-2018, expensive veteran quarterbacks' average annual salary as a percentage of the cap has increased by 4.31% points more than that of other players. Cousins's contract was a catalyst that led to a valuation shift in the NFL's critical position (Corry 2024).

The rest of the paper proceeds as follows. Section 2 situates our analysis within the economics literatures on spillover effects, production functions, and the use of sports as a laboratory to study economic phenomena. Section 3 presents our definition of asymmetric spillovers, along with a proof that such spillovers, if not properly accounted for, make the critical position appear less valuable than it is. Section 4 begins our empirical application by providing the baseline salary cap optimization model, along with estimates of player complementarities using only season-level data. Section 5 then uses game-level data on within-season quarterback changes to estimate quarterbacks' marginal win productivity and quantify the asymmetric spillovers that quarterbacks have on their teammates. Section 6 incorporates these estimates into our calibrated optimization model, adjusts the optimal positional allocations accordingly, and breaks down similarities, differences, and time trends between the pre and post-2018 periods. Finally, Section 7 concludes

[4]The NFL has an annual seven-round draft of college players. The worst teams get the top picks in each round.

by summarizing our results and discussing the broader implications of our findings on modeling resource optimization under critical position-driven asymmetric spillovers.

2 Literature Review

This paper bridges literatures on spillover effects, production functions, and the use of sports as a laboratory to study economic phenomena. Our main contribution is that this paper is the first to provide a framework for asymmetric spillovers and implement an empirical application of it. We also summarize the existing papers on NFL salary cap optimization and quarterback valuation.

Spillover Effects: A large empirical literature examines how the productivity of one worker, manager, or executive affects that of others. Falk and Ichino (2006) use a field experiment to show that workers' productivity increases when they are paired with more productive colleagues, therefore providing clean evidence of peer effects. Moretti (2004) demonstrates that cities with faster increases in college-educated workers experience faster productivity growth due to spillovers, and Mas and Moretti (2009) find strong peer effects among retail cashiers, in which positive spillovers dominate any free-riding effects. Lazear, Shaw, and Stanton (2015) then quantify the large productivity impact of supervisors. Studies exploiting shocks like Nguyen and Nielsen (2014) quantify how firms' valuations of CEOs manifest in stock price reactions to sudden CEO deaths, which is relevant because CEOs affect the performances of the workers underneath them. These studies collectively establish that spillovers are real and potentially asymmetric.

There are also sports economics papers that provide evidence of spillovers. In baseball, Gould and Winter (2009) find that both batters and pitchers perform better when matched with better batters and pitchers respectively. In contrast, Guryan, Kroft, and Notowidigdo (2009) do not find strong peer effects in professional golf tournaments, though in golf, playing partners are not teammates. Finally, in basketball, Arcidiacono, Kinsler, and Price (2017) both show that star players improve teammates' performance, analogous to how a good quarterback improves his offensive teammates' performance. However, none of these papers, in sports or otherwise, study the implications of when such spillovers induce mismeasured inputs of a production function.

Production Functions: A longstanding literature estimates workers' marginal productivity by mapping observable performance into firm outcomes, such as Frank (1984), who estimates the marginal products of salespeople and university professors. More recently, Herkenhoff et al. (2024) combine theory and empirics to show that production functions are supermodular when low-ability workers can learn from high-ability colleagues. While this paper analyzes complementarities, which are not spillovers, high-ability workers might also have asymmetric spillovers on low-ability workers. Finally, Collard-Wexler and De Loecker (2025) show that measurement error in the capital input of a production function can lead firms to undervalue capital. But this measurement error is different from that induced by spillovers. In sports, Scully (1974) provides a seminal example by estimating baseball team production functions and showing that player salaries were below marginal revenue product. Collectively, these works underscore the economic importance of correctly estimating production functions and valuing workers.

Sports as a Laboratory: Our approach also connects to studies treating professional sports as a laboratory to test broader economic theories, such as Rottenberg (1956) and Fort and Quirk (1995), who both model how league structures and incentives shape labor outcomes. Vrooman (2009) and Coates et al. (2024) debate whether teams maximize profits or wins, with evidence generally pointing to win maximization in the NFL given its hard cap and floor. Moreover, Romer (2006) and Massey and Thaler (2013) show that NFL teams do not always optimize, whether in fourth-down decisions or the draft, though O'Connell (2022) later documents how teams, spurred by analytical models, began to align their choices more closely with Romer (2006)'s fourth-down recommendations. Palacios-Huerta (2025) emphasizes the advantages of sports data for economics: compared to most real-world settings, objectives are clear, performance is easily observable, and contests are high-stakes. We build on this literature by using the NFL to study resource optimization under critical position-driven asymmetric spillovers.

Salary Cap Optimization and Quarterback Valuation: Two papers stand out as most relevant to our approach. Mulholland and Jensen (2019) estimate positional importance and cost effectiveness equations to solve a constrained optimization model of how NFL teams should allocate the salary cap. They conclude that teams should pay more to guards, defensive linemen, and linebackers, while avoiding large investments in running backs and left tackles. However, their framework omits rookie contract structures, as well as the asymmetric spillovers generated by quarterbacks on their teammates on offense. Gregory-Smith (2021) takes a different approach by examining whether quarterback pay aligns with productivity. First, in games where the starting quarterback gets injured, he estimates the pay differential between the starter and backup that induces a game win probability decrease corresponding to one fewer win per season. Second, he estimates the amount of team revenue that one additional win per season generates. Both estimates converge to about $10 million, leading him to conclude that quarterbacks were, on average, correctly valued. Our paper unifies Mulholland and Jensen (2019) and Gregory-Smith (2021)'s frameworks while also modeling rookie contracts and identifying asymmetric spillovers.

Other work provides additional context. Leeds and Kowalewski (2001) show that the salary cap compresses superstar pay, limiting the ability of high performers to fully capture their market value. Borghesi (2008) and Mondello and Maxcy (2009) find that more equitable pay distributions correlate with better team performance. Berri and Schmidt (2013) show that kicker pay is based more on field goals and extra points than kickoffs, even though the former are less predictable across seasons. The unpredictability of kicker scoring is in part why we find that veteran kickers were overpaid. Calvetti (2023) revisits Mulholland and Jensen with a focus on offensive positions and models rookie contracts and complementarities. Finally, Roach (2024) shows that teams with head coaches from offensive backgrounds allocate more of the cap to offense.

3 Asymmetric Spillovers

We begin by defining asymmetric spillovers. Intuitively, suppose a firm has multiple positions, and each position's observed quality measure is a function of the latent true qualities of all positions, including but not limited to the position's own true quality. In addition, such spillovers are of different magnitudes for each position. That is, some positions' observed qualities mainly depend on their own true qualities, whereas other positions' observed qualities are more strongly related to the true qualities of other positions. Mathematically, suppose we have the following production function, where $y =$ output, $q =$ observed quality, $Q =$ true quality, and $p =$ position:

$$y = f(q_1(Q_1, \ldots, Q_P), \ldots, q_P(Q_1, \ldots, Q_P)). \tag{1}$$

Taking the Jacobian matrix of q with respect to Q, we obtain $J_q = \begin{bmatrix} \frac{\partial q_1}{\partial Q_1} & \cdots & \frac{\partial q_1}{\partial Q_P} \\ \vdots & \ddots & \vdots \\ \frac{\partial q_P}{\partial Q_1} & \cdots & \frac{\partial q_P}{\partial Q_P} \end{bmatrix}$.

Definition 1. *There are spillovers in production if J_q is not diagonal.*

Definition 2. *The spillovers are asymmetric if J_q is asymmetric.*

The definition of spillovers stands in contrast to that of complementarities. Taking the Hessian matrix of f with respect to q, we obtain $H_f = \begin{bmatrix} \frac{\partial^2 f}{\partial Q_1^2} & \cdots & \frac{\partial^2 f}{\partial Q_1 \partial Q_P} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial Q_P \partial Q_1} & \cdots & \frac{\partial^2 f}{\partial Q_P^2} \end{bmatrix}$.

Definition 3. *There are complementarities in production if H_f is not diagonal.*

Provided f has continuous second-order partial derivatives, H_f is symmetric by Schwarz's theorem. Therefore, in nearly all commonly-used production functions, complementarities must be symmetric. If for example, an improvement in Position 1's observed quality makes Position 2's observed quality more important for production, then an identical improvement in Position 2's observed quality must make Position 1's observed quality more important for production by the same amount. Spillovers, however, need not be symmetric mathematically or in practice. Simply put, complementarities are about the production function, whereas spillovers are about its inputs.

To study the implications of asymmetric spillovers, suppose for simplicity that we have data on a firm with two positions. Also, the spillovers are such that each q_p is a convex combination of Q_p and $Q_{p'}$ parameterized by θ_p and an intercept that ensures the error u has expectation zero:

$$\begin{aligned} q_{1i} &= \theta_{10} + \theta_{11} Q_{1i} + (1 - \theta_{11}) Q_{2i} + u_{1i} \\ q_{2i} &= \theta_{20} + \theta_{21} Q_{2i} + (1 - \theta_{21}) Q_{1i} + u_{2i} \end{aligned} \tag{2}$$

Regarding the production function, suppose f is linear in its own parameters β. It also has an intercept that ensures its own error ε has expectation zero. If for instance the variables y and q are in logs, then f is Cobb-Douglas, though they can be in levels in the case of perfect substitutes:

$$y_i = \beta_0 + \beta_1 q_{1i} + \beta_2 q_{2i} + \varepsilon_i \tag{3}$$

If we wish to model complementarities, we can add an interaction term so the cross-partials are not zero. If f without an interaction is Cobb-Douglas, then with an interaction, it is translog:

$$y_i = \beta_0 + \beta_1 q_{1i} + \beta_2 q_{2i} + \beta_{12} q_{1i} q_{2i} + \varepsilon_i \tag{4}$$

Because we parameterize the spillovers as convex combinations, θ_{11} and θ_{21} are both between 0 and 1. To make the spillovers asymmetric, suppose $\theta_{11} > \theta_{21}$, which means that Position 1 is the critical position that has asymmetric spillovers on Position 2. Because Q_1 and Q_2 are unobservable, when we estimate the production function, we must regress y on q_1 and q_2. As such, we may misattribute some of the effect that Position 1 has on output to Position 2. Formally:

Theorem 1. *If* $0 < \text{AME}_{q_1} \leq \text{AME}_{q_2}$, *then* $\text{AME}_{q_1} - \text{AME}_{Q_1} < 0$ *and* $\text{AME}_{q_2} - \text{AME}_{Q_2} > 0$.

Proof. See Appendix A.

That is, if q_1's average marginal effect (AME) on y is less than that of q_2,[5] then we know for certain that the AME of q_1 is too low relative to that of Q_1, and the AME of q_2 is too high relative to that of Q_2. The AMEs of Q_1 and Q_2 are the quantities of interest for the decision-maker when deciding how much of the firm's resources they should allocate toward Positions 1 and 2. For example, if Position 1 is a "glue employee" whose presence makes Position 2 perform better, then Position 1 is valuable even if their own observed quality seems not to matter much for production. As such, asymmetric spillovers misattribution[6] will cause the firm to undervalue Position 1 and overvalue Position 2. This theorem also holds with the interaction term, meaning that interactions cannot help identify asymmetric spillovers. The reason is that spillovers are not complementarities. In turn, other methods, such as selection on unobservables, are required.

Suppose that without loss of generality, the available data only allow us to identify the AME of Q_1. Perhaps, as will be the case in our football application where Position 1 is the quarterback position, there are more granular performance data available for Position 1 that let us employ a selection on unobservables identification strategy. In contrast, Position 2, or other positions in general if we allow for multiple positions, may be more numerous, interchangeable, and/or hard to measure. By numerous and interchangeable, we refer to situations where there are many positions whose functions are interchangeable (e.g. wide receivers and tight ends both catch passes),

[5]If $\text{AME}_{q_1} > \text{AME}_{q_2}$, then we cannot definitively sign the misattribution inequalities, as shown in Appendix A. However, as long as AME_{q_1} is not too large relative to AME_{q_2}, the result holds.

[6]We use the term *misattribution* as opposed to *bias* because the estimates of AME_{q_1} and AME_{q_2} are not biased. Rather, part of the effect of Position 1 on output is misattributed to Position 2 due to the asymmetric spillovers.

or situations where there are many individuals in each position who have the same function (e.g. three wide receivers on the field at the same time). Note that in this example, Position 1 is the critical position because it has asymmetric spillovers on Position 2, and we also suppose that we have superior data for the critical position. That is the case in football, and in other contexts as well where the critical position is a single position, or even a single individual such as a supervisor, that has asymmetric spillovers on numerous and interchangeable other positions.

Back to our two position example, can we use the identified AME of Q_1, along with the AMEs of q_1 and q_2, which we obtain by regressing y on q_1 and q_2, to recover the AME of Q_2? One method is constrained least squares (CLS), whose formula with two regressors is:

$$\beta_2^C = \beta_2 + \frac{\text{Cov}(q_1, q_2)}{\text{Var}(q_2)}(\beta_1 - \beta_1^C). \tag{5}$$

Here, we suppose there is no interaction term, in which case $\beta_1 = \text{AME}_{q_1}$, $\beta_2 = \text{AME}_{q_2}$, and $\beta_1^C = \text{AME}_{Q_1}$, where C stands for constrained. When is it the case that $\beta_2^C = \text{AME}_{Q_2}$?

Theorem 2. *The slope coefficient from regressing q_1 on $(1, q_2)$ is strictly positive. If it equals 1, then $\beta_2^C = \text{AME}_{Q_2}$. That is, CLS perfectly recovers AME_{Q_2}.*

Proof. See Appendix A.

Intuitively, $\frac{\text{Cov}(q_1,q_2)}{\text{Var}(q_2)}$ is the slope from regressing q_1 on an intercept and q_2. Because we assume that the convex combination spillover parameters are between 0 and 1, this slope must be positive. In addition, because we proved that $\text{AME}_{q_1} < \text{AME}_{Q_1}$, it must be the case that $\beta_1 < \beta_1^C$. In turn, $\beta_2^C < \beta_2$, which is as desired because we also proved that $\text{AME}_{Q_2} < \text{AME}_{q_2}$.

We show in Appendix A that if $\frac{\text{Cov}(q_1,q_2)}{\text{Var}(q_2)} < 1$, then $\beta_2^C > \text{AME}_{Q_2}$ (i.e. CLS does not correct enough); if $\frac{\text{Cov}(q_1,q_2)}{\text{Var}(q_2)} > 1$, then $\beta_2^C < \text{AME}_{Q_2}$ (i.e. CLS corrects too much); and if $\frac{\text{Cov}(q_1,q_2)}{\text{Var}(q_2)} = 1$, then $\beta_2^C = \text{AME}_{Q_2}$ (i.e. CLS corrects perfectly). If $\frac{\text{Cov}(q_1,q_2)}{\text{Var}(q_2)} = 1$, then the slope is 45 degrees, which geometrically is midway between a slope of 0 and an infinite slope. In our football application, there are far more than two positions (18 to be precise), but given this result and that we can identify only the critical quarterback position's AME using granular data, we employ a CLS-like procedure as the best available option to recover the true AMEs of all the other positions.[7]

When we estimate a representative NFL team's production function by essentially regressing team wins on player performance for each position, we find that the quarterback position's AME is less than those of the running back and wide receiver positions, which is an implausible result (Groysberg et al. 2019). We then use granular game-level data and an identification strategy based on within-season quarterback changes, such as those due to injuries, to identify the effect of a quarterback's true quality on wins. Finally, we recover the other positions' true AMEs by constraining the quarterback's AME to match the true effect and re-estimating the remaining

[7]We use nonlinear least squares instead of CLS because we impose an additional non-negativity constraint on the long snapper's coefficient (see Section 6). Long snappers aside, our results are robust to using CLS.

parameters. While the models and identification in this paper are framed for the NFL, we also present a generalized version of them in Appendix B that can be applied to other settings.

In addition, we provide empirical evidence that asymmetric spillovers are behind the aforementioned implausible result. Specifically, in Section 5, we show that the negative effect of quarterback injuries, which induce a largely exogenous change in true quarterback quality, on the performance of offensive skill positions (i.e. running backs, wide receivers, and tight ends) is over twice as large as the negative effect of skill position injuries on quarterback performance. As such, skill position performance is more a function of quarterback quality than quarterback performance is a function of skill position quality, which supports the idea that asymmetric spillovers exist and are responsible for the quarterback position's low AME in the baseline model.

4 Baseline Salary Cap Optimization

We now turn to to the NFL, where teams optimize their positional allocations under quarterback-driven asymmetric spillovers. Before addressing these spillovers, we construct a baseline equilibrium salary cap optimization model, in which cap allocations map into team wins via player performance. This mapping builds on Mulholland and Jensen (2019) by adding controls, fixed effects, and contract types, and it builds on Equations 29 and 30 in Section 3 by adding contract types. Recall that the NFL has rookie and veteran contracts; rookie contracts are for a player's first four to five years and based on draft position, whereas veteran contracts are for subsequent years and based on NFL performance. Rookie contracts are also largely non-negotiable and therefore the cheaper of the two. For brevity, we use the term "rookie" to denote all players on rookie contracts, even though rookies are commonly defined as players in their first season only.

The goal is to estimate each position's importance (how strongly performance affects wins) and cost effectiveness (how efficiently spending translates into performance). After solving the model, these estimates will yield optimal positional allocations, which we can compare to the actual allocations. We first model team wins on the season level (in the NFL, a season is the long-run optimization period) as a function of the performance measure Approximate Value (AV), which "puts a single numerical value on any player's season, at any position, from any year" (Drinen 2008). Both team (e.g. points per possession) and individual (e.g. games started, Pro Bowl selections, passing yards, etc.) statistics factor into AV, and crucially, AV is on the same scale for all positions,[8] which makes it the standard for comparing performance across positions. For team i, season j, position p, and contract type c, the importance equation is:

$$\text{Wins}_{ij} = \sum_{p \in P} \beta_p \left(\text{AV}_{ijp,c=\text{Rook}} + \text{AV}_{ijp,c=\text{Vet}}\right) + x_{ij}\delta + \xi_i + \eta_j + \varepsilon_{ij}, \tag{6}$$

[8]The best players accrue about 20 AV in a season, average starters about 10, and the worst players about 0.

Table 1: Baseline Importance & Cost Effectiveness Results ($N = 448$)

	Importance (DV = Wins)	Cost Effectiveness: Rookies (DV = Position AV)						Cost Effectiveness: Veterans (DV = Position AV)					
	Coefficient	log(Cap%)	Cap% = 0	Vegas Wins	2011 Colts	Season	R^2 [Adj R^2]	log(Cap%)	Cap% = 0	Vegas Wins	2011 Colts	Season	R^2 [Adj R^2]
Quarterbacks AV	.0966**	1.8601***	-2.6043***	-.0127	-4.1832***	-.0559	.3961	3.3879***	-1.4979	1.1076***	-7.9127***	-.0085	.5762
	(.0417)	(.2144)	(.3663)	(.1994)	(.5986)	(.0851)	[.3432]	(.2962)	(1.3686)	(.1776)	(.5228)	(.0698)	[.5390]
Running Backs AV	.1198***	3.7807***	-2.4636**	.0811	-5.8766***	.0405	.3467	3.4248***	-1.0088**	.4185***	-5.4264***	.0331	.4915
	(.0266)	(.4996)	(1.0190)	(.1789)	(.5197)	(.0575)	[.2895]	(.2385)	(.4769)	(.1236)	(.4557)	(.0550)	[.4469]
Wide Receivers AV	.1325***	6.1095***		.0087	-1.1949**	-.0287	.3999	4.9145***	.7413	.7676***	-4.9893***	-.0370	.4631
	(.0278)	(.5842)		(.1412)	(.4910)	(.0713)	[.3489]	(.3873)	(.9078)	(.2225)	(.6741)	(.0932)	[.4161]
Tight Ends AV	.0785**	1.1534***	-.6011***	-.0447	-3.0052***	-.0087	.2788	1.9266***	-1.3245***	.3571***	-5.0502***	.0159	.4727
	(.0319)	(.1500)	(.1937)	(.1015)	(.3818)	(.0538)	[.2156]	(.2010)	(.4127)	(.0916)	(.3846)	(.0462)	[.4265]
Left Tackles AV	.0729***	1.3365***	-3.0069***	-.0851	-1.7852***	-.0586	.4773	1.8242***	-4.0006***	.3742***	1.6398***	.0042	.5267
	(.0218)	(.1195)	(.3901)	(.0932)	(.3829)	(.0534)	[.4315]	(.1021)	(.3179)	(.1147)	(.4389)	(.0559)	[.4852]
Guards AV	.0822***	2.4859***	-2.7690***	.3271**	-4.3781***	-.1040*	.4655	3.2490***	-5.4888***	.4054***	-1.0670	-.1239	.4688
	(.0208)	(.3566)	(.7031)	(.1397)	(.6500)	(.0541)	[.4187]	(.3481)	(.6317)	(.1560)	(.6654)	(.0853)	[.4223]
Centers AV	.0854**	1.2721***	-3.0244***	.0758	-.3065	-.0294	.4845	2.0915***	-4.5578***	.0806	.0805	-.1121**	.4941
	(.0377)	(.1214)	(.2552)	(.1083)	(.3262)	(.0412)	[.4394]	(.1668)	(.3586)	(.0954)	(.4563)	(.0477)	[.4498]
Right Tackles AV	.0877***	1.5697***	-2.9120***	.1865*	1.2033***	-.0475	.4895	1.8328***	-4.0504***	.1624	2.9601***	-.0169	.4624
	(.0283)	(.1168)	(.3219)	(.1130)	(.2573)	(.0371)	[.4448]	(.1877)	(.4294)	(.1195)	(.5478)	(.0590)	[.4153]
Defensive Ends AV	.0811***	3.2037***	-1.0690	.0210	-.2812	-.0965	.4912	3.9095***	-3.5915***	.4044**	-1.7965**	-.0389	.5193
	(.0138)	(.4376)	(.8327)	(.1507)	(.4553)	(.0649)	[.4466]	(.2986)	(.6171)	(.1868)	(.7049)	(.0813)	[.4772]
Defensive Tackles AV	.0880***	3.1745***	-2.5036*	-.2246	-.0267	-.1092*	.4798	2.9213***	-.5875	.4463***	-1.4581***	.2684***	.4834
	(.0146)	(.3412)	(1.4669)	(.1474)	(.5382)	(.0579)	[.4342]	(.3554)	(2.4300)	(.1522)	(.4748)	(.0739)	[.4382]
Inside Linebackers AV	.0905***	2.3579***	-2.2986***	.2096*	6.0805***	-.0681	.4837	3.0794***	-3.4558***	.1974	-7.7645***	.0568	.4732
	(.0178)	(.2911)	(.5093)	(.1177)	(.3612)	(.0546)	[.4385]	(.3229)	(.6633)	(.1762)	(.4627)	(.0641)	[.4270]
Outside Linebackers AV	.1110***	3.2974***		.0555	-2.2312***	-.0516	.4055	3.1841***	-4.2268***	.1972	.5474	.0103	.4403
	(.0144)	(.4455)		(.1365)	(.4372)	(.0651)	[.3550]	(.3234)	(.8644)	(.1349)	(.7850)	(.0855)	[.3913]
Cornerbacks AV	.1073***	4.6463***		-.1750	6.9461***	.0542	.3712	3.6465***		.4207**	-.1931	-.0056	.4150
	(.0189)	(.4810)		(.1522)	(.6406)	(.0792)	[.3178]	(.3007)		(.1841)	(.9141)	(.0774)	[.3653]
Free Safeties AV	.1267***	1.6911***	-2.7087***	.0057	-3.6104***	-.0575	.4208	2.1529***	-3.8411***	.2600**	-3.4035***	-.0552	.5155
	(.0285)	(.1668)	(.5756)	(.1059)	(.3661)	(.0520)	[.3701]	(.1795)	(.3273)	(.1269)	(.4705)	(.0465)	[.4730]
Strong Safeties AV	.0777***	1.1836***	-2.6172***	-.0267	.6130*	-.0081	.3903	1.9068***	-3.3502***	.2613***	-4.2103***	-.0022	.5083
	(.0239)	(.1236)	(.3750)	(.1191)	(.3285)	(.0424)	[.3369]	(.1942)	(.2370)	(.0919)	(.2634)	(.0383)	[.4652]
Kickers AV	.0260	.3656***	-1.6991***	.0017	.0733	-.0189	.5062	.5502***	-2.5193***	-.0203	.8098***	.0204	.3622
	(.0486)	(.0414)	(.1984)	(.0366)	(.1178)	(.0141)	[.4629]	(.0714)	(.1302)	(.0500)	(.1062)	(.0154)	[.3064]
Punters AV	.0831	.3377***	-1.7708***	-.0268	1.0194***	.0081	.7104	.5497***	-1.9227***	-.0195	.1752	.0269**	.5804
	(.0815)	(.0239)	(.1046)	(.0255)	(.1076)	(.0101)	[.6851]	(.0705)	(.0706)	(.0295)	(.1206)	(.0133)	[.5437]
Long Snappers AV	-.0429	.1679***	-.7781***	-.0032	-.2527***	-.0087***	.7537	.4281***	-1.4438***	-.0007	-.4785***	-.0410***	.4952
	(.0895)	(.0137)	(.0596)	(.0057)	(.0230)	(.0030)	[.7322]	(.0586)	(.1032)	(.0209)	(.0625)	(.0123)	[.4510]
Vegas Wins O/U	.1172***												
	(.0437)												
2011 Indianapolis Colts	-1.6478***												
	(.3298)												
17 Game Season	.2212												
	(.1621)												
R^2	.8231												
Adjusted R^2	.7998												

*p<0.10, **p<0.05, ***p<0.01. Team-clustered standard errors are in parentheses.

where x_{ij} = preseason Vegas win total over/unders, ξ_i = team fixed effects, and η_j = a 17-game season binary variable.[9] Also, for all position and contract types, we estimate separate cost effectiveness equations with a level-log specification (i.e. we set $\gamma \to 1$), which is due to diminishing returns to salary cap percentage *Cap%*. Cost effectiveness is different for players on rookie contracts than veteran ones because a position may be cost effective in the draft but not in the veteran market, or vice versa. For example, it is hard to evaluate quarterback prospects out of college. Therefore, many highly-drafted quarterbacks fail in the NFL, making rookie quarterbacks less cost effective than veterans (see Table 1). The cost effectiveness equations are:

$$\text{AV}_{ijpc} = \alpha_{pc} \log(\text{Cap\%}_{ijpc}) \mathbb{1}(\text{Cap\%}_{ijpc} > 0) + \alpha'_{pc} \mathbb{1}(\text{Cap\%}_{ijpc} = 0) + x_{ij}\delta_{pc} + \xi_{ipc} + \eta_{jpc} + \nu_{ijpc}. \quad (7)$$

To ensure robustness, we also estimate cost effectiveness using $\log(\text{Cap\%} + \varepsilon)$ and $\text{arsinh}(\text{Cap\%}/\varepsilon)$

[9]The NFL increased the number of games from 16 to 17 in 2021

without the indicator functions and across a spectrum of ε values.[10] Position groups with a small number of players, such as kicker, are more likely to have zero-valued observations (e.g. a team not rostering any rookie kickers) than larger position groups, such as wide receiver. Without loss of generality, if ε is relatively small, then a small position group will have more very negative observations, which will flatten the regression line, reduce the cost effectiveness estimate, and reduce that position's optimal allocation. As such, following Chen and Roth (2024), we estimate cost effectiveness on the intensive margin to preserve scale invariance, which results in optimal allocations in the middle of the ε spectrum (and similar to those from a $\sqrt{\text{Cap\%}}$ specification).

We define an equilibrium as a set of $\{\text{Cap\%}^*_{pc}\}_{(p,c)\in P\times C=\{\text{Rook,Vet}\}}$ such that:

1. **Optimization**: In each representative season, the representative team solves the problem:

$$\max_{\text{Cap\%}_{ijpc}} \widehat{\text{Wins}}_{ij}, \text{ where } \forall c \in C\colon \sum_{p\in P} \text{Cap\%}_{ijpc} = 100\%, \text{ and } \forall (p,c) \in P\times C,\ a_{ijpc} \geq 0\%, \tag{8}$$

with resulting optimal interior positional and contract type allocations:

$$\text{Cap\%}^*_{ijpc} = \text{Cap\%}^*_{pc} = \frac{100\%\hat{\beta}_p\hat{\alpha}_{pc}}{\sum_{p\in P}\hat{\beta}_p\hat{\alpha}_{pc}}. \tag{9}$$

2. **Market Clearing:** Because the optimal cap allocations are the same for each ij:

$$\forall c \in C\colon \frac{1}{IJ}\sum_{(i,j,p,c)\in I\times J\times P\times C} a^*_{ijpc} = \sum_{(p,c)\in P\times C} a^*_{pc} = 100\%. \tag{10}$$

Notably, there are two market clearing conditions, one for rookies and one for veterans. The reason is that the representative team cannot change its rookie vs. veteran allocation. Because the rookie budget consists of fixed-value contracts based on draft position (the representative team has 28 mid-round draft picks over each four-year horizon, i.e. seven picks per year, with undrafted free-agent contracts cheap enough to be negligible), the veteran budget equals the salary cap minus the rookie budget. An individual team can increase (decrease) its rookie budget by trading for (away) picks, but the representative team cannot because in a closed league like the NFL (a "perfect portfolio," as Vrooman 2009 writes), every buyer in a trade requires a seller.

However, the representative team can change its positional allocations *within* a contract type. For example, they can increase their veteran quarterback allocation by paying a veteran more, or their rookie quarterback allocation by drafting a quarterback with a higher pick. Rookie allocations are somewhat less flexible because the contract values are predetermined, but each contract is small enough that the representative team can essentially achieve the optimal allocations. Thus,

[10] Mathematically, $\log(\text{Cap\%}+\varepsilon)$ and $\text{arsinh}(\text{Cap\%}/\varepsilon)$ are analogous (Chen & Roth 2024). $\log(\text{Cap\%}+\varepsilon) = \log(\varepsilon(\text{Cap\%}/\varepsilon+1)) = \log(\varepsilon)+\log(\text{Cap\%}/\varepsilon+1)$. $\log(\varepsilon)$ is absorbed into the intercept, leaving $\log(\text{Cap\%}/\varepsilon+1)$ to be approximated by $\text{arsinh}(\text{Cap\%}/\varepsilon)$. In general, $\text{arsinh}(x)$ can be useful for negative x, but it is not scale invariant.

this optimization model is sufficient to characterize an equilibrium of 18 rookie and 18 veteran positional allocations, with both sets of allocations summing to 100%. Due to heterogeneity across team needs and frictions, such as existing contracts, the reality for an individual team is more complicated. But the results will show if teams optimize in the aggregate or not.

