Expected value curves don't tell the full story: exploring NFL draft position trade value curves derived from alternative nonlinear value functions

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Abstract. Football analysts traditionally value a future draft pick position by its expected performance or surplus value. But, these expected value curves do not match the valuation implied by the observed trade market. One takeaway is general managers are making terrible trades on average. An alternative explanation is they are using some other value function that captures an essential piece of the puzzle missing from previous analyses. We are partial to the latter explanation. In particular, traditional analyses don't consider how variance in performance outcomes changes over the draft. Because variance decays convexly across the draft, eliteness (e.g., right tail probability) decays much more steeply than expected value. We suspect general managers value performance nonlinearly, placing exponentially higher value on players as their eliteness increases. This is because elite players have an outsize influence on winning the Super Bowl. Thus, in this paper we consider nonlinear draft value curves that capture the outsize influence of elite players. Such nonlinear value functions produce steeper draft value curves that more closely resemble the observed trade market.

I. Introduction

Each year, each National Football League (NFL) team is granted a draft pick in each of the seven rounds of the NFL draft. The draft allows teams to add players from college football to their rosters. In each round, teams draft in reverse order of their standing from the previous season. The worst team drafts first and the best team (who won the Super Bowl) drafts last. Because player quality generally decays convexly across the draft – the best players get drafted very early and the draft quickly descends below mediocrity – the draft order promotes league parity, allowing worse teams to get better players. Successful draft picks can greatly influence a team's success because they are young players who haven't yet experienced the wear and tear of the NFL, they can have long careers ahead of them, and some of them turn out to be amazing players.

Each drafted player is granted a four year rookie contract, with an optional fifth year for first-round picks if the team opts for it. Rookie contract compensation is a deterministic function of draft position. Once a rookie contract expires, a player may sign a second contract in free agency. The value of a contract signed in free agency is a reflection of a player's market value. In particular, the value of the second contract is a reflection of his performance in his rookie contract. Rookie contracts are generally worth much less than contracts given to veterans in free agency, which makes drafted players who play even more valuable. Thus, it is important for NFL teams to understand the value of their draft picks so that they can make informed draft decisions and acquire players who will contribute positively to the team.

There are several reasons a team may be interested in trading its draft picks for other teams' draft picks. They may want a specific player, or a player of a certain caliber at a specific position, who may only be available earlier in the draft. For example, in 2021, the 49ers traded up in the draft to be able to select quarterback Trey Lance because they liked his specific qualities.[1] Teams may also want to take advantage of other teams' draft policies, which they may view as suboptimal, by gouging them on a trade. For example, when the 49ers traded three first round picks to the Dolphins for the third pick in 2021 (which the 49ers used to draft Trey Lance), the Dolphins received a huge load of valuable picks.[2] Also, the best available player at a team's draft position may not be a position of need. In those scenarios, a team can trade the pick for a large return. The Lance example also applies here.

Teams often find themselves wanting to trade draft picks, but it is not obvious whether a trade is good or bad for each team and by how much. For example, if the 49ers offer the Dolphins the fifteenth pick in 2021 and two future first round picks for the third overall pick in 2021, should the Dolphins accept?[3] And how good is this trade quantitatively? More specifically, we are interested in the relative value of NFL draft picks. Mike McCoy, general manager of the Dallas Cowboys in the 1990s, devised the first NFL draft trade value chart, which assigns each draft pick a point value.[4] Named after then Cowboys coach Jimmy Johnson, this Jimmy Johnson chart says that a trade is fair if the sum of the values of the picks on each side of the trade is equal. McCoy used intuition, not mathematics or statistics, to create his chart. In other words, it is arbitrary.[5]

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[1] Maiocco, Matt. "How Trading up for Lance in 2021 Draft Ultimately Didn't Derail 49ers." NBC Sports Bay Area & California, April 24, 2024. https://www.nbcsportsbayarea.com/nfl/san-francisco-49ers/trey-lance-selection-nfl-draft/1728364/.
[2] Ibid.
[3] Ibid.
[4] Nathanson, Ari. "Exploring the Evolution of the NFL Draft Pick Trade Market over Time." Dartmouth Sports Analytics, April 19, 2024. https://sites.dartmouth.edu/sportsanalytics/2024/04/19/exploring-the-evolution-of-the-nfl-draft-pick-trade-market-over-time/.
[5] Ibid.

In the 2013 paper *The Loser's Curse: Decision Making and Market Efficiency in the National Football League Draft,* Massey and Thaler developed an NFL draft trade value chart using statistical modeling.[6] The basic idea is that the value of a draft position should be proportional to the expected "value" of players drafted at that position.[7] The value of a player should reflect how his performance contributed to his team's success. This high-level idea naturally raises two questions. First, how should we define player value? Also, how should we estimate expected value as a function of draft position?

We want to choose a measure of player value that allows us to compare players across positions. It is not immediately obvious how to compare the contributions of a quarterback (e.g., touchdowns and yards thrown) to those of a linebacker (e.g., tackles or assisted tackles). We need a measure of player value that puts the contributions of all players on the same scale. Salary in dollars is one such measure. Massey and Thaler map first contract performance categories (e.g., number of starts, number of pro bowls, etc.) to second contract compensation.[8] Recall that second contract compensation is a proxy for first contract performance because it is negotiated in free agency and is a reflection of the market. In this paper, we use actual second contract compensation to measure player performance value in his first contract. In particular, we consider compensation as a percentage of the salary cap, also known as APY (Annual Percentage Yield) Cap Percentage, to adjust for inflation of the cap.

