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The Loser's Curse and the Critical Role of the Utility Function

Ryan S. Brill[a] and Abraham J. Wyner[b]

[a]Graduate Group in Applied Mathematics and Computational Science, University of Pennsylvania, Philadelphia, PA; [b]Department of Statistics and Data Science, The Wharton School, University of Pennsylvania, Philadelphia, PA

ABSTRACT

A longstanding question in the judgment and decision making literature is whether experts, even in high-stakes environments, exhibit the same cognitive biases observed in controlled experiments with inexperienced participants. Massey and Thaler claim to have found an example of bias and irrationality in expert decision making: general managers' behavior in the National Football League draft pick trade market. They argue that general managers systematically overvalue top draft picks, which generate less surplus value on average than later first-round picks, a phenomenon known as the loser's curse. Their conclusion hinges on the assumption that general managers should use expected surplus value as their utility function for evaluating draft picks. This assumption, however, is neither explicitly justified nor necessarily aligned with the strategic complexities of constructing a National Football League roster. In this article, we challenge their framework by considering alternative utility functions, particularly those that emphasize the acquisition of transformational players—those capable of dramatically increasing a team's chances of winning the Super Bowl. Under a decision rule that prioritizes the probability of acquiring elite players, which we construct from a novel Bayesian hierarchical Beta regression model, general managers' draft trade behavior appears rational rather than systematically flawed. More broadly, our findings highlight the critical role of carefully specifying a utility function when evaluating the quality of decisions.

1. Introduction

A longstanding question in the judgment and decision making literature is whether experts, when making high-stakes decisions, exhibit the same cognitive biases and irrational behaviors documented in studies involving inexperienced participants in low-stakes environments. Critics of this literature argue that biases may be overstated, as most studies do not analyze decision making in real-world, high-stakes settings. Massey and Thaler (2013) claim to have found an exception, applying behavioral economic principles to a context—the National Football League (NFL) draft—where decision makers, namely NFL general managers, are highly experienced, financially incentivized, and have access to extensive data and learning opportunities.

Massey and Thaler's study has had a significant impact not just in sports analytics but in the broader decision making literature, reinforcing the notion that systematic biases can persist even in expert settings. They argue that general managers systematically overpay for top draft picks despite evidence that these selections generate less "surplus value"—the difference between the value of a player's performance and his cost—than later first-round picks, on average. This so-called "loser's curse," widely cited as evidence of irrational decision making, is the subject of their ultimate striking assertion: "top draft picks are significantly overvalued in a manner that is inconsistent with

rational expectations and efficient markets, and consistent with psychological research" (Massey and Thaler 2013).

In this article, we challenge that assertion. Massey and Thaler's conclusion critically depends on a single questionable assumption, namely that general managers should maximize expected surplus value. We argue that this assumption is overly simplistic and does not necessarily capture the strategic objectives of NFL general managers. Winning in the NFL may depend less on accumulating surplus value and more on acquiring transformational players—those capable of fundamentally altering a team's trajectory. If general managers instead prioritize maximizing the probability of drafting elite players, their decisions—while appearing suboptimal under Massey and Thaler's framework—may in fact be entirely rational.

In other words, we question whether expected surplus value is the proper "rational" criterion for evaluating risky prospects. It is well known that individuals play the lottery and prior research has shown that individuals sometimes have a preference for positively skewed payoffs (e.g., Barberis and Huang 2008). However, a preference for positively skewed payoffs is often viewed as irrational in the context of traditional economic theories, which assume that individuals make decisions based on maximizing expected utility or wealth. The present research, in contrast, highlights an important decision context where, under reason-
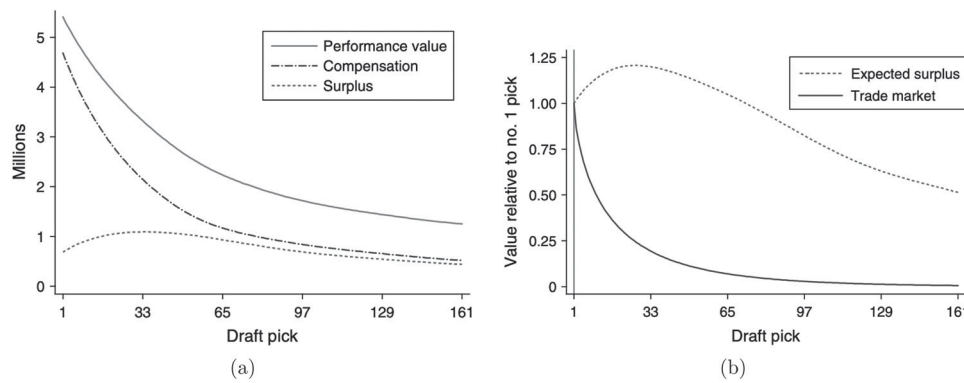
Figure 1. Figure 3 from Massey and Thaler (2013), which summarizes their results. In (a) they visualize expected performance value (solid line), first contract compensation (dot-dashed line), and expected surplus value (dashed line) versus draft position, expressed on a salary-equivalent scale. In (b) they visualize expected surplus value (dashed line) and the trade market curve (solid line) versus draft position, expressed relative to the value of the first pick.

able assumptions, a preference for positively skewed payoffs may be perfectly rational.

This perspective provides a more nuanced view of decision making in high-stakes environments. Perhaps irrationality and cognitive biases are not as pervasive as Massey and Thaler, along with the broader judgment and decision making literature, assert. Our findings underscore the importance of specifying a decision-maker's utility function before labeling behavior as irrational. More broadly, we highlight the risks of applying oversimplified economic models to complex, domain-specific decision-making contexts without considering alternative utility functions.

Below, we begin with an exposition of the setting of our case study—the NFL draft—and then give a more detailed overview of Massey and Thaler's analysis and our rebuttal.

1.1. Overview

Players entering the NFL are allocated to 32 teams through an annual draft. The draft consists of seven rounds, in which teams take turns selecting players in reverse order of the previous season's win–loss records. The team with the worst record picks first, while the reigning Super Bowl champion selects last (with some minor exceptions). There are up to 256 total draft picks because the NFL adds up to 32 additional "compensatory free agent" draft picks—creating a hidden eigth round—that allow teams to replace players who they lost in free agency.[1] Trading draft picks, involving the exchange of current and future draft selections as well as active players, is a fundamental component of constructing an NFL roster. Teams typically engage in these trades to secure specific players or improve positional depth. For example, in 2013 the Oakland Raiders traded the 3rd overall pick to the Miami Dolphins in exchange for the 12th and 42nd overall picks.[2] Trades like this raise fundamental questions about the valuation of draft picks. How did the Dolphins and Raiders determine that their trade was mutually beneficial? More broadly, if a team seeks to acquire a specific draft pick, what constitutes an appropriate offer? If presented with a trade proposal involving multiple draft picks, how should a team evaluate its value and decide whether to accept or reject the exchange? A rigorous analysis of draft pick valuation is essential to understanding the trade dynamics that shape NFL roster management.

For decades, analysts and researchers have used *draft position value curves* to quantify the value of draft positions and assess the fairness of trades involving draft picks. Draft position value curves assign a numerical point value to each draft position 1, ..., 256 and are typically additive: the value of a bundle of picks is the sum of the values of each individual pick. A trade is considered fair if the sum of the values on both sides is equal. In the 1990s, at the request of Dallas Cowboys head coach Jimmy Johnson, vice president Mike McCoy developed the first draft position value curve[3] based on intuition and an analysis of past trades. This curve assigns the highest value to the first overall pick and follows a steep, convex decline. For instance, in the 2013 draft trade between the Dolphins and the Raiders, Johnson's curve suggests the Dolphins' draft capital increased by 31%. The Raiders traded a single pick worth 2200 points in exchange for two picks collectively worth 1680 points (1200 and 480, respectively). Although Johnson's chart is ad hoc and lacks formal rigor, it remained widely used by general managers for decades, and some teams continue to rely on it today.

More recently, Massey and Thaler (2013) developed less ad hoc draft position value curves, visualized in Figure 1. The solid line in Figure 1(a) denotes expected performance value, which quantifies the expected on-field performance of players drafted at a given position, expressed on a salary-equivalent scale. The dot-dashed line reflects first contract compensation, which denotes the cost of drafted players during their first contract. A player's first contract compensation is essentially deterministic, as it is dictated by draft position.[4] However, this compensation is often much lower than the value of the player's on-field performance, leading to what is known as first contract surplus value. The dashed lines in Figure 1(a) and (b) reflect expected surplus value, which measures the expected difference between a player's first contract performance and his cost. Finally, the solid line

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[1] https://operations.nfl.com/journey-to-the-nfl/the-nfl-draft/the-rules-of-the-draft

[2] https://bleacherreport.com/articles/1618345-miami-dolphins-select-dion-jordan-with-no-3-pick-in-trade-with-oakland-raiders

[3] https://www.the33rdteam.com/jimmy-johnsons-draft-trade-value-chart-set-standard-but-clearly-outdated/

[4] Drafted rookies may negotiate certain contract elements, such as performance bonuses or injury guarantees.

in Figure 1(b) is the trade market curve, a draft position value curve that best fits the dataset of all observed trades involving only draft picks. This curve reflects the draft value implied by actual trade market behavior.

Massey and Thaler asserted two main takeaways from their analysis displayed in Figure 1. First, they claimed to have found a *loser's curse*, visualized in Figure 1(a). Teams with the worst win-loss records in the previous season—the losers—receive the top draft picks, which produce higher performance on average since expected performance value declines monotonically and convexly throughout the draft. However, these teams are cursed because top draft picks generate less surplus value on average than mid-to-late first-round picks, which typically belong to better teams. Expected surplus value (i.e., expected performance above cost) increases throughout the early first round, peaking in the middle of the round. Second, Massey and Thaler asserted that, if one adopts the expected surplus value utility function, the draft pick trade market is highly inefficient, visualized in Figure 1(b). The trade market curve is much steeper than the expected surplus value curve and differs in shape. Thus, teams consistently overpay to trade up in the draft, investing excessive draft capital to select "top draft picks [that] are significantly overvalued" (Massey and Thaler 2013). In contrast, trading down and accumulating additional draft picks is an effective strategy to maximize surplus value. For example, consider the 2013 draft trade between the Dolphins and the Raiders. Using expected surplus value,[5] the Raiders' draft capital increased by 135%. The Dolphins traded two picks collectively worth 2.40 points (1.51 and 0.89, respectively) in exchange for a single pick worth 1.02. Notably, the 12th overall pick had a higher expected surplus value than the 3rd overall pick (i.e., 1.51 > 1.02). Although the Dolphins won the trade according to Jimmy Johnson's draft value chart, the Raiders accumulated substantially more expected surplus value.

Massey and Thaler's assertions, summarized in Figure 1, replicate to recent data (see Figure 2 in Section 3). Despite the widespread recognition of their work over an extended period, the draft strategies employed by general managers in the NFL have remained largely unchanged. This persistence raises an important question: why has there been no apparent adjustment in decision making? One possible explanation is that NFL general managers are resistant to change and continue to engage in suboptimal trade practices due to cognitive biases or misjudgment. However, this perspective prompts further inquiry: are these executives, responsible for managing multi-billion-dollar franchises, fundamentally misguided, or is there a crucial element missing from existing analyses? This article explores the latter hypothesis, proposing an alternative explanation. Specifically, we argue that there may be a sound economic rationale underlying observed trade behavior. It is plausible that general managers are employing a different, yet entirely rational, utility function that does not rely solely on the expected future surplus value of a player at a given draft position.