We estimate the model's parameters with 2011–2024 season-level data from *Pro Football Reference* (2025) and *Spotrac* (2025), where an example observation is the 2011 Arizona Cardinals. The starting point is 2011 because the 2011 collective bargaining agreement implemented the current rookie salary scale (Clayton 2011).[11] Our 14-season panel thus includes seven pre-2018 and seven post-2018 years. In addition, we pool fullbacks with running backs and evenly split the pay and performance of the few players listed as "tackle" into left and right tackles, "linebacker" into inside and outside linebackers, and "safety" into free and strong safeties. Regarding control variables, we omit *Strength of Schedule* as an opponents control because its effect on *Wins* is absorbed by AV, and for now, we omit a *Coach of the Year* votes dummy variable as a coaching control because voters may vote for the coach of a winning team even if he is not primarily responsible for his team's success. To preserve degrees of freedom, we use a *17 Game Season* dummy[12] instead of a full set of season fixed effects. All cap figures are normalized as percentages to account for cap inflation over time. Summary statistics are in Table 8 of Appendix C.

Table 1's estimates are reasonable, as all positions except kicker, punter, and long snapper have significantly positive importance coefficients, and all positions have significantly positive cost effectiveness coefficients. The model also has high explanatory power, with an importance R^2 of .8231 and cost effectiveness R^2s from .2788 to .7537. However, there are two anomalies. First, the quarterback importance coefficient of .0966 is less than that of running backs (.1198) and wide receivers (.1325). Per Table 9 of Appendix C, most offense AVs are positively correlated (e.g. r between quarterbacks and wide receivers is .7379). As such, the smaller quarterback coefficient likely reflects asymmetric spillovers: good quarterback play boosts the AV of pass catchers more than the other way around (Groysberg et al. 2019). Also, the running back importance coefficient is inflated because teams run more when winning (the game clock stops after an incomplete pass, which is undesirable when trying to retain a lead). In Figure 7 of Appendix C, we plot the cost effectiveness curves for each position-contract type group, which lets us illustrate differences across groups (e.g. low cost effectiveness coefficients for long snappers). The cost effectiveness results are also robust to a $\sqrt{\text{Cap\%}}$ specification, per Table 10 of Appendix C.

Table 2 compares the actual and optimal allocations.[13] The mean absolute difference between

[11] Before 2011, rookie contracts were much more expensive. For instance, 2010 first overall pick Sam Bradford's six-year, $78M contract was larger than 2025 first overall pick Cam Ward's four-year, $48.75M contract, even though both players are quarterbacks, and the salary cap has more than doubled since 2010.

[12] This dummy equals 1 for all observations from 2021 onward, except for the 2022 Buffalo Bills and Cincinnati Bengals, whose matchup was cancelled due to Damar Hamlin's cardiac arrest injury.

[13] Per Tables 11 and 12 of Appendix C, the intervals are robust to the delta method, which assumes zero covariance across regressions, and to a $\sqrt{\text{Cap\%}}$ cost effectiveness specification.

them is only 1.5% points, suggesting that teams allocated nearly optimally in the aggregate. Still, systematic deviations exist. Left tackles, rookie tight ends, and veteran kickers were significantly overallocated, while veteran running backs were significantly underallocated (though this result is due to the simultaneity between wins and running back AV, which we address in Section 6). Rookie and veteran quarterbacks were overallocated by 2.6 and 3.2% points respectively, but not significantly so. The wide team-clustered bootstrap 95% confidence intervals (1,000 iterations) for quarterbacks reflect the multicollinearity between them and pass catchers. We also obtain an insignificantly negative allocation for long snappers due to their negative importance coefficient, which we will remedy by constraining all importance coefficients to be nonnegative.

Table 2: Actual vs. Baseline Optimal Allocations, Team-Clustered Bootstrap Confidence Intervals

	Rookies				Veterans			
	Actual	Optimal	95% CI	Difference	Actual	Optimal	95% CI	Difference
Quarterbacks	6.8%	4.5%	(1.1%, 9.1%)	2.4%	11.0%	7.5%	(1.9%, 14.1%)	3.5%
Running Backs	7.1%	11.2%	(5.7%, 18.4%)	-4.1%	5.2%	9.5%	(5.6%, 14.1%)	-4.3%
Wide Receivers	12.3%	20.1%	(12.2%, 27.6%)	-7.8%	11.3%	15.0%	(9.3%, 21.5%)	-3.7%
Tight Ends	4.9%	2.2%	(0.2%, 4.0%)	2.7%	5.0%	3.5%	(0.4%, 5.7%)	1.6%
Left Tackles	4.8%	2.4%	(0.9%, 3.8%)	2.4%	5.1%	3.1%	(1.2%, 4.7%)	2.1%
Guards	6.9%	5.1%	(2.3%, 7.8%)	1.9%	6.0%	6.2%	(2.9%, 9.2%)	-0.2%
Centers	2.6%	2.7%	(0.6%, 5.0%)	-0.1%	3.4%	4.1%	(0.9%, 7.9%)	-0.7%
Right Tackles	4.0%	3.4%	(1.3%, 5.5%)	0.5%	3.3%	3.7%	(1.4%, 5.8%)	-0.4%
Defensive Ends	9.1%	6.4%	(4.0%, 10.0%)	2.7%	8.9%	7.3%	(4.9%, 10.2%)	1.6%
Defensive Tackles	7.3%	6.9%	(4.0%, 9.8%)	0.4%	7.4%	5.9%	(3.8%, 8.2%)	1.5%
Inside Linebackers	5.8%	5.3%	(2.9%, 7.8%)	0.5%	5.2%	6.4%	(3.8%, 9.2%)	-1.2%
Outside Linebackers	8.3%	9.1%	(6.6%, 12.0%)	-0.8%	7.9%	8.1%	(5.8%, 11.0%)	-0.2%
Cornerbacks	11.4%	12.4%	(7.7%, 18.1%)	-0.9%	9.8%	9.0%	(6.3%, 12.3%)	0.8%
Free Safeties	3.9%	5.3%	(3.1%, 7.3%)	-1.4%	3.6%	6.3%	(3.7%, 8.9%)	-2.7%
Strong Safeties	3.6%	2.3%	(1.1%, 3.7%)	1.3%	3.2%	3.4%	(1.6%, 5.8%)	-0.2%
Kickers	0.4%	0.2%	(-0.6%, 1.1%)	0.2%	1.8%	0.3%	(-0.9%, 1.4%)	1.5%
Punters	0.6%	0.7%	(-0.6%, 1.9%)	-0.1%	1.2%	1.1%	(-0.9%, 2.8%)	0.1%
Long Snappers	0.3%	-0.2%	(-0.9%, 0.6%)	0.5%	0.7%	-0.4%	(-2.3%, 1.2%)	1.1%

Finally, we test for complementarities using Calvetti (2023)'s interactions: quarterback AV interacted with wide receiver AV, running back with offensive line, quarterback with tight end, left tackle with the rest of the offensive line, and offense with defense. Table 13a of Appendix C shows offense and defense were submodular, consistent with Super Bowl-winning coach Brian Billick's observation that his defense was good enough not to need an elite quarterback (Billick & Dale 2020). Also, in Table 13b, we present results from Cobb-Douglas and restricted translog estimates. Expressed as a Cobb-Douglas production function, the importance specification is:

$$\text{Wins}_{ij} = \prod_{p\in P} (\text{AV}_{ijp})^{\beta_p} \prod_{k\in K} (x_{ijk})^{\delta_k} \exp(\xi_i + \eta_j + \varepsilon_{ij}). \tag{11}$$

Taking logarithms of both sides, we can then run the following regression:

$$\log(\text{Wins}_{ij}) = \log(\text{AV}_{ij})\beta + \log(x_{ij})\delta + \xi_i + \eta_j + \varepsilon_{ij}. \tag{12}$$

In contrast to the linear model, we find that offense and defense were log-supermodular. Due to the 2017 Cleveland Browns winning zero games and due to some observations having zero or even negative positional AVs, we use the inverse hyperbolic sine as an approximation for the logarithm, though this result is robust to dropping the problematic observations instead.

Overall, the baseline model indicates that teams as a whole allocate resources efficiently. The small average gap between actual and optimal allocations is notable given that the model is not estimated using teams' choice data. Notably however, the optimal quarterback allocations appear too low, a result in accordance with unmodeled asymmetric spillovers that interaction terms cannot identify, as interactions can only identify complementarities. In essence, quarterbacks have a pivotal role for the team unlike any other position due to their direct, upstream involvement in every offensive play. Regarding other alternatives to interactions, *Pro Football Focus* (2025)'s game-film-based grades are theoretically exogenous, but they are also subjective. For example, an elite quarterback could influence the grader to grade the wide receivers too highly. Meanwhile, most other performance statistics are not available for all positions, so we cannot obtain more accurate results simply by using statistics other than AV. Therefore, to better identify quarterbacks' marginal win productivity, we first exploit game-level data as a short-run period and exploit within-season quarterback changes. Then we recalibrate the model accordingly.

5 Quarterback Valuation

Our goal in this section is to identify quarterbacks' marginal win productivity using game-level data (see Tables 14 and 15 of Appendix D for summary statistics). 32 teams, 14 seasons from 2011 to 2024, and 16–17 games per season yield 7,296 observations.[14] Since AV does not exist on the game level, the quarterback statistics we use for the treatment variable are passer rating, Adjusted Net Yards per Attempt (ANY/A), Total Adjusted Net Yards per Attempt (TANY/A), and Fantasy Points per Attempt (FP/A). The formulas for these statistics are in Appendix D.

But before doing so, we provide empirical evidence that asymmetric spillovers exist in football, specifically between the quarterback and the offensive skill positions for which fantasy points are available (running back, wide receiver, and tight end). To do so, we use a stacked regression where our two outcomes are *Quarterback Fantasy Points* and *Skill Position Fantasy Points*, and there are 14,476 total observations. Our independent variables are *Log Quarterback Injured Money*, *Log Skill Position Injured Money*, *Log Non-Skill Position Injured Money*, *Log Opponent Injured Money*, a home team dummy variable to control for home-field advantage, and team-season and opponent-season fixed effects. We also have separate parameters depending on whether the observation is from the dataset with the quarterback or skill position outcome.

The injured money variables measure the cap spending on players who missed the game due

[14] After dropping ties, the winless 2017 Browns whose fixed effect is inestimable, and the Damar Hamlin game (see Section 4), we have 7,238 observations, for which the outcome variable is whether the team won the game.

to injury, and so represent a mostly exogenous change in their position's true quality (Gregory-Smith 2021).[15] In addition, we standardize all continuous variables because there are fewer quarterbacks than skill position players on each team, though our results are robust to not standardizing them. We index teams with i, opponents with k, seasons with j, games with t, and positions with $p \in \{\text{Quarterback}, \text{Skill Position}\}$. Let $y =$ *Standardized Fantasy Points*, $x =$ the vector of independent variables, and $\xi =$ fixed effects. Then the regression equation is:

$$y_{ijtp} = x_{ijt}\beta_p + \xi_{ijp} + \xi_{kjp} + \varepsilon_{ijtp}. \tag{13}$$

Table 3: Asymmetric Spillovers Results, 894 Fixed Effects

DV = Standardized Fantasy Points	Quarterback	Skill Position
Standardized Log Quarterback Injured Money	-.1529***	-.1515***
	(.0353)	(.0351)
Quarterback Injured Money = 0	.1842***	.1023**
	(.0406)	(.0403)
Standardized Log Skill Position Injured Money	-.0209	-.0264*
	(.0148)	(.0145)
Skill Position Injured Money = 0	.0623	.0701
	(.0634)	(.0592)
Standardized Log Non-Skill Position Injured Money	.0060	-.0195
	(.0147)	(.0150)
Non-Skill Position Injured Money = 0	.5217**	.2563
	(.2315)	(.2133)
Standardized Log Opponent Injured Money	.0042	.0216
	(.0143)	(.0146)
Home	.1442***	.1541***
	(.0186)	(.0186)
P-Value: QB → Skill = Skill → QB	.0007	
R^2	.3166	
Adjusted R^2	.2211	

*p<0.10, **p<0.05, ***p<0.01. Game-clustered standard errors are in parentheses.

In Table 3, we find that the negative effect of quarterback injuries on skill position performance is several times the size of that of skill position injuries on quarterback performance. As such, a change in the quarterback's true quality affects skill position performance considerably more so than the other way around. Our stacked regression design also lets us test whether these negative effects are equal in magnitude while accounting for any cross-equation correlation in the error terms. We find that the effects are statistically significantly different at the 1% level.

[15]Because there are zero-valued observations due to games with no quarterback or skill position injuries, we estimate the intensive margins, though our results are robust to using the inverse hyperbolic sine instead.

Given that we have provided evidence that asymmetric spillovers exist to a meaningful degree, we proceed to identifying quarterbacks' marginal win productivity. To control for the quarterback's teammates, we use teammate fantasy points. But fantasy points do not exist for some positions, such as the offensive line, so selection on only observables is insufficient. As such, we rely on an additional identification strategy: teams changing quarterbacks within the season and the resulting change in win probability.[16] Ultimately, about 60% of our observations come from teams with more than one quarterback per season, giving us sufficient identifying variation.

While changes due to injury are plausibly exogenous, other changes, such as benchings, may be endogenous. Therefore, observables must be constant across quarterbacks within seasons. This requirement could be problematic if, for example, a quarterback is unfairly benched due to temporarily poor offensive line play. The resulting biases may cancel out if quarterbacks are unfairly benched for different reasons (temporarily poor offensive teammate play biases the quarterback coefficient upward, whereas temporarily poor defensive play biases it downward). Still, we take steps to address this endogeneity problem, starting with Section 3's assumptions:

Assumption 1.1. *In each team-season, teammate and opponent qualities are stable across games.*

This assumption makes 447 team-season fixed effects (448 minus the 2017 Browns) sufficient to absorb much of the endogeneity resulting from the quarterback's teammates and opponents.[17] But there are still within-season unobservables, so to address them, we add Gregory-Smith (2021)'s game-varying controls.[18] In our preferred specification, one of his controls, *Vegas Spread*, becomes a mediator for quarterback ability, so we omit it. We also omit another of his controls, $Win\%_{t-1}$, since the team-season fixed effects flip its sign. The reason is that within a team-season combination whose final win percentage is known, a relatively high win percentage before the current game means the team is less likely to win that game. Finally, unlike him, we include non-quarterback fantasy points to control for within-season teammate and opponent quality. However, as we stated earlier, because fantasy points are unobservable for some positions, selection on only observables is not sufficient. Therefore, we make two more assumptions:

Assumption 1.2. *Each quarterback's quality is constant across games.*

Assumption 1.3. *In each team-season, teammate and opponent qualities, as well as any remaining unobservables, are stable across quarterbacks.*[19]

[16] For example, the 2014 Arizona Cardinals went 6–0 with their starter Carson Palmer, who had an above-average passer rating of 95.6. But Palmer tore his ACL midseason, and the Cardinals then went 5–5 with their backups Drew Stanton and Ryan Lindley, who had below average (78.7) and far below average (56.8) passer ratings respectively.

[17] Gregory-Smith also uses fixed effects, but he uses team + season fixed effects instead of team × season.

[18] These controls are *Vegas Spread* = pregame Vegas spread, *Log Injured Money* = logarithm of cap spending on players who missed the game due to injury, *Gini coefficient* = Gini coefficient of spending across starters, *Starter/nonstarter* = ratio of spending between starters and non-starters, *Away* = home vs. away dummy, *Rest Days* = number of rest days before the game, and $Win\%_{t-1}$ = team's season win percentage before the game.

[19] Per former NFL player Geoff Schwartz in 2019, "tanking" teams, or those hoping to lose for a better draft pick, generally do not start tanking midseason but rather go into the season with a non-competitive roster.

As such, instead of using (without loss of generality) *Game Passer Rating* (*GPR*) as the treatment, we proxy it with *Season Passer Rating* (*SPR*), a weighted average by passing attempts of the season passer ratings of each quarterback who played in the game. *SPR* reflects quarterback ability rather than unobservables, and it helps identify any asymmetric spillovers with teammate fantasy points because *SPR* is on the quarterback-season level, whereas fantasy points are on the game level.[20] To test Assumption 1.2, we run a specification dropping games whose primary quarterback is in his first year in the NFL and so may improve within the season. Also, to test Assumption 1.3, we drop games whose primary quarterback is not the primary quarterback for at least four games in the season, as given a larger sample size, the remaining unobservables are more likely to average out. These specifications balance purging endogeneity with introducing selection bias, but we show in Table 17 of Appendix D that our results are robust across them.

Table 4: Quarterback Valuation Results, Passer Rating, 447 Fixed Effects ($N = 7,238$)

DV = Win	Game			Season			Game, Season IV	
	Logit	AME	Linear	Logit	AME	Linear	Q1-Q4	Q1-Q3
Passer Rating	.0603***	.0047***	.0050***	.0352***	.0035***	.0034***	.0077***	.0066***
	(.0037)	(.0002)	(.0002)	(.0081)	(.0008)	(.0007)	(.0014)	(.0017)
Non-QB Fantasy Points	.1098***	.0085***	.0067***	.1331***	.0133***	.0118***	.0038**	.0050***
	(.0065)	(.0004)	(.0004)	(.0056)	(.0003)	(.0003)	(.0016)	(.0018)
Home	.2593***	.0201***	.0177***	.2473***	.0247***	.0212***	.0163***	.0169***
	(.0684)	(.0052)	(.0057)	(.0563)	(.0056)	(.0061)	(.0057)	(.0057)
Rest Days	.0095	.0007	.0004	.0082	.0008	.0006	.0002	.0003
	(.0281)	(.0022)	(.0024)	(.0235)	(.0023)	(.0026)	(.0024)	(.0024)
Log Injured Money	-.0559	-.0043	-.0025	-.0221	-.0022	-.0023	-.0037	-.0032
	(.1316)	(.0102)	(.0112)	(.1049)	(.0105)	(.0118)	(.0112)	(.0110)
Starter Gini	3.1143*	.2415*	.2185	2.8606*	.2861*	.2650	.1917	.2025
	(1.7440)	(.1354)	(.1621)	(1.5826)	(.1586)	(.1731)	(.1593)	(.1583)
Starter/Non-Starter	.2440	.0189	.0180	.2135	.0214	.0124	.0196	.0189
	(.2471)	(.0192)	(.0213)	(.2069)	(.0207)	(.0226)	(.0210)	(.0207)
Pseudo-R^2 | R^2	.6424		.5669	.5452		.5087	.5492	.5606
Adjusted Pseudo-R^2 | R^2	.6410		.5389	.5439		.4769	.5200	.5322

*p<0.10, **p<0.05, ***p<0.01. Game-clustered standard errors are in parentheses.
"Game" refers to using *GPR*, "Season" to using *SPR* as a proxy for *GPR*, and "Game, Season IV" to using *SPR* as an instrument for *GPR*.
"Q1–Q3" means *SPR* is constructed without fourth quarter statistics.

Mathematically, we estimate game win probabilities conditional on the team and opponent. Letting team i's quality in game t of season j be $Win^*_{ijt} = x_{ijt}\beta + \xi_{ij} + \varepsilon_{ijt}$ (and opponent k's quality be analogous), we assume ε_{ijt} has a Type 1 extreme value distribution. x_{ijt} contains *QB Statistic*, *Non-QB Fantasy Points*, and other controls, and ξ_{ij} are team-season fixed effects. Then:

$$PWin_{ijt} = \frac{\exp(x_{ijt}\beta + \xi_{ij})}{\exp(x_{ijt}\beta + \xi_{ij}) + \exp(x_{kjt}\beta + \xi_{kj})}, \tag{14}$$

[20]It also makes *Vegas Spread* a mediator because previous games' passer ratings can influence the spread.

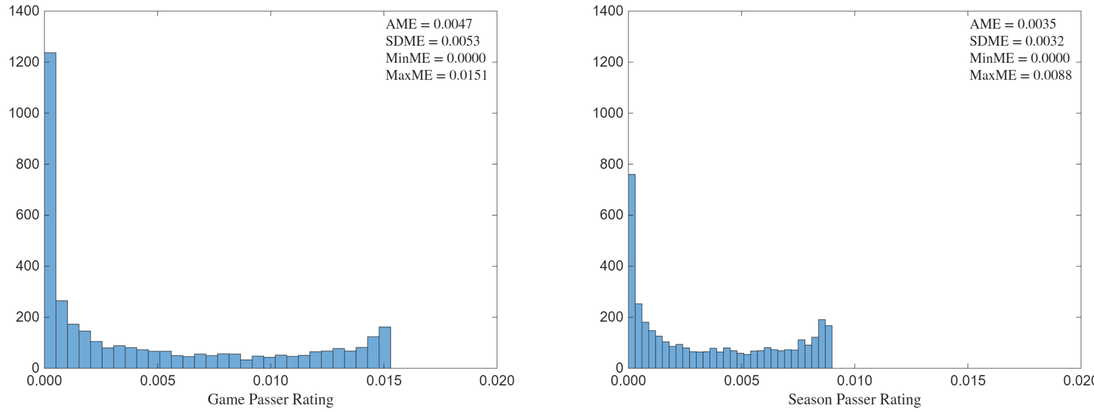

Figure 1: Distributions of Marginal Effects, Passer Rating

which we can estimate with maximum likelihood as a logistic regression of Win_{ijt} on $(x_{ijt} - x_{kjt}, \xi_{ij} - \xi_{kj})$. The marginal effects of β are $ME_{ijt} = PWin_{ijt}(1 - PWin_{ijt})\beta$. Given this model is nonlinear and has fixed effects, there could be an incidental parameters problem (Neyman & Scott 1948). However, empirically, the problem is minimal since, as we will show, a linear analogue's coefficients are approximately equal to the nonlinear average marginal effects (AMEs).

It is also worth noting that we use *SPR* as a proxy for *GPR* instead of an instrument, for multiple reasons. First, if we were to use it as an instrument, we would have to switch to a linear probability or probit specification. The reason is that the Type 1 extreme value distribution is incompatible with a linear first stage, and given that true win probabilities are unobservable (and there are no historical Vegas moneylines, only spreads and over/unders), we cannot invert them to generate a log-linear second stage, as is done in logit demand estimation. Still, we try instrumental variables on a linear analogue of our specification as a robustness check. Second, because *SPR* is on the same scale as *GPR*, we can use it as a proxy. That is, we can interpret its coefficient as if it were *GPR*, unlike for instance (incorrectly) using steel price as a proxy for car price when estimating demand for cars. Most importantly, however, *SPR* violates the exclusion restriction because it affects win probability via an additional channel. Even if two quarterbacks were to have the same passer rating in the same game, the higher-ability quarterback with the higher *SPR* will be more likely to win by playing well in important moments, such as late in close games. Worse still, since *Non-QB Fantasy Points* must be included in the first stage, *SPR*'s effect on *GPR* is weakened, which magnifies the exclusion restriction violation. In Table 4's "Season IV" columns, we can see that *GPR*'s coefficient is biased upward. However, when used as a proxy, *SPR* is uncorrelated with the error term, and so its coefficient is asymptotically unbiased.

We also wondered if we could include both *GPR* and *SPR* in the main specification and use one as a control for the other. However, despite being a confounder, *SPR* is insufficient as a control for *GPR* because there are other unobservables, such as offensive line performance, that vary within seasons. Therefore, *SPR* as a control barely decreases *GPR*'s estimate. We cannot use

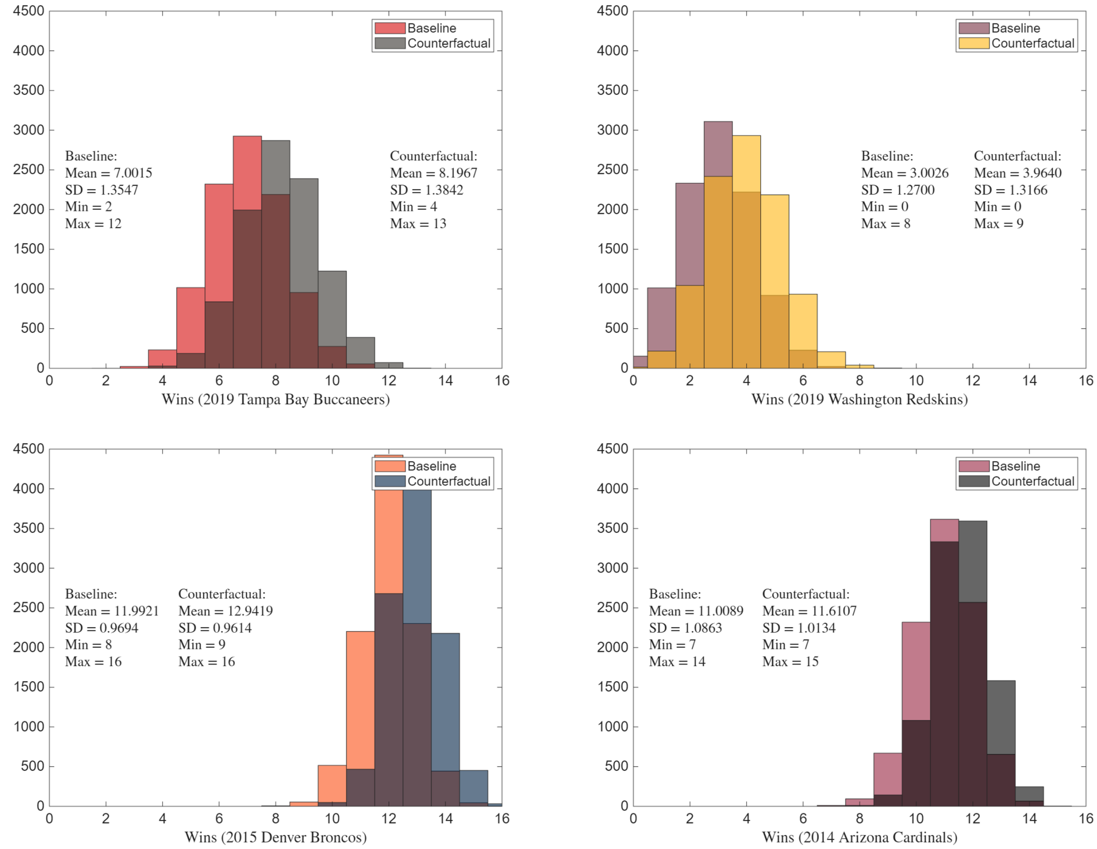

Figure 2: Distributions of Simulated Wins, Season Passer Rating

GPR as a control for *SPR* either because *GPR* is a mediator for *SPR* (see Figure 8 of Appendix D) and so drops *SPR*'s estimate too low. As a final attempt to make *SPR* work as an instrument, we try differencing out fourth-quarter statistics from it to eliminate the aforementioned "clutch factor." This effort is analogous to Borusyak and Hull (2022)'s elimination of the endogenous part of shift-share instruments by differencing out the expected instrument over time. While we manage to decrease *GPR*'s coefficient in Table 4 from .0077 to .0066, it is still higher than *GPR's* OLS coefficient because important moments can occur before the fourth quarter. For example, better quarterbacks are better at executing two-minute drills at the end of the first half, avoiding failed completions (i.e. third-down completions too short for a first down), and not suddenly playing better in the third quarter of a blowout when the opposing defense eases up.

As a result, we stick to *SPR* as a proxy for *GPR* in our preferred specification. Per Column 5 of Table 4, *SPR*'s statistically significant average marginal effect (AME) of .0035 implies that a one standard deviation increase in *SPR* of 10.98 points induced a 3.87% point increase in win probability, or .63 additional wins per season. Going from the worst starting quarterback to the best spanned 5.58 standard deviations, or 3.52 additional wins per season. Also, *Non-QB Fantasy Points* and *Home* are always significant, with *Home*'s AME representing the win probability gain relative to a neutral field. The other variables have the expected signs but except for *Starter Gini* are not significant, though the Pseudo-R^2 and R^2s of all the regressions are greater than .5. In Table 16 of Appendix D, we provide the same estimates but for ANY/A, TANY/A, and FP/A.

In Figure 1, we present histograms of the marginal effects of Columns 1 and 4. Marginal effects within a game are identical, so the number of observations in the histograms are half that in the regressions. Generally speaking, quarterback ability matters more when teams are evenly matched; that is, when the predicted win probability is close to .5. While *SPR* provides less predictive power than *GPR*, *Non-QB Fantasy Points* provides enough predictive power for *SPR* to yield fitted values sufficiently far from .5 for *SPR* to retain *GPR*'s right skew. In Figure 9 of Appendix D, we provide the same histograms but for ANY/A, TANY/A, and FP/A.

For further intuition, we use the quarterback valuation model to simulate each team's season 10,000 times under various counterfactuals. First, what if the Tampa Bay Buccaneers had acquired Tom Brady in 2019 as opposed to 2020? They won the Super Bowl with him in 2020 after going 7–9 in 2019 with mostly the same roster; could the 2019 team have also won the Super Bowl with him? Second, what if the much weaker 2019 Washington Redskins had him instead? Unlike the Buccaneers, they were not seen as a quarterback away from contention. Third, what if 2015 Denver Broncos' quarterback Peyton Manning were still elite? He was no longer elite in 2015, but the rest of the team was so good that they won the Super Bowl despite his subpar play. Finally, how would the 2014 Cardinals's season have finished had Palmer not gotten injured?

Figure 2 illustrates that due to the logit model, the quarterback effect is largest for teams neither too weak (e.g. the 2019 Redskins) nor too strong (e.g. the 2015 Broncos).[21] This result is sensible from a football perspective, considering that in extreme cases, a non-NFL caliber team cannot win regardless of the quarterback, whereas an elite team cannot exceed 16 or 17 wins per season. The 2020 Buccaneers were an outlier in that with Brady, they won four more games than in 2019, plus the Super Bowl. However, Brady not only provided better quarterback play but also changed the team culture (Giardi 2021). At this point, we have estimated a quarterback's marginal win productivity using game-level data. Now we must scale this estimate up to the season level and use it to calibrate our cap optimization model, which we do in the next section.