[6] Massey, Cade, and Richard H. Thaler. "The Loser's Curse: Decision Making and Market Efficiency in the National Football League Draft." *Management Science* 59, no. 7 (July 2013): 1479–95. https://doi.org/10.1287/mnsc.1120.1657.
[7] Ibid.
[8] Ibid.

Then, given a measure of player performance value, Massey and Thaler estimate the expected value of each draft position using a spline regression.[9] They estimate both expected performance value and expected surplus value (first contract performance value minus first contract compensation) as a function of draft pick.[10] They consider surplus value because rookie contracts are so much cheaper than contracts awarded in free agency. Both of these draft value curves are conditional mean curves – they consider the average outcome of a drafted player given the draft position.

Since the publication of their 2013 paper, the NFL draft trade chart discourse has mostly centered on creating expected value draft charts using other outcome variables beyond Massey and Thaler's initial outcome. For example, instead of salary, Pro Football Focus uses PFF WAR and Chase Stuart uses Approximate Value (AV, a WAR-like measure) to measure player performance.[11, 12] Each of those draft value charts are also expected value curves – fit expected performance value as a function of draft position.

Expected performance value (EV) decays convexly over the course of the draft – EV declines sharply early in the draft and plateaus to more and more of a gradual decline as the draft progresses. Variance of performance value also decays convexly across the draft, beginning with a steep decline and then petering out. Previous NFL draft position value analyses do not consider the implications of the decrease in variance over the draft. We should care about variance because expected performance or surplus value is only a proxy for the actual objective

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9 Massey, Cade, and Richard H. Thaler. "The Loser's Curse: Decision Making and Market Efficiency in the National Football League Draft." *Management Science* 59, no. 7 (July 2013): 1479–95. https://doi.org/10.1287/mnsc.1120.1657.
10 Ibid.
11 "The PFF Draft Value Chart." PFF, April 25, 2024. https://www.pff.com/news/draft-pff-draft-value-chart.
12 Baldwin, Ben. "NFL Draft Value Chart." Open Source Football, March 28, 2024. https://opensourcefootball.com/posts/2023-02-23-nfl-draft-value-chart/.

function a team is interested in. The goal of a team is to win the Super Bowl, or more formally, to choose the bundle of draft picks that maximizes Super Bowl win probability. Though choosing a bundle of picks that has higher expected performance or surplus value is correlated with Super Bowl win probability, they are not the same. Depending on the composition of a football team, certain higher EV players may not significantly increase its Super Bowl win probability. Perhaps only an elite player can, whereas an average or even an above average player cannot. After all, Patrick Mahomes and Tom Brady won 7 of the last 10 Super Bowls, and for many teams it is plausible that only highly elite players like these can give them a fair opportunity to win it all.[13]

As expected value is just a proxy for Super Bowl win probability and is not the right objective function, how variance changes across the draft could alter our valuation of draft picks. In particular, the convexity of variance inflates the value of earlier picks if you are interested in drafting elite players. One definition of eliteness is to exceed a certain threshold of value. Exceeding a high threshold requires not only high expected value but also high variance. Thus, accounting for variance and valuing eliteness should produce steeper draft value curves that place higher value on earlier picks relative to later picks.

Thus, in this paper, we create draft value curves that account for how variance changes across the draft. We consider various alternative value functions of player performance that place considerable value on eliteness. In particular, we consider right tail probability, which considers being elite (exceeding some threshold) a success and being less than elite a failure. These value functions may be better proxies of Super Bowl win probability than expected

[13] Lynch, Kyle. "Tom Brady vs Patrick Mahomes: Stats, Records, Playoff History, Full QB Comparison for the NFL's Goat Debate." NBC Sports, February 9, 2024. https://www.nbcsports.com/nfl/news/tom-brady-vs-patrick-mahomes-stats-records-playoff-history-full-qb-comparison-for-the-nfls-goat-debate.

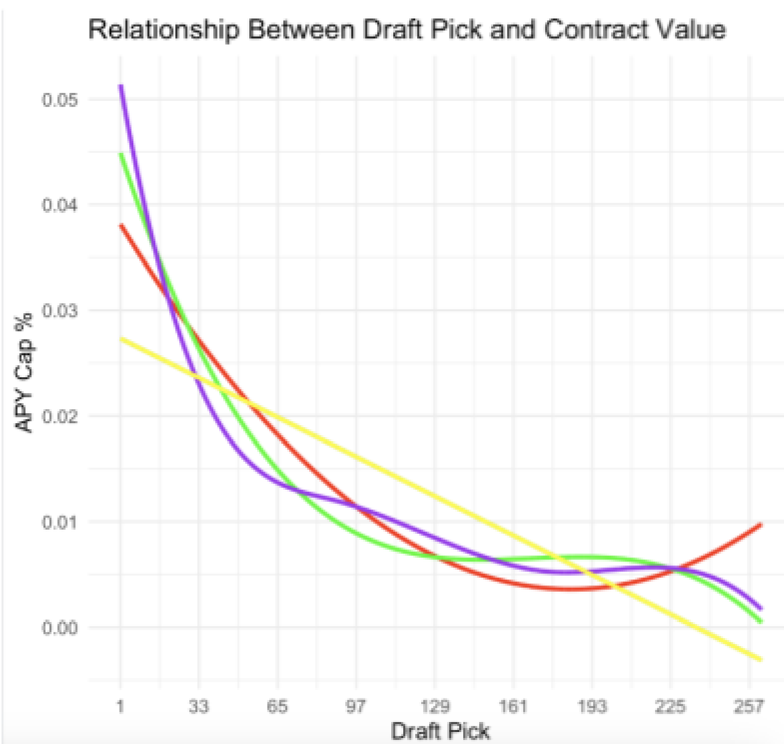
performance or surplus value. We show that drafting based on eliteness produces much steeper draft value curves that upweight earlier picks relative to later picks.