Perhaps the overarching strategic objective of NFL teams is to win the Super Bowl—a goal consistently emphasized by team owners, general managers, coaches, and players. As Kansas City Chiefs quarterback Patrick Mahomes succinctly stated, "the only goal is to win the Super Bowl."[6] Massey and Thaler's conclusions are predicated on the assumption that general managers, in pursuit of this objective, should adopt expected surplus value as their guiding utility function. However, while their analysis relies on this assumption, they do not explicitly acknowledge the primacy of winning the Super Bowl or establish a direct link between maximizing expected surplus value and achieving that goal. While it is possible that maximizing expected surplus value contributes to winning, alternative utility functions may yield entirely different strategic conclusions. This article develops that possibility, exploring the idea that Super Bowl success hinges on acquiring transformational players—those capable of profoundly altering a team's trajectory—rather than optimizing expected surplus value. One example is the selection of Patrick Mahomes in the 2017 NFL Draft, which fundamentally elevated the Chiefs from a playoff-caliber team to a perennial Super Bowl contender.[7] Another is Josh Allen, selected in 2018, who elevated the Buffalo Bills from years of ineptitude to one of the league's top teams.[8] Under a different, but perhaps entirely reasonable, utility function—maximizing the probability of drafting transformational or elite players—decisions that appear suboptimal under Massey and Thaler's framework may actually be entirely rational.

It is possible that the most effective strategy for constructing a Super Bowl caliber roster is not maximizing expected surplus value but rather valuing draft positions based on the likelihood of acquiring elite talent. These two objective functions—maximizing expected surplus value versus maximizing the expected number of elite players—differ significantly in their strategic implications. While both are based on expected values, the latter considers the probability that a player will produce exceptional, high-impact performance, thereby capturing the importance of *tail* outcomes in shaping team success.

A key insight, overlooked by previous researchers, is how *variance* in performance value changes over the course of the draft. Just as expected performance value declines convexly throughout the draft (see Figure 1(a)), so does variance (see Figure 3 in Section 4). We hypothesize that general managers are not only trading for expected surplus value but also for variance, which is directly related to the probability of acquiring a transformational player in the far right tail of performance. For example, consider the 2013 draft trade between the Dolphins and the Raiders. In this exchange, the Dolphins traded expected surplus value to the Raiders in exchange for variance. Based on the expected number of elite players,[9] the Dolphins' draft capital increased by 40%. The Raiders traded a single pick worth 0.893 expected elite players for two picks collectively

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[5]This calculation is based on our expected surplus value curve, visualized in Figure 2 in Section 3, as the exact values from Massey and Thaler's curve are unavailable.

[6]*https://x.com/_MLFootball/status/1826003252460269907?t=JvStTWyM92jEe21LxqOTPw&s=19*

[7]From 2013 to 2017, under coach Andy Reid but without starting quarterback Patrick Mahomes, the Chiefs made the playoffs in four of five seasons but won just one playoff game. From 2018 to 2023, the Chiefs had four Super Bowl appearances and won three.

[8]From 2000 to 2017, the Bills made the playoffs once (in 2017). From 2018 to 2024, the Bills made the playoffs six times and made the AFC championship game twice.

[9]Here, we define an elite player as one at least as valuable as Jared Goff, represented by the purple curve in Figure 14 in Section 6.

worth 0.639 (0.538 and 0.101). Although the Raiders accumulated substantially more expected surplus value, the Dolphins increased their expected number of elite players. Further, notice how much less the 42nd pick is worth than before—it produces 89% fewer expected elite players than the 3rd pick, but just 13% less expected surplus value. The likelihood of acquiring transformational players decays precipitously across the draft.

Hence, in this article we construct Bayesian hierarchical draft position value curves that reflect the probability of drafting an elite player. We find that general managers' behavior in the trade market aligns with a decision rule that prioritizes variance and right-tail outcomes—seeking players with the potential to be game-changing superstars, even if they are riskier investments. Quarterbacks in particular follow a more extreme version of this pattern. Under the lens of drafting elite players, particularly for teams seeking a franchise quarterback, general managers' behavior in the draft pick trade market appears rational rather than systematically flawed.

The remainder of this article is organized as follows. We begin in Section 2 by defining the value of an NFL player's performance. Then, in Section 3, we review the traditional approach to constructing draft position value curves, similar to those devised in Massey and Thaler (2013). In Section 4 we elaborate on our research hypothesis, describing how general managers' decision making may be rational under alternative utility functions that prioritize variance and right-tail outcomes over expected surplus value. To construct other draft position value curves built from alternative value functions, we estimate the full conditional density of player performance given draft position and player position in Section 5. We present our results in Section 6 and conclude in Section 7.

2. Measuring Player Performance

Since the value of a draft pick is realized by the on-field performance of the player it yields, a crucial first step is to measure the value of a player's performance. Doing so takes care and consideration. Each play in American football consists of a complex interplay between 22 players of varying roles interacting in continuous time and space. This makes it difficult to measure how a player's individual performance impacts the ultimate outcome of a play. For instance, a linebacker may impact a play simply by occupying space. He could cause the ball carrier to move in a different direction, and there is no easy way to measure the impact of that action. There is no industry-standard way of measuring player performance on a given play in American football, particularly in a way that measures players of all positions on the same scale. Hence, analysts use performance proxies. Each measure is imperfect and has its own drawbacks. We describe many of these performance measures in detail in Appendix B, supplementary materials. Throughout this article, for simplicity, we use one performance outcome variable, detailed below.

In free agency, NFL players who are not bound by a contract can sign a new contract with any team. Following Massey and Thaler, we assume the free agent market is relatively efficient and thus reflects the performance value of players. Therefore, following Baldwin (2024), in this study we measure performance value by the average salary per year of a contract signed in free agency. We consider salary as a percentage of the cap—a rule that determines the maximum amount any team can pay its players in a given year—to adjust for inflation. Over time the cap has increased from $123 million in 2013 to $224.8 million in 2023.

Researchers, beginning with Massey and Thaler (2013), have been interested in particular in the value of a player's performance during his first contract. This is because an NFL player is paid particularly cheaply during his first contract. A player's first contract is determined by his draft position and can be much lower than the value of his performance, creating a first contract "surplus value." Teams can take advantage of the resulting extra salary cap space by signing good veteran players in free agency. The drawback of focusing solely on a player's first contract is that the very best players stay with the same team across multiple contracts, providing value across their entire careers. For example, Tom Brady played in the NFL for 23 seasons and won seven Super Bowls, playing almost the entirety of his career with the team that drafted him. Continuing with the precedent set by Massey and Thaler (2013) and subsequent analyses, in this study we consider just first contract performance and surplus value.

Throughout this article, we measure a player's first contract performance by his second contract's average salary per year as a percentage of the cap. This is a reflection of the value of a player's first contract performance because he signs his second contract in free agency just after his first contract ends. Players who don't sign a second contract have zero performance value. We acknowledge that free agent annualized cap percentage is an imperfect measure of a player's performance (see Appendix B, supplementary materials) and first contract value is an incomplete measure of the total value he provides to his team (as it excludes the rest of his career). Nonetheless, the focus of this article is to value draft picks given a performance measure, not to choose the best performance measure. We leave further analysis of various measures of performance to future work.

3. Traditional Draft Position Value Curves

We review the traditional approach to constructing draft position value curves. Prior to the draft, we do not know how well a player drafted at draft position $x \in \{1, \ldots, 256\}$ will perform in the NFL. Thus, we think of the performance outcome Y associated with position x as a random variable, denoted by a capital letter. Recall that, throughout this article, we let the realization of Y be a player's annualized second contract value as a percentage of the salary cap. Then, from the dataset of all recent draft picks in NFL history, we want to estimate a de-noised relationship between pick number x and performance outcome Y. Traditional analyses use a standard approach but with different measures of performance, detailed in Appendix B, supplementary materials (Massey and Thaler 2013; Stuart 2012; Fitzgerald and Spielberger 2024; Pro Football Focus 2024; Baldwin 2024). The de-noised relationship they estimate from data is the expected value of Y given x.

This traditional approach proceeds as follows. First, fit the expected performance value curve, or the conditional mean $x \mapsto \mathbb{E}[Y|x]$. Second, calculate the cost curve, $x \mapsto \text{cost}(x)$. Cost is first contract compensation, which is essentially a deter-
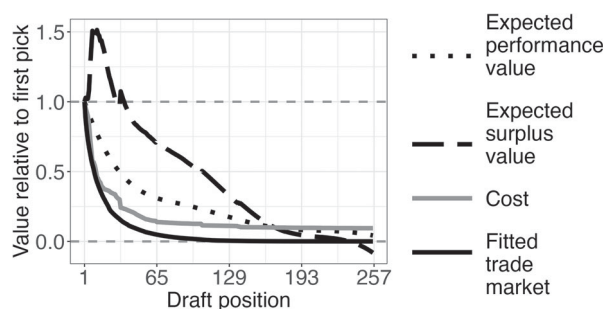
Figure 2. Each curve is a valuation of draft position x relative to the first pick. The dotted black line is the expected performance value curve, proportional to $x \mapsto \mathbb{E}[Y|x]$. The solid gray line is the cost curve, proportional to $x \mapsto \text{cost}(x)$. The long-dashed black line is the expected surplus value curve, proportional to $x \mapsto \mathbb{E}[Y - \text{cost}(x)|x]$. The solid black line is the draft position value curve implied by the trade market.

ministic function of x. Third, calculate the expected surplus value curve, or the expected value of the difference between performance and cost, $x \mapsto \mathbb{E}[Y - \text{cost}(x)|x]$. Finally, normalize each of these curves by dividing by the value of the first pick. Value is then relative to the first pick, whose value is one.

We fit these traditional draft position value curves using our outcome variable Y (second contract annualized cap percentage), which we visualize in Figure 2. We use spline regression to fit the expected performance value curve from a dataset of all draft picks from 2013 to 2023 (Ho and Carl 2024). We calculate the cost curve as in Baldwin (2024): beginning with the actual 2023 salary cap (about $225 million) and assuming a cap growth rate of 7% over the next three seasons (2024, 2025, and 2026), we convert the total dollar amount of the rookie contract into a percentage of the cap. Then, for each draft position we average the compensation values across the four seasons. We calculate the expected surplus value curve as the difference between the expected performance value curve and cost curve. Finally, we normalize each of these curves so that value is relative to the first pick. Because of this normalization, note that the expected surplus value curve in Figure 2 does not visually look like the expected performance value curve minus the cost curve. In Figure 2 we also visualize a draft position value curve implied by the trade market. Devised in Massey and Thaler (2013), the fitted trade market curve is a singular draft position value curve that best fits the dataset of all observed trades. We derive this curve in detail in Appendix C, supplementary materials.