6 Calibrated Salary Cap Optimization

Having identified a quarterback's marginal win productivity, we re-estimate the importance equation in what we refer to as the calibrated cap optimization model. This procedure is in accordance with the re-estimation proposed in Section 3. First, we constrain the quarterback importance coefficient to match that implied by the quarterback valuation model:

$$\hat{\beta}^{C}_{QB} = \overline{T}\left[\widehat{\text{AME}} \circ \frac{\sigma}{\sigma_{\text{QBAV}}}\right]' \frac{\hat{\Sigma}^{-1}\iota}{\iota'\hat{\Sigma}^{-1}\iota}. \tag{15}$$

[21]Figure 10 of Appendix D illustrates the same simulations but using *GPR* instead of *SPR*.

That is, to obtain the constrained coefficient $\hat{\beta}^C_{QB}$, we rescale passer rating, ANY/A, TANY/A, and FP/A's AMEs by the ratio of each statistic's standard deviation to that of quarterback AV. We then average the four rescaled AMEs with minimum-variance weights derived from the game-clustered bootstrap scaled variance matrix $\hat{\Sigma}$ and multiply by the average games per season $\overline{T} \approx 16.3$. The result is a coefficient greater than before (.1538 as opposed to .0966) and greater than the running back and wide receiver coefficients, along with all other importance coefficients.

Second, we add a *Coach of the Year* votes dummy variable (*COTY*) as an additional control. We refrained earlier because while *COTY* offers the benefit of controlling for coaching beyond what is embedded in the preseason Vegas odds (unlike $COTY_{-1}$), it may also be a function of *Wins* if the team's record unduly influences voters. However, the main empirical difference that including *COTY* makes is reducing the running back importance coefficient. Recall that teams typically run the ball more when winning because incomplete passes stop the game clock. Doing so induces an upward simultaneity bias in the running back coefficient that including *COTY* reduces by absorbing part of *Wins*' effect on running back AV. For this reason and because coaching is a confounder, we ultimately include *COTY*. Finally, we constrain all non-quarterback importance coefficients $\beta_{\neg\text{QB}}$ to be non-negative by estimating $\log(\beta_{\neg\text{QB}})$ and exponentially transforming it, as the long snapper coefficient and optimal allocation were previously (insignificantly) negative. We estimate this new model, in which *COTY* is added to x_{it}, with nonlinear least squares:

$$\text{Wins}_{ij} = \hat{\beta}^C_{QB}\text{AV}^{\text{QB}}_{ij} + \text{AV}^{\neg\text{QB}}_{ij} e^{\log(\beta_{\neg\text{QB}})} + x_{ij}\delta + \xi_i + \eta_j + \varepsilon_{ij}. \quad (16)$$

In Table 5, we present estimates for four different importance specifications. "Baseline" means we do not calibrate the quarterback coefficient or constrain the coefficients to be non-negative, whereas "Calibrated" means we do both these things (and as such, the long snapper coefficient is now 0). Also, "COTY" means we include *COTY*. In our preferred specification, "Calibrated COTY," the quarterback coefficient is now greater than before and greater than the running back and wide receiver coefficients. Moreover, the running back coefficient decreases as a result of including *COTY*. Looking at *COTY*'s coefficient, we find that receiving at least one Coach of the Year vote was associated with about 1.5 additional wins per season. But because of simultaneity and because positional AVs are a mediator for *COTY* (as a good coach can help his team win by helping his players perform better), this estimate may not be causal. Our cost effectiveness regressions with *COTY* included, which go into our calibrated optimal allocations, are in Table 18 of Appendix E; the results are nearly identical to those in Table 1 without *COTY*.

We present the calibrated optimal allocations plus team-clustered bootstrap confidence intervals (non-negativity constraints violate the delta method's normality assumption) in Table 6. Our bootstrapping procedure accounts for the error in generating $\hat{\beta}^C_{QB}$ by bootstrapping the game-level regressions and pairing a game-level bootstrapped iteration with each season-level iteration. Per Tables 2 and 6, the baseline optimal quarterback allocation is outside the calibrated allocation's confidence interval and therefore significantly different. Also, per Table 6, the mean absolute difference between the actual and optimal allocations is now 1.4% points, and we find that left tack-

Table 5: Baseline vs. Calibrated Importance Results, Team Fixed Effects ($N = 448$)

DV = Wins	Baseline	Calibrated	Baseline COTY	Calibrated COTY
Quarterbacks AV	.0966**	.1538***	.0936***	.1538***
	(.0417)	(.0364)	(.0328)	(.0364)
Running Backs AV	.1198***	.1139***	.0929***	.0867***
	(.0266)	(.0260)	(.0263)	(.0259)
Wide Receivers AV	.1325***	.1163***	.1183***	.1015***
	(.0278)	(.0228)	(.0263)	(.0222)
Tight Ends AV	.0785**	.0615**	.0756***	.0580**
	(.0319)	(.0281)	(.0287)	(.0271)
Left Tackles AV	.0729***	.0617***	.0660***	.0541***
	(.0218)	(.0217)	(.0203)	(.0206)
Guards AV	.0822***	.0739***	.0762***	.0674***
	(.0208)	(.0199)	(.0217)	(.0209)
Centers AV	.0854**	.0790**	.0760**	.0692**
	(.0377)	(.0351)	(.0376)	(.0346)
Right Tackles AV	.0877***	.0777***	.0704***	.0597**
	(.0283)	(.0284)	(.0268)	(.0270)
Defensive Ends AV	.0811***	.0802***	.0684***	.0674***
	(.0138)	(.0133)	(.0129)	(.0124)
Defensive Tackles AV	.0880***	.0888***	.0777***	.0784***
	(.0146)	(.0137)	(.0128)	(.0122)
Inside Linebackers AV	.0905***	.0922***	.0851***	.0869***
	(.0178)	(.0166)	(.0157)	(.0145)
Outside Linebackers AV	.1110***	.1122***	.0999***	.1012***
	(.0144)	(.0139)	(.0138)	(.0130)
Cornerbacks AV	.1073***	.1060***	.0875***	.0864***
	(.0189)	(.0191)	(.0171)	(.0174)
Free Safeties AV	.1267***	.1248***	.1019***	.1001***
	(.0285)	(.0261)	(.0273)	(.0251)
Strong Safeties AV	.0777***	.0750***	.0739***	.0711***
	(.0239)	(.0232)	(.0239)	(.0231)
Kickers AV	.0260	.0267	.0187	.0190
	(.0486)	(.0330)	(.0435)	(.0293)
Punters AV	.0831	.0978	.0814	.0965
	(.0815)	(.0688)	(.0731)	(.0642)
Long Snappers AV	-.0429	.0000	-.0609	.0000
	(.0895)	(.0379)	(.0964)	(.0342)
Vegas Wins O/U	.1172***	.1152***	.1928***	.1903***
	(.0437)	(.0429)	(.0414)	(.0405)
2011 Indianapolis Colts	-1.6478***	-1.4578***	-1.9970***	-1.7714***
	(.3298)	(.2819)	(.3206)	(.2914)
17 Game Season	.2212	.2128	.1843	.1816
	(.1621)	(.1558)	(.1513)	(.1447)
Coach of the Year			1.4999***	1.4936***
			(.2568)	(.2475)
R^2	.8231	.8221	.8453	.8441
Adjusted R^2	.7998	.8164	.8245	.8391
Standard Errors	Team-Clustered	TC Bootstrap	Team-Clustered	TC Bootstrap

*p<0.10, **p<0.05, ***p<0.01. Standard errors are in parentheses.

les, rookie tight ends, and veteran kickers were significantly overallocated (see Section 7 for more discussion). The optimal long snapper allocation is 0%, which is not allowed due to the NFL's minimum salary scale. But this result says that long snappers are interchangeable and represent a minimal fixed cost against the cap. As such, we can rescale the actual allocations by removing long snapper spending, though any change in the results is negligible. Per Tables 19 and 20 of Appendix E, the results are robust to a $\sqrt{\text{Cap\%}}$ cost effectiveness specification.

Table 6: Actual vs. Calibrated Optimal Allocations, Team-Clustered Bootstrap Confidence Intervals

	Rookies				Veterans			
	Actual	Optimal	95% CI	Difference	Actual	Optimal	95% CI	Difference
Quarterbacks	6.8%	8.2%	(4.5%, 13.9%)	-1.4%	11.0%	13.7%	(8.1%, 22.1%)	-2.6%
Running Backs	7.1%	9.7%	(3.7%, 16.6%)	-2.6%	5.2%	7.8%	(3.6%, 12.7%)	-2.7%
Wide Receivers	12.3%	18.3%	(9.5%, 26.4%)	-6.1%	11.3%	12.9%	(7.0%, 18.1%)	-1.7%
Tight Ends	4.9%	2.0%	(0.0%, 3.9%)	2.9%	5.0%	2.9%	(0.0%, 5.2%)	2.2%
Left Tackles	4.8%	2.1%	(0.4%, 3.6%)	2.7%	5.1%	2.5%	(0.5%, 4.2%)	2.6%
Guards	6.9%	4.9%	(1.7%, 8.2%)	2.0%	6.0%	5.8%	(2.0%, 9.7%)	0.2%
Centers	2.6%	2.6%	(0.0%, 5.1%)	0.0%	3.4%	3.8%	(0.0%, 7.7%)	-0.4%
Right Tackles	4.0%	2.7%	(0.1%, 5.2%)	1.2%	3.3%	2.9%	(0.1%, 5.4%)	0.4%
Defensive Ends	9.1%	6.3%	(3.9%, 9.7%)	2.8%	8.9%	6.9%	(4.4%, 9.9%)	1.9%
Defensive Tackles	7.3%	7.2%	(4.6%, 10.1%)	0.1%	7.4%	6.0%	(3.9%, 8.4%)	1.4%
Inside Linebackers	5.8%	5.9%	(3.4%, 8.6%)	-0.2%	5.2%	7.0%	(4.3%, 9.6%)	-1.8%
Outside Linebackers	8.3%	9.7%	(7.1%, 12.8%)	-1.4%	7.9%	8.5%	(5.9%, 11.8%)	-0.6%
Cornerbacks	11.4%	11.8%	(7.0%, 17.6%)	-0.4%	9.8%	8.3%	(5.5%, 11.6%)	1.5%
Free Safeties	3.9%	4.9%	(2.5%, 7.0%)	-1.0%	3.6%	5.7%	(2.9%, 8.4%)	-2.1%
Strong Safeties	3.6%	2.5%	(1.0%, 4.0%)	1.1%	3.2%	3.6%	(1.3%, 6.1%)	-0.3%
Kickers	0.4%	0.2%	(0.0%, 1.1%)	0.2%	1.8%	0.3%	(0.0%, 1.4%)	1.5%
Punters	0.6%	1.0%	(0.0%, 2.3%)	-0.4%	1.2%	1.4%	(0.0%, 3.2%)	-0.2%
Long Snappers	0.3%	0.0%	(0.0%, 0.6%)	0.3%	0.7%	0.0%	(0.0%, 1.3%)	0.7%

We emphasize that these results are derived for the representative team, and teams should not pursue the optimal allocations at the cost of ignoring their individual roster situations. For example, if a team has an elite quarterback, they may justifiably have to spend over twice the optimal allocation to retain him. The deviations we uncover are solely for the league in aggregate. In the left panel of Figure 3, we illustrate heterogeneity in actual allocations across teams averaged over seasons. Teams that struggled in our sample period, such as the Detroit Lions, had earlier draft picks and so had a higher percentage of their cap allocated to rookies. The Lions allocated the highest percentage of their cap to rookies, the Pittsburgh Steelers to veterans, the Atlanta Falcons to offense, the Miami Dolphins to defense, the Lions to quarterbacks ($\sim$7%), and the Cincinnati Bengals to non-quarterbacks ($\sim$ 14%). In the right panel, we plot actual vs. compensated wins (see Mulholland and Jensen 2019) for each team averaged across over seasons. Compensated wins are distinct from fitted wins in that they do not account for controls or fixed effects. Rather,

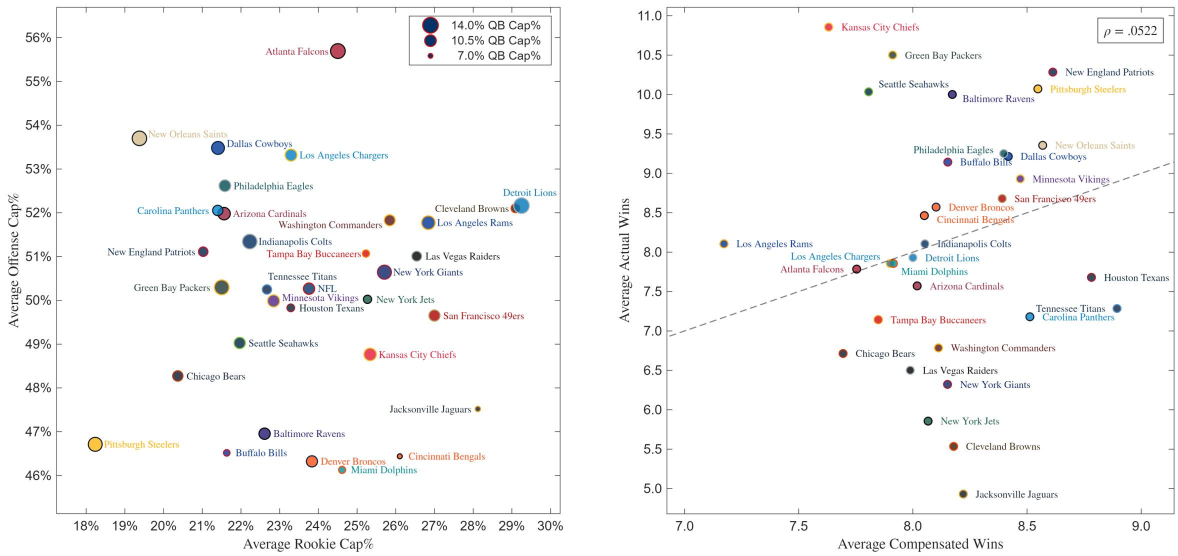

Figure 3: Actual Allocations, and Actual vs. Compensated Wins

they depend only on how close a team's actual cap allocations are to the optimal ones:

$$\text{CompWins}_i = \frac{1}{14}\sum_{j=2011}^{2024}\Big\{\sum_{p\in P}\hat{\beta}_p \sum_{c\in\{\text{Rook},\text{Vet}\}}\big[\hat{\alpha}_{pc}\log(\text{Cap\%}_{ijpc})\mathbb{1}(\text{Cap\%}_{ijpc}>0)+\hat{\alpha}'_{pc}\mathbb{1}(\text{Cap\%}_{ijpc}=0)+\hat{\eta}_{jpc}\big]+\hat{\eta}_j\Big\}. \tag{17}$$

Despite an importance R^2 of .8441 in Column 4 of Table 5 and cost effectiveness R^2s from .2788 to .7539 in Table 1, the correlation between actual and compensated wins was just .0522 because of the omission of the controls and fixed effects. This result reinforces that individual team situations matter when deciding how much of the cap to allocate to each position and contract type. Nevertheless, in the aggregate, we find four significant deviations out of 36 position-contract type groups, which at $11.\bar{1}\%$ is greater than the 5% we would expect if the true data-generating process had no deviations. Yet given the mean absolute difference of only 1.4% percentage points between the representative team's actual and optimal allocations, which are not estimated with teams' choice data, the NFL has behaved strongly in accordance with our model.

Having estimated a quarterback's marginal productivity and calibrated our cap optimization model to find the optimal allocations, we now analyze how the quarterback market has evolved over the duration of our sample. The purpose of this analysis is to provide a case study of a critical position's value changing over time, along with an industry updating its valuation of that critical position. Recall Figures 4 and 5 in Section 3, which show using hypothetical parameter values the magnitude of resource misallocation when failing to account for asymmetric spillovers and therefore undervaluing the critical position. It follows that if the industry starts to account for asymmetric spillovers, we should observe an increase in the critical position's valuation.

In Section 1, we reference Corry (2024), who wrote that since Kirk Cousins's free agency and subsequent record-setting contract in 2018, the quarterback position has undergone a "salary explosion." But we must still verify that such an explosion actually happened. We begin by rerunning our entire analysis but with the sample restricted to pre and post-2018. Per Table 7, actual rookie and veteran quarterback allocations increased post-2018 but by less than 1.5% points. This result is notable for rookie contracts because it happened in spite of the quarterbacks from 2011 to 2015 who were drafted before the 2011 collective bargaining agreement took effect.

However, the larger increase is in the optimal rookie and veteran quarterback valuations, which was caused largely by an increase in quarterback importance, as shown in Tables 21 and 22 of Appendix E. As a result, Table 7 shows that post-2018, rookie quarterbacks were significantly underdrafted by 7.0% points. This number is equivalent to drafting a quarterback every four years with the 25th instead of the 7th pick. There were several significant deviations post-2018, though some of them were likely due to the small sample relative to the number of parameters in the model, which does not decrease with the sample size. For example, the optimal kicker allocation was 0%, the optimal running back allocation was high (though still lower than in the baseline version in Table 23b of Appendix E),[22] and the optimal tight end and left tackle allocations were low. However, their 95% confidence bounds are reasonable, and the optimal quarterback allocation is less affected by the small sample than the other allocations. The reason is that this allocation is largely driven by the game-level quarterback valuation analysis, in which, given the presence of team-season fixed effects, the number of parameters decreases with the sample size.

Nevertheless, regardless of the increases in the optimal rookie and veteran quarterback allocations, the increases in the actual allocations were not much of an explosion. The contracts increased substantially in dollar terms, but that increase was due to the cap increasing from \$120,375,000 in 2011 to \$255,400,000 in 2024, not anything quarterback-specific. But what if the explosion were limited to expensive veteran quarterbacks like Cousins? Regarding those quarterbacks, Corry (2024) wrote, "The top of the quarterback market has more than doubled over the last seven years," and "Cousins broke new ground with the NFL's first lucrative fully guaranteed veteran contract during free agency." To answer this question, we use difference in differences to see if expensive (i.e. starting-caliber) veteran quarterback pay increased post-2018.

The details of this analysis are in Appendix F, and in Tables 25–27 of this appendix, we show that expensive veteran quarterback pay increased by 4.31% points relative to that of other players. Given that the representative team's actual and optimal allocations for veteran quarterbacks in Table 6 are 11.0% and 13.7% respectively, 4.31% points is a meaningfully large number. As such, in the case of expensive veteran quarterbacks, the NFL did in fact update its valuation of the critical position. Putting it all together, we find that in the NFL, the optimal valuation of inexperienced critical resources increased, and so did the actual valuation of expensive experienced critical resources. The main takeaway from this analysis is therefore that generally speaking, both the actual and optimal valuations of a critical position can change over time.

[22] Baseline results for the pre and post-2018 periods are in Tables 23 and 24 of Appendix E.

Table 7: Actual vs. Calibrated Optimal Allocations, Pre and Post-2018

(a) Pre-2018, Team-Clustered Bootstrap Confidence Intervals

	Rookies				Veterans			
	Actual	Optimal	95% CI	Difference	Actual	Optimal	95% CI	Difference
Quarterbacks	6.6%	4.5%	(0.8%, 11.1%)	2.1%	10.5%	11.9%	(2.1%, 24.8%)	-1.4%
Running Backs	7.4%	5.1%	(0.0%, 12.3%)	2.3%	5.9%	5.9%	(0.0%, 12.9%)	0.0%
Wide Receivers	12.2%	18.7%	(5.7%, 28.1%)	-6.5%	10.7%	11.1%	(2.9%, 18.0%)	-0.4%
Tight Ends	4.6%	2.8%	(0.0%, 5.9%)	1.8%	5.2%	4.5%	(0.0%, 9.5%)	0.7%
Left Tackles	5.5%	2.8%	(0.5%, 5.2%)	2.6%	4.5%	3.7%	(0.7%, 6.5%)	0.8%
Guards	7.5%	3.9%	(1.0%, 8.6%)	3.6%	6.0%	5.2%	(1.2%, 10.2%)	0.8%
Centers	2.6%	2.9%	(0.4%, 5.7%)	-0.2%	3.2%	4.9%	(0.7%, 9.8%)	-1.6%
Right Tackles	3.5%	1.9%	(0.0%, 5.1%)	1.6%	2.9%	2.1%	(0.0%, 5.5%)	0.8%
Defensive Ends	8.8%	8.2%	(4.3%, 13.6%)	0.6%	8.8%	7.6%	(4.5%, 11.6%)	1.2%
Defensive Tackles	8.0%	7.9%	(3.0%, 13.7%)	0.1%	7.0%	6.4%	(2.4%, 11.3%)	0.6%
Inside Linebackers	5.4%	6.0%	(2.1%, 10.4%)	-0.6%	5.5%	6.5%	(2.5%, 11.7%)	-0.9%
Outside Linebackers	8.5%	10.8%	(6.7%, 15.8%)	-2.3%	8.8%	8.5%	(4.9%, 13.4%)	0.3%
Cornerbacks	10.3%	14.4%	(5.8%, 23.3%)	-4.1%	10.3%	8.0%	(3.5%, 12.6%)	2.3%
Free Safeties	4.2%	5.7%	(2.7%, 9.3%)	-1.5%	3.4%	5.7%	(2.8%, 9.4%)	-2.3%
Strong Safeties	3.5%	2.5%	(0.7%, 5.2%)	1.0%	3.3%	4.5%	(1.2%, 8.2%)	-1.2%
Kickers	0.5%	0.8%	(0.0%, 2.0%)	-0.4%	1.9%	1.3%	(0.0%, 3.6%)	0.6%
Punters	0.6%	1.2%	(0.0%, 3.3%)	-0.6%	1.4%	2.3%	(0.0%, 6.8%)	-0.9%
Long Snappers	0.4%	0.0%	(0.0%, 0.8%)	0.4%	0.7%	0.0%	(0.0%, 1.9%)	0.7%

(b) Post-2018, Team-Clustered Bootstrap Confidence Intervals

	Rookies				Veterans			
	Actual	Optimal	95% CI	Difference	Actual	Optimal	95% CI	Difference
Quarterbacks	7.1%	14.4%	(7.4%, 24.6%)	-7.3%	11.6%	17.5%	(9.6%, 29.1%)	-5.9%
Running Backs	6.9%	20.1%	(8.3%, 28.0%)	-13.2%	4.4%	12.0%	(5.3%, 18.0%)	-7.6%
Wide Receivers	12.3%	13.8%	(2.5%, 23.1%)	-1.5%	11.9%	11.2%	(2.1%, 17.7%)	0.7%
Tight Ends	5.2%	0.0%	(0.0%, 2.0%)	5.2%	4.9%	0.0%	(0.0%, 3.2%)	4.9%
Left Tackles	4.1%	0.4%	(0.0%, 3.5%)	3.7%	5.7%	0.5%	(0.0%, 4.0%)	5.2%
Guards	6.4%	3.1%	(0.0%, 7.2%)	3.3%	5.9%	3.5%	(0.0%, 7.9%)	2.4%
Centers	2.5%	2.1%	(0.0%, 5.4%)	0.4%	3.5%	3.2%	(0.0%, 7.9%)	0.3%
Right Tackles	4.4%	2.4%	(0.0%, 7.0%)	2.0%	3.7%	3.0%	(0.0%, 8.7%)	0.6%
Defensive Ends	9.4%	3.8%	(0.2%, 8.8%)	5.6%	9.0%	5.3%	(0.3%, 10.7%)	3.6%
Defensive Tackles	6.7%	3.2%	(0.0%, 7.7%)	3.5%	7.9%	3.6%	(0.0%, 8.3%)	4.3%
Inside Linebackers	6.1%	5.0%	(2.0%, 8.6%)	1.1%	4.9%	6.0%	(2.4%, 9.3%)	-1.1%
Outside Linebackers	8.0%	10.0%	(5.9%, 15.4%)	-2.0%	7.1%	9.1%	(5.4%, 12.9%)	-2.0%
Cornerbacks	12.5%	13.1%	(5.9%, 21.6%)	-0.6%	9.4%	10.5%	(4.5%, 16.7%)	-1.1%
Free Safeties	3.6%	4.9%	(2.3%, 7.2%)	-1.3%	3.7%	8.6%	(3.8%, 12.6%)	-4.9%
Strong Safeties	3.6%	3.0%	(1.0%, 5.4%)	0.6%	3.2%	5.0%	(1.8%, 8.3%)	-1.8%
Kickers	0.3%	0.0%	(0.0%, 0.2%)	0.3%	1.7%	0.0%	(0.0%, 0.3%)	1.7%
Punters	0.6%	0.4%	(0.0%, 2.5%)	0.2%	1.0%	0.5%	(0.0%, 3.4%)	0.5%
Long Snappers	0.2%	0.2%	(0.0%, 1.3%)	0.0%	0.6%	0.5%	(0.0%, 2.5%)	0.1%

7 Conclusion

This paper studies how decision-makers allocate resources when production depends on critical-position driven asymmetric spillovers. We start by definining asymmetric spillovers, which occur when the observable performances of some positions depend asymmetrically on the unobservable true qualities of other positions. Next, we show that if there is a critical position that has asymmetric spillovers on the other positions, decision-makers may misattribute the critical position's effect on output to the other positions and so undervalue the critical position. Finally, we provide an identification strategy to recover the effects of each position's true quality on output.

We then provide an empirical application of this framework, with a significant challenge being that in many industry settings, the necessary data are private. Therefore, we follow the guidance of Palacios-Huerta (2025) and use professional sports, in particular the NFL, as a laboratory for our study. As such, we build a production function model that maps salary cap spending across positions and contract types into team wins, estimate the marginal win productivity of quarterbacks with game-level data, and use that estimate to calibrate the model and calculate the optimal cap allocation for each position and contract type. The NFL's institutional design, namely its hard cap and floor and its transparent performance measures, creates a uniquely structured environment for studying resource optimization in the presence of asymmetric spillovers.

We find that NFL teams exhibited a high degree of allocative efficiency. Although the model-implied optimal allocations are not estimated with teams' choice data, the mean absolute difference across all positions and contract types between the actual and optimal allocations was just 1.4% points. This result implies that, at least in the aggregate, teams behaved like decision-makers maximizing expected output subject to binding constraints. Such near-optimality is notable given that the model abstracts from dynamic factors, heterogeneity in team objectives (which is why our results are for the representative team), and frictions from existing contracts.

At the same time, there were a few systematic deviations. Quarterbacks emerged as the most valuable position, with elite starters contributing about 3.5 wins per season above replacement. Once we explicitly identify quarterbacks' marginal win productivity and account for asymmetric spillovers between quarterbacks and other offensive players, we no longer observe a lower importance effect for quarterbacks than for running backs and wide receivers. As such, veteran quarterback pay appears consistent with optimal behavior. However, since 2018, rookie quarterbacks have become underdrafted relative to model predictions. One plausible explanation is risk aversion. Because failed quarterback selections are highly visible and costly, teams may prefer to avoid taking a large risk when drafting a quarterback, even if the upside is high. Also, since Kirk Cousins's free agency in 2018, expensive veteran quarterback pay has significantly increased.

In addition, we find that teams overvalued left tackles (in accordance with Mulholland and Jensen 2019), rookie tight ends, and veteran kickers. Left tackles, who protect their team's quarterback, may serve as insurance against quarterback injury and so command a premium due to teams' risk aversion. Highly-drafted rookie tight ends, by contrast, have historically underperformed their draft positions, while some of the best tight ends were drafted outside the first round (Helman 2023). For this reason, rookie tight ends have the lowest cost effectiveness estimate across all offensive and defensive positions and contract types. Finally, the overpayment of veteran kickers reflects three factors. First is the high volatility of kicker performance across seasons (Berri & Schmidt 2013). Outside a few consistently elite kickers, past success was only weakly predictive of future outcomes. Therefore, the best kickers were often not the highest-paid ones, which results in lower kicker cost effectiveness estimates than any on offense or defense. (Though as with tight ends, if teams improve at valuing kickers, then optimal kicker pay will increase.) Second is that kicker AV does not factor in performance on kickoffs (Drinen 2008), which reduces the importance estimate. And third is that teams may be willing to pay a premium to avoid losing a game on a last-minute missed kick. Overall, these patterns show that even optimizing decision-makers may misallocate resources when facing noisy signals of productivity.

Ultimately however, even as the model abstracts from dynamics, heterogeneity, frictions, and incentives other than win maximization, it still fits the behavior of NFL teams across most positions and contract types. We believe that this result is due to the hard salary cap that makes Vrooman (2009) deem the NFL a "perfect portfolio," plus the floor preventing owners from maximizing profits at the expense of wins (Coates et al. 2024). Moreover, competition and transparent incentives can induce nearly optimal behavior even in complex, interdependent production settings like the NFL. Future work might model cap optimization dynamics, explore heterogeneity across team philosophies, study frictions that prevent teams from achieving their preferred allocations, and factor in any second-order profit-maximizing behavior. Yet models such as this one still fit the data well and can guide the league toward better decision-making. Finally, of no less importance, they can serve as a framework to study decision-makers engaging in production function-based resource optimization under critical position-driven asymmetric spillovers.

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A Proofs of Theorems

Theorem 1. *If* $0 < \text{AME}_{q_1} \leq \text{AME}_{q_2}$*, then* $\text{AME}_{q_1} - \text{AME}_{Q_1} < 0$ *and* $\text{AME}_{q_2} - \text{AME}_{Q_2} > 0$*.*

Proof. Recall that each q_i is a convex combination of Q_i and Q_j:

$$\begin{aligned} q_{1i} &= \theta_{10} + \theta_{11} Q_{1i} + (1-\theta_{11}) Q_{2i} + u_{1i}, \\ q_{2i} &= \theta_{20} + \theta_{21} Q_{2i} + (1-\theta_{21}) Q_{1i} + u_{2i}. \end{aligned} \tag{18}$$

We start with the specification without an interaction term:

$$y_i = \beta_0 + \beta_1 q_{1i} + \beta_2 q_{2i} + \varepsilon_i. \tag{19}$$

The AMEs of q_1, Q_1, q_2, and Q_2 are as follows:

$$\begin{aligned} \text{AME}_{q_1} = \beta_1,\ \text{AME}_{Q_1} = \beta_1\theta_{11} + \beta_2(1-\theta_{21}), \\ \text{AME}_{q_2} = \beta_2,\ \text{AME}_{Q_2} = \beta_2\theta_{21} + \beta_1(1-\theta_{11}). \end{aligned} \tag{20}$$

Taking differences and using the assumptions in the theorem, we have:

$$\begin{aligned} \text{AME}_{q_1} - \text{AME}_{Q_1} = (1-\theta_{11})\beta_1 - (1-\theta_{21})\beta_2 < 0, \\ \text{AME}_{q_2} - \text{AME}_{Q_2} = (1-\theta_{21})\beta_2 - (1-\theta_{11})\beta_1 > 0. \end{aligned} \tag{21}$$

Intuitively, suppose Position 1 has greater spillovers on Position 2 than vice versa, and the effect of Position 2's observed quality on output is greater than that of Position 1. Then Position 1's effect on output is too low relative to that of its true quality, and Position 2's is too high.