The remainder of this paper is organized as follows. In Section II we discuss traditional expected performance value draft trade curves. In Section III we detail how variance in performance value changes across the draft. In Section IV we explain this via the density of performance given draft position, and in Section V we model that conditional density using Beta regression. Then, in Section VI we create draft value curves from alternative objective functions that place considerable value on eliteness. Finally, we conclude in Section VII.

II. Traditional Draft Trade Value Curves

First, we model expected performance value as a function of draft position. These draft value curves form the foundation of traditional draft value analyses. As discussed previously, in this work we define performance value by a player's free agent second contract salary as a percentage of the cap (also known as annual percentage yield, or APY cap percentage). We fit the following models from a historical dataset consisting of players' draft positions and second contract outcomes. We scraped the data from NFL Readr and it includes all draft picks from 1997–2024.

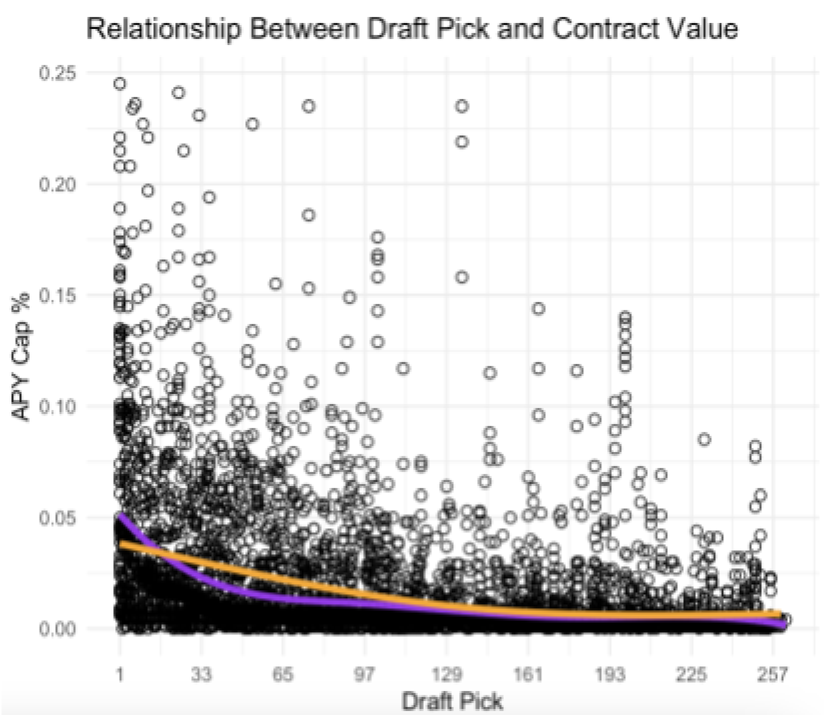
First, we fit a linear model (the yellow line). The purple, green and red lines are spline regressions, each using different knots. The green line is the best spline model since it is monotonic decreasing and not too wobbly or overfit. The spline model produces a key takeaway: expected performance value decays convexly as draft position increases. On average, players drafted earlier provide significantly more expected performance value than players drafted later. Interestingly, even late round picks provide positive value on average.



Graph 1: Estimated expected performance value (y-axis) versus draft position (x-axis). Each line denotes a different regression model (yellow is linear, the other lines are spline regressions with varying knots). Recall that we define a player's performance value by his second contract salary as a proportion of the cap.

III. Variance in Performance Value across the Draft

These traditional draft value curves that analysts use today consider just expected value over the course of the draft. These analyses ignore how variance in performance outcomes changes over the draft. Throughout the draft, both the expected value and variance of a player's performance changes. To accurately value NFL draft picks, it is important to understand this variance.



Graph 2: Each dot represents a player and denotes his actual performance outcome (second contract APY Cap %, y axis) and his draft position (x axis). The purple line is the expected performance value curve, fit using a spline regression. The orange line is the conditional standard deviation at each draft pick, smoothed using a GAM. Both the conditional mean and S.D. decay convexly over the draft.

In this scatterplot we visualize variance in performance outcomes across the draft. Each dot denotes an individual player, whose draft position is on the x-axis and whose performance outcome (second contract value) is on the y-axis. We smooth these data points using a spline regression to form the expected performance value curve (the purple line). We also compute the standard deviation at each draft position and smooth the s.d.'s using a GAM (the orange line). We see that both expected value and variance decays convexly across the draft, and it is important to consider the implications of that observation.