Expected performance value is less steep than cost, indicating that players are underpaid on average in their first contracts. This produces positive expected surplus value across most of the draft (the long-dashed black line is mostly positive). Expected surplus value is larger than one throughout the first round, peaking in the middle of the first round. This surplus spike is what Massey and Thaler (2013) assert is the "loser's curse": top draft picks, belonging to last year's worst teams, produce less surplus value on average than draft picks later in the first round that belong to better teams.

The trade market curve (solid black line) is much steeper than the expected performance value curve (dotted black line) and the expected surplus value curve (long-dashed black line). This implies that teams aren't valuing draft positions by expected performance value or expected surplus value. Alternatively, if general managers are in fact adopting either of these as the utility function, they are trading suboptimally: they don't trade down often enough, and they often overpay when they trade up. According to expected surplus value, even teams at the very top of the draft should trade down, particularly toward the middle of the first round. This result is counterintuitive because very top picks are so highly regarded by general managers and football fans.

4. Research Hypothesis

Massey and Thaler (2013) developed the traditional analytical approach to constructing draft position value curves. Their study produced two key findings. First, they claimed to have found a loser's curse—last years worst teams are "cursed" with the ostensible gifts of the top picks, which cost a lot (in compensation) without delivering enough on-field value to compensate. Second, they asserted that the draft pick trade market is highly inefficient—if one adopts the expected surplus value utility function, teams significantly overvalue top draft picks, consistently overpaying to trade up in the draft without trading down often enough.

Despite the widespread dissemination of these findings, general managers' draft behavior has remained largely unchanged. When applied to recent data (2013–2023), the loser's curse persists and the fitted trade market curve remains similar (see Section 3). If general managers were optimizing for expected performance value or expected surplus value, their continued reluctance to trade down and their willingness to pay a premium for higher picks would suggest systematic misjudgment. One possible explanation is that general managers have simply failed to learn from these analyses. An alternative explanation is that general managers are instead operating under a fundamentally different utility function. If maximizing expected surplus value does not align with their actual objectives, then their observed behavior may be rational, even if it appears suboptimal under Massey and Thaler's framework. This article challenges Massey and Thaler's core assumption, that general managers should adopt expected surplus value as their utility function in valuing draft picks. This assumption is neither explicitly justified in their analysis nor necessarily optimal in the context of NFL decision making.

A general manager's primary objective is typically considered to be constructing a Super Bowl-winning roster. Achieving this goal requires assembling a team capable of reaching and surpassing an elite performance threshold. Mathematically, thinking of team performance as a random variable, winning the Super Bowl is analogous to exceeding a high threshold of team performance relative to other teams. In such a setting, maximizing expected surplus value alone may not be optimal. A strategy that emphasizes high-variance outcomes-seeking players with the potential for extreme right-tail performance-may be preferable, even if it sacrifices consistency.

This framework has direct implications for evaluating draft picks. If elite players—those in the far right tail of the performance distribution—are disproportionately valuable in constructing a championship team, then upweighting variance in
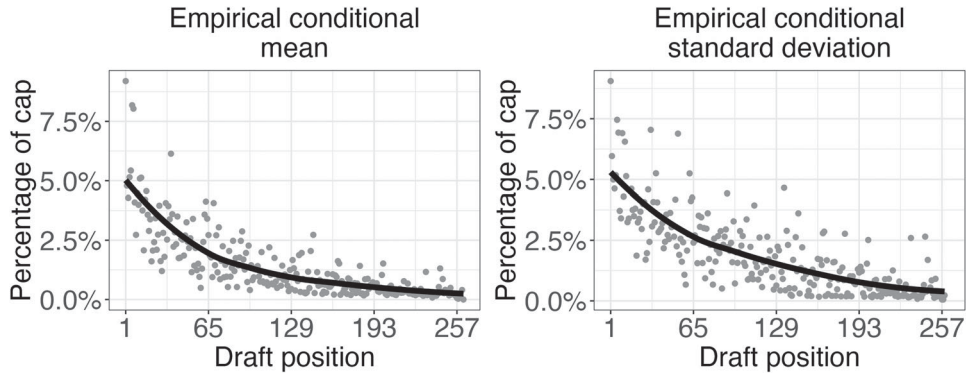
Figure 3. The gray dots denote the empirical mean (left) and standard deviation (right) of performance Y given draft position x. The black lines are smoothed curves $x \mapsto \mathbb{E}[Y|x]$ (left) and $x \mapsto \text{sd}(Y|x)$ (right).

draft selections is rational. Figure 3 shows that both the expected performance value and variance of performance decreases as draft position increases. Critically, the decline in variance suggests that higher draft picks offer significantly greater potential for elite outcomes, reinforcing the rationale for teams to value them more than suggested by expected surplus value models.

Thus, rather than viewing general managers' draft strategies as systematically flawed, we propose that their behavior aligns with a decision rule that accounts for variance and right-tail outcomes. Our hypothesis is that, in trading draft picks, teams prioritize something closer to the probability of drafting transformational players over maximizing expected surplus value. These alternative valuation functions lead to steeper draft position value curves that are more consistent with observed trade behavior.

5. Conditional Density Estimation

By modeling the distribution of performance as a function of relevant covariates, we can construct a broad class of draft position value curves that extend beyond expected performance value or expected surplus value. Hence, in this section, we estimate the conditional density of performance given draft position (Section 5.1) and given both draft position and player position (Section 5.2).

5.1. Position-Agnostic Conditional Density

In Figure 4 we visualize the empirical conditional density of performance Y given draft position x. The empirical densities are extremely wobbly and noisy due to limited data for each individual draft position. But there is a general trend: we see a spike near zero that grows upwards as draft position increases and a right tail that shifts leftwards and diminishes as draft position increases. This motivates our "Bayesian spike plus Beta regression" model of $\mathbb{P}(Y|x)$.[10]

We model the spike near zero, the *bust spike*, using logistic regression. We let a *bust* be a player whose performance outcome Y is smaller than some cutoff y_{bust}. We model the bust probabil-

ity $\text{bp}(x) := \mathbb{P}(Y \leq y_{\text{bust}}|x)$ by

$$1\{Y \leq y_{\text{bust}}\}|x \sim \text{Bernoulli}(\text{bp}(x)), \qquad (1)$$

where

$$\text{bp}(x) = \text{logistic}(\alpha_0 + \alpha_1 \cdot x). \qquad (2)$$

Next, we model the right tail using Beta regression. We view the Beta distribution as a natural way to model Y because it lies in $[0, 1]$ and aligns well with the empirical densities. We model

$$Y|x, Y > y_{\text{bust}} \sim \text{Beta}(\mu(x), \phi(x)). \qquad (3)$$

Here, we use the mean-precision parameterization of the Beta distribution. The mean μ and precision ϕ are related to the traditional Beta distribution parameters shape_1 and shape_2 by $\text{shape}_1 = \mu \cdot \phi$ and $\text{shape}_2 = (1 - \mu) \cdot \phi$. We let the mean and precision parameters vary as draft position x varies via $\mu(x)$ and $\phi(x)$ to capture that different draft positions x yield different outcome distributions. The conditional mean is $\mathbb{E}[Y|x, Y > y_{\text{bust}}] = \mu(x)$ and the conditional variance is $\text{var}[Y|x, Y > y_{\text{bust}}] = \mu(x) \cdot (1 - \mu(x))/(1 + \phi(x))$. So, the precision is inversely proportional to the variance. We use spline regression to model the conditional mean,

$$\mu(x) = \text{logistic}(\widetilde{x}^\top \beta), \qquad (4)$$

where $\widetilde{x}$ is a B-spline basis.[11] We model the conditional precision by

$$\phi(x) = \exp(\gamma_0 + \gamma_1 \cdot x). \qquad (5)$$

We use $y_{\text{bust}} = 0.5\%$ and model the log-odds of the mean $\mu(x)$ using a spline, the log of the precision $\phi(x)$ with a line, and the log-odds of the bust probability $\text{bp}(x)$ with a line because these parameterizations fit the data well—for instance, Figure 5 shows that the fitted curves closely track the trends of the empirical curves. Other values of y_{bust} produced poorer fits (e.g., the fitted curves in Figure 5 tracked the empirical curves less closely). Modeling the precision with a spline led to overfitting, and using a spline for the bust probability produced negligible improvements over the linear model.

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[10]We initially tried a lone Beta regression model without the spike near zero, which less successfully fit the right tail.

[11]The R code we used to generate the spline basis is `splines::bs(x, degree=3, df=4, intercept=T)`.
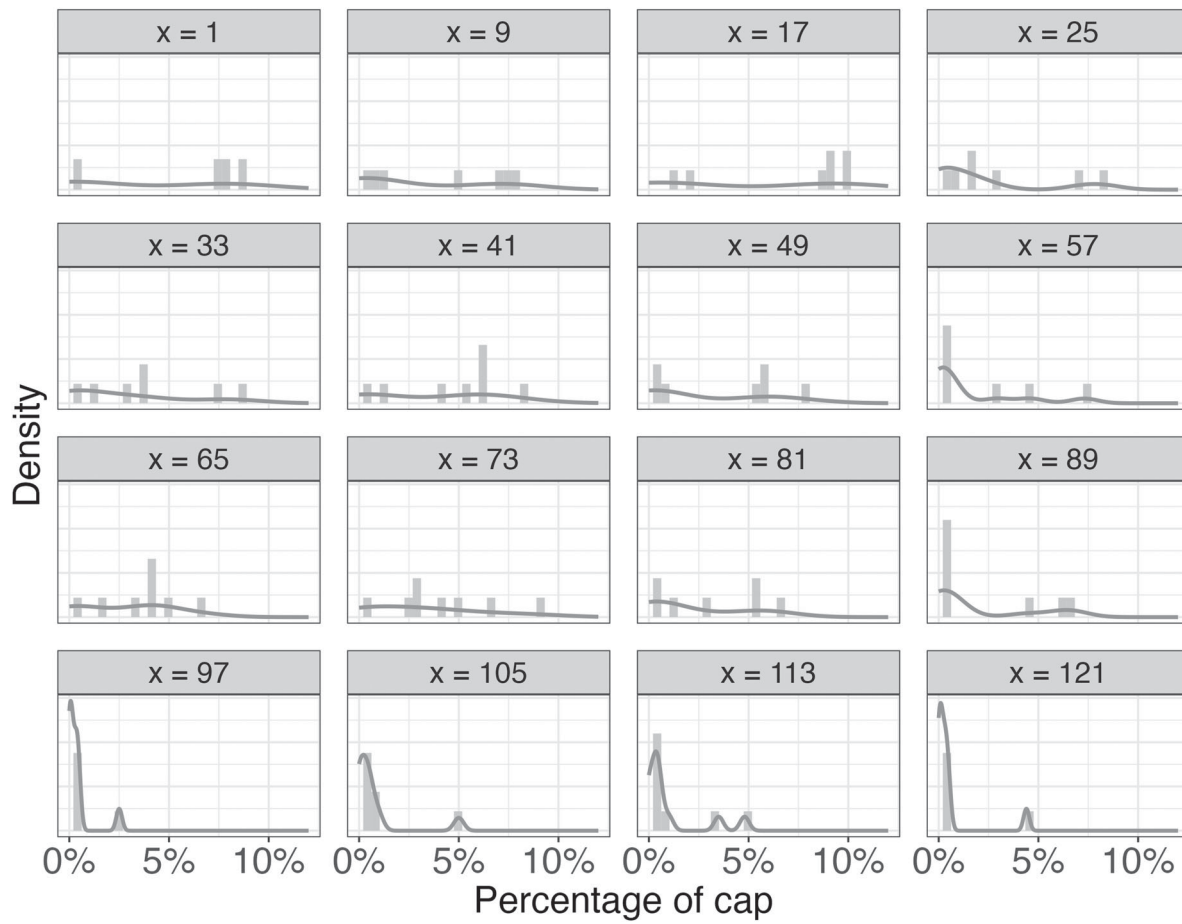
Figure 4. Empirical distribution (histogram and smoothed density) of performance Y (x-axis) given draft position x (facet).
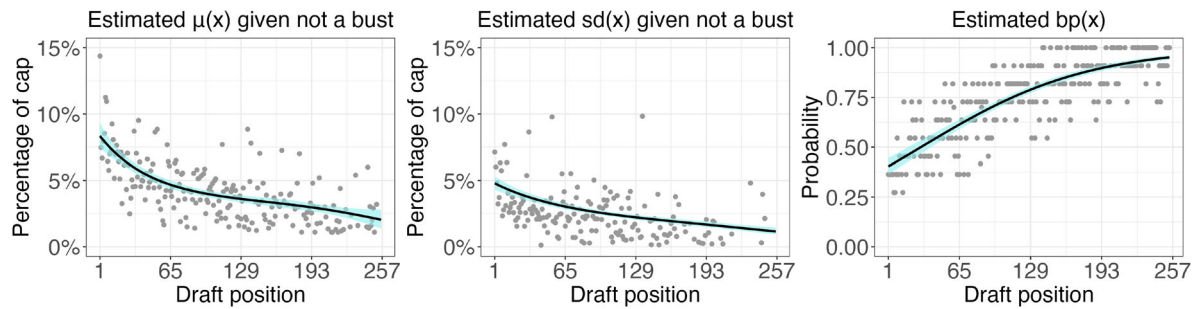