Next, we proceed to the specification with an interaction term:

$$y_i = \beta_0 + \beta_1 q_{1i} + \beta_2 q_{2i} + \beta_{12} q_{1i} q_{2i} + \varepsilon_i. \tag{22}$$

Assuming $\mathbb{E}[u_1] = \mathbb{E}[u_2] = 0$, the AMEs of q_1 and q_2 are:

$$\begin{aligned} \text{AME}_{q_1} &= \beta_1 + \beta_{12}\mathbb{E}[q_2] \\ &= \beta_1 + \beta_{12}\mathbb{E}[\theta_{20} + \theta_{21}Q_2 + (1-\theta_{21})Q_1 + u_2] \\ &= \beta_1 + \beta_{12}(\theta_{20} + \theta_{21}\mathbb{E}[Q_2] + (1-\theta_{21})\mathbb{E}[Q_1]), \\ \text{AME}_{q_2} &= \beta_2 + \beta_{12}(\theta_{10} + \theta_{11}\mathbb{E}[Q_1] + (1-\theta_{11})\mathbb{E}[Q_2]). \end{aligned} \tag{23}$$

In addition, the AMEs of Q_1 and Q_2 are:

$$\begin{aligned} \text{AME}_{Q_1} &= \beta_1\theta_{11} + \beta_2(1-\theta_{21}) + \beta_{12}\mathbb{E}[\theta_{11}(\theta_{20} + \theta_{21}Q_2 + (1-\theta_{21})Q_1 + u_1) + (1-\theta_{21})(\theta_{10} + \theta_{11}Q_1 + (1-\theta_{11})Q_2 + u_2)] \\ &= \beta_1\theta_{11} + \beta_2(1-\theta_{21}) + \beta_{12}(\theta_{11}\theta_{20} + \theta_{11}\theta_{21}\mathbb{E}[Q_2] + \theta_{11}(1-\theta_{21})\mathbb{E}[Q_1] + (1-\theta_{21})\theta_{10} + (1-\theta_{21})\theta_{11}\mathbb{E}[Q_1] + (1-\theta_{21})(1-\theta_{11})\mathbb{E}[Q_2 \\ \text{AME}_{Q_2} &= \beta_2\theta_{21} + \beta_1(1-\theta_{11}) + \beta_{12}(\theta_{21}\theta_{10} + \theta_{21}\theta_{11}\mathbb{E}[Q_1] + \theta_{21}(1-\theta_{11})\mathbb{E}[Q_2] + (1-\theta_{11})\theta_{20} + (1-\theta_{11})\theta_{21}\mathbb{E}[Q_2] + (1-\theta_{11})(1-\theta_{21})\mathbb{E}[Q_1 \end{aligned} \tag{24}$$

Taking differences and using the assumptions in the theorem, we have:

$$\begin{aligned} \text{AME}_{q_1} - \text{AME}_{Q_1} &= (1-\theta_{11})(\beta_1 + \beta_{12}(\theta_{20} + \theta_{21}\mathbb{E}[Q_2] + (1-\theta_{21})\mathbb{E}[Q_1])) - (1-\theta_{21})(\beta_1 + \beta_{12}(\theta_{10} + \theta_{11}\mathbb{E}[Q_1] + (1-\theta_{11})\mathbb{E}[Q_2])) \\ &= (1-\theta_{11})\text{AME}_{q_1} - (1-\theta_{21})\text{AME}_{q_2} < 0, \\ \text{AME}_{q_2} - \text{AME}_{Q_2} &= (1-\theta_{21})(\beta_1 + \beta_{12}(\theta_{10} + \theta_{11}\mathbb{E}[Q_1] + (1-\theta_{11})\mathbb{E}[Q_2])) - (1-\theta_{11})(\beta_1 + \beta_{12}(\theta_{20} + \theta_{21}\mathbb{E}[Q_2] + (1-\theta_{21})\mathbb{E}[Q_1])) \\ &= (1-\theta_{21})\text{AME}_{q_2} - (1-\theta_{11})\text{AME}_{q_1} > 0. \end{aligned} \tag{25}$$

As such, while including an interaction term accounts for any complementarities in the production function, doing so does not correct asymmetric spillovers misattribution from the inputs.

Theorem 2. *The slope coefficient from regressing q_1 on $(1, q_2)$ is strictly positive. If it equals 1, then $\beta_2^C = \text{AME}_{Q_2}$. That is, CLS perfectly recovers AME_{Q_2}.*

Proof. The slope from regressing q_1 on $(1, q_2)$ is $\frac{\text{Cov}(q_1,q_2)}{\text{Var}(q_2)}$. Assuming Q_1 and Q_2 are independent and not constant; and assuming u_1 and u_2 are independent of Q_1, Q_2, and each other:

$$\begin{aligned}\text{Cov}(q_1,q_2) &= \text{Cov}(\theta_{10}+\theta_{11}Q_1+(1-\theta_{11})Q_2+u_1, \theta_{20}+\theta_{21}Q_2+(1-\theta_{21})Q_1+u_2) \\ &= \theta_{11}(1-\theta_{21})\text{Var}(Q_1)+(1-\theta_{11})\theta_{21}\text{Var}(Q_2) > 0.\end{aligned} \tag{26}$$

Intuitively, if two positions have positive spillovers on each other, then their observable qualities will be positively correlated. Since $\text{Var}(q_2)$ is also strictly positive, the slope coefficient is strictly positive, though it has no upper bound. Recall that with two regressors, CLS's formula is:

$$\beta_2^C = \beta_2 + \frac{\text{Cov}(q_1,q_2)}{\text{Var}(q_2)}(\beta_1 - \beta_1^C) \tag{27}$$

Suppose we identified the true AME_{Q_1}, which we denote as $\beta_1^C = \beta_1\theta_{11} + \beta_2(1-\theta_{21})$. Then:

$$\begin{aligned}\beta_2^C &= \beta_2 + \frac{\text{Cov}(q_1,q_2)}{\text{Var}(q_2)}(\beta_1(1-\theta_{11}) - \beta_2(1-\theta_{21})) \\ &= \beta_2\theta_{21} + \beta_1(1-\theta_{11}) \\ &= \text{AME}_{Q_2}.\end{aligned} \tag{28}$$

Because $\beta_1(1-\theta_{11}) - \beta_2(1-\theta_{21}) < 0$, the correction on $\text{AME}_{q_2} = \beta_2$ is downward. If $\frac{\text{Cov}(q_1,q_2)}{\text{Var}(q_2)} \in (0,1)$, then CLS undercorrects, whereas if it is greater than 1, then CLS overcorrects. In contrast, if it equals 1, then CLS corrects perfectly and recovers AME_{Q_2}. This procedure also works both ways; we can analagously use CLS to recover AME_{Q_1} if we identified AME_{Q_2}.

B General Model

We present a general framework for modeling the resource optimization problem of decision-makers under critical position-driven asymmetric spillovers. For example, suppose a firm has to decide how much of its budget to allocate toward its workers and machines, but it employs a supervisor who affects these other resources more than the other way around. As such, if the firm does not account for those asymmetric spillovers, then it will undervalue the supervisor.

In the following equations, let y be the gross objective (e.g. revenue) of the decision-makers being modeled, q be positional performance measures for the resources (e.g. performance reviews),[23] x be control variables and/or (in Equation 29 only) interaction terms for the positional performance measures, and a be positional allocations. Then for decision-maker i, long-run period j (i.e. sufficiently long to choose an allocation), position p, and critical position p^*:

$$y_{ij} = \beta_{p^*} q_{ijp^*} + q_{ij\neg p^*} \beta_{\neg p^*} + x_{ij}\delta + \xi_i + \eta_j + \varepsilon_{ij}, \tag{29}$$

$$\text{where } \forall p \in P,\ q_{ijp} = \alpha_p \frac{a_{ijp}^{1-\gamma}}{1-\gamma} + x_{ij}\delta_p + \xi_{ip} + \eta_{jp} + \nu_{ijp}. \tag{30}$$

Regarding the parameters, β_p measures the effect of each position's performance on the gross objective y, α_p the effect of each position's allocation a on its performance q, δ and δ_p the effects of the control variables and any interactions on y and q respectively, and γ the relative degree of diminishing returns to a as part of an isoelastic transformation. To ensure a closed-form solution to the optimization problem, γ must be constant across p. For example, for the semi-elastic interpretability of a linear-log model, we can choose $\gamma \to 1$. However, if a has any zero-valued observations, $\gamma \in (0,1)$ (e.g. $\gamma = \frac{1}{2}$, which results in $\sqrt{a}$) is required to handle them.

Despite the inclusion of decision-maker and time fixed effects ξ_i and η_j in both equations, it is necessary for y_{ij}, q_{ijp}, x_{ij}, and a_{ijp} to be normalized by the decision-maker's period budget constraint $\overline{a}_{ij}$, which transforms a_{ijp} into allocation shares. Otherwise, if there were an ij combination with an unusually high $\overline{a}$, the allocation chosen in that ij may spuriously appear effective, even if the high budget were the cause of that effectiveness, as opposed to the allocation itself. As long as there is variation in the normalized variables across j, this setup can model a single decision-maker's optimization problem. And with variation across i, it can also model multiple decision-makers in one long-run period. Thus, it remains useful if data exist only across i or j.

Ultimately, Equations 29 and 30 decompose the optimization problem into two stages, which we deem "importance" (the importance of each position to the decision-maker) and "cost effectiveness" (how effective allocating resources toward a position is at increasing that position's performance). Without loss of generality, it is possible to have a position with high importance and low cost effectiveness. For example, a position at a firm may be important to the firm but also

[23] The measures may differ across the positions whose allocations the decision-makers choose (e.g. performance reviews for workers or overall equipment effectiveness for machines), as q is an intermediary in mapping a to y.

hard to evaluate at the time of the hiring or retention decision. Therefore, empirically, allocating more of the budget toward that position will yield barely any performance gains. As such, despite that position's importance, it may not be a good idea for the firm to allocate too much toward it.

We decompose the problem in this way so that we can estimate each position's cost effectiveness separately, which is necessary because due to the budgetary normalization, $a_{ijp} = 100\% - \sum_{p' \neq p} a_{ijp'}$. As such, estimating a one-stage model where $y = f(a)$, or letting each position's performance depend on the allocations of all the positions, would result in near-perfect multicollinearity. To circumvent this problem, we follow Mulholland and Jensen (2019) and assume the allocation of position $p' \neq p$ does not affect the performance of p. While the performance of p' can affect the performance of p, we account for that effect in Equation 29.

Given Equations 29 and 30, an equilibrium is a set of allocations $\{a_p^*\}_{p \in P}$ such that:

1. **Optimization:** In each representative long-run period j, each representative decision-maker i maximizes $\hat{y}$ (i.e. gross output as a function of a and estimates $\hat{\beta}$ and $\hat{\alpha}$) subject to their budget constraint, along with non-negativity constraints for each positional allocation:

$$\max_{a_{ijp}} \hat{y}_{ij}, \text{ where } \sum_{p \in P} a_{ijp} = 100\%, \text{ and } \forall p \in P,\ a_{ijp} \geq 0\%. \tag{31}$$

   If Equation 29 has no interactions, solving a Lagrangian yields optimal interior allocations:

$$a_{ijp}^* = a_p^* = \frac{100\% (\hat{\beta}_p \hat{\alpha}_p)^{\frac{1}{\gamma}}}{\sum_{p \in P} (\hat{\beta}_p \hat{\alpha}_p)^{\frac{1}{\gamma}}}. \tag{32}$$

2. **Market Clearing:** Because the optimal allocations are the same for each ij:

$$\frac{1}{IJ} \sum_{(i,j,p) \in I \times J \times P} a_{ijp}^* = \sum_{p \in P} a_p^* = 100\%. \tag{33}$$

There is not a market clearing condition for each position because in each period j, each decision-maker i can choose to allocate anywhere from 0% to their entire budget to each position. We do not model a fixed amount of resources for each position to be allocated across each i and j.

In addition, in this model, constrained maximization is a generalization of unconstrained maximization. By recasting the problem as the unconstrained maximization of the decision-maker's net objective, it reduces to a static (i.e. with budget constant across ij) competitive market, in which the optimal allocation for each position is a function of that position's marginal product:

$$\max_{a_{ijp}} \left(\hat{y}_{ij} - \sum_{p \in P} a_{ijp} \right) \Rightarrow a_p^* = (\hat{\beta}_p \hat{\alpha}_p)^{\frac{1}{\gamma}}, \text{ with market clearing: } \sum_{p \in P} a_p^* = \sum_{p \in P} (\hat{\beta}_p \hat{\alpha}_p)^{\frac{1}{\gamma}}. \tag{34}$$

Now suppose the critical position p^* has asymmetric positive spillovers on the other positions $\neg p^*$. Perhaps p^* is the supervisor position that affects the other positions in the firm more than the other way around. Then in the estimation of Equation 29, $\hat{\beta}_{p^*}$ will be too low, and $\hat{\beta}_{\neg p^*}$ will be too high. In turn, given Equation 32, $a^*_{p^*}$ will be too low and $a^*_{\neg p^*}$ will be too high, which means the decision-maker will undervalue the critical position and overvalue the other ones. Although adding interactions to Equation 29 would allow us to identify any complementarities, interactions cannot identify asymmetric spillovers because spillovers are distinct from complementarities. For this reason, we omit interactions from Equation 32, though the model still works with them.

Therefore, we proceed as follows. For each short-run period t (i.e. too short for the decision-maker to change their allocation across t) within long-run j, the importance equation is:

$$y_{ijt} = \tilde{\beta}_{p^*}\tilde{q}_{ijtp^*} + \tilde{x}_{ijt}\tilde{\delta} + \tilde{\xi}_{ij} + \tilde{\varepsilon}_{ijt}. \tag{35}$$

To obtain a consistent estimate of the parameter of interest $\hat{\tilde{\beta}}_{p^*}$, we first need a short-run performance measure for p^*, which need not be normalized with respect to the budget because we will later rescale $\hat{\tilde{\beta}}_{p^*}$. We also need to assume that within decision-maker-long-run period pairs ij:

Assumption 2.1. *The aggregate quality of the non-critical positions $\neg p^*$ is stable across t.*

Under this assumption, fixed effects ξ_{ij} are able to control for that quality. Controls $\tilde{x}_{ijt}$, which also need not be normalized, help account for any instability. ξ_{ij} and $\tilde{x}_{ijt}$ may be sufficient to estimate $\hat{\tilde{\beta}}_{p^*}$ consistently, but if $\tilde{q}_{ijtp^*}$ is still endogenous, we can select on unobservables as well as observables. To do so, we need changes in the availabilities of specific critical resources n, where n is a component of p^*. For example, if a specific supervisor $n \in p^*$ takes a sick day, a different supervisor $n' \in p^*$ may temporarily replace him or her. We assume that within ij pairs:

Assumption 2.2. *The quality of each critical resource n is constant across short-run periods t.*

Assumption 2.3. *The aggregate quality of the non-critical positions $\neg p^*$, as well as any remaining unobservables, are constant across n.*

Intuitively, suppose Supervisor 2 is Supervisor 1's replacement. Then we assume both supervisors' unobserved true qualities (which are distinct from their performances) are constant across t within ij, and we assume that (without loss of generality) Supervisor 1 does not have access to better resources than Supervisor 2. The latter assumption is weaker than assuming that the quality of the non-critical positions is constant across t because the quality of the non-critical positions may average out across t within n. As such, we can use $\tilde{q}_{ijnp^*}$ as a proxy or an instrument for $\tilde{q}_{ijtp^*}$, where $\tilde{q}_{ijnp^*}$ is n's average $\tilde{q}_{ijtp^*}$ across t within ij. We can also now control for $\tilde{q}_{ijt\neg p^*}$ (if a short-run performance measure for $\neg p^*$ exists) while avoiding asymmetric spillovers misattribution, since $\tilde{q}_{ijt\neg p^*}$ is on a different level from $\tilde{q}_{ijnp^*}$ and so provides sufficient identifying variation. If there are machines, $\tilde{q}_{ijt\neg p^*}$ could be their daily overall equipment effectivenesses.

The next step, once we have obtained a consistent $\hat{\tilde{\beta}}_{p^*}$, is to use it to calibrate Equation 29 by first transforming it to $\hat{\beta}_{p^*}$'s scale, where τ is a short to long-run period conversion factor:

$$\hat{\beta}^C_{p^*} = \tau\hat{\tilde{\beta}}_{p^*}\frac{\sigma_{\tilde{q}_{ijp^*}}}{\sigma_{q_{ijp^*}}}. \tag{36}$$

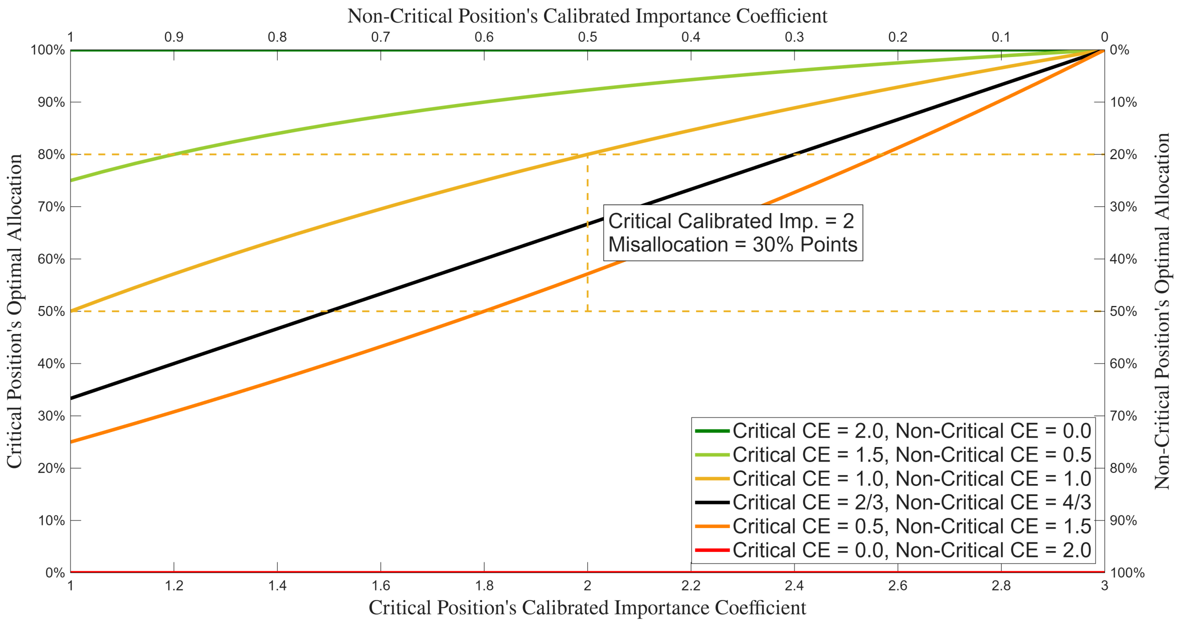


Figure 4: Comparative Statics for $(\alpha_{p^*}, \alpha_{\neg p^*})$

For this transformation to work, the short-run objective y_{ijt} must sum to the long-run objective y_{ij} across t within ij. This property holds if, for example, $y =$ the firm's daily vs. annual revenue. If short-run performance $\tilde{q}_{ijtp^*}$ likewise increases when summing across t (i.e. $\tilde{q}$ is a count measure, such as tasks completed), $\tau = 1$ and is therefore unnecessary. (In contrast, if $\tilde{q}_{ijtp^*}$ is a rate measure, such as percentage of tasks completed, then $\tau = \overline{T}$, the average number of short-run periods per ij.) And if the short-run performance measure $\tilde{q}$ is the same as the long-run measure q, $\sigma_{\tilde{q}_{ijp^*}} = \sigma_{q_{ijp^*}}$ and the σ ratio is unnecessary. Finally, we use $\hat{\beta}^C_{p^*}$ to calibrate Equation 29:

$$y_{ij} = \hat{\beta}^C_{p^*} q_{ijp^*} + q_{ij\neg p^*}\beta_{\neg p^*} + x_{ij}\delta + \xi_i + \eta_j + \varepsilon_{ij}. \tag{37}$$

The simplest way to estimate the rest of Equation 29's parameters is constrained least squares with constraint $R\beta = \beta_{p^*} = \hat{\beta}^C_{p^*} = r$, where C stands for calibrated. In Figures 4 and 5, we use the two-position case, in which constrained least squares reduces to $\hat{\beta}^C_{\neg p^*} = \hat{\beta}_{\neg p^*} + \rho \frac{\sigma_{q_{p^*}}}{\sigma_{q_{\neg p^*}}} (\hat{\beta}_{p^*} - \hat{\beta}^C_{p^*})$, to illustrate a simple example. Without loss of generality, σ_{q_p} is the variance of q_p, and ρ is the correlation between q_{p^*} and $q_{\neg p^*}$. Nonlinear least squares can also work to estimate the rest of the parameters if we wish to impose additional nonlinear constraints, such as nonnegativity constraints on $\beta_{\neg p^*}$. Either way, since $\hat{\beta}^C_{p^*}$ is a generated regressor, the standard errors, along with any confidence intervals about a^*_p, must be bootstrapped across the entire procedure.

Both figures are analogous to an Edgeworth box, in which the bottom x-axis is the critical position's calibrated importance coefficient $\hat{\beta}^C_{p^*}$, the left y-axis is the critical position's optimal allocation $a^*_{p^*}$, and the top and right axes are the non-critical position's $\hat{\beta}^C_{\neg p^*}$ and $a^*_{\neg p^*}$, respectively. In Figure 4, we initialize $\gamma \to 1$, $\hat{\beta}_{p^*} = \hat{\beta}_{\neg p^*} = 1$, $\sigma^2_{q_{p^*}} = \sigma^2_{q_{\neg p^*}} = 1$, and $\rho = 0.5$. As we move rightward along the bottom axis, $\hat{\beta}^C_{p^*}$ increases from 1 (i.e. no asymmetric spillovers) to 3,

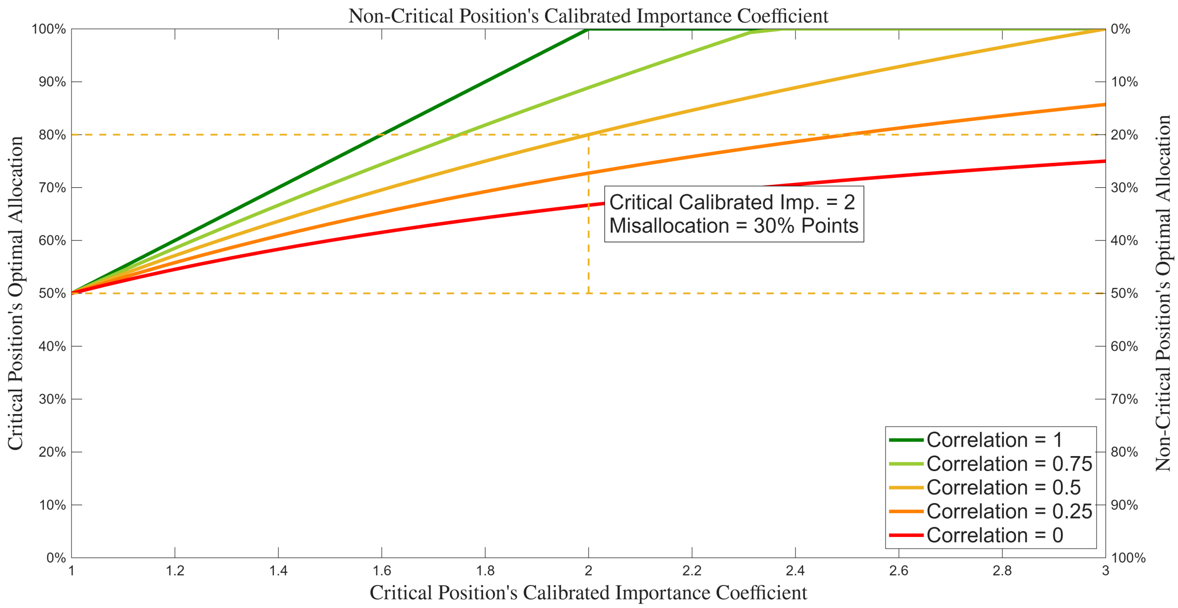


Figure 5: Comparative Statics for ρ

meaning that $\hat{\beta}^C_{\neg p^*}$ decreases per the constrained least squares formula, and $a^*_{p^*}$ and $a^*_{\neg p^*}$ change accordingly. Each separate line represents different cost-effectiveness parameters α_{p^*} and $\alpha_{\neg p^*}$. Linearity occurs at $\alpha_{p^*} = \frac{2}{3}$ and $\alpha_{\neg p^*} = \frac{4}{3}$, and the horizontal dark green and red lines correspond to the cases where one of the positions has zero cost effectiveness. As p^*'s relative cost effectiveness increases, there is a greater level shift toward $a^*_{p^*}$. Also, if $\hat{\beta}^C_{p^*} = 2$ and $\alpha_{p^*} = \alpha_{\neg p^*} = 1$, the misallocation if we fail to account for asymmetric spillovers is 30% points, which is the difference between $a^*_{p^*} = 50\%$ and $a^*_{p^*} = 80\%$. Meanwhile, Figure 5 differs from Figure 4 in that we initialize $\alpha_{p^*} = \alpha_{\neg p^*} = 1$ and instead allow ρ to vary from 1 to 0 across lines. The stronger the correlation between q_{p^*} and $q_{\neg p^*}$, the greater the marginal shift toward $a^*_{p^*}$ as $\hat{\beta}^C_{p^*}$ increases.

Ultimately, this model is both general in that it can handle a variety of situations in which asymmetric spillovers affect resource optimization, and simple in that we do not include any more features than are generally necessary. In the main paper, we apply this model to the NFL and add additional features, such as rookie vs. veteran contracts. Likewise, for a different setting, we recommend adding any features necessary for that setting. But the NFL is ideal for our empirical application because unlike other settings, all the necessary data are publicly available.