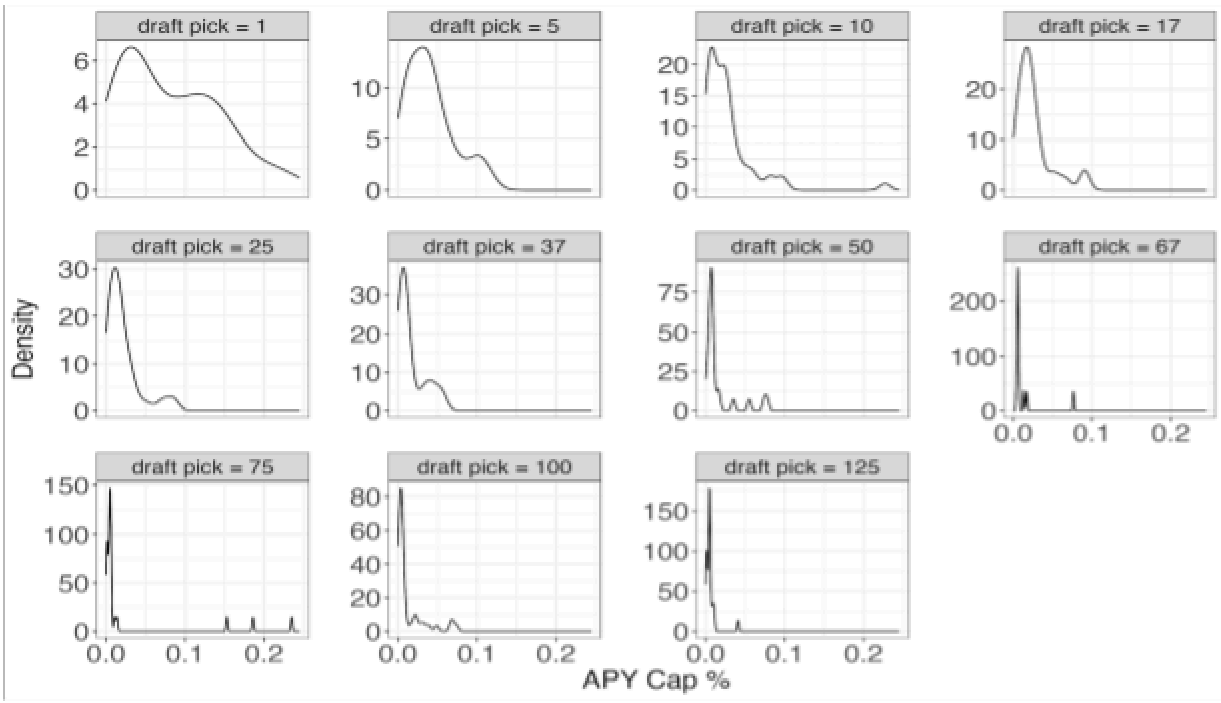
Because earlier draft picks have a much higher expected performance value and variance than later picks, earlier picks have a much higher potential to become extremely successful or elite players. They also have a large potential to become busts. As the draft progresses, the range of probable performance outcomes narrows, and players are more likely to bust. They are also much less likely to become elite players, even less so than it seems when you just consider the conditional mean curve.

If your goal is to win the Super Bowl, it is plausibly much more important to acquire elite players, not necessarily players who have high expected value. After all, there is a reason that 7 of the last 10 Super Bowl winning teams featured Tom Brady and Patrick Mahomes.[14] Acquiring elite players is like exceeding a threshold of performance, which requires a high expected value and a high variance. In light of this, when considering the nonlinearity of variance across the draft, earlier picks become much more valuable than before.

[14] Lynch, Kyle. "Tom Brady vs Patrick Mahomes: Stats, Records, Playoff History, Full QB Comparison for the NFL's Goat Debate." NBC Sports, February 9, 2024. https://www.nbcsports.com/nfl/news/tom-brady-vs-patrick-mahomes-stats-records-playoff-history-full-qb-comparison-for-the-nfls-goat-debate.

IV. Density of Performance Value given Draft Position

To create draft value curves that account for both expected performance value and variance, we need to consider the full conditional density of performance given draft position. Below, we visualize the empirical density for an assortment of draft positions.



Graph 3: The empirical density of performance (second contract APY cap percentage, x axis) given draft position (facet).

Earlier draft picks feature substantial variance in outcomes. Early picks can result in great players, mediocre players, or terrible players, each with nontrivial probability. As the draft progresses, the mean and variance of performance decreases. In particular, the density morphs into a spike near zero. This shows that the players selected in the later rounds of the draft have a very high probability of having a very small or zero second contract value (i.e., of becoming a bust).