Figure 5. Left: our estimate of the conditional mean $x \mapsto \mu(x) = \mathbb{E}[Y|x, Y > y_{\text{bust}}]$ given not a bust. Middle: our estimate of the conditional standard deviation $x \mapsto \text{sd}(x) = \text{sd}(Y|x, Y > y_{\text{bust}})$ given not a bust. Right: our estimate of bust probability $x \mapsto \text{bp}(x) = \mathbb{P}(Y \leq y_{\text{bust}}|x)$. The solid black lines are the posterior means, the cyan shaded regions are the 95% credible intervals, and the gray dots are the empirical mean, empirical standard deviation, and empirical proportion values, respectively, for each draft position x.

To capture uncertainty in the parameters, we use a Bayesian model, placing priors on the parameters. We put a weakly informative Normal prior with mean zero and standard deviation ten on each of the α, β, and γ parameters. Finally, we assume that Y is uniformly distributed within the bust spike in a way that doesn't vary with x: $Y|x, Y \leq y_{\text{bust}} \sim \text{Unif}[0, y_{\text{bust}}]$.[12]

Because the posterior distribution of (α, β, γ) is not analytically tractable, we use Markov Chain Monte Carlo (MCMC) to draw approximate samples from the posterior distribution. We implement our sampler in **Stan** (Carpenter et al. 2017) and perform our MCMC simulation using the **rstan** package (Stan

Development Team 2022). To obtain our posterior samples, we run one MCMC chain for 2500 iterations. After discarding the first 1250 iterations of each chain as "burn-in", the Gelman-Rubin $\hat{R}$ statistic for each parameter is less than 1.1, suggesting convergence (Gelman and Rubin 1992).

In Figure 5 we see that our estimates of the conditional mean $\mu(x)$, conditional standard deviation $\text{sd}(x)$, and bust probability $\text{bp}(x)$ fit the data well. In Figure 6 we see that our estimates of the right tail $\mathbb{P}(Y|x, Y > y_{\text{bust}})$ fit the data well enough. As expected, the right tail shifts leftwards as draft position increases. In Figure 7 we visualize the conditional density $\mathbb{P}(Y|x)$ for values Y in the right tail $Y > y_{\text{bust}}$. By Bayes rule, this is equal to $\mathbb{P}(Y|x, Y > y_{\text{bust}}) \cdot (1 - \text{bp}(x))$. The right tail, measuring

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[12]We assess the reasonableness of this assumption later in this section.
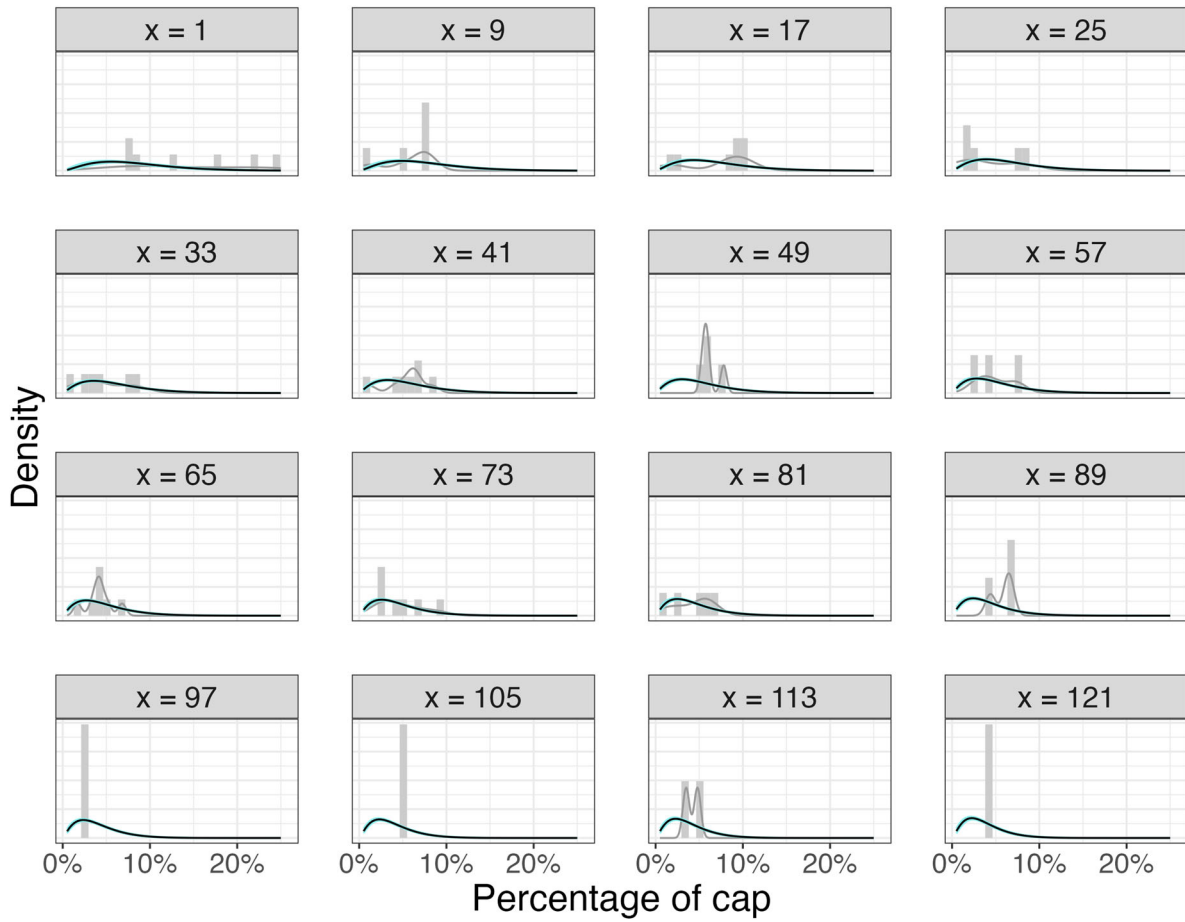
Figure 6. The distribution of performance Y (x-axis) given draft position x (facet). The solid black lines are the fitted conditional densities $\mathbb{P}(Y|x, Y > y_{\text{bust}})$ (the posterior mean curves) and the cyan shaded regions are the 95% credible intervals, which overlay the empirical distributions (histograms and smoothed densities) in gray.
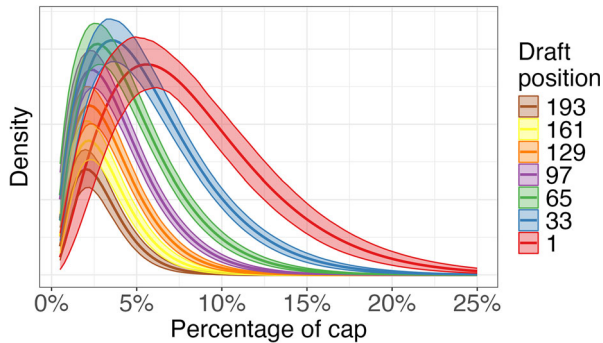

Figure 7. For values Y in the right tail $Y > y_{\text{bust}}$, the estimated conditional density $\mathbb{P}(Y|x) = \mathbb{P}(Y|x, Y > y_{\text{bust}}) \cdot (1 - \text{bp}(x))$ for various values of draft position x (color). The lines are posterior mean density curves and the shaded regions are 95% credible intervals of those curves.

the probability of drafting an elite player, shifts leftwards and decreases in size as draft position increases. In Figure 8 we visualize the conditional density of surplus $S = Y - \text{cost}(x)$. The high cost of first round picks shifts those curves so much to the left that there is substantial probability mass on negative (below-replacement) outcomes.

Finally, in Figure 9 we assess the assumption that the bust spike conditional distribution of $Y|x, Y \leq y_{\text{bust}}$ is uniform in a way that doesn't vary with x. The empirical conditional mean stays essentially constant over x and the empirical conditional

variance slightly decreases linearly in x. This admittedly renders the uniform assumption imperfect. Nonetheless, we ultimately feel it is good enough. The assumption is benign because when $Y \leq y_{\text{bust}}$, Y is essentially 0 and so negligibly impacts the right tail probability calculations that form the draft trade value curves that we detail in this article.

5.2. Position-Specific Conditional Density

Now, we extend the "Bayesian spike plus Beta regression" model from the previous section to adjust for player position, henceforth referred to as just "position" and denoted pos. We use 11 position groups: quarterback (QB), wide receiver (WR), running back / fullback (RB/FB), tight end (TE), offensive tackle (OT), interior offensive lineman (IOL), interior defensive lineman (DL), edge (ED), linebacker (LB), cornerback (CB), and safety (S). We filter out all draft picks from our dataset belonging to other positions (e.g., punter, kicker, etc.).