C Appendix: Baseline Salary Cap Optimization

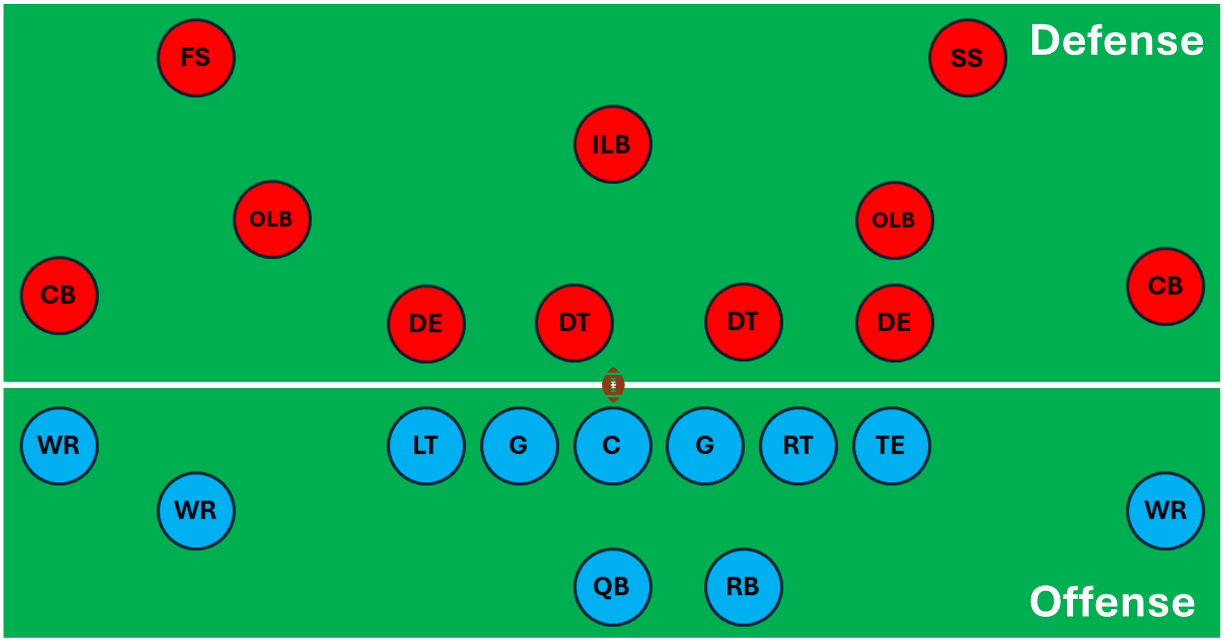


Figure 6: Shotgun Offense vs. Cover 2 Defense

Offense (Blue): QB = Quarterback, RB = Running Back, WR = Wide Receiver, TE = Tight End, LT = Left Tackle, G = Guard, C = Center, RT = Right Tackle

Defense (Red): DE = Defensive End, DT = Defensive Tackle, ILB = Inside Linebacker, OLB = Outside Linebacker, CB = Cornerback, FS = Free Safety, SS = Strong Safety

Special Teams (Not Pictured): K = Kicker, P = Punter, LS = Long Snapper

Table 8: Cap Optimization Summary Statistics, 2011–2024 ($N = 448$)

	Mean	SD	Min	Max
Wins	8.14	3.11	0	15
Vegas Wins O/U	8.27	1.76	4	13
Coach of the Year	0.21	0.41	0	1
Approximate Value (AV)	206.44	26.82	144	282
Cap Spending	$170,181,777	$40,567,335	$87,714,296	$261,363,792
Rookie AV	85.84	17.64	39	147
Veteran AV	120.60	24.30	61	214
Rookie Cap%	23.76%	6.51%	9.72%	53.86%
Veteran Cap%	76.24%	6.51%	46.14%	90.28%
Offense AV	100.21	21.50	47	170
Quarterbacks AV	12.73	4.00	-3	27
Running Backs AV	14.93	4.15	5	31
Wide Receivers AV	22.42	5.65	8	47
Tight Ends AV	7.09	2.88	1	24
Left Tackles AV	9.03	4.00	0	23
Guards AV	16.56	5.78	3	53
Centers AV	8.61	3.65	0	22
Right Tackles AV	8.85	3.98	0	23
Defense AV	99.54	15.28	61	169
Defensive Ends AV	17.09	7.65	0	41
Defensive Tackles AV	16.44	6.22	2	38
Inside Linebackers AV	14.55	6.67	0	43
Outside Linebackers AV	16.95	6.66	4	48
Cornerbacks AV	18.43	4.84	7	39
Free Safeties AV	8.62	4.17	0	25
Strong Safeties AV	7.46	4.06	0	27
Special Teams AV	6.68	1.80	2	14
Kickers AV	3.14	1.40	-2	8
Punters AV	2.30	0.90	0	6
Long Snappers AV	1.25	0.74	0	6
Offense Cap%	50.27%	5.86%	29.35%	71.52%
Quarterbacks Cap%	10.28%	4.65%	0.64%	26.18%
Running Backs Cap%	5.60%	2.61%	1.54%	14.91%
Wide Receivers Cap%	11.48%	3.76%	3.50%	23.72%
Tight Ends Cap%	5.01%	2.16%	1.27%	15.58%
Left Tackles Cap%	5.10%	2.95%	0.00%	15.37%
Guards Cap%	6.15%	2.82%	0.70%	18.78%
Centers Cap%	3.19%	1.94%	0.00%	10.06%
Right Tackles Cap%	3.45%	2.08%	0.00%	12.22%
Defense Cap%	46.67%	5.82%	27.37%	67.09%
Defensive Ends Cap%	8.94%	4.83%	0.23%	22.88%
Defensive Tackles Cap%	7.40%	4.11%	0.38%	24.22%
Inside Linebackers Cap%	5.28%	2.93%	0.39%	16.00%
Outside Linebackers Cap%	7.98%	4.54%	0.41%	24.63%
Cornerbacks Cap%	10.08%	3.96%	2.19%	22.15%
Free Safeties Cap%	3.66%	2.32%	0.32%	11.99%
Strong Safeties Cap%	3.33%	2.25%	0.15%	12.01%
Special Teams Cap%	3.06%	1.16%	0.90%	9.58%
Kickers Cap%	1.45%	0.83%	0.00%	4.16%
Punters Cap%	1.04%	0.69%	0.00%	4.58%
Long Snappers Cap%	0.57%	0.19%	0.00%	1.20%

Table 9: Correlations of AV Across Positions ($N = 448$)

	QB	RB	WR	TE	LT	G	C	RT	DE	DT	ILB	OLB	CB	FS	SS	K	P	LS
Quarterbacks	1																	
Running Backs	.6311	1																
Wide Receviers	.7379	.4555	1															
Tight Ends	.5202	.3713	.1758	1														
Left Tackles	.4213	.3315	.3245	.2574	1													
Guards	.4587	.4344	.4020	.2860	.0450	1												
Centers	.4161	.3452	.3276	.2800	.2388	-.0833	1											
Right Tackles	.3762	.2619	.3261	.2357	-.1812	-.0769	.2105	1										
Defensive Ends	-.0170	.0493	-.0499	-.1022	.0394	-.0227	-.0191	-.1039	1									
Defensive Tackles	.0613	.0503	.0602	.0334	-.0692	-.0044	.0425	.1203	-.2425	1								
Inside Linebackers	-.0440	.0140	-.0777	.0211	.1258	-.0544	-.0309	-.0822	-.1069	-.0008	1							
Outside Linebackers	.0538	.0624	.0539	.1178	.0198	-.0113	.1540	.1200	-.2624	.0051	-.1481	1						
Cornerbacks	-.0079	-.0068	-.0178	-.0566	-.0351	-.0299	-.0607	.0127	.1562	.1836	.1559	.1585	1					
Free Safeties	-.0360	.0303	-.1131	.0612	.0622	-.0322	.0457	-.1619	.0903	.1608	.1925	.0486	.0849	1				
Strong Safeties	.1255	.0625	.1410	-.0360	.0692	-.0230	.0932	.0716	.0160	-.0067	.0116	.0892	-.0317	-.4530	1			
Kickers	.0983	.1159	.0465	.1121	.0712	-.0116	.1109	.0650	-.0444	-.0572	.0194	.0315	.0441	.0182	.0105	1		
Punters	-.2322	-.1267	-.1937	-.0625	-.0744	-.1127	-.1651	-.0883	.0796	-.0866	.0185	-.0172	-.0405	.0168	-.0036	-.0535	1	
Long Snappers	-.0125	.0219	.0032	-.0520	-.0365	.0136	.0621	.0281	.0362	.0184	-.1210	.0492	-.1055	.0052	.0054	.0471	-.0274	1

Table 10: $\sqrt{\text{Cap\%}}$ Cost Effectiveness Results ($N = 448$)

	Rookies					Veterans				
	$\sqrt{\text{Cap\%}}$	Vegas Wins	2011 Colts	Season	R^2 [Adj R^2]	$\sqrt{\text{Cap\%}}$	Vegas Wins	2011 Colts	Season	R^2 [Adj R^2]
Quarterbacks AV	2.7705***	-.0065	-3.5072***	-.0145	.5030	2.9989***	1.1193***	-8.9760***	-.0276	.5780
	(.2006)	(.1586)	(.5610)	(.0781)	[.4607]	(.1925)	(.1746)	(.4832)	(.0644)	[.5422]
Running Backs AV	3.2853***	.0845	-5.7588***	.0606	.3380	3.9022***	.4299***	-4.7676***	.0758	.5008
	(.3944)	(.1863)	(.5367)	(.0569)	[.2818]	(.2830)	(.1230)	(.4581)	(.0541)	[.4584]
Wide Receivers AV	3.7418***	-.0116	-.8550*	-.0122	.3923	3.8460***	.7693***	-4.9375***	-.0444	.4706
	(.3892)	(.1380)	(.5006)	(.0734)	[.3406]	(.2617)	(.2229)	(.6764)	(.0935)	[.4256]
Tight Ends AV	1.9843***	-.0439	-2.4590***	-.0344	.3491	2.4302***	.3383***	-5.1899***	.0212	.4911
	(.1530)	(.0978)	(.3338)	(.0491)	[.2938]	(.1842)	(.0896)	(.4059)	(.0443)	[.4478]
Left Tackles AV	2.5061***	-.0417	-1.4687***	-.0013	.6144	2.8582***	.3887***	1.8941***	-.0187	.5459
	(.1925)	(.0859)	(.3655)	(.0464)	[.5817]	(.1236)	(.1275)	(.3565)	(.0474)	[.5074]
Guards AV	3.0057***	.2964**	-2.8049***	-.0812	.5071	4.1376***	.3590**	-.4905	-.0948	.4881
	(.2415)	(.1250)	(.5699)	(.0528)	[.4652]	(.3842)	(.1509)	(.5673)	(.0832)	[.4446]
Centers AV	2.7683***	.0845	-3.0221***	-.0338	.5916	3.3839***	.0781	-.0355	-.1140**	.4827
	(.1886)	(.0916)	(.3949)	(.0369)	[.5569]	(.2330)	(.0993)	(.4690)	(.0468)	[.4387]
Right Tackles AV	2.8501***	.1911*	1.1543***	-.0677*	.5710	3.4181***	.2358**	3.7430***	-.0278	.5235
	(.2175)	(.1076)	(.2527)	(.0351)	[.5346]	(.1886)	(.1112)	(.3735)	(.0482)	[.4831]
Defensive Ends AV	3.4095***	-.0580	-.0775	-.1201*	.5918	4.0227***	.3601**	-1.6188**	-.0004	.5442
	(.2153)	(.1379)	(.4416)	(.0631)	[.5571]	(.2526)	(.1639)	(.6342)	(.0771)	[.5055]
Defensive Tackles AV	3.7418***	-.3381***	.1758	-.0688	.5756	3.9678***	.4757***	.4891	.2365***	.5442
	(.2255)	(.1202)	(.3944)	(.0522)	[.5395]	(.2722)	(.1367)	(.4624)	(.0752)	[.5055]
Inside Linebackers AV	3.2367***	.0814	6.7969***	-.0869**	.5284	3.9806***	.1984	-6.2965***	.0891	.5054
	(.3638)	(.1099)	(.3010)	(.0443)	[.4884]	(.2565)	(.1794)	(.4484)	(.0644)	[.4634]
Outside Linebackers AV	3.2267***	.0117	-1.6140***	-.0376	.4506	3.7837***	.3491***	-2.6645***	.0019	.4823
	(.2878)	(.1383)	(.4621)	(.0654)	[.4040]	(.2332)	(.1215)	(.5723)	(.0789)	[.4383]
Cornerbacks AV	3.0240***	-.1861	7.3080***	.0546	.3613	3.3976***	.4068**	-2.7342***	.0211	.4346
	(.3407)	(.1588)	(.6348)	(.0801)	[.3070]	(.2794)	(.1831)	(.8256)	(.0765)	[.3865]
Free Safeties AV	2.7575***	.0139	-2.9823***	-.0423	.5038	3.6377***	.2407**	-4.7333***	-.0633	.5696
	(.2564)	(.0965)	(.3217)	(.0454)	[.4617]	(.1995)	(.1188)	(.4638)	(.0422)	[.5330]
Strong Safeties AV	2.3800***	.0405	.3735	-.0059	.4883	3.0795***	.2684***	-3.8608***	-.0072	.5429
	(.1605)	(.1151)	(.3152)	(.0436)	[.4448]	(.2661)	(.1009)	(.2883)	(.0411)	[.5040]
Kickers AV	1.7003***	-.0029	.1185	-.0133	.5827	1.4575***	-.0156	.7466***	.0360**	.3115
	(.1581)	(.0333)	(.1153)	(.0132)	[.5473]	(.1364)	(.0526)	(.1162)	(.0161)	[.2530]
Punters AV	1.5093***	-.0117	1.1886***	.0110	.7385	1.5802***	-.0064	.1836	.0372***	.5631
	(.1139)	(.0213)	(.1336)	(.0101)	[.7163]	(.0849)	(.0312)	(.1180)	(.0134)	[.5260]
Long Snappers AV	.7058***	-.0072	-.2407***	-.0073**	.7856	1.4339***	.0015	-.4784***	-.0348***	.4866
	(.0601)	(.0059)	(.0226)	(.0029)	[.7674]	(.1091)	(.0211)	(.0601)	(.0119)	[.4430]

*p<0.10, **p<0.05, ***p<0.01. Team-clustered standard errors are in parentheses.

Table 11: Actual vs. Baseline Optimal Allocations, Delta-Method Confidence Intervals

	Rookies				Veterans			
	Actual	Optimal	95% CI	Difference	Actual	Optimal	95% CI	Difference
Quarterbacks	6.8%	4.5%	(0.4%, 8.5%)	2.4%	11.0%	7.5%	(1.0%, 14.1%)	3.5%
Running Backs	7.1%	11.2%	(5.8%, 16.6%)	-4.1%	5.2%	9.5%	(5.2%, 13.7%)	-4.3%
Wide Receivers	12.3%	20.1%	(11.7%, 28.5%)	-7.8%	11.3%	15.0%	(8.2%, 21.8%)	-3.7%
Tight Ends	4.9%	2.2%	(0.4%, 4.1%)	2.7%	5.0%	3.5%	(0.6%, 6.4%)	1.6%
Left Tackles	4.8%	2.4%	(0.9%, 3.9%)	2.4%	5.1%	3.1%	(1.2%, 4.9%)	2.1%
Guards	6.9%	5.1%	(2.2%, 7.9%)	1.9%	6.0%	6.2%	(3.0%, 9.3%)	-0.2%
Centers	2.6%	2.7%	(0.3%, 5.0%)	-0.1%	3.4%	4.1%	(0.6%, 7.6%)	-0.7%
Right Tackles	4.0%	3.4%	(1.2%, 5.7%)	0.5%	3.3%	3.7%	(1.3%, 6.1%)	-0.4%
Defensive Ends	9.1%	6.4%	(3.7%, 9.2%)	2.7%	8.9%	7.3%	(4.7%, 9.9%)	1.6%
Defensive Tackles	7.3%	6.9%	(4.1%, 9.7%)	0.4%	7.4%	5.9%	(3.5%, 8.3%)	1.5%
Inside Linebackers	5.8%	5.3%	(2.9%, 7.7%)	0.5%	5.2%	6.4%	(3.7%, 9.1%)	-1.2%
Outside Linebackers	8.3%	9.1%	(5.9%, 12.2%)	-0.8%	7.9%	8.1%	(5.6%, 10.7%)	-0.2%
Cornerbacks	11.4%	12.4%	(7.8%, 16.9%)	-0.9%	9.8%	9.0%	(5.7%, 12.3%)	0.8%
Free Safeties	3.9%	5.3%	(2.8%, 7.8%)	-1.4%	3.6%	6.3%	(3.5%, 9.1%)	-2.7%
Strong Safeties	3.6%	2.3%	(0.9%, 3.7%)	1.3%	3.2%	3.4%	(1.3%, 5.5%)	-0.2%
Kickers	0.4%	0.2%	(-0.6%, 1.1%)	0.2%	1.8%	0.3%	(-0.9%, 1.5%)	1.5%
Punters	0.6%	0.7%	(-0.7%, 2.0%)	-0.1%	1.2%	1.1%	(-1.0%, 3.1%)	0.1%
Long Snappers	0.3%	-0.2%	(-0.9%, 0.6%)	0.5%	0.7%	-0.4%	(-2.2%, 1.3%)	1.1%

Table 12: $\sqrt{\text{Cap\%}}$ Actual vs. Baseline Optimal Allocations, Team-Clustered Bootstrap Confidence Intervals

	Rookies				Veterans			
	Actual	Optimal	95% CI	Difference	Actual	Optimal	95% CI	Difference
Quarterbacks	6.8%	5.2%	(0.3%, 17.3%)	1.7%	11.0%	4.4%	(0.3%, 15.2%)	6.6%
Running Backs	7.1%	11.2%	(2.8%, 24.9%)	-4.0%	5.2%	11.6%	(3.5%, 22.1%)	-6.4%
Wide Receivers	12.3%	17.7%	(5.9%, 31.3%)	-5.4%	11.3%	13.7%	(4.9%, 23.9%)	-2.5%
Tight Ends	4.9%	1.7%	(0.0%, 4.8%)	3.1%	5.0%	1.9%	(0.0%, 4.8%)	3.1%
Left Tackles	4.8%	2.4%	(0.3%, 5.3%)	2.4%	5.1%	2.3%	(0.3%, 5.2%)	2.8%
Guards	6.9%	4.4%	(0.8%, 9.1%)	2.5%	6.0%	6.1%	(1.1%, 12.5%)	-0.2%
Centers	2.6%	4.0%	(0.2%, 11.8%)	-1.5%	3.4%	4.4%	(0.2%, 14.0%)	-1.0%
Right Tackles	4.0%	4.5%	(0.5%, 11.1%)	-0.5%	3.3%	4.8%	(0.7%, 10.5%)	-1.5%
Defensive Ends	9.1%	5.5%	(2.1%, 10.3%)	3.6%	8.9%	5.6%	(2.0%, 10.0%)	3.2%
Defensive Tackles	7.3%	7.8%	(2.6%, 13.9%)	-0.5%	7.4%	6.4%	(2.3%, 11.6%)	1.0%
Inside Linebackers	5.8%	6.2%	(1.9%, 12.9%)	-0.4%	5.2%	6.9%	(2.6%, 12.1%)	-1.6%
Outside Linebackers	8.3%	9.2%	(4.7%, 13.3%)	-1.0%	7.9%	9.3%	(4.6%, 14.4%)	-1.4%
Cornerbacks	11.4%	7.6%	(2.7%, 15.9%)	3.8%	9.8%	7.0%	(2.7%, 13.8%)	2.8%
Free Safeties	3.9%	8.8%	(3.0%, 15.5%)	-4.9%	3.6%	11.2%	(3.9%, 18.8%)	-7.7%
Strong Safeties	3.6%	2.5%	(0.5%, 6.0%)	1.1%	3.2%	3.0%	(0.6%, 7.7%)	0.2%
Kickers	0.4%	0.1%	(0.0%, 2.5%)	0.3%	1.8%	0.1%	(0.0%, 1.4%)	1.7%
Punters	0.6%	1.1%	(0.0%, 7.1%)	-0.5%	1.2%	0.9%	(0.0%, 6.0%)	0.3%
Long Snappers	0.3%	0.1%	(0.0%, 1.8%)	0.2%	0.7%	0.2%	(0.0%, 4.9%)	0.5%

Table 13: Baseline Importance Results ($N = 448$)

(a) Interactions

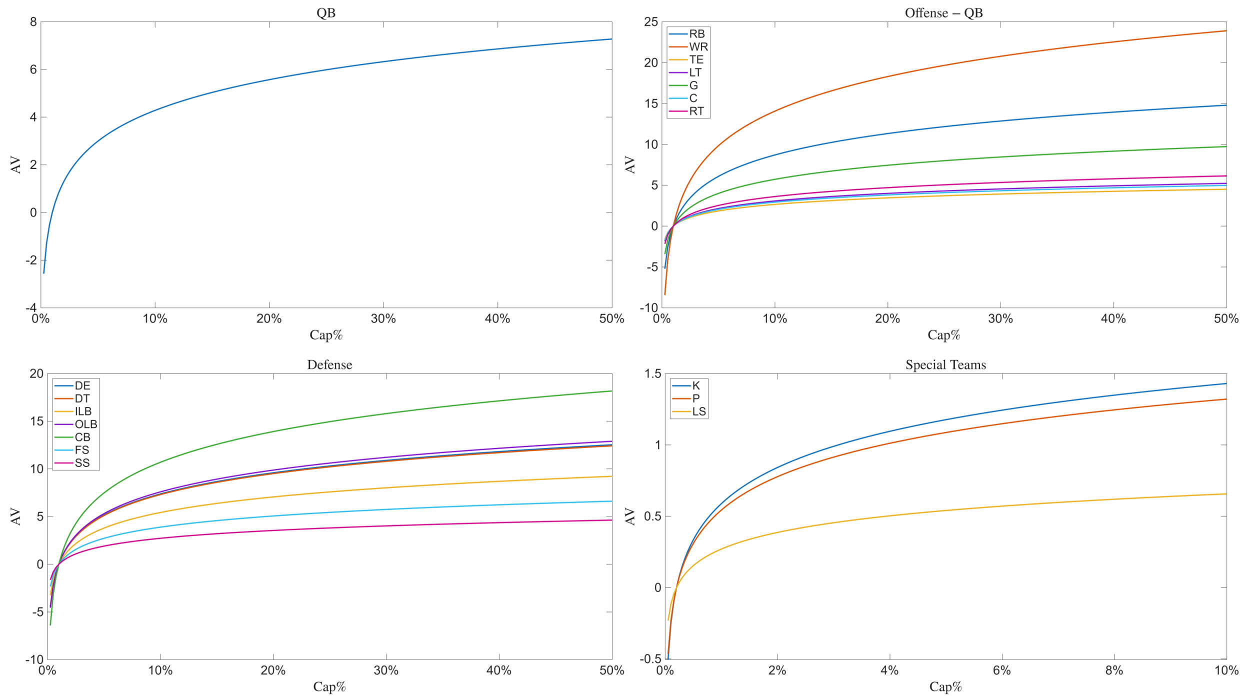
DV = Wins	G_0	G_1	G_2	G_3
Quarterbacks AV	.0966**	.1284*	.1326*	.1807***
	(.0417)	(.0667)	(.0745)	(.0671)
Running Backs AV	.1198***	.0765	.0758	.1823***
	(.0266)	(.1051)	(.1174)	(.0441)
Wide Receivers AV	.1325***	.1561***	.1555***	.1844***
	(.0278)	(.0594)	(.0578)	(.0472)
Tight Ends AV	.0785**	.0795**	.0881	.1335***
	(.0319)	(.0331)	(.0740)	(.0493)
Left Tackles AV	.0729***	.0556	.0489	.1338***
	(.0218)	(.0475)	(.0954)	(.0422)
Guards AV	.0822***	.0657	.0636	.1408***
	(.0208)	(.0483)	(.0554)	(.0371)
Centers AV	.0854**	.0703	.0682	.1423***
	(.0377)	(.0506)	(.0562)	(.0375)
Right Tackles AV	.0877***	.0717	.0699	.1480***
	(.0283)	(.0493)	(.0551)	(.0431)
Defensive Ends AV	.0811***	.0811***	.0811***	.1340***
	(.0138)	(.0139)	(.0142)	(.0307)
Defensive Tackles AV	.0880***	.0879***	.0878***	.1401***
	(.0146)	(.0147)	(.0148)	(.0266)
Inside Linebackers AV	.0905***	.0907***	.0906***	.1440***
	(.0178)	(.0178)	(.0180)	(.0340)
Outside Linebackers AV	.1110***	.1109***	.1107***	.1660***
	(.0144)	(.0144)	(.0147)	(.0315)
Cornerbacks AV	.1073***	.1064***	.1065***	.1641***
	(.0189)	(.0190)	(.0190)	(.0264)
Free Safeties AV	.1267***	.1265***	.1265***	.1857***
	(.0285)	(.0286)	(.0286)	(.0376)
Strong Safeties AV	.0777***	.0780***	.0780***	.1366***
	(.0239)	(.0237)	(.0241)	(.0353)
Kickers AV	.0260	.0259	.0258	.0204
	(.0486)	(.0484)	(.0486)	(.0473)
Punters AV	.0831	.0807	.0804	.0805
	(.0815)	(.0826)	(.0830)	(.0837)
Long Snappers AV	-.0429	-.0433	-.0425	-.0411
	(.0895)	(.0882)	(.0893)	(.0895)
Vegas Wins O/U	.1172***	.1186***	.1188***	.1173***
	(.0437)	(.0439)	(.0441)	(.0442)
2011 Indianapolis Colts	-1.6478***	-1.6895***	-1.6752***	-1.2889***
	(.3298)	(.3549)	(.3456)	(.3317)
17 Game Season	.2212	.2169	.2139	.2286
	(.1621)	(.1646)	(.1643)	(.1631)
$AV_{QB} \times AV_{WR}$		-.0015	-.0015	
		(.0029)	(.0028)	
$AV_{RB} \times AV_{OL}$		.0010	.0010	
		(.0022)	(.0024)	
$AV_{QB} \times AV_{TE}$			-.0006	
			(.0041)	
$AV_{LT} \times AV_{OL-LT}$			.0002	
			(.0023)	
$AV_{QB} \times AV_{Off-QB}$				-.0003
				(.0007)
$AV_{Off} \times AV_{Def}$				-.0006**
				(.0003)
R^2	.8231	.8233	.8233	.8253
Adjusted R^2	.7998	.7990	.7980	.8013

*p<0.10, **p<0.05, ***p<0.01. Team-clustered standard errors are in parentheses.

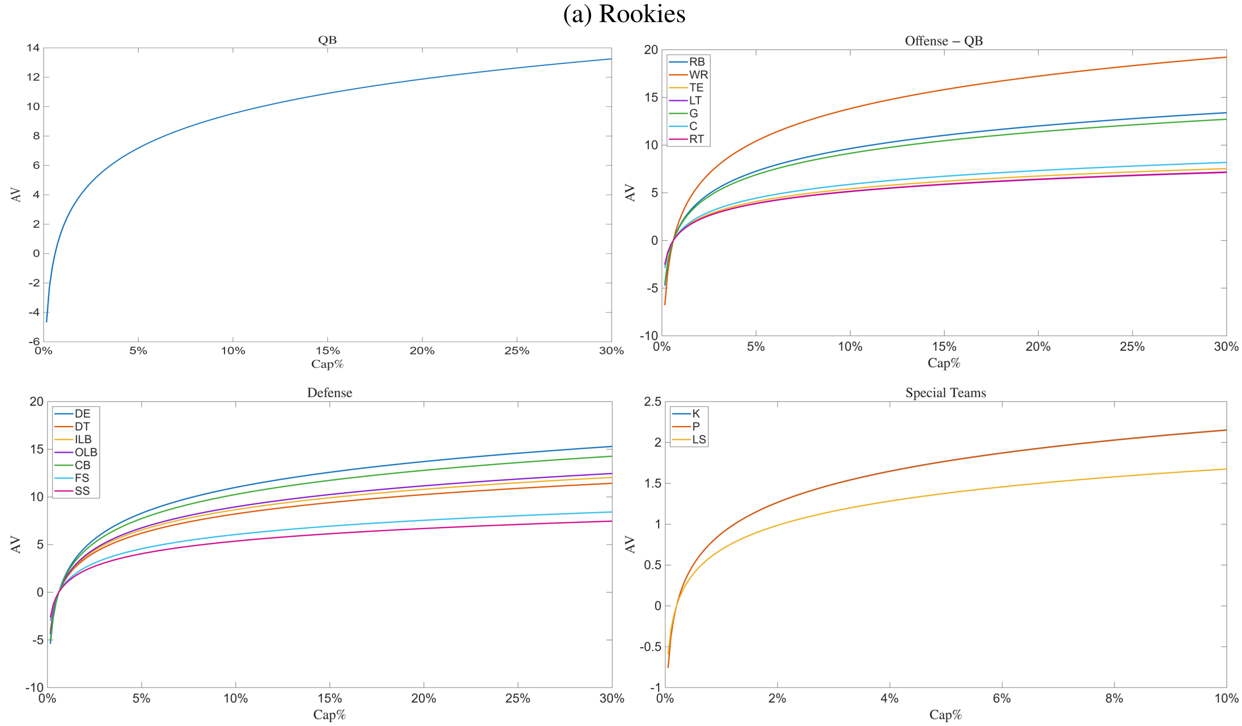
(b) Restricted Translog

DV = Wins	G_0	G_1	G_2	G_3
Log Quarterbacks AV	.0558	.4981	.5307	.5101
	(.0525)	(.5523)	(.4968)	(.4056)
Log Running Backs AV	.3629***	-.3754	-.2846	.0680
	(.0817)	(.2878)	(.6151)	(.1011)
Log Wide Receivers AV	.6235***	.9825	.7822	.2174
	(.1228)	(.6553)	(.7169)	(.1847)
Log Tight Ends AV	.1245***	.0960**	.3791*	.0180
	(.0356)	(.0381)	(.2244)	(.0513)
Log Left Tackles AV	.0286	-.0111	-.1742	.0016
	(.0311)	(.0347)	(.6501)	(.0324)
Log Guards AV	.0601	-.0491	-.0561	.0102
	(.0555)	(.0646)	(.0651)	(.0523)
Log Centers AV	.0645**	.0145	.0114	.0168
	(.0317)	(.0314)	(.0313)	(.0292)
Log Right Tackles AV	-.0067	-.0375*	-.0364*	-.0183
	(.0212)	(.0205)	(.0209)	(.0207)
Log Defensive Ends AV	.1000***	.1005***	.0988***	-.0561**
	(.0331)	(.0342)	(.0356)	(.0277)
Log Defensive Tackles AV	.1414***	.1389***	.1351***	-.0645*
	(.0385)	(.0404)	(.0398)	(.0350)
Log Inside Linebackers AV	.0800***	.0772***	.0765***	-.0446
	(.0288)	(.0285)	(.0278)	(.0277)
Log Outside Linebackers AV	.1954***	.1977***	.1954***	-.0310
	(.0410)	(.0419)	(.0415)	(.0388)
Log Cornerbacks AV	.3604***	.3590***	.3592***	.0166
	(.0615)	(.0633)	(.0625)	(.0678)
Log Free Safeties AV	.1188***	.1257***	.1256***	.0250
	(.0310)	(.0324)	(.0331)	(.0297)
Log Strong Safeties AV	.0754***	.0763***	.0768***	-.0081
	(.0264)	(.0267)	(.0275)	(.0265)
Log Kickers AV	.0042	.0013	.0016	.0091
	(.0242)	(.0254)	(.0255)	(.0204)
Log Punters AV	.0125	.0188	.0184	.0050
	(.0361)	(.0360)	(.0354)	(.0328)
Log Long Snappers AV	-.0112	-.0107	-.0095	-.0145
	(.0326)	(.0299)	(.0302)	(.0284)
Vegas Wins O/U	.0317***	.0317***	.0323***	.0213**
	(.0100)	(.0104)	(.0105)	(.0098)
2011 Indianapolis Colts	-.6857***	-.7262***	-.6786***	-.5795***
	(.0665)	(.0752)	(.0994)	(.0601)
17 Game Season	.0096	.0271	.0255	.0356
	(.0267)	(.0277)	(.0280)	(.0270)
Log $AV_{QB} \times$ Log AV_{WR}		-.1361	-.0789	
		(.1717)	(.1899)	
Log $AV_{RB} \times$ Log AV_{OL}		.1555***	.1328	
		(.0535)	(.1345)	
Log $AV_{QB} \times$ Log AV_{TE}			-.0914	
			(.0719)	
Log $AV_{LT} \times$ Log AV_{OL-LT}			.0368	
			(.1443)	
Log $AV_{QB} \times$ Log AV_{Off-QB}				-.1218
				(.0886)
Log $AV_{Off} \times$ Log AV_{Def}				.2962***
				(.0347)
R^2	.7134	.7195	.7205	.7602
Adjusted R^2	.6756	.6810	.6805	.7273

*p<0.10, **p<0.05, ***p<0.01. Team-clustered standard errors are in parentheses.