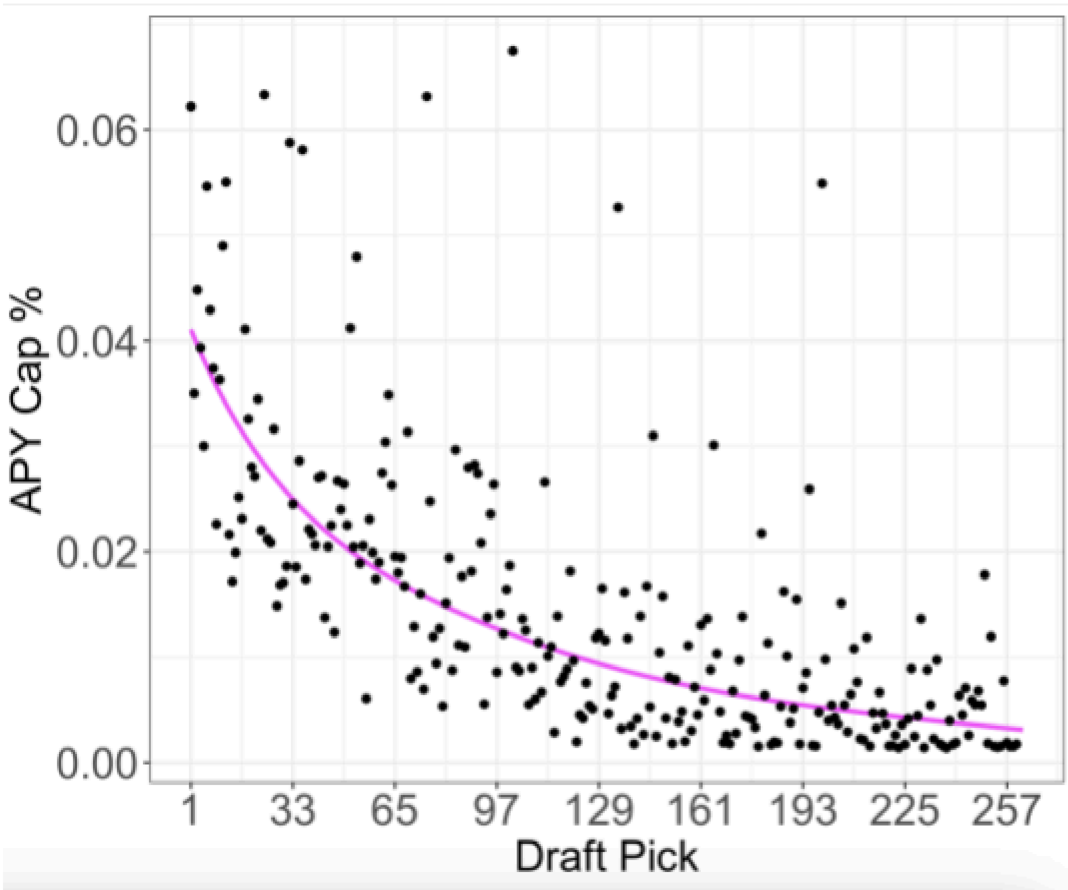
The problem with the empirical conditional density is that there is not enough data in each bin; the densities are far too noisy. Therefore, we need to model the conditional density. We use beta regression to model the conditional density since the outcome variable lies in [0,1] and the densities look like beta densities.

Our beta regression model proceeds as follows. Denote a player's performance outcome by Y and his draft position by x. We model the conditional density of Y given x by $Y|x \sim Beta(\mu(x), \phi(x))$. 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 $shape_1 = \mu \cdot \phi$ and $shape_2 = (1 - \mu) \cdot \phi$. 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 have different outcome distributions. The conditional mean is $E[Y|x] = \mu(x)$ and the conditional variance is $Var(Y|x) = \mu(x) \cdot (1 - \mu(x)) / (1 + \phi(x))$. So, the precision is inversely proportional to the variance. We use spline regression to model the conditional mean, $\mu(x) = logistic(\widetilde{x} \cdot \beta)$, where $\widetilde{x}$ is a spline basis. We model the conditional precision by $\phi(x) = \exp(\gamma_0 + \gamma_1 \cdot x)$. We fit this beta regression model in **R**, estimating the parameters β and γ_0, γ_1, using maximum likelihood via the **betareg** package.[15]

Now, we visualize estimated expected performance value $\mu(x)$ versus draft position x according to our beta regression model (the pink line). The dots denote the empirical conditional mean (e.g., the average performance outcome for the first pick is about 0.06). We see that the

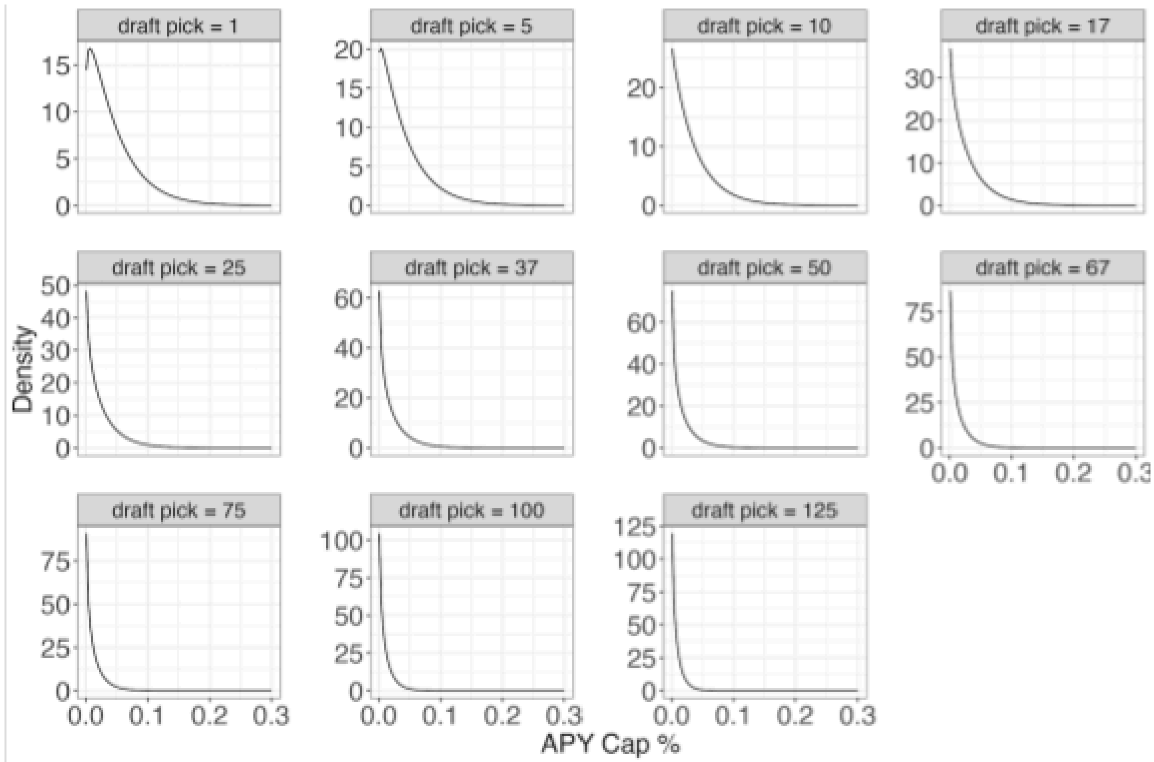
[15] Achim Zeileis [aut, cre]. "Betareg: Beta Regression Version 3.1-4 from Cran." version 3.1-4 from CRAN, February 10, 2021. https://rdrr.io/cran/betareg/.