It is imperative to use a Bayesian model to adjust for position, rather than fitting separate curves for each position, due to limited data. Across each of the positions, the median sample size in our dataset is 269 players, with a maximum of 350 and a minimum of 127. Spread across 256 total draft pick positions, we are left with an average of about one observation per combination of position and draft position. A Bayesian hierarchical model is an excellent choice here because it allows us to share
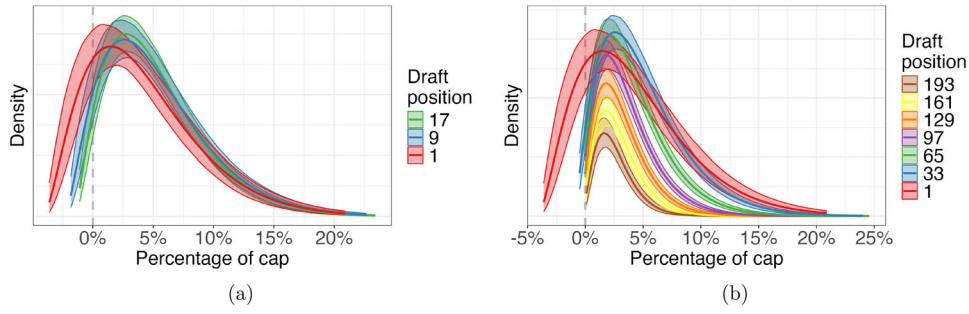
Figure 8. For values Y in the right tail $Y > y_{\text{bust}}$, the estimated conditional surplus density $\mathbb{P}(S|x) = \mathbb{P}(Y - \text{cost}(x)|x, Y > y_{\text{bust}}) \cdot (1 - \text{bp}(x))$ for various values of draft position x (color) in the first round (a) and throughout the draft (b). The lines are posterior mean density curves and the shaded regions are 95% credible intervals of those curves.
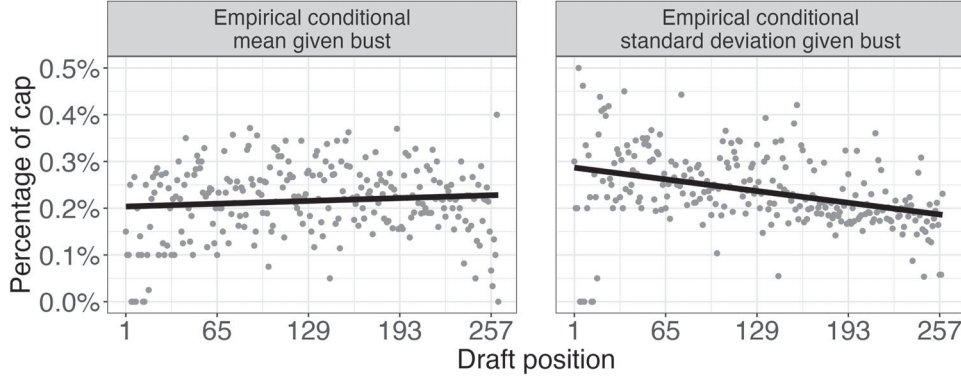

Figure 9. The gray dots display the empirical mean (left) and standard deviation (right) of performance Y given draft position x conditional on being a bust $Y \leq y_{\text{bust}}$. The black lines are smoothed lines.

information across observations via shrinkage and to capture uncertainty in position curves.

We devise a Bayesian hierarchical model that includes position-specific parameters for each of the α, β, and γ parameters from the previous model. We model the right tail conditional density by

$$Y|x, \text{pos}, Y > y_{\text{bust}} \sim \text{Beta}(\mu(x, \text{pos}), \phi(x, \text{pos})), \quad (6)$$

where

$$\mu(x, \text{pos}) = \text{logistic}(\widetilde{x}^\top \beta_{\text{pos}}) \quad (7)$$

and

$$\phi(x, \text{pos}) = \exp(\gamma_{0,\text{pos}} + \gamma_{1,\text{pos}} \cdot x). \quad (8)$$

As before, $\widetilde{x}$ is a B-spline basis on the x variable. We model bust probability by

$$\begin{aligned} \text{bp}(x, \text{pos}) &:= \mathbb{P}(Y \leq y_{\text{bust}}|x, \text{pos}) \\ &= \text{logistic}(\alpha_{0,\text{pos}} + \alpha_{1,\text{pos}} \cdot x). \end{aligned} \quad (9)$$

We shrink the position-specific coefficients $\alpha_{*,\text{pos}}$, $\beta_{*,\text{pos}}$, and $\gamma_{*,\text{pos}}$ toward overall mean parameters α_*, β_*, and γ_*. For example, we model the position-specific coefficients $\alpha_{0,\text{pos}}$ as a draw from a Normally distributed prior with mean α_0 and standard deviation τ_{α_0}. We put a weakly informative Normal prior with mean zero and standard deviation 10 on the prior mean parameter α_0. We put a mild positive standard Normal prior on the prior standard deviation parameter τ_{α_0}. The priors and hyperpriors are the same for the other parameters.
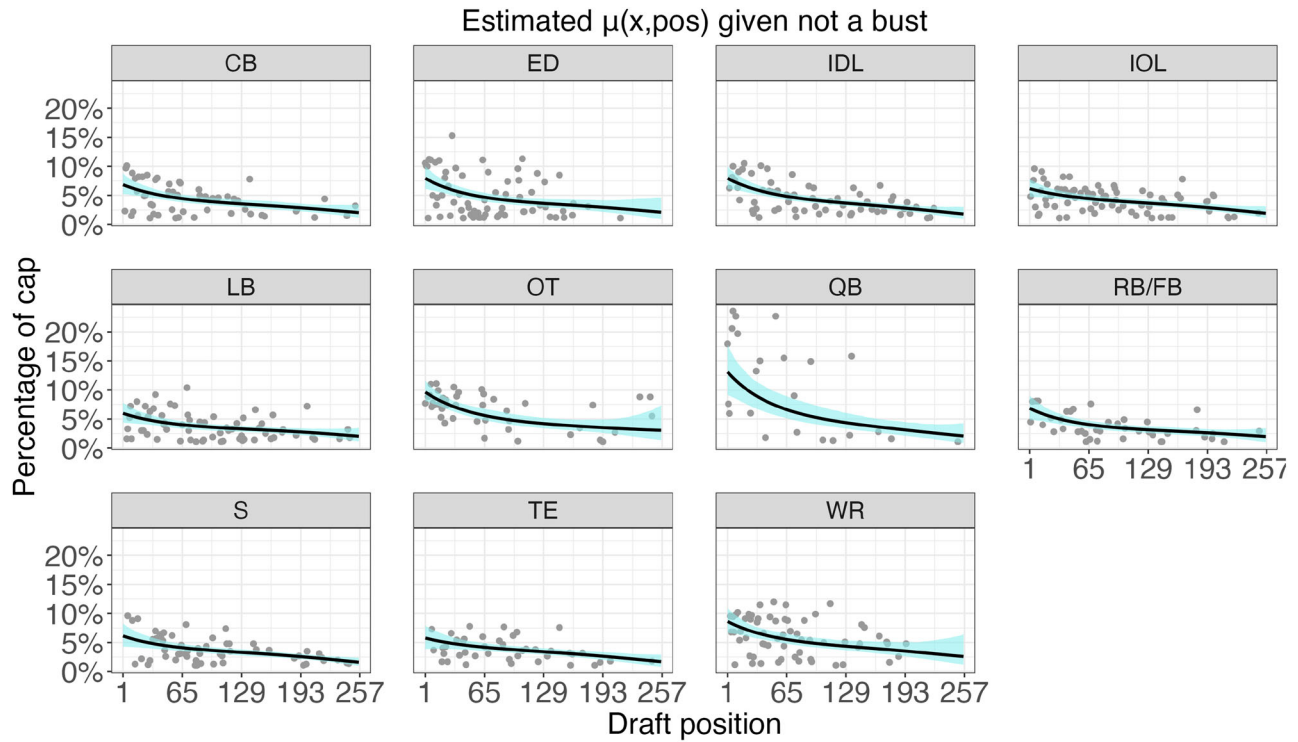
We again use **Stan** to draw approximate posterior samples of the parameters (α, β, γ), running one chain for 50,000 iterations. After discarding the first 25,000 iterations of each chain

as "burn-in", the Gelman-Rubin $\hat{R}$ statistic for each parameter is less than 1.1, suggesting convergence (Gelman and Rubin 1992).
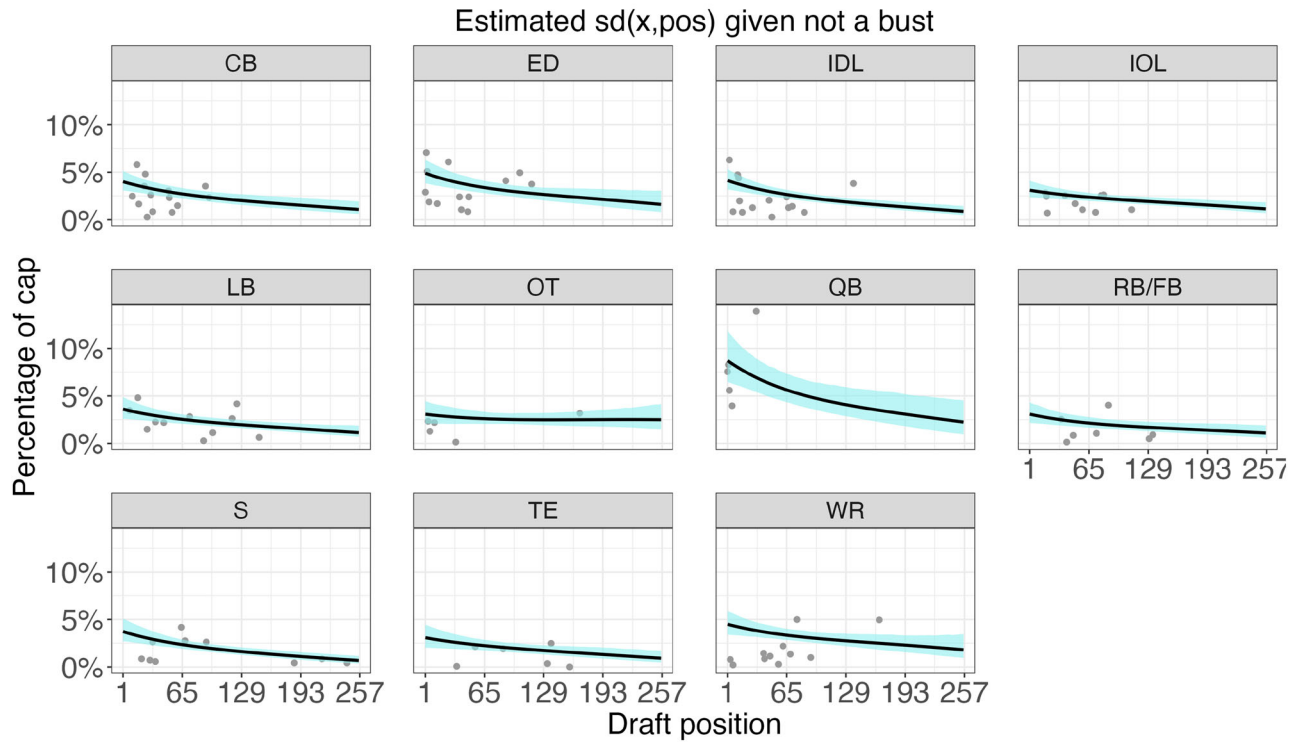
In Figure 10(a) we see that our estimate of the conditional mean $\mu(x, \text{pos})$ fits the data well. The empirical standard deviation values in Figure 10(b) we are much more sparse than the empirical conditional mean values in Figure 10(a). This is because, for each position pos and for many draft positions x, just zero or one player of position pos was drafted at x. Thus, there is no empirical standard deviation at many combination of x and pos. Nonetheless, based on the data we have observed, our estimate of the conditional standard deviation $\text{sd}(x, \text{pos})$ fits the data reasonably well.