(a) Rookies



(b) Veterans

Figure 7: Cost Effectiveness by Position

D Appendix: Quarterback Valuation

Formulas for Game-Level Quarterback Statistics:

- **Passer Rating:** Let $a = 5\left(\frac{\text{Completions}}{\text{Attempts}} - .3\right)$, $b = .25\left(\frac{\text{Yards}}{\text{Attempts}} - 3\right)$, $c = \frac{20\times\text{Touchdowns}}{\text{Attempts}}$, and $d = 2.375 - \frac{25\times\text{Interceptions}}{\text{Attempts}}$. Without loss of generality, let $A = \min\{\max\{a, 0\}, 2.375\}$:

$$\text{Passer Rating} = \frac{100}{6}(A + B + C + D)$$

- **Adjusted Net Yards per Attempt:**

$$\text{ANY/A} = \frac{\text{Yards} + 20 \times \text{Touchdowns} - 45 \times \text{Interceptions} - \text{Sack Yards}}{\text{Attempts} + \text{Sacks}}$$

- **Total Adjusted Net Yards per Attempt:**

$$\text{TANY/A} = \frac{\text{Yards} + \text{Rushing Yards} + 20 \times (\text{Touchdowns} + \text{Rushing Touchdowns}) - 45 \times (\text{Interceptions} + \text{Fumbles Lost}) - \text{Sack Yards}}{\text{Attempts} + \text{Sacks} + \text{Rushing Attempts}}$$

- **Fantasy Points per Attempt (NFL Support 2025):**

$$\text{FP/A} = \frac{.04 \times \text{Yards} + 4 \times \text{Touchdowns} - 2 \times \text{Interceptions} + .1 \times \text{Rushing Yards} + 6 \times \text{Rushing Touchdowns} - 2 \times \text{Fumbles Lost} + 2 \times 2\ \text{Point Conversions}}{\text{Attempts} + \text{Rushing Attempts} + 2\ \text{Point Attempts}}$$

We do not observe two point conversions or attempts at the player level, so we omit them.

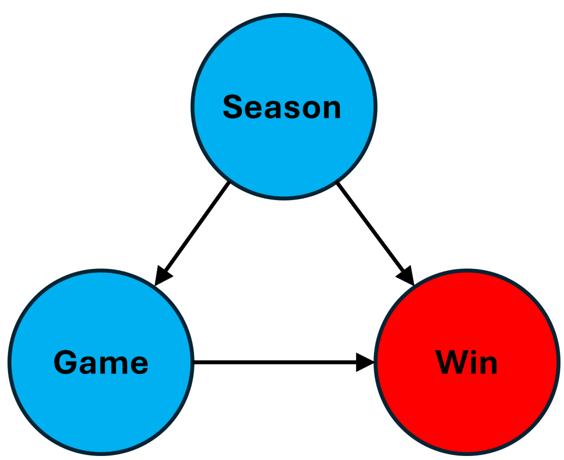


Figure 8: Win, Game, and Season Directed Acyclic Graph

Table 14: Asymmetric Spillovers Summary Statistics, 2011–2024 ($N = 7,238$)

	Mean	SD	Min	Max
Quarterback Fantasy Points	16.25	7.67	0	51.88
Skill Position Fantasy Points	58.24	16.14	0	145.20
Quarterback Injured Money	$2,042,115	$5,778,160	$0	$46,174,540
Skill Position Injured Money	$5,382,689	$5,750,469	$0	$48,465,476
Non-Skill Position Injured Money	$16,110,983	$11,474,997	$0	$82,276,928
Opponent Injured Money	$23,535,787	$15,710,266	$84,022	$133,936,848
Home	0.5	0.5	0	1

Table 15: Quarterback Valuation Summary Statistics, 2011–2024 ($N = 7,238$)

	Mean	SD	Min	Max
Game Passer Rating	89.94	26.09	0.00	158.33
Season Passer Rating	89.23	12.60	0.00	128.76
Game ANY/A	6.21	2.83	-7.80	19.61
Season ANY/A	6.07	1.29	-7.80	10.15
Game TANY/A	5.82	2.63	-10.81	16.96
Season TANY/A	5.73	1.22	-5.92	9.49
Game FP/A	0.43	0.21	-0.48	1.43
Season FP/A	0.43	0.10	-0.25	0.76
Non-QB Fantasy Points	66.88	17.32	4	155
Home	0.50	0.50	0.00	1.00
Rest Days	6.94	2.81	3	17
Log Injured Money	16.65	0.75	11	18
Starter Gini	0.48	0.06	0	1
Starter/Non-Starter	1.21	0.49	0.10	4.10
Game Passer Rating (Win = 1)	102.26	23.60	2.78	158.33
Season Passer Rating (Win = 1)	92.74	11.55	31.25	128.76
Game ANY/A (Win = 1)	7.56	2.60	-3.41	19.61
Season ANY/A (Win = 1)	6.45	1.16	0.76	10.15
Game TANY/A (Win = 1)	7.03	2.36	-1.19	16.96
Season TANY/A (Win = 1)	6.07	1.09	0.84	9.49
Game FP/A (Win = 1)	0.52	0.21	0.03	1.43
Season FP/A (Win = 1)	0.45	0.09	0.07	0.76
Non-QB Fantasy Points (Win = 1)	74.44	15.52	4.00	155.20
Home (Win = 1)	0.56	0.50	0.00	1.00
Rest Days (Win = 1)	6.96	2.84	3.00	17.00
Log Injured Money (Win = 1)	16.61	0.74	11.34	18.35
Starter Gini (Win = 1)	0.48	0.06	0	1
Starter/Non-Starter (Win = 1)	1.25	0.49	0.18	4.10
Game Passer Rating (Win = 0)	77.63	22.39	0.00	150.48
Season Passer Rating (Win = 0)	85.72	12.62	0.00	122.46
Game ANY/A (Win = 0)	4.86	2.36	-7.80	13.13
Season ANY/A (Win = 0)	5.70	1.31	-7.80	9.39
Game TANY/A (Win = 0)	4.62	2.30	-10.81	14.22
Season TANY/A (Win = 0)	5.39	1.26	-5.92	8.98
Game FP/A (Win = 0)	0.35	0.17	-0.48	1.19
Season FP/A (Win = 0)	0.40	0.10	-0.25	0.72
Non-QB Fantasy Points (Win = 0)	59.33	15.64	6.00	122.30
Home (Win = 0)	0.44	0.50	0.00	1.00
Rest Days (Win = 0)	6.93	2.78	3.00	17.00
Log Injured Money (Win = 0)	16.70	0.75	12.80	18.38
Starter Gini (Win = 0)	0.48	0.06	0	1
Starter/Non-Starter (Win = 0)	1.17	0.49	0.10	3.90

Table 16: Quarterback Valuation Results, 447 Fixed Effects ($N = 7,238$)

(a) ANY/A

DV = Win	Game			Season			Game, Season IV	
	Logit	AME	Linear	Logit	AME	Linear	Q1-Q4	Q1-Q3
ANY/A	.6064***	.0472***	.0460***	.3199***	.0320***	.0292***	.0723***	.0582***
	(.0365)	(.0022)	(.0022)	(.0734)	(.0073)	(.0063)	(.0150)	(.0172)
Non-QB Fantasy Points	.1034***	.0080***	.0064***	.1328***	.0133***	.0118***	.0032*	.0049**
	(.0066)	(.0004)	(.0004)	(.0056)	(.0003)	(.0003)	(.0019)	(.0022)
Home	.2533***	.0197***	.0186***	.2464***	.0247***	.0213***	.0177***	.0182***
	(.0669)	(.0052)	(.0058)	(.0561)	(.0056)	(.0061)	(.0057)	(.0056)
Rest Days	-.0124	-.0010	-.0003	.0090	.0009	.0006	-.0009	-.0006
	(.0279)	(.0022)	(.0024)	(.0235)	(.0024)	(.0026)	(.0024)	(.0024)
Log Injured Money	-.1306	-.0102	-.0035	-.0288	-.0029	-.0025	-.0053	-.0043
	(.1305)	(.0101)	(.0112)	(.1042)	(.0104)	(.0118)	(.0112)	(.0110)
Starter Gini	3.4221*	.2662*	.2569	2.8083*	.2812*	.2702	.2504	.2539
	(1.7499)	(.1360)	(.1632)	(1.6031)	(.1608)	(.1735)	(.1595)	(.1580)
Starter/Non-Starter	.1025	.0080	.0139	.1891	.0189	.0115	.0132	.0136
	(.2409)	(.0187)	(.0214)	(.2058)	(.0206)	(.0226)	(.0211)	(.0207)
Pseudo-R^2 | R^2	.6424		.5619	.5448		.5081	.5434	.5579
Adjusted Pseudo-R^2 | R^2	.6410		.5335	.5434		.4763	.5138	.5293

*p<0.10, **p<0.05, ***p<0.01. Game-clustered standard errors are in parentheses.

(b) TANY/A

DV = Win	Game			Season			Game, Season IV	
	Logit	AME	Linear	Logit	AME	Linear	Q1-Q4	Q1-Q3
TANY/A	.6434***	.0508***	.0466***	.3397***	.0340***	.0335***	.0823***	.0700***
	(.0368)	(.0024)	(.0024)	(.0734)	(.0073)	(.0063)	(.0157)	(.0174)
Non-QB Fantasy Points	.1097***	.0087***	.0070***	.1334***	.0133***	.0119***	.0030*	.0044**
	(.0066)	(.0004)	(.0004)	(.0056)	(.0003)	(.0003)	(.0018)	(.0020)
Home	.2150***	.0170***	.0164***	.2471***	.0247***	.0215***	.0136**	.0146**
	(.0655)	(.0051)	(.0058)	(.0562)	(.0056)	(.0061)	(.0059)	(.0059)
Rest Days	-.0182	-.0014	-.0004	.0090	.0009	.0006	-.0013	-.0010
	(.0269)	(.0021)	(.0024)	(.0236)	(.0024)	(.0026)	(.0025)	(.0024)
Log Injured Money	-.1037	-.0082	-.0028	-.0363	-.0036	-.0034	-.0047	-.0041
	(.1265)	(.0100)	(.0112)	(.1041)	(.0104)	(.0118)	(.0113)	(.0111)
Starter Gini	2.3569	.1862	.2326	2.6284	.2629	.2527	.2052	.2146
	(1.7870)	(.1410)	(.1653)	(1.6026)	(.1605)	(.1732)	(.1636)	(.1616)
Starter/Non-Starter	.0349	.0028	.0117	.1651	.0165	.0087	.0091	.0100
	(.2429)	(.0192)	(.0216)	(.2067)	(.0207)	(.0226)	(.0216)	(.0212)
Pseudo-R^2 | R^2	.6372		.5540	.5451		.5088	.5254	.5417
Adjusted Pseudo-R^2 | R^2	.6358		.5251	.5437		.4770	.4946	.5120

*p<0.10, **p<0.05, ***p<0.01. Game-clustered standard errors are in parentheses.

(c) FP/A

DV = Win	Game			Season			Game, Season IV	
	Logit	AME	Linear	Logit	AME	Linear	Q1-Q4	Q1-Q3
FP/A	7.8925***	.6018***	.5096***	5.1542***	.5133***	.5208***	.8479***	.7240***
	(.4635)	(.0275)	(.0265)	(.9374)	(.0924)	(.0829)	(.1351)	(.1424)
Non-QB Fantasy Points	.1405***	.0107***	.0087***	.1345***	.0134***	.0119***	.0064***	.0073***
	(.0068)	(.0003)	(.0003)	(.0056)	(.0003)	(.0003)	(.0010)	(.0010)
Home	.1817***	.0139***	.0132**	.2487***	.0248***	.0213***	.0087	.0104*
	(.0671)	(.0051)	(.0058)	(.0564)	(.0056)	(.0061)	(.0060)	(.0060)
Rest Days	-.0148	-.0011	-.0002	.0076	.0008	.0005	-.0009	-.0007
	(.0281)	(.0021)	(.0025)	(.0236)	(.0024)	(.0026)	(.0024)	(.0024)
Log Injured Money	-.1795	-.0137	-.0049	-.0416	-.0041	-.0039	-.0080	-.0069
	(.1271)	(.0097)	(.0112)	(.1040)	(.0104)	(.0118)	(.0112)	(.0110)
Starter Gini	2.4764	.1888	.1963	2.3720	.2362	.2266	.1486	.1661
	(1.8280)	(.1396)	(.1640)	(1.5891)	(.1585)	(.1724)	(.1614)	(.1603)
Starter/Non-Starter	-.0486	-.0037	.0107	.1326	.0132	.0056	.0079	.0090
	(.2469)	(.0188)	(.0215)	(.2070)	(.0206)	(.0226)	(.0213)	(.0210)
Pseudo-R^2 | R^2	.6502		.5547	.5469		.5102	.5330	.5460
Adjusted Pseudo-R^2 | R^2	.6488		.5259	.5455		.4785	.5027	.5166

*p<0.10, **p<0.05, ***p<0.01. Game-clustered standard errors are in parentheses.

Table 17: Quarterback Valuation Results, Robustness Checks

(a) No Rookies, 432 Fixed Effects ($N = 5,798$)

DV = Win	Game			Season			Game, Season IV	
	Logit	AME	Linear	Logit	AME	Linear	Q1-Q4	Q1-Q3
Passer Rating	.0608***	.0046***	.0049***	.0330***	.0032***	.0036***	.0088***	.0081***
	(.0043)	(.0003)	(.0003)	(.0104)	(.0010)	(.0008)	(.0019)	(.0023)
Non-QB Fantasy Points	.1190	.0090	.0071	.1418	.0138	.0121	.0027	.0035
	(.0075)	(.0004)	(.0005)	(.0067)	(.0004)	(.0003)	(.0021)	(.0026)
Home	.2065***	.0156***	.0108	.1683***	.0164***	.0134	.0094	.0096
	(.0793)	(.0060)	(.0065)	(.0640)	(.0062)	(.0069)	(.0065)	(.0065)
Rest Days	.0301	.0023	.0011	.0144	.0014	.0009	.0012	.0012
	(.0356)	(.0027)	(.0029)	(.0282)	(.0028)	(.0030)	(.0029)	(.0028)
Log Injured Money	-.0212	-.0016	-.0018	.0268	.0026	-.0018	-.0036	-.0032
	(.1591)	(.0120)	(.0126)	(.1237)	(.0121)	(.0131)	(.0129)	(.0127)
Starter Gini	4.0246	.3046	.2407	3.6818	.3594	.2834	.2015	.2091
	(2.0859)	(.1579)	(.1825)	(1.8831)	(.1842)	(.1935)	(.1821)	(.1807)
Starter/Non-Starter	.2515	.0190	.0181	.1672	.0163	.0099	.0223	.0215
	(.2829)	(.0215)	(.0234)	(.2356)	(.0230)	(.0248)	(.0235)	(.0232)
Pseudo-R^2 | R^2	.6504		.5696	.5557		.5167	.5327	.5456
Adjusted Pseudo-R^2 | R^2	.6486		.5356	.5540		.4784	.4957	.5096

*p<0.10, **p<0.05, ***p<0.01. Game-clustered standard errors are in parentheses.

(b) ≥4 Games, 447 Fixed Effects ($N = 6,496$)

DV = Win	Game			Season			Game, Season IV	
	Logit	AME	Linear	Logit	AME	Linear	Q1-Q4	Q1-Q3
Passer Rating	.0601***	.0046***	.0050***	.0247	.0025	.0035***	.0083***	.0067
	(.0039)	(.0002)	(.0002)	(.0123)	(.0012)	(.0011)	(.0025)	(.0033)
Non-QB Fantasy Points	.1143	.0088	.0067	.1380	.0138	.0119	.0031	.0049
	(.0075)	(.0004)	(.0004)	(.0064)	(.0003)	(.0003)	(.0027)	(.0036)
Home	.3163	.0244	.0205	.2986	.0299	.0243	.0182	.0193
	(.0757)	(.0058)	(.0062)	(.0610)	(.0060)	(.0066)	(.0064)	(.0064)
Rest Days	.0151	.0012	.0012	.0103	.0010	.0012	.0011	.0012
	(.0296)	(.0023)	(.0026)	(.0239)	(.0024)	(.0027)	(.0025)	(.0025)
Log Injured Money	-.0611	-.0047	-.0050	-.0353	-.0035	-.0027	-.0075	-.0063
	(.1443)	(.0111)	(.0121)	(.1120)	(.0112)	(.0127)	(.0123)	(.0121)
Starter Gini	5.0420	.3896	.3021	3.9788	.3988	.3470	.2970	.2995
	(2.0341)	(.1569)	(.1783)	(1.7752)	(.1780)	(.1939)	(.1749)	(.1723)
Starter/Non-Starter	.3054	.0236	.0141	.1874	.0188	.0083	.0188	.0165
	(.2755)	(.0213)	(.0235)	(.2278)	(.0229)	(.0251)	(.0237)	(.0233)
Pseudo-R^2 | R^2	.6437		.5661	.5456		.5077	.5384	.5590
Adjusted Pseudo-R^2 | R^2	.6421		.5346	.5440		.4719	.5048	.5269

*p<0.10, **p<0.05, ***p<0.01. Game-clustered standard errors are in parentheses.

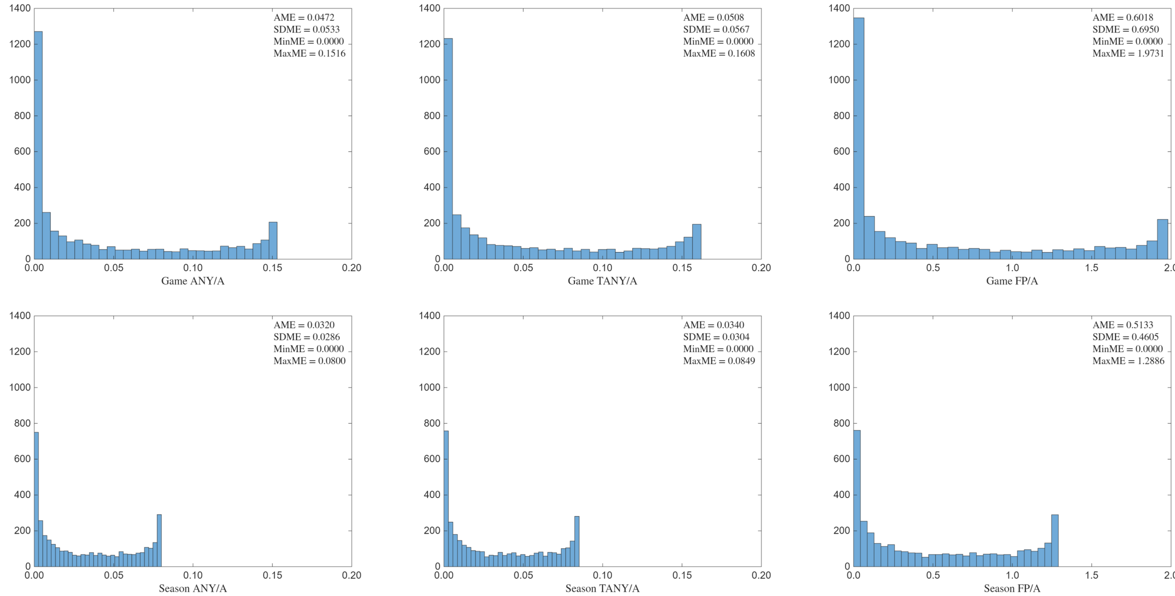


Figure 9: Distributions of Marginal Effects, ANY/A, TANY/A, and FP/A

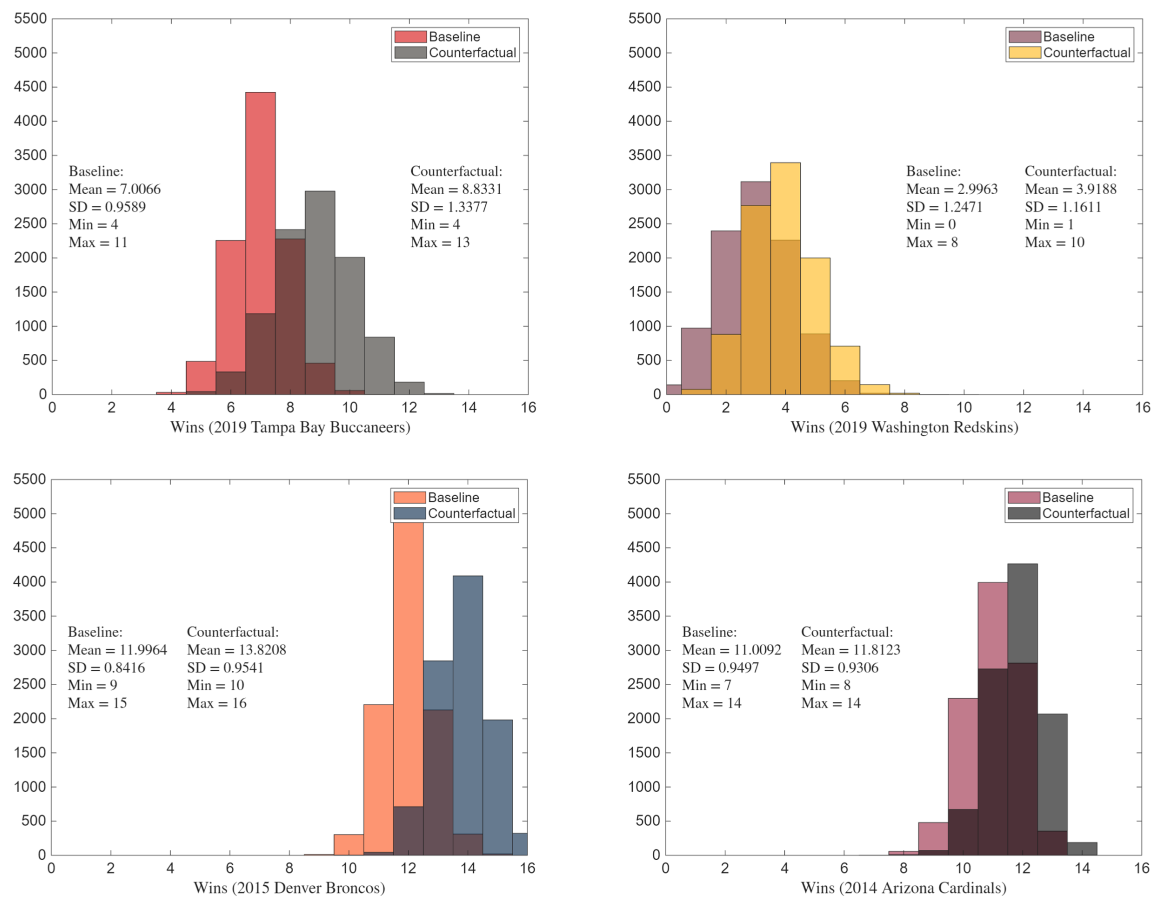


Figure 10: Distributions of Simulated Wins, Game Passer Rating

E Appendix: Calibrated Salary Cap Optimization

Table 18: Cost Effectiveness Results, COTY, Team Fixed Effects ($N = 448$)

	Rookies							Veterans						
	log(Cap%)	Cap% = 0	Vegas Wins	2011 Colts	Season	COTY	R^2 [Adj R^2]	log(Cap%)	Cap% = 0	Vegas Wins	2011 Colts	Season	COTY	R^2 [Adj R^2]
Quarterbacks AV	1.8323***	-2.6545***	-.0088	-3.8744***	-.0659	2.3657***	.4174	3.3884***	-1.5102	1.1079***	-7.9045***	-.0089	.0745	.5762
	(.2122)	(.4118)	(.1994)	(.5856)	(.0840)	(.8341)	[.3649]	(.2973)	(1.3984)	(.1772)	(.5173)	(.0705)	(.7368)	[.5379]
Running Backs AV	3.8340***	-3.8624***	.0929	-5.6279***	.0293	2.3556***	.3733	3.4444***	-.7949	.4247***	-5.2554***	.0261	1.5414**	.5029
	(.4849)	(1.0129)	(.1736)	(.4898)	(.0567)	(.6958)	[.3167]	(.2311)	(.5013)	(.1220)	(.4731)	(.0532)	(.7307)	[.4581]
Wide Receivers AV	6.1771***		.0140	-1.0101**	-.0375	1.6127**	.4085	4.8516***	.7801	.7765***	-4.7723***	-.0438	1.6115*	.4707
	(.5919)		(.1426)	(.4784)	(.0717)	(.7296)	[.3567]	(.3791)	(.9158)	(.2187)	(.6648)	(.0926)	(.9234)	[.4229]
Tight Ends AV	1.1528***	-.5398***	-.0459	-3.0408***	-.0072	-.3010	.2800	1.8947***	-1.4587***	.3597***	-4.9306***	.0119	.7215*	.4783
	(.1496)	(.1754)	(.1027)	(.3908)	(.0535)	(.3616)	[.2151]	(.2027)	(.4418)	(.0934)	(.3789)	(.0454)	(.4308)	[.4312]
Left Tackles AV	1.3340***	-3.0364***	-.0864	-1.8289***	-.0572	-.3597	.4783	1.7918***	-4.0837***	.3792***	1.7173***	-.0029	1.3413***	.5370
	(.1187)	(.3840)	(.0929)	(.3888)	(.0530)	(.4964)	[.4312]	(.0985)	(.3288)	(.1131)	(.4454)	(.0578)	(.4900)	[.4952]
Guards AV	2.4894***	-2.6660***	.3301**	-4.2689***	-.1084**	.8737	.4692	3.2733***	-5.1789***	.4100***	-.9108	-.1282	.9941	.4722
	(.3664)	(.6869)	(.1433)	(.6984)	(.0532)	(.6370)	[.4214]	(.3504)	(.7032)	(.1525)	(.6962)	(.0839)	(.6955)	[.4245]
Centers AV	1.2778***	-3.0189***	.0772	-.2587	-.0319	.4855	.4868	2.0824***	-4.4758***	.0860	.1593	-.1174**	1.2063***	.5037
	(.1217)	(.2578)	(.1090)	(.3289)	(.0408)	(.4181)	[.4405]	(.1595)	(.3442)	(.0881)	(.4736)	(.0462)	(.4589)	[.4589]
Right Tackles AV	1.5620***	-2.9977***	.1900*	1.3130***	-.0523	.9085	.4955	1.8265***	-4.1092***	.1642	3.0027***	-.0206	.5550	.4644
	(.1178)	(.3585)	(.1114)	(.2625)	(.0369)	(.5559)	[.4500]	(.1847)	(.4278)	(.1200)	(.5474)	(.0582)	(.4102)	[.4160]
Defensive Ends AV	3.1927***	-1.3038	.0225	-.1929	-.1002	.7404	.4934	3.9106***	-4.4845***	.4100**	-1.5540**	-.0515	2.1335***	.5314
	(.4355)	(.8499)	(.1491)	(.4631)	(.0652)	(.5697)	[.4476]	(.2874)	(.9370)	(.1788)	(.6823)	(.0809)	(.6193)	[.4891]
Defensive Tackles AV	3.1476***	-2.5027*	-.2201	.0441	-.1139*	.8154	.4824	2.9223***	-.5855	.4471***	-1.4308***	.2672***	.2232	.4836
	(.3436)	(1.4765)	(.1444)	(.5424)	(.0583)	(.4962)	[.4357]	(.3575)	(2.4592)	(.1540)	(.4584)	(.0753)	(.6185)	[.4370]
Inside Linebackers AV	2.3314***	-2.4224***	.2118*	6.1791***	-.0718	.7310*	.4863	3.0752***	-3.4455***	.1966	-7.7855***	.0576	-.1774	.4733
	(.2940)	(.3354)	(.1180)	(.3669)	(.0536)	(.4415)	[.4399]	(.3206)	(.6683)	(.1768)	(.4381)	(.0654)	(.7216)	[.4257]
Outside Linebackers AV	3.2705***		.0624	-2.0560***	-.0589	1.4860*	.4146	3.2063***	-4.2992***	.2033	.6316	.0058	1.0846	.4442
	(.4309)		(.1300)	(.4460)	(.0642)	(.7887)	[.3633]	(.3188)	(.8576)	(.1307)	(.7926)	(.0854)	(.6945)	[.3940]
Cornerbacks AV	4.6613***		-.1704	7.0837***	.0477	1.2157*	.3785	3.6619***		.4273**	.0678	-.0143	1.7936***	.4275
	(.4908)		(.1531)	(.6267)	(.0796)	(.7101)	[.3240]	(.3017)		(.1810)	(.9436)	(.0765)	(.6110)	[.3773]
Free Safeties AV	1.6680***	-2.6432***	.0092	-3.4941***	-.0626	.9851*	.4298	2.1528***	-3.8287***	.2603**	-3.3902***	-.0556	.0974	.5155
	(.1616)	(.5551)	(.1051)	(.3524)	(.0513)	(.5136)	[.3784]	(.1800)	(.3266)	(.1274)	(.4701)	(.0468)	(.2792)	[.4718]
Strong Safeties AV	1.1831***	-2.6351***	-.0262	.6326*	-.0089	.1594	.3906	1.9047***	-3.3656***	.2600***	-4.2469***	-.0008	-.3004	.5091
	(.1239)	(.3629)	(.1207)	(.3580)	(.0415)	(.5167)	[.3356]	(.1943)	(.2485)	(.0925)	(.2775)	(.0380)	(.3868)	[.4648]
Kickers AV	.3679***	-1.6962***	.0024	.0952	-.0198	.2166	.5101	.5517***	-2.5220***	-.0198	.8236***	.0198	.1226	.3629
	(.0413)	(.1975)	(.0359)	(.1186)	(.0140)	(.1676)	[.4659]	(.0712)	(.1315)	(.0504)	(.0995)	(.0157)	(.2326)	[.3054]
Punters AV	.3378***	-1.7709***	-.0270	1.0121***	.0084	-.0605	.7108	.5496***	-1.9224***	-.0195	.1732	.0270**	-.0136	.5804
	(.0241)	(.1044)	(.0256)	(.1098)	(.0100)	(.0869)	[.6847]	(.0702)	(.0706)	(.0296)	(.1200)	(.0133)	(.1302)	[.5426]
Long Snappers AV	.1679***	-.7784***	-.0031	-.2513***	-.0088***	.0109	.7538	.4283***	-1.4456***	-.0004	-.4670***	-.0415***	.0881	.4966
	(.0136)	(.0591)	(.0057)	(.0223)	(.0029)	(.0263)	[.7316]	(.0592)	(.1058)	(.0206)	(.0663)	(.0122)	(.1146)	[.4511]

*p<0.10, **p<0.05, ***p<0.01. Team-clustered standard errors are in parentheses.