beta regression's conditional mean fits the data well. As before, expected performance value decreases convexly as the draft progresses.



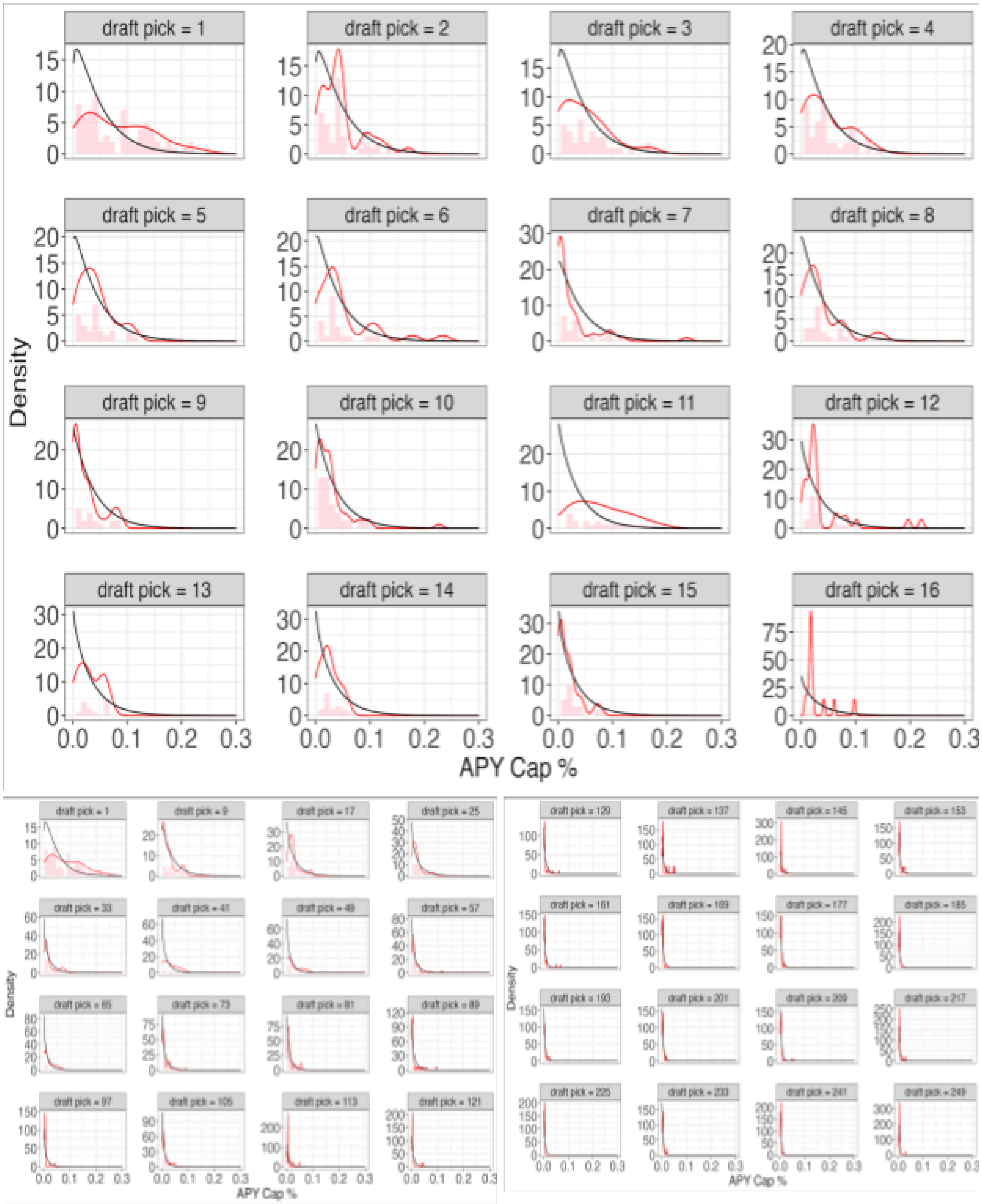
Graph 4: Expected performance value (y axis) versus draft position (x axis) according to our beta regression model (the pink line). The dots denote the empirical conditional mean (e.g., the y value of the dot for draft position 1 is the average performance outcome for pick 1.