We see in Figure 10 that the quarterback mean and standard deviation curves stand out relative to every other position. In Figure 11, we view this through a different lens. In Figure 11(a) we visualize our estimates of the conditional mean, standard deviation, and bust probability given position and draft position. Though the posterior mean curves vary by position, the posterior credible intervals are wide. The non-quarterback mean and standard deviation curves jumble into one big clump. Hence, in Figure 11(b) we average all of the non-quarterback curves into the black curves, $\mu(x, \text{not qb}) = \frac{1}{\#\text{pos}-1}\sum_{\text{pos}'\neq\text{qb}} \mu(x, \text{pos}')$ and similarly for $\text{sd}(x, \text{not qb})$ and $\text{bp}(x, \text{not qb})$. As expected, quarterbacks have a higher mean than other positions. More interestingly, quarterbacks have a much higher variance than other positions. This is what drives the fat far right tail of top-pick quarterback performance.

In Figure 12 we visualize the conditional density $\mathbb{P}(Y|x, \text{pos})$ for $\text{pos} \in \{\text{qb}, \text{not qb}\}$ (where the not qb density is the average

Estimated μ(x,pos) given not a bust

(a)

Estimated sd(x,pos) given not a bust

(b)

Figure 10. Our estimates of the conditional mean $\mu(x, \text{pos}) = \mathbb{E}[Y|x, \text{pos}, Y > y_{\text{bust}}]$ (a) and standard deviation $\text{sd}(x, \text{pos}) = \text{sd}(Y|x, \text{pos}, Y > y_{\text{bust}})$ (b) given not a bust. The solid black lines are the posterior means, the cyan shaded regions are the 95% credible intervals, and the gray dots are the empirical base-rates.

of all the non-quarterback positional densities). As the draft progresses, for both qb's and not qb's the right tail shifts leftwards and decreases in size as draft position increases. Notably, the qb right tails are much fatter than the not qb tails. This reflects the immense value of quarterbacks, and top-pick quarterbacks in particular.
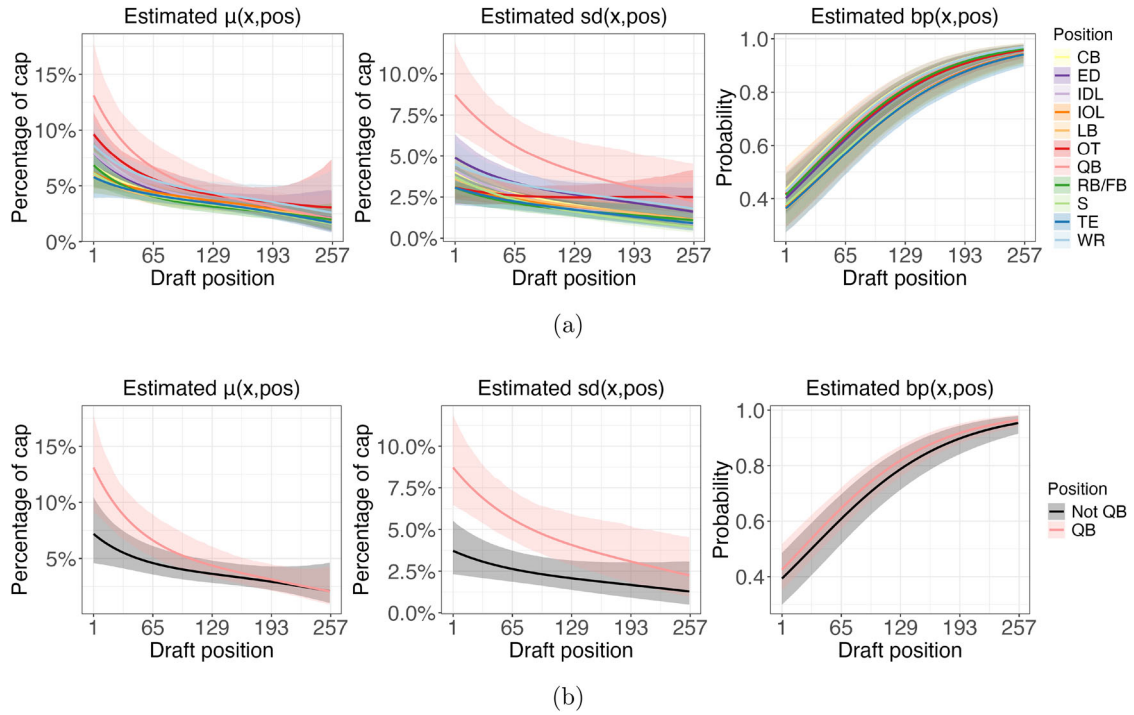
(a)

(b)

Figure 11. (a): The posterior mean estimates (lines) and 95% credible intervals (shaded regions) of $\mu(x, \text{pos})$ (left), $\text{sd}(x, \text{pos})$ (middle), and $\text{bp}(x, \text{pos})$ (right) as a function of draft position x and position pos (color). (b): These curves for pos $\in$ {qb, not qb}.
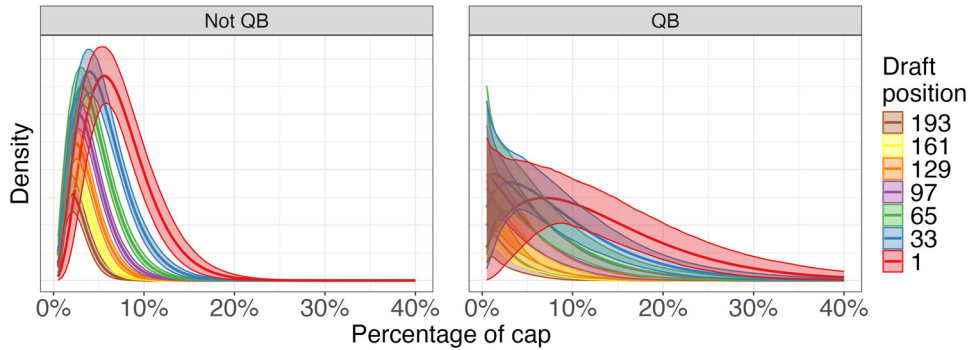

Figure 12. For values of Y in the right tail $Y > y_{\text{bust}}$, the posterior mean estimates (lines) and 95% credible intervals (shaded regions) of the conditional density $\mathbb{P}(Y|x, \text{pos}) = \mathbb{P}(Y|x, \text{pos}, Y > y_{\text{bust}}) \cdot (1 - \text{bp}(x, \text{pos}))$, for pos $\in$ {qb, not qb} (facet) and various values of draft position x (color) throughout the draft.

6. Results

Given our estimated conditional density of performance given draft position and player position, in this section we construct draft position value curves from alternative utility functions. We move beyond expected performance value and expected surplus value to utility functions that emphasize elite, right-tail outcomes.

6.1. Right Tail Probability

An intuitive approach to valuing a draft position in a way that prioritizes eliteness is by right-tail probability. Formally, we consider the probability that the performance Y of a player drafted at position x exceeds a threshold r, $\mathbb{P}(Y > r|x)$. The threshold r is determined relative to a percentage of the NFL salary cap. For example, a general manager may be interested in the probability that a drafted player achieves at least the performance level of quarterback Derek Carr ($r = 15.0\%$). Since the expected

value of an indicator function is its probability, this equivalently measures the number of elite players expected to arise from a given pick.

We compute right tail probabilities from the estimated conditional density $\mathbb{P}(Y|x)$. As both the mean and variance of Y decrease convexly as the draft progresses (see Figure 3)—because the densities of top picks feature fat right tails, which shift leftward and morph into a spike near zero as the draft progresses (see Figure 7)—the right tail of the performance distribution exhibits a similar convex decay, which we visualize in Figure 13. We consider five eliteness cutoffs r: 24.5%, 17.8% 15.0%, 11.0%, and 8.7%. Among quarterbacks in our dataset who secured multi-year second contracts as regular starters, Joe Burrow has the highest performance value ($r = 24.5\%$) and Derek Carr has the lowest ($r = 15.0\%$). Jared Goff lies near the midpoint of these two benchmarks ($r = 17.8\%$). Among non-quarterbacks, offensive tackle Penei Sewell ranks at the 99th percentile ($r = 11.0\%$),
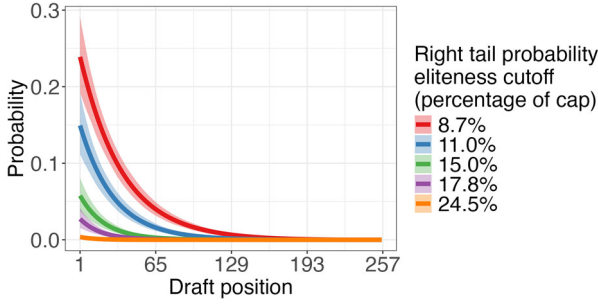
Figure 13. Estimated right tail probability $\mathbb{P}(Y > r|x)$ (y-axis) as a function of draft position x and eliteness cutoff r (color). The lines are the posterior means and the shaded regions are the 95% credible intervals.
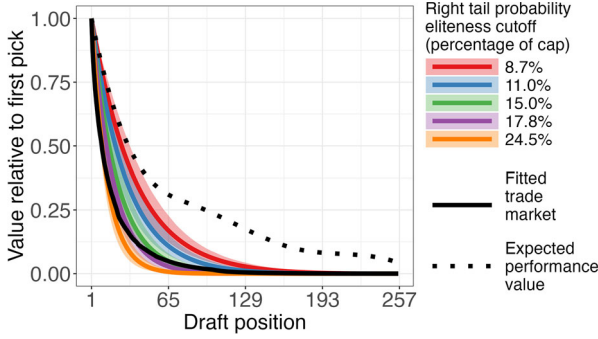

Figure 14. Value relative to the first pick (y-axis) as a function of draft position x. The dotted black line is the expected performance value curve. The solid black line is the fitted trade market curve. The colored lines are proportional to right tail probability $x \mapsto \mathbb{P}(Y > r|x)$, where r is an eliteness cutoff (color). The lines are the posterior means and the shaded regions are the 95% credible intervals.

while cornerback Tre'Davious White lies at the 90th percentile ($r = 8.7\%$).

In Figure 14 we visualize draft position value curves proportional to right tail probability, $x \mapsto \mathbb{P}(Y > r|x)/\mathbb{P}(Y > r|x = 1)$. We overlay the expected performance value curve and the fitted trade market curve from Figure 2. Notably, the right tail probability curves are steeper than the expected performance value curve. This suggests that if teams prioritize eliteness rather than expected performance value, earlier draft picks hold substantially greater value relative to later picks. Furthermore, as the eliteness threshold r increases, right-tail draft position value curves progressively steepen, ultimately converging to or even surpassing the fitted trade market curve.