Table 19: $\sqrt{\text{Cap\%}}$ Cost Effectiveness Results, COTY, Team Fixed Effects ($N = 448$)

	Rookies						Veterans					
	$\sqrt{\text{Cap\%}}$	Vegas Wins	2011 Colts	Season	COTY	R^2 [Adj R^2]	$\sqrt{\text{Cap\%}}$	Vegas Wins	2011 Colts	Season	COTY	R^2 [Adj R^2]
Quarterbacks AV	2.7485***	-.0006	-3.2063***	-.0261	2.4263***	.5254	2.9999***	1.1196***	-8.9652***	-.0282	.1013	.5781
	(.2051)	(.1588)	(.5418)	(.0753)	(.7733)	[.4838]	(.1931)	(.1740)	(.4784)	(.0651)	(.7413)	[.5411]
Running Backs AV	3.3316***	.0925	-5.5190***	.0504	2.2588***	.3626	3.9186***	.4358***	-4.5957***	.0689	1.5043**	.5118
	(.3898)	(.1803)	(.5299)	(.0559)	(.6793)	[.3068]	(.2787)	(.1214)	(.4829)	(.0520)	(.7072)	[.4690]
Wide Receivers AV	3.7885***	-.0065	-.6625	-.0211	1.6506**	.4013	3.8011***	.7781***	-4.7167***	-.0515	1.6690*	.4787
	(.3898)	(.1388)	(.4932)	(.0735)	(.7477)	[.3489]	(.2536)	(.2195)	(.6601)	(.0930)	(.9321)	[.4331]
Tight Ends AV	1.9815***	-.0447	-2.4851***	-.0333	-.2186	.3498	2.4050***	.3410***	-5.0648***	.0173	.7781*	.4977
	(.1548)	(.0985)	(.3487)	(.0487)	(.3985)	[.2928]	(.1735)	(.0908)	(.3779)	(.0434)	(.4582)	[.4537]
Left Tackles AV	2.5040***	-.0429	-1.5000***	.0000	-.2699	.6150	2.8265***	.3944***	2.0056***	-.0231	1.1776***	.5539
	(.1921)	(.0858)	(.3602)	(.0464)	(.4580)	[.5812]	(.1227)	(.1255)	(.3450)	(.0490)	(.4553)	[.5149]
Guards AV	3.0159***	.3006**	-2.6626***	-.0862	1.0453*	.5124	4.1523***	.3626**	-.3573	-.0996	.9682	.4913
	(.2441)	(.1271)	(.6078)	(.0525)	(.6271)	[.4697]	(.3825)	(.1483)	(.5760)	(.0823)	(.6423)	[.4468]
Centers AV	2.7766***	.0861	-2.9739***	-.0365	.5288	.5943	3.3457***	.0825	.0223	-.1186***	.9473**	.4885
	(.1908)	(.0917)	(.3984)	(.0366)	(.3769)	[.5588]	(.2255)	(.0945)	(.4697)	(.0456)	(.4516)	[.4437]
Right Tackles AV	2.8455***	.1948*	1.2744***	-.0724**	.9874*	.5781	3.4163***	.2377**	3.8025***	-.0303	.5105	.5252
	(.2155)	(.1069)	(.2574)	(.0349)	(.5244)	[.5411]	(.1824)	(.1122)	(.3792)	(.0477)	(.4351)	[.4837]
Defensive Ends AV	3.4096***	-.0545	.0353	-.1247*	.9424*	.5954	4.0339***	.3671**	-1.3666**	-.0104	2.0015***	.5550
	(.2132)	(.1363)	(.4421)	(.0637)	(.5384)	[.5600]	(.2495)	(.1566)	(.6266)	(.0770)	(.6647)	[.5160]
Defensive Tackles AV	3.7177***	-.3334***	.2429	-.0733	.7419*	.5778	3.9717***	.4770***	.5368	.2345***	.3689	.5447
	(.2295)	(.1174)	(.3953)	(.0521)	(.4334)	[.5408]	(.2730)	(.1384)	(.4614)	(.0763)	(.5871)	[.5048]
Inside Linebackers AV	3.2116***	.0858	6.9156***	-.0916**	.9748**	.5330	3.9753***	.1976	-6.3216***	.0900	-.1914	.5056
	(.3626)	(.1111)	(.3023)	(.0429)	(.4210)	[.4921]	(.2545)	(.1802)	(.4267)	(.0655)	(.6690)	[.4623]
Outside Linebackers AV	3.1983***	.0186	-1.4604***	-.0444	1.3527**	.4582	3.8014***	.3546***	-2.5939***	-.0023	.9702	.4854
	(.2779)	(.1328)	(.4725)	(.0646)	(.6843)	[.4107]	(.2419)	(.1184)	(.5885)	(.0786)	(.6474)	[.4403]
Cornerbacks AV	3.0325***	-.1817	7.4454***	.0483	1.1970*	.3683	3.4126***	.4133**	-2.4800***	.0124	1.8117***	.4473
	(.3425)	(.1600)	(.6246)	(.0803)	(.7185)	[.3129]	(.2717)	(.1793)	(.8358)	(.0757)	(.6138)	[.3988]
Free Safeties AV	2.7233***	.0169	-2.8910***	-.0468	.8399*	.5103	3.6374***	.2420**	-4.6916***	-.0650	.3441	.5704
	(.2511)	(.0962)	(.3217)	(.0452)	(.4540)	[.4674]	(.1999)	(.1197)	(.4624)	(.0429)	(.2834)	[.5327]
Strong Safeties AV	2.3830***	.0417	.4051	-.0073	.2824	.4892	3.0770***	.2676***	-3.8902***	-.0060	-.2418	.5434
	(.1612)	(.1172)	(.3355)	(.0428)	(.4422)	[.4445]	(.2659)	(.1015)	(.2986)	(.0410)	(.3792)	[.5034]
Kickers AV	1.7001***	-.0022	.1418	-.0143	.1956	.5859	1.4583***	-.0153	.7561***	.0356**	.0817	.3118
	(.1575)	(.0327)	(.1135)	(.0133)	(.1401)	[.5496]	(.1363)	(.0530)	(.1111)	(.0166)	(.2467)	[.2515]
Punters AV	1.5091***	-.0118	1.1848***	.0112	-.0319	.7386	1.5797***	-.0065	.1796	.0374***	-.0280	.5631
	(.1139)	(.0215)	(.1364)	(.0100)	(.0676)	[.7157]	(.0850)	(.0314)	(.1186)	(.0134)	(.1208)	[.5249]
Long Snappers AV	.7058***	-.0072	-.2402***	-.0073**	.0043	.7856	1.4349***	.0019	-.4682***	-.0352***	.0806	.4877
	(.0599)	(.0060)	(.0217)	(.0029)	(.0216)	[.7668]	(.1105)	(.0209)	(.0629)	(.0119)	(.1158)	[.4428]

*$p<0.10$, **$p<0.05$, ***$p<0.01$. Team-clustered standard errors are in parentheses.

Table 20: $\sqrt{\text{Cap\%}}$ Actual vs. Calibrated Optimal Allocations, Team-Clustered Bootstrap Confidence Intervals

	Rookies				Veterans			
	Actual	Optimal	95% CI	Difference	Actual	Optimal	95% CI	Difference
Quarterbacks	6.8%	16.8%	(5.7%, 34.7%)	-10.0%	11.0%	14.9%	(4.8%, 31.5%)	-3.9%
Running Backs	7.1%	7.9%	(1.1%, 20.9%)	-0.7%	5.2%	8.1%	(1.5%, 19.1%)	-2.9%
Wide Receivers	12.3%	13.9%	(3.3%, 26.9%)	-1.6%	11.3%	10.5%	(2.7%, 19.0%)	0.8%
Tight Ends	4.9%	1.2%	(0.0%, 4.1%)	3.7%	5.0%	1.4%	(0.0%, 4.1%)	3.7%
Left Tackles	4.8%	1.7%	(0.0%, 4.6%)	3.1%	5.1%	1.6%	(0.0%, 4.5%)	3.5%
Guards	6.9%	3.9%	(0.4%, 9.5%)	3.0%	6.0%	5.5%	(0.5%, 13.6%)	0.4%
Centers	2.6%	3.5%	(0.0%, 11.6%)	-0.9%	3.4%	3.8%	(0.0%, 14.0%)	-0.4%
Right Tackles	4.0%	2.7%	(0.0%, 8.7%)	1.2%	3.3%	2.9%	(0.0%, 8.6%)	0.4%
Defensive Ends	9.1%	5.0%	(1.7%, 9.4%)	4.1%	8.9%	5.2%	(1.8%, 9.5%)	3.7%
Defensive Tackles	7.3%	8.0%	(3.1%, 13.8%)	-0.7%	7.4%	6.8%	(2.6%, 12.1%)	0.6%
Inside Linebackers	5.8%	7.3%	(2.3%, 14.4%)	-1.6%	5.2%	8.4%	(3.2%, 13.9%)	-3.2%
Outside Linebackers	8.3%	9.8%	(4.9%, 14.2%)	-1.6%	7.9%	10.4%	(4.9%, 16.3%)	-2.4%
Cornerbacks	11.4%	6.5%	(2.0%, 13.6%)	5.0%	9.8%	6.1%	(2.3%, 12.2%)	3.7%
Free Safeties	3.9%	7.0%	(1.7%, 13.7%)	-3.1%	3.6%	9.3%	(2.3%, 16.6%)	-5.8%
Strong Safeties	3.6%	2.7%	(0.3%, 6.7%)	0.9%	3.2%	3.4%	(0.4%, 8.8%)	-0.1%
Kickers	0.4%	0.1%	(0.0%, 2.4%)	0.3%	1.8%	0.1%	(0.0%, 1.3%)	1.7%
Punters	0.6%	2.0%	(0.0%, 9.7%)	-1.4%	1.2%	1.6%	(0.0%, 8.4%)	-0.4%
Long Snappers	0.3%	0.0%	(0.0%, 0.7%)	0.3%	0.7%	0.0%	(0.0%, 2.2%)	0.7%

Table 21: Quarterback Valuation Results, Pre and Post-2018 Season

(a) Pre-2018, 223 Fixed Effects ($N = 3,542$)

DV = Win	Passer Rating			ANY/A			TANY/A			FP/A		
	Logit	AME	Linear	Logit	AME	Linear	Logit	AME	Linear	Logit	AME	Linear
Quarterback Statistic	.0354***	.0035***	.0035***	.3045***	.0298***	.0303***	.3007***	.0294***	.0330***	3.8494***	.3771***	.4720***
	(.0118)	(.0011)	(.0010)	(.1067)	(.0104)	(.0099)	(.1084)	(.0105)	(.0098)	(1.4845)	(.1447)	(.1328)
Non-QB Fantasy Points	.1351	.0132	.0117	.1347	.0132	.0116	.1353	.0132	.0117	.1359	.0133	.0118
	(.0080)	(.0004)	(.0004)	(.0080)	(.0004)	(.0004)	(.0080)	(.0004)	(.0004)	(.0079)	(.0004)	(.0004)
Home	.3544	.0347	.0294	.3533	.0346	.0296	.3528	.0345	.0297	.3535	.0346	.0295
	(.0846)	(.0081)	(.0088)	(.0840)	(.0080)	(.0088)	(.0841)	(.0080)	(.0088)	(.0842)	(.0081)	(.0088)
Rest Days	-.0373	-.0037	-.0028	-.0357	-.0035	-.0027	-.0360	-.0035	-.0026	-.0377	-.0037	-.0029
	(.0327)	(.0032)	(.0036)	(.0327)	(.0032)	(.0036)	(.0328)	(.0032)	(.0036)	(.0326)	(.0032)	(.0036)
Log Injured Money	-.1516	-.0148	-.0163	-.1577	-.0154	-.0168	-.1574	-.0154	-.0171	-.1505	-.0147	-.0167
	(.1663)	(.0162)	(.0192)	(.1655)	(.0162)	(.0192)	(.1652)	(.0161)	(.0191)	(.1642)	(.0160)	(.0191)
Starter Gini	.4689	.0459	.0085	.6094	.0597	.0345	.3460	.0339	.0099	.0690	.0068	-.0278
	(2.4668)	(.2416)	(.2675)	(2.4791)	(.2432)	(.2663)	(2.4699)	(.2420)	(.2668)	(2.4698)	(.2420)	(.2686)
Starter/Non-Starter	.0581	.0057	-.0062	.0379	.0037	-.0073	.0258	.0025	-.0090	.0260	.0025	-.0097
	(.3106)	(.0304)	(.0337)	(.3093)	(.0303)	(.0336)	(.3081)	(.0302)	(.0336)	(.3080)	(.0302)	(.0338)
Pseudo-R^2 | R^2	.5559		.5149	.5553		.5144	.5552		.5149	.5550		.5152
Adjusted Pseudo-R^2 | R^2	.5531		.4823	.5524		.4818	.5524		.4823	.5521		.4827

*p<0.10, **p<0.05, ***p<0.01. Game-clustered standard errors are in parentheses.

(b) Post-2018, 224 Fixed Effects ($N = 3,696$)

DV = Win	Passer Rating			ANY/A			TANY/A			FP/A		
	Logit	AME	Linear	Logit	AME	Linear	Logit	AME	Linear	Logit	AME	Linear
Quarterback Statistic	.0380***	.0038***	.0035***	.3531***	.0358***	.0292***	.3998***	.0404***	.0347***	6.5194***	.6522***	.5676***
	(.0111)	(.0011)	(.0009)	(.0989)	(.0100)	(.0082)	(.0989)	(.0099)	(.0084)	(1.2255)	(.1207)	(.1072)
Non-QB Fantasy Points	.1329	.0134	.0120	.1329	.0135	.0120	.1335	.0135	.0120	.1357	.0136	.0121
	(.0081)	(.0005)	(.0004)	(.0082)	(.0005)	(.0004)	(.0082)	(.0004)	(.0004)	(.0082)	(.0004)	(.0004)
Home	.1442*	.0146*	.0135	.1428*	.0145*	.0136	.1437*	.0145*	.0137	.1433*	.0143*	.0136
	(.0761)	(.0077)	(.0086)	(.0761)	(.0077)	(.0086)	(.0761)	(.0077)	(.0086)	(.0767)	(.0076)	(.0086)
Rest Days	.0631*	.0064*	.0044	.0630*	.0064*	.0044	.0643*	.0065*	.0044	.0668*	.0067*	.0045
	(.0339)	(.0034)	(.0037)	(.0339)	(.0034)	(.0037)	(.0340)	(.0034)	(.0037)	(.0346)	(.0034)	(.0037)
Log Injured Money	.0941	.0095	.0080	.0838	.0085	.0080	.0687	.0070	.0066	.0511	.0051	.0051
	(.1359)	(.0137)	(.0149)	(.1354)	(.0137)	(.0149)	(.1353)	(.0137)	(.0149)	(.1360)	(.0136)	(.0149)
Starter Gini	4.4005**	.4453**	.4283*	4.1919**	.4248**	.4177*	4.1051*	.4152*	.4071*	4.0018*	.4004*	.3957*
	(2.0803)	(.2098)	(.2284)	(2.1209)	(.2143)	(.2299)	(2.1200)	(.2136)	(.2288)	(2.1037)	(.2096)	(.2257)
Starter/Non-Starter	.3164	.0320	.0211	.2843	.0288	.0208	.2461	.0249	.0166	.1635	.0164	.0101
	(.2854)	(.0289)	(.0311)	(.2850)	(.0289)	(.0311)	(.2873)	(.0291)	(.0311)	(.2872)	(.0287)	(.0311)
Pseudo-R^2 | R^2	.5395		.5046	.5391		.5039	.5399		.5048	.5445		.5073
Adjusted Pseudo-R^2 | R^2	.5367		.4726	.5364		.4718	.5372		.4728	.5418		.4756

*p<0.10, **p<0.05, ***p<0.01. Game-clustered standard errors are in parentheses.

Table 22: Calibrated Importance & Cost Effectiveness Results, Pre and Post-2018 $(N = 224)$

(a) Pre-2018

	Importance (DV = Wins)	Cost Effectiveness: Rookies (DV = Position AV)							Cost Effectiveness: Veterans (DV = Position AV)						
	Coefficient	log(Cap%)	Cap% = 0	Vegas Wins	2011 Colts	Season	COTY	R^2 [Adj R^2]	log(Cap%)	Cap% = 0	Vegas Wins	2011 Colts	Season	COTY	R^2 [Adj R^2]
Quarterbacks AV	.1252**	1.2919***	-4.3189***	-.1140	-8.1778***	-.3536	2.5883*	.5105	3.4909***	-.8374	.9451***	-5.1140***	-.0328	.4210	.6276
	(.0595)	(.2707)	(1.4874)	(.2906)	(.8433)	(.2185)	(1.4835)	[.4131]	(.4014)	(1.4233)	(.2165)	(.8846)	(.2170)	(1.4399)	[.5535]
Running Backs AV	.0628*	2.8926***	-6.9594***	.1094	-1.3278*	.2599	1.4199	.4005	3.4762***	-.4887	.4098**	-5.2555***	.0355	2.2158**	.6092
	(.0363)	(.4931)	(1.2899)	(.3908)	(.7348)	(.1685)	(.9495)	[.2812]	(.3787)	(.7447)	(.1946)	(.5432)	(.1555)	(1.0425)	[.5314]
Wide Receivers AV	.1039***	6.4857***		-.0579	-2.6106***	-.5205**	2.0305*	.5051	3.9173***	-1.9198	.0920	-5.4436***	-.0082	-.1517	.6574
	(.0331)	(.9158)		(.3815)	(.8626)	(.2383)	(1.1456)	[.4098]	(.6119)	(1.2584)	(.2880)	(.6244)	(.1843)	(1.2850)	[.5893]
Tight Ends AV	.0871*	1.1679***	-.8390*	-.0923	-4.9550***	-.2819**	-.2192	.3728	1.8847***	-1.1695	.3600**	-5.1048***	.2162*	.1118	.5809
	(.0451)	(.2470)	(.4310)	(.1678)	(.4704)	(.1306)	(.8348)	[.2481]	(.3895)	(.7359)	(.1555)	(.9748)	(.1218)	(.5434)	[.4976]
Left Tackles AV	.0805**	1.2722***	-3.4942***	-.1167	-2.5220***	-.2341*	-.4158	.6023	1.6894***	-3.7591***	.4525**	1.0744	.0523	.8049	.6533
	(.0342)	(.1919)	(.5757)	(.1612)	(.5493)	(.1377)	(.7670)	[.5232]	(.2357)	(.5960)	(.2006)	(.8199)	(.1258)	(.7964)	[.5843]
Guards AV	.0614**	2.2711***	-3.5051**	.7308***	-3.5419***	-.0889	1.9348	.5015	3.1284***	-4.2764***	.3962	-.3420	.0232	-.8283	.6132
	(.0249)	(.6681)	(1.6509)	(.2321)	(1.0795)	(.2045)	(1.2499)	[.4023]	(.4800)	(1.3001)	(.3438)	(.7302)	(.2092)	(1.2511)	[.5363]
Centers AV	.0820**	1.2648***	-3.2918***	.0997	-.1489	.1476	.9193*	.5432	2.1788***	-4.2153***	-.2095	-.0115	-.1115	1.1495	.5408
	(.0358)	(.1800)	(.5823)	(.2096)	(.4486)	(.1231)	(.5363)	[.4524]	(.2995)	(.5546)	(.1855)	(.8312)	(.1688)	(.7752)	[.4495]
Right Tackles AV	.0470	1.4357***	-3.5726***	.1234	2.0749***	-.1259	.2812	.5638	1.6606***	-3.3858***	-.0166	3.7413***	.2161	.8434	.5603
	(.0340)	(.1728)	(.6234)	(.1610)	(.4549)	(.1535)	(.8484)	[.4770]	(.2709)	(.5944)	(.2080)	(.8035)	(.1687)	(.8221)	[.4729]
Defensive Ends AV	.0845***	3.4847***	-1.5826	.0382	.0869	-.3119*	1.0817	.5684	3.3069***	-5.4454***	.2970	-.7006	.0787	3.7352***	.6304
	(.0145)	(.8043)	(1.5771)	(.2267)	(.7259)	(.1843)	(.8542)	[.4826]	(.4214)	(1.3387)	(.3139)	(.6831)	(.1913)	(1.3930)	[.5568]
Defensive Tackles AV	.0919***	3.0944***	-5.9204**	-.2888	-.9004	-.0576	1.0267	.5438	2.5642***	.9939	.3035	2.4146***	.3768*	.5592	.5336
	(.0249)	(.5877)	(2.9150)	(.3207)	(.8545)	(.2028)	(.7184)	[.4531]	(.3981)	(3.7094)	(.2240)	(.8374)	(.2163)	(.9594)	[.4408]
Inside Linebackers AV	.0901***	2.3921***	-4.6071***	.1468	9.0208***	.0969	1.0835	.5055	2.6337***	-3.4929***	.7032*	-9.8302***	.0722	-.2849	.5758
	(.0258)	(.5365)	(1.3502)	(.2541)	(.5988)	(.1716)	(1.1143)	[.4071]	(.5905)	(.7794)	(.4266)	(.7755)	(.2104)	(1.4804)	[.4914]
Outside Linebackers AV	.0922***	4.2191***		-.1798	.9930	-.3390*	.6863	.5040	3.3870***	-4.6211***	.2386	.1655	.0000	.5868	.4409
	(.0194)	(.6084)		(.2780)	(.6529)	(.1780)	(1.5044)	[.4085]	(.5197)	(.7117)	(.3103)	(.7304)	(.2008)	(.9768)	[.3297]
Cornerbacks AV	.0956***	5.4152***		-.3161	5.7924***	-.2709	2.3868	.4577	3.0875***		.4173	-.6813	.1331	1.2317	.4752
	(.0298)	(.6760)		(.2284)	(.8331)	(.1900)	(1.4886)	[.3533]	(.3847)		(.3379)	(1.5362)	(.2080)	(.9626)	[.3742]
Free Safeties AV	.1172***	1.7414***	-1.4134**	-.1455	-2.1880***	-.0425	.4433	.5369	1.7953***	-3.0867***	.7168***	-2.8272***	.1508	1.1979**	.6431
	(.0358)	(.2127)	(.6179)	(.2162)	(.5099)	(.1564)	(.6474)	[.4447]	(.2719)	(.6160)	(.1767)	(.4246)	(.1330)	(.5920)	[.5721]
Strong Safeties AV	.0899**	1.0017***	-3.1650***	-.0852	1.2687**	-.1141	-.4453	.4905	1.8243***	-3.4099***	.5413***	-4.9461***	-.0330	1.2709*	.5725
	(.0390)	(.2045)	(.6757)	(.2411)	(.5344)	(.1072)	(.6139)	[.3892]	(.2771)	(.5193)	(.1690)	(.3463)	(.1013)	(.7210)	[.4875]
Kickers AV	.0773	.3755***	-2.0267***	.0269	-.0289	-.0453	.0873	.6277	.6265***	-2.2745***	-.0868	.1905	.0955	-.0411	.4774
	(.0576)	(.0562)	(.2860)	(.0478)	(.1400)	(.0367)	(.2496)	[.5537]	(.1724)	(.1935)	(.0948)	(.2530)	(.0760)	(.2649)	[.3735]
Punters AV	.1461	.2955***	-1.7284***	-.0492	1.1491***	.0396*	.1200	.7792	.5902***	-1.8340***	-.0091	-.0075	-.0353	.0363	.6361
	(.1193)	(.0257)	(.1525)	(.0480)	(.1435)	(.0229)	(.1290)	[.7352]	(.1303)	(.1425)	(.0616)	(.1592)	(.0435)	(.2168)	[.5637]
Long Snappers AV	.0000	.1726***	-.7844***	-.0151	-.5455***	-.0350***	-.0457	.7949	.4548***	-1.2891***	-.0007	.0103	-.0247	.1698	.6796
	(.0462)	(.0172)	(.0795)	(.0117)	(.0582)	(.0104)	(.0480)	[.7541]	(.0760)	(.1010)	(.0201)	(.0857)	(.0224)	(.1946)	[.6158]
Vegas Wins O/U	.1045														
	(.0796)														
2011 Indianapolis Colts	-2.0992***														
	(.4270)														
Coach of the Year	1.4917***														
	(.3394)														
R^2	.8683														
Adjusted R^2	.8640														
Standard Errors	TC Bootstrap	Team-Clustered							Team-Clustered						

*p<0.10, **p<0.05, ***p<0.01. Standard errors are in parentheses.

(b) Post-2018

	Importance	Cost Effectiveness: Rookies						Cost Effectiveness: Veterans					
	(DV = Wins)	(DV = Position AV)						(DV = Position AV)					
	Coefficient	log(Cap%)	Cap% = 0	Vegas Wins	Season	COTY	R^2 [Adj R^2]	log(Cap%)	Cap% = 0	Vegas Wins	Season	COTY	R^2 [Adj R^2]
Quarterbacks AV	.1990***	2.5147***	-2.0767**	.0215	-.1253	2.1200***	.5794	3.0905***		1.1647***	.2307	.4500	.6267
	(.0505)	(.3440)	(.9505)	(.2616)	(.2127)	(.7734)	[.4984]	(.4131)		(.2499)	(.1927)	(.6902)	[.5573]
Running Backs AV	.1372***	5.1002***		.0006	-.2115	2.7485***	.5096	3.0737***		.2965**	.1497	.9656	.5318
	(.0348)	(.5665)		(.1942)	(.2238)	(.9761)	[.4183]	(.3631)		(.1503)	(.1328)	(.9118)	[.4447]
Wide Receivers AV	.0793***	6.0634***		-.1491	.0905	.9948	.4293	4.9462***		.9144***	-.0590	2.8380***	.4875
	(.0296)	(.8743)		(.2680)	(.2729)	(1.0712)	[.3231]	(.5146)		(.2813)	(.1875)	(.9853)	[.3920]
Tight Ends AV	.0000	1.0448***	.0583	-.1923	.0416	-.4159	.4506	1.6149***	-1.2065	.2213	.0660	.9099**	.5672
	(.0185)	(.2321)	(.3735)	(.1455)	(.1289)	(.6031)	[.3448]	(.3763)	(.7646)	(.1545)	(.1217)	(.4140)	[.4838]
Left Tackles AV	.0107	1.3632***	-2.0615***	-.2036	.1326	-.0858	.4895	1.6808***	-3.9152***	.4988**	-.0788	2.2781***	.5535
	(.0250)	(.1851)	(.5609)	(.1517)	(.1289)	(.7778)	[.3912]	(.1088)	(1.0603)	(.1961)	(.1569)	(.6726)	[.4676]
Guards AV	.0437	2.4539***	-1.4890***	.2198	-.1055	.4486	.5531	2.8326***	-1.9075***	.0995	-.2874*	2.4680**	.5042
	(.0281)	(.3477)	(.3540)	(.2015)	(.1818)	(.8008)	[.4670]	(.4341)	(.6554)	(.1994)	(.1509)	(.9615)	[.4087]
Centers AV	.0551	1.3295***	-2.7157***	.0564	-.0109	.0856	.5525	2.0707***	-4.6185***	.2703	-.1742	1.3283**	.5552
	(.0376)	(.1776)	(.3459)	(.1113)	(.1222)	(.6441)	[.4664]	(.2009)	(.6059)	(.1731)	(.1379)	(.6121)	[.4696]
Right Tackles AV	.0545	1.5595***	-2.7204***	.1333	-.1341	1.3076	.5190	1.9483***	-3.1823***	.2000	-.0130	.3693	.4810
	(.0426)	(.1626)	(.5872)	(.1901)	(.1461)	(.9427)	[.4264]	(.2542)	(.5973)	(.1715)	(.1439)	(.5369)	[.3810]
Defensive Ends AV	.0441**	3.0024***	-2.6859***	-.0386	-.1344	.6255	.5535	4.2612***		.3033	.0968	.3500	.5261
	(.0224)	(.5670)	(.6729)	(.2703)	(.1692)	(.8686)	[.4675]	(.4347)		(.2277)	(.2312)	(1.0607)	[.4379]
Defensive Tackles AV	.0416*	2.7079***	.1803	-.2209	-.1637	.6649	.5126	3.0341***	-2.9100***	.7903***	.1893	.4899	.5287
	(.0235)	(.4197)	(.6430)	(.1884)	(.1792)	(.6649)	[.4188]	(.6503)	(.9003)	(.2720)	(.2337)	(.8809)	[.4379]
Inside Linebackers AV	.0719***	2.4254***	-.9703	.1898	-.2050	-.4242	.5940	2.9117***	-3.0672*	.3665	.1305	1.0294	.5143
	(.0216)	(.3252)	(1.6263)	(.1777)	(.1526)	(.8524)	[.5159]	(.4186)	(1.7198)	(.2696)	(.1960)	(1.1023)	[.4208]
Outside Linebackers AV	.1063***	3.2786***		.0274	-.3368	1.0318	.5215	3.0020***	-4.2745***	.2256	.1337	1.5191	.5397
	(.0174)	(.7125)		(.1760)	(.2261)	(.9327)	[.4324]	(.4291)	(1.4624)	(.2274)	(.2255)	(1.1336)	[.4511]
Cornerbacks AV	.0935***	4.8832***		-.1220	.1059	-.0690	.4920	3.9397***		.2367	-.0037	1.8842*	.5800
	(.0270)	(.5523)		(.2466)	(.1920)	(.7314)	[.3974]	(.4870)		(.3265)	(.1797)	(1.0112)	[.5018]
Free Safeties AV	.1272***	1.3535***	-3.3618***	.1282	-.1595	1.1662*	.4847	2.3711***	-3.2763***	.0475	-.1093	-.5068	.5141
	(.0316)	(.2217)	(1.2918)	(.1744)	(.1323)	(.6219)	[.3855]	(.3333)	(.4196)	(.2037)	(.1526)	(.6679)	[.4206]
Strong Safeties AV	.0848***	1.2395***	-2.0740***	.2150	-.0130	.8247	.4416	2.0563***	-3.4614***	.0463	.1709	-1.5198***	.5933
	(.0286)	(.2564)	(.3992)	(.1812)	(.1359)	(.7267)	[.3341]	(.2138)	(.3311)	(.1515)	(.1242)	(.4418)	[.5150]
Kickers AV	.0000	.3521***	-1.5567***	.0158	.0154	.3211	.5177	.4448***	-2.5277***	-.0222	.0092	.0812	.3221
	(.0080)	(.0553)	(.2835)	(.0489)	(.0409)	(.2121)	[.4249]	(.0906)	(.2132)	(.0693)	(.0728)	(.3733)	[.1916]
Punters AV	.0345	.3922***	-1.7420***	-.0337	.0205	-.1578	.7182	.5319***	-2.0440***	-.0562*	.0858**	.0040	.6118
	(.0691)	(.0469)	(.1211)	(.0366)	(.0298)	(.1591)	[.6639]	(.0947)	(.1194)	(.0325)	(.0421)	(.2117)	[.5371]
Long Snappers AV	.0551	.1511***	-.6907***	-.0012	-.0065	.0021	.7709	.3157***	-1.2574***	-.0121	-.0555**	.0174	.3843
	(.0902)	(.0159)	(.0819)	(.0078)	(.0068)	(.0356)	[.7268]	(.0801)	(.1434)	(.0259)	(.0234)	(.1155)	[.2658]
Vegas Wins O/U	.2302***												
	(.0727)												
17 Game Season	.3706**												
	(.1561)												
Coach of the Year	1.5581***												
	(.3363)												
R^2	.8605												
Adjusted R^2	.8560												
Standard Errors	TC Bootstrap	Team-Clustered						Team-Clustered					

*p<0.10, **p<0.05, ***p<0.01. Standard errors are in parentheses.