Next, we visualize the fitted densities. We plot the fitted performance value density according to our beta regression model for various draft positions. These look like smoothed versions of the empirical densities that we plotted previously. As the draft progresses, the densities morph into a spike near zero.



Graph 5: The fitted density of performance (second contract APY cap percentage, x axis) given draft position (facet) according to our beta regression model.

To fully appreciate the efficacy of our beta regression model, we overlay our model with the empirical density in the graph below. We see that our beta regression model fits the data well – the black densities reasonably fit the red densities. Our model successfully captures the general trend while smoothing out the noise.



Graph 6: The empirical density (red line), empirical histogram (red histogram), and fitted density (black line) of performance (second contract APY cap percentage, x axis) given draft position (facet).

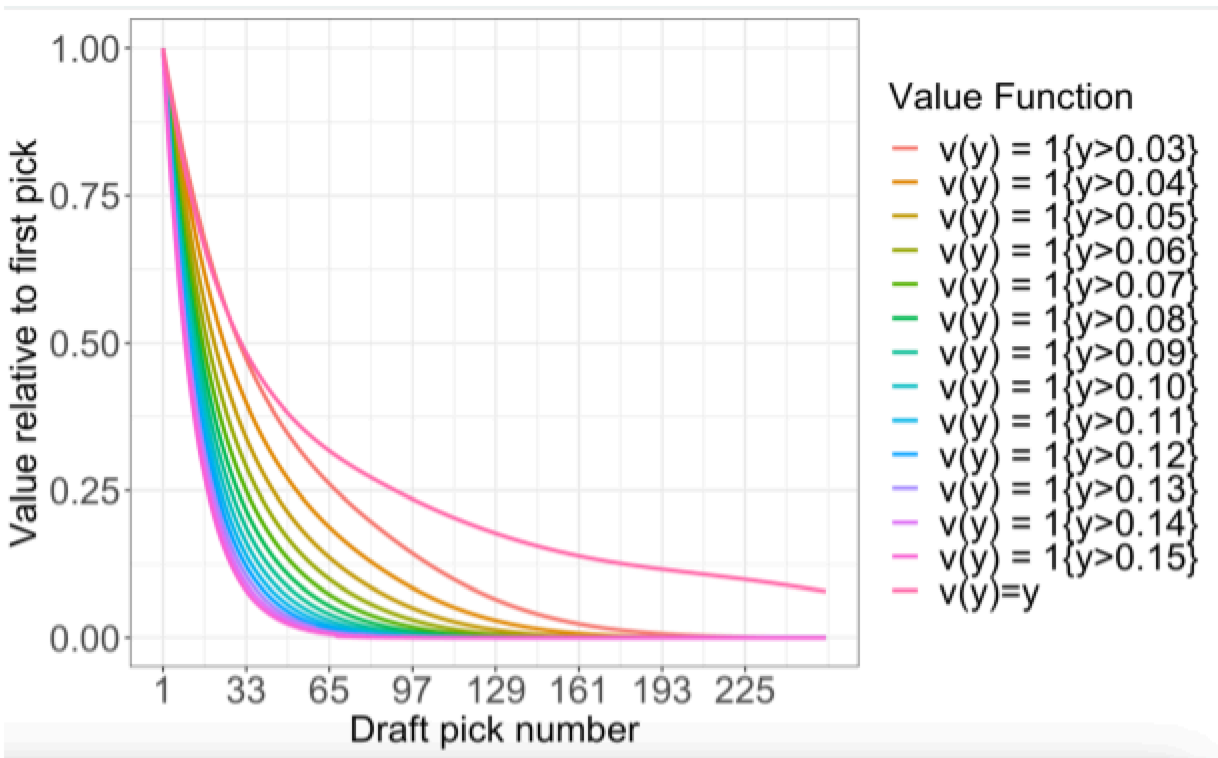
V. Draft trade value curves derived from nonlinear transformations of performance value

A general manager may heavily value eliteness if his goal is to win the Super Bowl. The difference in Super Bowl win probability between adding an elite player and an above average player may be much larger than the difference between adding an above average player and an average player. In other words, it is plausible that individual player performance outcomes should be valued nonlinearly.

Expected performance value is linear and doesn't necessarily value eliteness heavily enough. It is important to consider other nonlinear transformations of performance value that place extra value on eliteness. The clearest example of this is the probability that a draft pick results in an elite player. Equivalently, we want to consider valuing a pick by the expected number of elite players it will produce. Here, we construct such draft value curves using our fitted density of performance given draft position.

Formally, we consider draft value curves proportional to $E[v(Y)|x]$, where x is draft position, Y is performance outcome (second contract APY cap percentage), and v is some transformation of performance value (which we call a value function). The linear value function $v(y) = y$ corresponds to the expected performance curve $E[Y|x]$, which is the traditional draft value curve. This curve, normalized so that the value of the first pick is 1, is the top pink line in Graph 8 below (it is also the pink line in Graph 4). This expected value curve places more value on performance as performance increases in a linear fashion.