Further, we find that general managers trade draft picks as if they value a draft position by the probability it produces a player whose second contract exceeds 19.7% of the salary cap. Specifically, the mean absolute error between the fitted trade market curve and a right tail probability curve with eliteness threshold r is minimized by $r = 19.7\%$ (note that Deshaun Watson has $r = 19.7\%$). This is a high bar of eliteness: among players in our dataset who secured multi-year second contracts as regular starters, just 12.3% of quarterbacks (8/65) and zero non-quarterbacks met this criterion. Although we cannot directly observe general managers' internal valuation models, the trade market aligns closely with what we would expect if teams were optimizing for elite player acquisition rather than expected performance value.
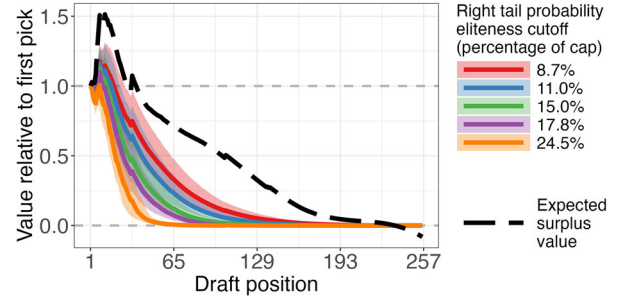

Figure 15. Value relative to the first pick (y-axis) as a function of draft position x. The long-dashed black line is the expected surplus value curve. The colored lines are proportional to right tail probability $x \mapsto \mathbb{P}(S > r|x)$, where r is an eliteness cutoff (color). The lines are the posterior means and the shaded regions are the 95% credible intervals.

6.2. Surplus Value

Massey and Thaler (2013) assess draft pick value through the lens of surplus value, the difference between a player's performance during his first contract and the cost associated with his draft position (see Figure 2). Formally, denoting the first contract compensation at draft position x by $\mathrm{cost}(x)$ and a drafted player's performance outcome by Y, surplus value is defined by $S = Y - \mathrm{cost}(x)$. While Massey and Thaler (2013) modeled expected surplus value, $\mathbb{E}[S|x]$, we consider the right tail of surplus value, $\mathbb{P}(S > r|x)$.

In Figure 15 we visualize expected surplus value (black dashed line) and the probability that surplus value exceeds a threshold (colored lines). Massey and Thaler's loser's curse—top draft picks yield lower expected surplus value than those selected later in the first round—manifests as a spike in the expected surplus value curve above one during the first round.

Although the point estimate of the probability that surplus value exceeds a high threshold has a spike—though one that is smaller than and earlier in the draft than that of expected surplus value—consideration of the entire posterior distribution shows that a monotonically decreasing relationship is highly compatible with the data and model.

6.3. Adjusting for Position

The distribution of performance value varies not only by draft position but also by player position (see Section 5.2). Quarterback performance in particular exhibits a substantially fatter right tail than other positions (see Figure 12). Hence, in this section, we construct separate draft position value curves for quarterbacks and non-quarterbacks.

We begin by visualizing performance value curves in Figure 16. For $\mathsf{pos} \in \{\mathsf{qb}, \mathsf{not\,qb}\}$, we compute expected performance value (proportional to $\mathbb{E}[Y|x, \mathsf{pos}]$) and right tail probability (proportional to $\mathbb{P}(Y > r|x, \mathsf{pos})$) from the estimated conditional density $\mathbb{P}(Y|x, \mathsf{pos})$. We compute value relative to a first pick qb. The position-specific curves exhibit the same broad pattern observed in the overall draft position value curves from Figure 14: right tail probability curves are steeper than expected performance value curves. As the eliteness threshold r increases, right tail probability curves become progressively
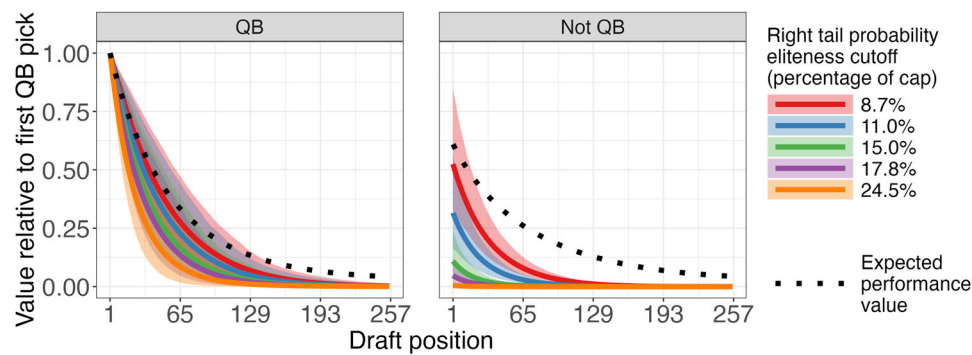
Figure 16. Value relative to the first qb pick (*y*-axis) as a function of draft position *x* and position (facet). The dotted black line is expected performance value. The colored lines are proportional to right tail probability $x \mapsto \mathbb{P}(Y > r|x, \text{pos})$, where *r* is an eliteness cutoff (color). The lines are posterior means and the shaded regions are 95% credible intervals.

Figure 17. Value relative to the first qb pick (*y*-axis) as a function of draft position *x* and position (facet). The long-dashed black line is expected surplus value. The colored lines are proportional to right tail surplus probability $x \mapsto \mathbb{P}(S > r|x, \text{pos})$, where *r* is an eliteness cutoff (color). The lines are posterior means and the shaded regions are 95% credible intervals.
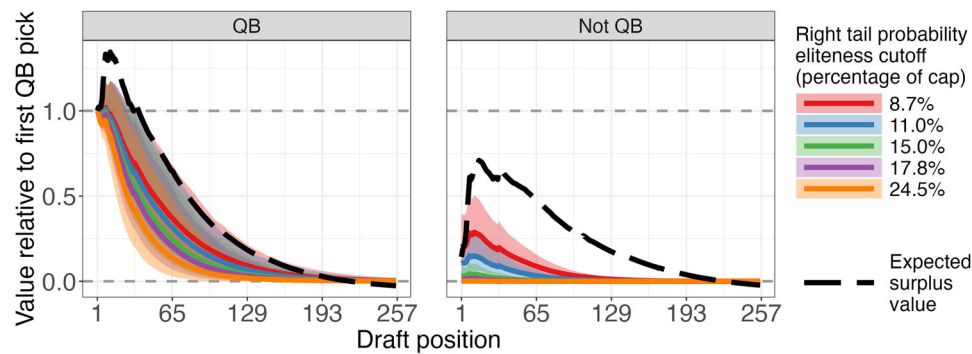
steeper, reinforcing the idea that teams prioritizing increasingly elite talent assign greater relative value to earlier picks.

In Figure 17 we visualize position-specific surplus value curves. For both quarterbacks and non-quarterbacks, expected surplus value peaks in the first round.

Although the point estimate of the probability that surplus value exceeds a high threshold has a spike for non-quarterbacks, there is no spike for quarterbacks. Further, consideration of the entire posterior distribution for both quarterbacks and non-quarterbacks shows that a monotonically decreasing relationship is highly compatible with the data and model. Thus, particularly for teams seeking elite quarterbacks, our analysis provides strong support for the notion that the extreme upside of top selections offsets their higher cost.

7. Discussion

A central premise in the judgment and decision making literature is that experts, even in high-stakes environments, exhibit systematic cognitive biases. Massey and Thaler (2013) applied this framework to the NFL draft, asserting that, according to expected surplus value, general managers overvalue top draft picks, a finding widely cited as evidence of irrational decision making. This assertion, however, hinges on the assumption that general managers should optimize for expected surplus value, an assumption that is neither explicitly justified nor necessarily aligned with the strategic realities of NFL team-building.

In this article, we challenge that assumption and present an alternative framework for evaluating the value of a draft

position. By estimating the full conditional density of player performance given draft position and player position, we construct draft position value curves from alternative utility functions. We focus on right tail probability—equivalently, the number of elite players expected to arise from a given pick—reflecting that general managers may be prioritizing the acquisition of elite, game-changing players. Under this perspective, top draft picks are not inefficiently overvalued but rather priced for their potential to produce transformational talent-players who can dramatically elevate a franchise's trajectory. When valuing draft position based on right tail probability rather than expected surplus value, the first-round spike in the value of a draft position largely disappears. Teams selecting at the top of the draft retain higher relative value when their objective is to secure elite talent rather than merely optimizing expected surplus value. This effect is particularly pronounced for quarterbacks, whose performance distributions exhibit extremely fat right tails.

This study contributes to the judgment and decision making literature by highlighting the importance of specifying the decision-maker's utility function before labeling behavior as irrational. If general managers value variance and right-tail outcomes rather than expected surplus value, then their draft strategies, far from being biased or inefficient, may be consistent with a rational objective function tailored to the realities of NFL competition. Perhaps irrationality and biases are not as pervasive as Massey and Thaler, along with the broader judgment and decision making literature, assert. More broadly, our findings underscore the risks of applying oversimplified economic mod-

els to complex, domain-specific decision-making environments without considering alternative utility functions.

While our analysis provides a compelling alternative to the traditional expected performance value and expected surplus value framework, it does not resolve the question of how general managers ought to value draft picks. A more comprehensive analysis would explicitly estimate the impact of draft selections on Super Bowl win probability, accounting for factors such as team composition—including projected current and future talent at each position—injury risk, salary cap constraints, and projected outcomes of available draft prospects. Prioritizing expected surplus value may be misguided, but so may prioritizing eliteness and variance; determining the optimal balance remains an open question. We suspect the best objective combines elements of both.

A broader implication of this study is the potential disconnect between formal decision models and the intuitive expertise of practitioners. NFL general managers may not be explicitly solving optimization problems or consciously weighing right-tail probabilities, yet their actions suggest an implicit alignment with valuing elite performance. This raises an important question: are expert decision-makers in other fields adept at intuitively navigating their domains in ways that are difficult for modelers to formalize? If so, then economists, statisticians, and decision scientists should approach expert behavior with greater humility before declaring it irrational. While analytical models provide valuable insights, they may overlook nuanced decision making processes that emerge from experience, tacit knowledge, and the complexity of real-world environments.

At the same time, our assumption that general managers' primary goal is to win the Super Bowl may not be entirely correct. It is possible that NFL general managers optimize for other outcomes, such as improving their win–loss record, making the playoffs, or simply preserving their own job security. Moreover, even if their decisions align with maximizing the probability of drafting elite players, this does not necessarily imply rationality. Their choices could stem from overconfidence in their ability to identify talent, a misperception of the distribution of player outcomes, or other psychological biases. The fact that the trade market aligns with a 19.7% of salary cap threshold of eliteness may be a coincidence rather than the product of deliberate strategic thinking. Future research should explore how expert intuition interacts with formal modeling across domains, identifying where models enhance decision making and where they risk oversimplifying the expertise of practitioners.

Finally, we conclude with a discussion of technical limitations of our study and directions for future work. First, the methodology underlying the fitted trade market curve (the Weibull curve from Appendix C, supplementary materials) has imperfections, which we detail in that section. In particular, if the team trading down uses a different value function than the team trading up, how do we explain trading? Second, in future work, we suggest exploring curves built from the sum of performance and surplus, rather than each one individually. When drafting a player, a general manager benefits from the value of his performance in addition to the extra cash from a cheap rookie contract. Third, a major assumption employed in this work and in previous work is additivity: the value of a bundle of draft picks $v(\{x_j\})$ equals its sum, $\sum_j v(x_j)$. Concretely, in terms of right tail probability, we consider the value of a bundle of picks by $\sum_j \mathbb{P}(Y_j > r)$, though the relationship between the picks may be nonadditive or something more general, like $\mathbb{P}(f(Y_1, \ldots, Y_n) > r)$. We leave an exploration of nonadditive draft position value curves to future work. Fourth, in this study we consider just first contract performance and surplus value. First contract value is an incomplete measure of the total value he provides to his team, as it excludes the rest of his career. Finally, we did not address a selection bias that was explored in Eager (2024): worse teams draft players earlier in each round of the draft than better teams, and a team's quality may influence the ultimate performance outcome of a drafted player. A more elaborate construction of NFL draft trade value curves should account for this selection bias, which we leave to future work.