Table 23: Actual vs. Baseline Optimal Allocations, Pre and Post-2018

(a) Pre-2018, Team-Clustered Bootstrap Confidence Intervals

	Rookies				Veterans			
	Actual	Optimal	95% CI	Difference	Actual	Optimal	95% CI	Difference
Quarterbacks	6.6%	2.9%	(-1.1%, 8.1%)	3.6%	10.5%	8.0%	(-2.6%, 19.8%)	2.5%
Running Backs	7.4%	6.9%	(1.1%, 14.1%)	0.5%	5.9%	8.7%	(1.3%, 15.9%)	-2.7%
Wide Receivers	12.2%	19.3%	(6.5%, 28.8%)	-7.1%	10.7%	11.7%	(3.5%, 20.0%)	-1.1%
Tight Ends	4.6%	2.4%	(-0.3%, 5.0%)	2.2%	5.2%	3.9%	(-0.4%, 8.7%)	1.3%
Left Tackles	5.5%	2.6%	(0.3%, 4.6%)	2.9%	4.5%	3.5%	(0.5%, 6.3%)	1.0%
Guards	7.5%	3.9%	(0.7%, 8.6%)	3.6%	6.0%	5.4%	(1.1%, 9.9%)	0.6%
Centers	2.6%	2.9%	(0.5%, 5.5%)	-0.2%	3.2%	5.2%	(0.9%, 10.2%)	-2.0%
Right Tackles	3.5%	2.2%	(-0.4%, 5.2%)	1.3%	2.9%	2.6%	(-0.5%, 5.7%)	0.3%
Defensive Ends	8.8%	7.9%	(4.0%, 14.1%)	1.0%	8.8%	7.6%	(4.7%, 11.5%)	1.1%
Defensive Tackles	8.0%	7.5%	(2.7%, 14.0%)	0.5%	7.0%	6.2%	(2.3%, 11.1%)	0.7%
Inside Linebackers	5.4%	5.5%	(1.8%, 9.8%)	-0.1%	5.5%	6.0%	(2.3%, 11.1%)	-0.5%
Outside Linebackers	8.5%	9.9%	(6.0%, 14.3%)	-1.4%	8.8%	8.1%	(4.6%, 12.7%)	0.7%
Cornerbacks	10.3%	15.9%	(8.2%, 23.7%)	-5.6%	10.3%	9.2%	(5.3%, 13.3%)	1.1%
Free Safeties	4.2%	6.2%	(3.3%, 9.2%)	-2.0%	3.4%	6.4%	(3.5%, 10.3%)	-3.0%
Strong Safeties	3.5%	2.7%	(1.0%, 5.2%)	0.9%	3.3%	4.9%	(1.8%, 8.6%)	-1.6%
Kickers	0.5%	0.6%	(-0.7%, 1.8%)	-0.2%	1.9%	1.1%	(-1.1%, 3.4%)	0.8%
Punters	0.6%	1.2%	(-0.6%, 3.1%)	-0.7%	1.4%	2.5%	(-1.4%, 6.7%)	-1.1%
Long Snappers	0.4%	-0.4%	(-1.6%, 0.8%)	0.7%	0.7%	-1.0%	(-4.8%, 2.1%)	1.7%

(b) Post-2018, Team-Clustered Bootstrap Confidence Intervals

	Rookies				Veterans			
	Actual	Optimal	95% CI	Difference	Actual	Optimal	95% CI	Difference
Quarterbacks	7.1%	9.6%	(1.5%, 17.9%)	-2.5%	11.6%	11.7%	(1.8%, 21.6%)	-0.1%
Running Backs	6.9%	21.3%	(8.6%, 31.0%)	-14.4%	4.4%	12.6%	(5.3%, 19.4%)	-8.2%
Wide Receivers	12.3%	16.0%	(4.4%, 26.5%)	-3.7%	11.9%	14.2%	(4.4%, 22.9%)	-2.3%
Tight Ends	5.2%	0.1%	(-2.6%, 2.8%)	5.1%	4.9%	0.1%	(-4.0%, 4.4%)	4.8%
Left Tackles	4.1%	1.2%	(-1.5%, 4.8%)	2.9%	5.7%	1.5%	(-2.2%, 5.4%)	4.2%
Guards	6.4%	4.2%	(-0.3%, 8.6%)	2.2%	5.9%	4.9%	(-0.4%, 9.4%)	1.0%
Centers	2.5%	2.4%	(-0.7%, 5.8%)	0.1%	3.5%	3.8%	(-1.1%, 8.5%)	-0.2%
Right Tackles	4.4%	2.9%	(-1.3%, 7.8%)	1.5%	3.7%	3.6%	(-1.6%, 9.9%)	0.0%
Defensive Ends	9.4%	4.3%	(0.7%, 9.6%)	5.1%	9.0%	6.1%	(1.1%, 11.7%)	2.8%
Defensive Tackles	6.7%	3.7%	(0.3%, 8.0%)	3.0%	7.9%	4.1%	(0.4%, 8.4%)	3.7%
Inside Linebackers	6.1%	4.7%	(2.1%, 8.3%)	1.4%	4.9%	5.8%	(2.8%, 9.6%)	-1.0%
Outside Linebackers	8.0%	9.9%	(5.9%, 16.6%)	-1.9%	7.1%	9.0%	(5.8%, 13.3%)	-1.9%
Cornerbacks	12.5%	12.7%	(5.7%, 20.9%)	-0.2%	9.4%	10.2%	(4.8%, 17.5%)	-0.8%
Free Safeties	3.6%	4.9%	(2.2%, 7.4%)	-1.3%	3.7%	8.6%	(3.9%, 12.4%)	-4.9%
Strong Safeties	3.6%	2.5%	(0.5%, 4.7%)	1.1%	3.2%	4.1%	(0.7%, 7.4%)	-0.9%
Kickers	0.3%	-0.6%	(-1.6%, 0.5%)	1.0%	1.7%	-0.8%	(-2.4%, 0.6%)	2.5%
Punters	0.6%	0.3%	(-1.9%, 2.3%)	0.3%	1.0%	0.4%	(-2.7%, 3.1%)	0.6%
Long Snappers	0.2%	-0.1%	(-2.2%, 0.9%)	0.3%	0.6%	-0.1%	(-4.7%, 1.8%)	0.7%

Table 24: Baseline Importance & Cost Effectiveness Results, Pre and Post-2018 $(N = 224)$

(a) Pre-2018

	Importance (DV = Wins)	Cost Effectiveness: Rookies (DV = Position AV)						Cost Effectiveness: Veterans (DV = Position AV)					
	Coefficient	log(Cap%)	Cap% = 0	Vegas Wins	2011 Colts	Season	R^2 [Adj R^2]	log(Cap%)	Cap% = 0	Vegas Wins	2011 Colts	Season	R^2 [Adj R^2]
Quarterbacks AV	.0925	1.3100***	-4.3800***	-.1953	-8.5382***	-.3236	.4895	3.4754***	-.7431	.9311***	-5.1458***	-.0250	.6272
	(.0734)	(.2675)	(1.4908)	(.3006)	(.8385)	(.2242)	[.3912]	(.4044)	(1.3482)	(.2133)	(.8769)	(.2131)	[.5554]
Running Backs AV	.0994**	2.8622***	-6.5061***	.0606	-1.5148**	.2732	.3930	3.5172***	-1.0932*	.3405*	-5.5819***	.0613	.5920
	(.0444)	(.5196)	(1.2436)	(.3826)	(.7270)	(.1733)	[.2761]	(.3947)	(.6591)	(.1860)	(.5350)	(.1547)	[.5134]
Wide Receivers AV	.1210***	6.5522***		-.1236	-2.9053***	-.4994**	.4952	3.9127***	-1.9057	.0972	-5.4215***	-.0099	.6574
	(.0436)	(.9156)		(.3794)	(.8591)	(.2462)	[.4013]	(.6175)	(1.2480)	(.2970)	(.6454)	(.1811)	[.5914]
Tight Ends AV	.0831*	1.1672***	-.7681***	-.0852	-4.9247***	-.2843**	.3724	1.8878***	-1.1528	.3564**	-5.1249***	.2175*	.5808
	(.0459)	(.2458)	(.2828)	(.1663)	(.4362)	(.1319)	[.2515]	(.3935)	(.7442)	(.1575)	(.9986)	(.1212)	[.5002]
Left Tackles AV	.0830**	1.2743***	-3.5048***	-.1025	-2.4674***	-.2392*	.6014	1.7110***	-3.7587***	.4278**	1.0173	.0623	.6504
	(.0370)	(.1930)	(.5803)	(.1576)	(.5050)	(.1387)	[.5247]	(.2343)	(.5955)	(.1943)	(.8261)	(.1252)	[.5831]
Guards AV	.0690**	2.3000***	-3.8517**	.6701***	-3.7700***	-.0636	.4884	3.1671***	-4.0676***	.4235	-.1813	.0162	.6118
	(.0274)	(.6358)	(1.5698)	(.2259)	(1.0111)	(.2187)	[.3900]	(.5056)	(1.3330)	(.3462)	(.7745)	(.2087)	[.5371]
Centers AV	.0947**	1.2563***	-3.3157***	.0711	-.2637	.1581	.5375	2.2175***	-4.1341***	-.2463	-.1978	-.0941	.5350
	(.0426)	(.1770)	(.5558)	(.2110)	(.4397)	(.1227)	[.4485]	(.3151)	(.5332)	(.1895)	(.7566)	(.1723)	[.4454]
Right Tackles AV	.0623	1.4407***	-3.5364***	.1139	2.0382***	-.1220	.5633	1.6728***	-3.2565***	-.0412	3.6958***	.2324	.5571
	(.0392)	(.1682)	(.5983)	(.1542)	(.4969)	(.1468)	[.4793]	(.2732)	(.5851)	(.2050)	(.8189)	(.1701)	[.4719]
Defensive Ends AV	.0933***	3.4642***	-1.4703	.0020	-.0504	-.2979	.5649	3.2975***	-3.9503***	.2004	-1.2151	.1208	.6049
	(.0163)	(.8010)	(1.4706)	(.2213)	(.7229)	(.1841)	[.4812]	(.4409)	(.7480)	(.3352)	(.7408)	(.1960)	[.5288]
Defensive Tackles AV	.0983***	3.1273***	-6.0379**	-.3273	-1.0118	-.0441	.5412	2.5635***	.9160	.2859	2.3371***	.3831*	.5327
	(.0284)	(.5997)	(2.9153)	(.3054)	(.8447)	(.2063)	[.4528]	(.3963)	(3.6627)	(.2260)	(.8234)	(.2156)	[.4427]
Inside Linebackers AV	.0921***	2.4501***	-4.9600***	.1115	8.8829***	.1105	.5016	2.6505***	-3.5007***	.7134*	-9.7778***	.0707	.5756
	(.0288)	(.5264)	(1.2274)	(.2489)	(.6165)	(.1689)	[.4057]	(.6138)	(.7794)	(.4126)	(.8255)	(.2074)	[.4939]
Outside Linebackers AV	.0963***	4.2420***		-.2035	.8967	-.3321*	.5025	3.3925***	-4.5345***	.2197	.0825	.0068	.4399
	(.0214)	(.6334)		(.2814)	(.6065)	(.1791)	[.4099]	(.5136)	(.6610)	(.3079)	(.7159)	(.1980)	[.3321]
Cornerbacks AV	.1207***	5.4226***		-.3929	5.4613***	-.2433	.4365	3.0924***		.3778	-.8336	.1476	.4711
	(.0296)	(.6321)		(.2435)	(.8861)	(.1997)	[.3316]	(.3717)		(.3287)	(1.4578)	(.2043)	[.3726]
Free Safeties AV	.1447***	1.7536***	-1.4038**	-.1583	-2.2509***	-.0371	.5357	1.7913***	-3.1610***	.6782***	-2.9939***	.1636	.6363
	(.0383)	(.2125)	(.5624)	(.2174)	(.5491)	(.1503)	[.4463]	(.2637)	(.6109)	(.1837)	(.4370)	(.1351)	[.5663]
Strong Safeties AV	.1078**	1.0166***	-3.2420***	-.0652	1.3003**	-.1195	.4885	1.8283***	-3.4856***	.5006***	-5.1197***	-.0182	.5611
	(.0442)	(.2032)	(.6287)	(.2395)	(.5417)	(.1055)	[.3900]	(.2800)	(.4863)	(.1632)	(.3627)	(.1024)	[.4766]
Kickers AV	.0691	.3756***	-2.0257***	.0241	-.0411	-.0443	.6273	.6258***	-2.2745***	-.0855	.1960	.0950	.4774
	(.0798)	(.0566)	(.2868)	(.0486)	(.1371)	(.0358)	[.5556]	(.1724)	(.1932)	(.0970)	(.2515)	(.0756)	[.3767]
Punters AV	.1734	.2952***	-1.7103***	-.0543	1.1417***	.0402*	.7779	.5903***	-1.8376***	-.0105	-.0098	-.0350	.6360
	(.1489)	(.0257)	(.1522)	(.0444)	(.1411)	(.0230)	[.7352]	(.1303)	(.1370)	(.0573)	(.1587)	(.0434)	[.5659]
Long Snappers AV	-.0874	.1731***	-.7864***	-.0137	-.5379***	-.0355***	.7940	.4640***	-1.2992***	-.0057	-.0106	-.0229	.6767
	(.1573)	(.0174)	(.0793)	(.0112)	(.0575)	(.0105)	[.7543]	(.0778)	(.0997)	(.0214)	(.0712)	(.0225)	[.6145]
Vegas Wins O/U	.0295												
	(.0931)												
2011 Indianapolis Colts	-2.2441***												
	(.4070)												
R^2	.8520												
Adjusted R^2	.8081												

*p<0.10, **p<0.05, ***p<0.01. Team-clustered standard errors are in parentheses.

(b) Post-2018

	Importance	Cost Effectiveness: Rookies					Cost Effectiveness: Veterans				
	(DV = Wins)	(DV = Position AV)					(DV = Position AV)				
	Coefficient	log(Cap%)	Cap% = 0	Vegas Wins	Season	R^2 [Adj R^2]	log(Cap%)	Cap% = 0	Vegas Wins	Season	R^2 [Adj R^2]
Quarterbacks AV	.1578**	2.5426***	-2.1045**	-.0156	-.1270	.5633	3.0860***		1.1553***	.2303	.6261
	(.0650)	(.3323)	(.8998)	(.2532)	(.2066)	[.4820]	(.4107)		(.2566)	(.1924)	[.5588]
Running Backs AV	.1733***	5.1588***		-.0599	-.2117	.4740	3.0300***		.2767*	.1511	.5271
	(.0489)	(.6212)		(.2058)	(.2457)	[.3794]	(.3511)		(.1511)	(.1302)	[.4421]
Wide Receivers AV	.1128***	5.9713***		-.1663	.0930	.4258	5.2444***		.8581***	-.0610	.4616
	(.0419)	(.8690)		(.2679)	(.2709)	[.3226]	(.5428)		(.2861)	(.1904)	[.3647]
Tight Ends AV	.0032	1.0513***	-.1518	-.1832	.0413	.4481	1.6476***	-.7265	.2062	.0642	.5579
	(.0494)	(.2292)	(.2210)	(.1409)	(.1294)	[.3453]	(.3835)	(.7577)	(.1521)	(.1211)	[.4756]
Left Tackles AV	.0369	1.3644***	-2.0518***	-.2016	.1327	.4894	1.7314***	-3.0817***	.4594**	-.0825	.5245
	(.0494)	(.1812)	(.5568)	(.1506)	(.1294)	[.3944]	(.1315)	(.9727)	(.2020)	(.1683)	[.4360]
Guards AV	.0714*	2.4462***	-1.4899***	.2104	-.1053	.5520	2.8754***	-2.3448***	.0465	-.2864*	.4760
	(.0394)	(.3449)	(.3508)	(.1950)	(.1810)	[.4686]	(.4027)	(.6222)	(.2211)	(.1658)	[.3784]
Centers AV	.0761	1.3275***	-2.7200***	.0545	-.0109	.5525	2.0672***	-4.9491***	.2446	-.1743	.5423
	(.0508)	(.1797)	(.3497)	(.1104)	(.1219)	[.4692]	(.2275)	(.5529)	(.1715)	(.1377)	[.4571]
Right Tackles AV	.0772	1.5586***	-2.6293***	.1069	-.1339	.5076	1.9452***	-3.2138***	.1924	-.0130	.4800
	(.0635)	(.1650)	(.6635)	(.1867)	(.1479)	[.4159]	(.2577)	(.5885)	(.1710)	(.1455)	[.3831]
Defensive Ends AV	.0597**	3.0160***	-2.4732***	-.0504	-.1346	.5519	4.2593***		.2962	.0965	.5258
	(.0280)	(.5653)	(.3970)	(.2732)	(.1698)	[.4685]	(.4326)		(.2286)	(.2296)	[.4405]
Defensive Tackles AV	.0566**	2.7325***	.1943	-.2339	-.1630	.5103	3.0309***	-2.5915***	.7805***	.1899	.5280
	(.0268)	(.4179)	(.6600)	(.1952)	(.1800)	[.4192]	(.6454)	(.7348)	(.2645)	(.2323)	[.4401]
Inside Linebackers AV	.0823***	2.4153***	-1.1327	.1982	-.2067	.5931	2.9473***	-3.0793**	.3443	.1277	.5101
	(.0229)	(.3262)	(1.5211)	(.1781)	(.1534)	[.5174]	(.4336)	(1.4569)	(.2579)	(.1947)	[.4189]
Outside Linebackers AV	.1260***	3.3033***		.0061	-.3381	.5171	2.9681***	-4.3550***	.1936	.1337	.5333
	(.0225)	(.7166)		(.1785)	(.2274)	[.4302]	(.4434)	(1.3597)	(.2318)	(.2286)	[.4464]
Cornerbacks AV	.1096***	4.8809***		-.1206	.1060	.4919	3.8622***		.2009	-.0065	.5652
	(.0320)	(.5511)		(.2516)	(.1921)	[.4005]	(.4646)		(.3444)	(.1810)	[.4870]
Free Safeties AV	.1512***	1.3659***	-3.5116***	.1046	-.1598	.4694	2.3610***	-3.1781***	.0568	-.1090	.5125
	(.0350)	(.2368)	(1.3539)	(.1718)	(.1354)	[.3706]	(.3301)	(.4627)	(.2020)	(.1524)	[.4217]
Strong Safeties AV	.0823**	1.2644***	-2.0388***	.1981	-.0146	.4347	2.0691***	-3.4545***	.0783	.1715	.5725
	(.0346)	(.2574)	(.5268)	(.1750)	(.1381)	[.3294]	(.2201)	(.4717)	(.1541)	(.1307)	[.4929]
Kickers AV	-.0775	.3416***	-1.5614***	.0097	.0143	.5077	.4419***	-2.5337***	-.0237	.0091	.3218
	(.0745)	(.0544)	(.2862)	(.0492)	(.0409)	[.4161]	(.0927)	(.2042)	(.0674)	(.0727)	[.1955]
Punters AV	.0315	.3930***	-1.7354***	-.0306	.0207	.7160	.5318***	-2.0439***	-.0563*	.0858**	.6118
	(.1195)	(.0469)	(.1196)	(.0352)	(.0300)	[.6631]	(.0949)	(.1201)	(.0316)	(.0420)	[.5395]
Long Snappers AV	-.0146	.1511***	-.6906***	-.0013	-.0065	.7709	.3148***	-1.2570***	-.0124	-.0555**	.3842
	(.1651)	(.0158)	(.0822)	(.0078)	(.0068)	[.7282]	(.0805)	(.1432)	(.0266)	(.0234)	[.2696]
Vegas Wins O/U	.1140										
	(.0806)										
17 Game Season	.4042**										
	(.1768)										
R^2	.8395										
Adjusted R^2	.7920										

*p<0.10, **p<0.05, ***p<0.01. Team-clustered standard errors are in parentheses.

F Evolution of the Quarterback Market

The data for our difference in differences analysis consist of 31,688 player-season-contract level observations from 2011 to 2024 (a player can have receive a second contract within a season, which overwrites the first one). Our pre-treatment period is 2011 to 2017, and our post-treatment period is 2018 to 2024. We also partition the data into quarterbacks vs. non-quarterbacks, players on rookie vs. veteran contracts, and expensive (i.e. starter-level money) vs. non-expensive contracts. Regarding the last partition, for all season-position-contract type groups, we rank players either by their salary cap hits (*Cap Hit*), or by their average cap hits per year (*APY*) across the duration of their contract. *Expensive* equals 1 for the top 16 rookie and top 16 veteran quarterbacks, since there are 32 starting quarterbacks, one per team. For positions with two starters per team, such as offensive guard, it equals 1 for the top 32 rookies and top 32 veterans. And for positions with three starters per team, such as wide receiver, it equals 1 for the top 48 rookies and top 48 veterans. If position is ambiguous (e.g. tackle), we classify it as the cheaper of the two positions (e.g. right, not left, tackle), though our results are robust to classifying it the other way.

Our dependent variable is either *Cap Hit/Cap* or *APY/Cap*, depending on which ranking we use. *APY/Cap* is ultimately a better measure because teams often intentionally delay the largest values of *Cap Hit/Cap* within a contract, especially when trying to win in the short term. Therefore, for recently-signed contracts, *Cap Hit/Cap* often appears small because the later seasons in those contracts will happen after 2024, so they do not appear in our sample. Nevertheless, for both dependent variables, we divide by the season-specific cap (as opposed to the cap in the season when the contract was signed) because we must account for the cap increasing over time.

In addition, we have two control variables: *Pre-2011*$\times$(1$-$*Veteran*) and *Length*, the latter only for the dependent variable *APY/Cap*. *Pre-2011* is a dummy that equals 1 if the player debuted before 2011 and controls for pre-2011 collective bargaining agreement rookie contracts. *Length* is the number of seasons in the contract, which is necessary for *APY/Cap* because long high-*APY* contracts may end up becoming cheap relative to the future cap. We also have two-way season and position fixed effects, plus team fixed effects. We need the two-way fixed effects because there are more than two seasons and positions (whereas there are only two contract types and expense levels). Meanwhile, the team fixed effects control for team-specific allocation strategies, and we cluster the standard errors by team-season units, as the cap binds at the team-season level. We present summary statistics for our difference in differences dataset in Table 25.

Let *Salary* be either *Cap Hit* or *APY*. Also, let *Treatment* be either $QB \times Veteran$ or $QB \times Veteran \times Expensive$. Then, our specification is as follows, with unsubscripted variables varying at the player-season-contract level; β_3 being the coefficient of interest; *Length* only appearing if *Salary* = *Cap Hit*; and η, ψ, and ξ being season, position, and team fixed effects respectively:

$$\begin{aligned}\text{Salary/Cap} = \beta_1\text{Post-2018} + \beta_2\text{Treatment} + \beta_3(\text{Post-2018}\times\text{Treatment}) + \\ \delta_1(\text{Pre-2011}\times(1-\text{Veteran})) + \delta_2\text{Length} + \eta_j + \psi_p + \xi_i + \varepsilon. \quad (38)\end{aligned}$$

Table 25: DID Summary Statistics, 2011–2024 ($N = 31,688$)

	Mean	SD	Min	Max
Post-2018	.5235	.4995	0	1
QB	.0440	.2051	0	1
Veteran	.5531	.4972	0	1
Expensive (Cap Hit/Cap)	.3419	.4744	0	1
Expensive (APY/Cap)	.3424	.4745	0	1
QB × Veteran	.0283	.1659	0	1
QB × Veteran × Expensive (Cap Hit/Cap)	.0071	.0840	0	1
QB × Veteran × Expensive (APY/Cap)	.0071	.0842	0	1
Post-2018 × QB × Veteran	.0156	.1238	0	1
Post-2018 × QB × Veteran × Expensive (Cap Hit/Cap)	.0035	.0593	0	1
Post-2018 × QB × Veteran × Expensive (APY/Cap)	.0036	.0599	0	1
Cap Hit/Cap	.0123	.0191	0	.2088
Cap Hit/Cap (Post-2018 × QB × Veteran = 1)	.0337	.0483	0	.2088
Cap Hit/Cap (Post-2018 × QB × Veteran = 0)	.0119	.0180	0	.1687
Cap Hit/Cap (Post-2018 × QB × Veteran × Expensive = 1)	.1132	.0367	0	.2088
Cap Hit/Cap (Post-2018 × QB × Veteran × Expensive = 0)	.0119	.0180	0	.1687
APY/Cap	.0150	.0232	0	.2466
APY/Cap (Post-2018 × QB × Veteran = 1)	.0500	.0705	0	.2466
APY/Cap (Post-2018 × QB × Veteran = 0)	.0144	.0212	0	.1780
APY/Cap (Post-2018 × QB × Veteran × Expensive = 1)	.1687	.0384	0	.2466
APY/Cap (Post-2018 × QB × Veteran × Expensive = 0)	.0144	.0212	0	.1780
Pre-2011 × (1 − Veteran)	.0423	.2012	0	1
Length	2.7870	1.4098	1	10

Overall, Table 26 verifies the post-2018 explosion in the expensive veteran quarterback market. Due to the aforementioned delayed large cap hits, *Treatment*'s effect is greater on *APY/Cap* than on *Cap Hit/Cap*. Also, when $Treatment = QB \times Veteran \times Expensive$ and $Salary = APY$, $\hat{\beta}_3$ is positive and significant at the 1% level. In magnitude, we find that post-2018, expensive veteran quarterbacks' *APY/Cap* increased by 4.31% points relative to that of other players. That is, rich quarterbacks became significantly richer after 2018, though their contracts have not always been worth it for teams. Sometimes the contacts work out (e.g. Patrick Mahomes, 2020 Kansas City Chiefs), but other times they do not (e.g. Deshaun Watson, 2022 Cleveland Browns).

Finally, in Table 27, we show that our results are robust to triple and quadruple difference in differences. That is, instead of setting *Treatment* equal to $QB \times Veteran$ or $QB \times Veteran \times Expensive$, we estimate separate coefficients for all the partitions and all their interactions. $Treatment = QB \times Veteran$ corresponds to triple differences, and $Treatment = QB \times Veteran \times Expensive$ corresponds to quadruple differences. The coefficient on the four-way interaction term with *APY/Cap* as the dependent variable is 3.91% points, which is close to the 4.31% points we obtain using *Treatment*. Ultimately, we conclude from this analysis that the expensive veteran quarterback market has become even more expensive since Cousins's 2018 free agency.

Table 26: DID Results, Season + Position + Team Fixed Effects ($N = 31,688$)

	QB × Veteran		QB × Veteran × Expensive	
	Cap Hit/Cap	APY/Cap	Cap Hit/Cap	APY/Cap
Post-2018	-.0051***	-.0010*	-.0052***	-.0017***
	(.0004)	(.0006)	(.0004)	(.0005)
Treatment	.0254***	.0414***	.0925***	.0996***
	(.0023)	(.0021)	(.0030)	(.0028)
Post-2018 × Treatment	-.0049**	.0032	.0084*	.0431***
	(.0025)	(.0027)	(.0045)	(.0042)
Pre-2011 × (1 − Veteran)	-.0014*	-.0086***	-.0014*	-.0083***
	(.0008)	(.0006)	(.0007)	(.0006)
Length		.0067***		.0056***
		(.0001)		(.0001)
R^2	.0775	.2439	.2160	.3768
Adjusted R^2	.0756	.2424	.2144	.3755

*p<0.10, **p<0.05, ***p<0.01. Team-season clustered standard errors are in parentheses.

Table 27: Triple & Quadruple DID Results, Season + Position + Team FEs ($N = 31,688$)

	Triple		Quadruple	
	Cap Hit/Cap	APY/Cap	Cap Hit/Cap	APY/Cap
Post-2018	-.0015***	.0003	-.0003	.0001
	(.0004)	(.0006)	(.0003)	(.0004)
QB	.0170***	.0198***	.0184***	.0204***
	(.0013)	(.0012)	(.0007)	(.0009)
Veteran	.0130***	.0248***	.0045***	.0116***
	(.0003)	(.0003)	(.0002)	(.0002)
Expensive			.0102***	.0064***
			(.0002)	(.0003)
Post-2018 × QB	.0008	.0025*	.0002	.0011**
	(.0017)	(.0014)	(.0002)	(.0005)
Post-2018 × Veteran	-.0052***	.0043***	-.0023***	-.0003
	(.0004)	(.0004)	(.0002)	(.0002)
Post-2018 × Expensive			-.0005	-.0005
			(.0003)	(.0004)
QB × Veteran	.0147***	.0227***	.0076***	.0109***
	(.0026)	(.0021)	(.0010)	(.0013)
QB × Expensive			.0141***	.0146***
			(.0027)	(.0022)
Veteran × Expensive			.0230***	.0216***
			(.0005)	(.0005)
Post-2018 × QB × Veteran	-.0032	.0000	-.0027**	-.0037**
	(.0035)	(.0031)	(.0013)	(.0017)
Post-2018 × QB × Expensive			-.0008	-.0009
			(.0033)	(.0026)
Post-2018 × Veteran × Expensive			.0008	.0087***
			(.0007)	(.0008)
QB × Veteran × Expensive			.0444***	.0531***
			(.0040)	(.0036)
Post-2018 × QB × Veteran × Expensive			.0116**	.0391***
			(.0058)	(.0051)
Pre-2011 × (1 − Veteran)	.0061***	.0032***	.0048***	.0040***
	(.0007)	(.0006)	(.0005)	(.0005)
Length		.0107***		.0044***
		(.0001)		(.0001)
R^2	.1436	.4879	.6414	.7489
Adjusted R^2	.1418	.4868	.6405	.7483

*p<0.10, **p<0.05, ***p<0.01. Team-season clustered standard errors are in parentheses.