The other curves in Graph 8 below place exponentially more value on performance as performance increases. Those curves consider elite players exponentially more valuable than other players. In particular, we use $v(y) = 1\{y > r\}$, which views a performance outcome above r as a total success and an outcome below r as a total failure. Here, an elite player is defined by his second contract exceeding a proportion r of the salary cap. The corresponding draft value curve $E[v(Y)|x]$ is equal to $P(Y > r|x)$, or the probability that a player drafted at position x is elite. We calculate these right tail probabilities for various values of r using our fitted beta regression density. We normalize each of these curves to be relative to the first pick by dividing by the value of the first pick. We visualize the traditional expected value curve and right tail probability value curves in the figure below.



Graph 8: Draft trade value curves proportional to E[v(Y)|x], where Y is performance outcome (second contract APY cap percentage), x is draft position, and v is a transformation of performance outcome. The top pink line uses the linear transformation v(y) = y, corresponding to the traditional expected performance value curve, proportional to E[Y|x]. The other lines use v(y) = 1{y>r}, where r is a threshold of eliteness, corresponding to the right tail probability curve, proportional to P(y>r|x). We see that draft value curves that emphasize the outsized value of elite players are much steeper than the traditional expected value curve.

The shape and steepness of draft value curves vary greatly depending on the transformation v. The more v heavily values eliteness, the steeper its draft value curve becomes. The traditional expected value curve is the shallowest curve, and the right tail curve with the highest cutoff defining eliteness ($r = 0.15$) is the steepest. As we lower the eliteness cutoff r, the curves become gradually less steep.

For a drafted player to become elite, his performance needs to exceed a high threshold r. A random variable with a high mean and a high variance is much more likely to exceed a high threshold than a random variable with low mean and low variance. Because both the mean and variance of performance decays convexly across the draft (see Section III), it makes sense that right tail draft value curves are so steep. Only earlier picks with high enough mean and variance have substantial probability of exceeding thresholds of eliteness. This makes earlier picks much more valuable relative to later picks.

This potentially explains the steepness of the draft value curve implied by the trade market.[16] It is plausible that teams actually trade based on eliteness: a trade is fair if the expected number of elite players on both sides of the trade is the same. Teams may only care about elite players because those are the players who contribute to winning the Super Bowl. After all, there is a reason that Tom Brady and Patrick Mahomes won 7 of the 10 Super Bowls.[17]

Nonetheless, a value function placing exponentially more value on eliteness may not be right for all teams and all situations. Teams that already have elite cornerstone players like the

[16] Massey, Cade, and Richard H. Thaler. "The Loser's Curse: Decision Making and Market Efficiency in the National Football League Draft." *Management Science* 59, no. 7 (July 2013): 1483. https://doi.org/10.1287/mnsc.1120.1657.
[17] Lynch, Kyle. "Tom Brady vs Patrick Mahomes: Stats, Records, Playoff History, Full QB Comparison for the NFL's Goat Debate." NBC Sports, February 9, 2024. https://www.nbcsports.com/nfl/news/tom-brady-vs-patrick-mahomes-stats-records-playoff-history-full-qb-comparison-for-the-nfls-goat-debate.

2023 Chiefs (i.e., Mahomes, Kelce, Jones) may only need average players to increase their Super Bowl win probability. A more balanced/risk-averse approach, using the traditional expected value curve, may make more sense for them. Other teams like the 2023 Bears have little hope of winning the Super Bowl without an elite player. Steeper value curves may make more sense for those clubs.

VI. Limitations

While our study contributes to the draft trade value curve literature, it has limitations. Firstly, our study examines and relies on historical player performance data. As league dynamics or contract structuring could change over time, draft trends may change over time. Second, using second contract value as a proxy for player performance can additionally overlook intangible elements of performance, such as leadership within the team. Additionally, second contracts can use a variety of structuring, such as deferrals, which may cause examination of gross second contract value to miss the full picture. Further, examining draft curves from a macro perspective can disregard team-specific factors behind draft day decisions. For example, teams may draft a player with a substantially higher or lower pick than the player's appropriate value, due to team-specific position needs. Finally, our beta regression is a simplified model, and it doesn't adjust for position.

VII. Conclusion

In this paper we explore the complexities of valuing NFL draft picks. We build upon the prominent Massey Thaler paper, which created draft value curves proportional to the expected value of a draft position.[18] They, however, ignore how variance in performance value decays convexly across the draft. We account for this by building draft value curves from nonlinear transformations of performance value. Using nonlinear transformations that emphasize eliteness, the resulting draft value curves are much steeper than traditional curves. For instance, right tail probability, which places high value on elite players and low value on other players, produces a much steeper draft value curve. That curve more closely resembles the observed trade market, suggesting that teams may value eliteness exponentially more than lower performance outcomes. Perhaps this is because elite players are the necessary components of winning a Super Bowl. In future work, we look forward to more fine grained analyses examining team-specific draft value strategies that consider the impact of drafting a player on a team's Super Bowl win probability.

[18] Massey, Cade, and Richard H. Thaler. "The Loser's Curse: Decision Making and Market Efficiency in the National Football League Draft." *Management Science* 59, no. 7 (July 2013): 1483. https://doi.org/10.1287/mnsc.1120.1657.

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