Supplementary Material

Appendix A. Our code

Our analysis in this paper is reproducible via the code that is publicly available on Github at *https://github.com/snoopryan123/NFL_draft_chart_Ryan*.

Appendix B. Measuring a player's performance value

Each play in American football consists of a complex interplay between 22 players of varying roles interacting in continuous time and space, making it difficult to measure how a player's individual performance impacts the ultimate outcome of the play. For instance, a linebacker may impact the outcome of a play simply by occupying space, causing the ball carrier to move in a different direction, and there is no easy way to measure the impact of that action. Since there is no easy or industry-standard way of measuring player performance on a given play, particularly for off-the-ball players, analysts use simpler proxies of performance value. Importantly, these proxies measure the performance of players of all positions on the same scale. Each of these are imperfect measures with their own drawbacks.

In free agency, NFL players who are not bound by a contract can sign a new contract with any team. Assuming the free agent market is efficient, it is a reflection of the true performance value of players. Hence, one popular measure of performance value is inflation-adjusted salary. Baldwin (2024) adjusts for inflation by measuring salary as a percentage of the salary cap, referred to as APY cap percentage (APY means average salary per year). Fitzgerald and Spielberger (2024) measure a player's performance value as his salary as a percentage of the average of the top five salaries at his position. For example, in 2024 the top five quarterback salaries have an APY of $51.2 million, so they grade Mahomes' APY of $45 million as an 88%. A drawback of measuring a player's value relative to other players at his position is it doesn't account for positional value, or the fact that some positions are inherently more valuable than others (e.g., an average quarterback is much more valuable than an average running back). A drawback of using the free agent market to measure performance is that the market is a reflection of projected future value, not past performance value. A running back who performs very well in his first contract may not receive a large second contract because running backs are injury prone and age quickly. For example, Saquon Barkley, one of the best running backs in the NFL during his rookie contract, signed a modest second contract in 2023 worth $10.1 million for one year. His free agent contract surely understates his first contract performance value.

To measure past performance value rather than projected future performance value, Massey and Thaler (2013) use the number of games a player started and whether he made the Pro Bowl. They then map this performance to salary by regressing a player's second contract compensation (the value of a player's first free agent contract) on his number of starts and Pro Bowls in his first contract (see Section 6.2 of their paper for the particulars of this regression). A drawback of their approach is that the number of starts and Pro Bowls is a crude measure of player performance. Two linebackers can have the same number of starts and Pro Bowls but have vastly different impacts on the games they played, for instance by having a different number of tackles or yards allowed.

Stuart (2012) measures player performance using Pro Football Reference's Approximate Value (AV) (**?**). AV maps more granular position-specific performance measures to a common scale. For offensive players, AV apportions the points per drive scored by a team's offense to each of its offensive players in proportion to position-specific performance measures. For skill position players, AV uses yards to measure performance (e.g., rushing yards for running backs and pasing yards for quarterbacks). AV uses more crude measures for offensive lineman (e.g., games played, games started, and All Pro). AV divides credit for an offensive team's points scored per drive using *ad hoc* multipliers (e.g., the offensive line gets 5/11 of the offensive credit since there are usually 5 offensive lineman on the field). AV works analogously for defensive players. Drawbacks of AV are that it is too simple, too *ad hoc*, and uses crude performance measures for non-skill position players.

Pro Football Focus (2024) (known as PFF) measures player performance using Wins Above Replacement (WAR) (**?**). WAR estimates an individual player's contribution to team performance on the scale of team wins relative to a replacement-level player (e.g., see **?** for an exposition of WAR for starting pitchers in baseball). PFF grades the performance of every player in every football game from -2 to $+2$ in increments of $1/2$, where 0 represents average performance. They then estimate WAR from these PFF grades using a Massey rating system (**?**). A drawback of PFF WAR is that it is a model-based metric and it is unclear how good or reliable this model is at measuring player performance. Some people take issue with PFF grades, which are subjective measures of player performance made by humans who watch the tape. For instance, a Pro Bowl NFL offensive lineman once told us that PFF often grades him incorrectly because it doesn't know the job his coach told him to do. He should've received a perfect grade for doing his job, which is not publicly available knowledge, even though watching the tape may make it seem like he played suboptimally.

Appendix C. Estimating the trade market value of draft picks

We follow the approach from Massey and Thaler (2013) to estimate the relative value of draft picks that is implied by the NFL trade market. This trade market value function v_{market} is a function of a bundle of picks $\{x_j\}_{j=1}^n$, where each pick x_j belongs to $\{1, ..., 256\}$. Without loss of generality, assume that picks in a bundle are ordered from earliest to latest pick, $x_1 \leq ... \leq x_n$. Also, $v_{\text{market}}(\{1\}) = v_{\text{market}}(1) = 1$ so that value is relative to the first pick.

Massey and Thaler (2013) make simplifying assumptions in fitting v_{market}. First, they assume additivity,

$$v_{\text{market}}(\{x_j\}_{j=1}^n) = \sum_{j=1}^n v_{\text{market}}(x_j). \tag{C1}$$

Second, they suppose that all teams use the same market value function v_{market} to value draft picks. Third, they assume that trades in the market are fair, so the market value of both teams' bundles of picks are equal.

Formally, denoting the bundle of picks initially belonging to the team trading down by $\{x_j^{(d)}\}_{j=1}^{n_d}$ and that of the team trading up by $\{x_j^{(u)}\}_{j=1}^{n_u}$, the trade is fair if

$$\sum_{j=1}^{n_d} v_{\text{market}}(\{x_j^{(d)}\}) = \sum_{j=1}^{n_u} v_{\text{market}}(\{x_j^{(u)}\}). \tag{C2}$$

Finally, they assume the market value of picks follows a Weibull distribution,

$$v_{\text{market}}(x) = e^{-\lambda(x-1)^\beta}, \tag{C3}$$

where λ and β are parameters to be estimated. They also consider a Weibull model with a discount rate ρ for a pick N years into the future,

$$v_{\text{market}}(x, N) = e^{-\lambda(x-1)^\beta} \cdot (1+\rho)^N. \tag{C4}$$

Combining equations (C2), (C1), and (C3), they calculate

$$\log(x_1^{(d)}) = \log\left(\left[-\frac{1}{\lambda} \log\left(\sum_{j=1}^{n_u} e^{-\lambda(x_j^{(u)}-1)^\beta} \right. \right.\right.$$
$$\left.\left.\left. - \sum_{j=2}^{n_d} e^{-\lambda(x_j^{(d)}-1)^\beta} \right) \right]^{1/\beta} \right), \tag{C5}$$

which expresses the value of the top pick in the trade acquired by the team trading down in terms of the other picks in the trade. They estimate the parameters λ and β in Equation (C5) using nonlinear regression. They use a similar approach to find a trade market value curve that incorporates the discount rate.

The aforementioned assumptions range from quite strong to very strong and deserve to be examined. The fourth assumption, that v_{market} follows a Weibull distribution, seems to be the most mild, as the Weibull is a sufficiently expressive family that can capture many different plausible draft position value curves. The first assumption, additivity, is wrong but mild. For instance, the value of a bundle of 12 picks is not additive because not all of these players can play on the field at the same time. But additivity doesn't seem to be a terrible assumption because most trades involve just a few picks. The third assumption is wrong; they probably meant to assume that observed trades are fair *on average*:

$$\sum_{j=1}^{n_d} v_{\text{market}}(\{x_j^{(d)}\}) = \sum_{j=1}^{n_u} v_{\text{market}}(\{x_j^{(u)}\}) + \varepsilon, \tag{C6}$$

where ε is mean zero noise. The analogue of Equation C5 under this new assumption is

$$\log(x_1^{(d)}) = \log\left(\left[-\frac{1}{\lambda} \log\left(\sum_{j=1}^{n_u} e^{-\lambda(x_j^{(u)}-1)^\beta} \right. \right.\right.$$
$$\left.\left.\left. - \sum_{j=2}^{n_d} e^{-\lambda(x_j^{(d)}-1)^\beta} + \varepsilon \right) \right]^{1/\beta} \right), \tag{C7}$$

which is not equal to

$$\log(x_1^{(d)}) = \log\left(\left[-\frac{1}{\lambda} \log\left(\sum_{j=1}^{n_u} e^{-\lambda(x_j^{(u)}-1)^\beta} \right.\right.\right.$$
$$\left.\left.\left. - \sum_{j=2}^{n_d} e^{-\lambda(x_j^{(d)}-1)^\beta} \right) \right]^{1/\beta} \right) + \varepsilon. \tag{C8}$$

The nonlinear regression they employ implicitly uses the form from Equation (C8) even though they should fit from Equation (C7). Notably, however, the second assumption (that all teams use the same market
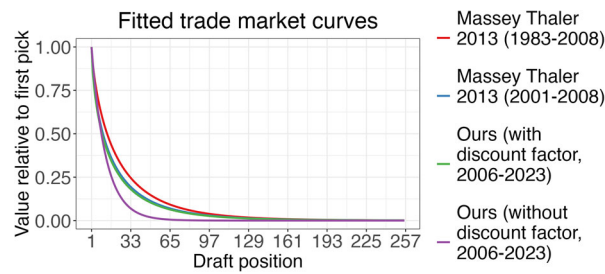
Figure 18. Weibull trade market value curves v_{market} according to Massey and Thaler (2013) and our replication. Massey and Thaler's curves here do not use a discount factor.

value function v_{market} to value draft picks) is the most egregious. Each general manager has his own value function, which changes from year to year and can be skewed by meddling owners or coaches. We could potentially treat the value function employed in each trade as a draw centered at v_{market}, with multiple levels of variance for each general manager and each year. There is likely not enough data to estimate such a hierarchical model well and its standard error would be large.

Despite these issues with the simplifying assumptions, we replicate the analysis discussed above from a dataset consisting of all draft trades consisting purely of draft picks from 2006–2023. In light of the aforementioned flaws, we use the fitted v_{market} curve to tell a general story about the steepness of the trade market. We take it with a grain of salt without obssessing over the exact shape of the curve or its minutae. We display the v_{market} from Massey and Thaler (2013) and from our replication, with and without the discount factor, in Figure 18. These curves share the same general shape–—a monotonically decreasing and extremely steep trend-–—indicating general managers' stark preference for top picks. Value declines rapidly, falling to between one-half and one-quarter of a first pick by the middle of the first round. Value then decays to less than a tenth of a first pick by the start of the second round before quickly plummeting to near-zero thereafter.

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The authors report there are no competing interests to declare.

ORCID

Ryan S. Brill ⬤ http://orcid.org/0000-0001-6387-7713

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