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Does Draft Currency Promote Competitive Balance? An Empirical Investigation of the National Football League 2002–2021

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Abstract

In the National Football League (NFL) annual draft, teams take turns selecting entering players. The draft is a market mechanism designed to promote competitive balance as the NFL assigns draft positions to teams in reverse order relative to last season's performance. Teams frequently trade draft picks for other picks and/or players. We use several market valuations of draft picks to define original draft currency as the total value of draft picks available before any trades and final draft currency as the total value of picks used after all trades. For the 2002–2021 period, we find that original draft currency does not affect the probability of reaching the playoffs, but final draft currency does. Usage of outdated market valuations of draft picks by most teams can help explain how the best team has used draft-pick trades to remain among the strongest teams over two decades thereby perpetuating competitive imbalance.

Keywords

National Football League, draft, pick-value chart, draft curves, competitive balance, least squares, logistic regression

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Introduction

> The Chart is an example of an especially interesting social phenomenon in which a bias or wrong belief becomes conventional wisdom and then, eventually, a norm. … the Chart appears both a symptom of biased judgment and also a self-perpetuating cause.
> –Massey and Thaler (2013, p.1493)

The National Football League (NFL) has substantial economic impact. For example, by 2019 the NFL had grown to a $15 billion business generating more than $3.4 billion in operating income. The attendance for a single regular season game averages more than 65,000 fans. A Thursday night football game attracts over 15 million viewers, whereas the Super Bowl (the final game of the season) attracts as many as 100 million viewers. The annual value of TV broadcasting rights is estimated at $5.9 billion (Statista, 2022).

Competitive excitement, in particular the uncertainty of the outcome of a game and the uncertainty of a season, attracts fans (Fort, 2012). Competitive balance, meaning teams of equal strength, boosts outcome uncertainty. In 1936, the NFL instituted the draft for entering players ("rookies") as a market mechanism to promote competitive balance. Other North American team sport leagues followed the NFL and based their draft systems on the NFL draft model (Maxcy, 2012). Currently, the NFL consists of 32 teams. After the conclusion of a season, the NFL creates a draft order assigning positions to teams in reverse order relative to last season's performance. The team with the worst win-loss record gets the number one position, and the Super Bowl champion gets the thirty-second position. The draft proceeds through seven rounds. In each round, each team owns the right to pick one player at their assigned position. The idea is to promote competitive balance as the worst team can pick the best available player. Drafted players can only sign a rookie contract (currently for four years) with the team that selected them. Nowadays, rookie contracts follow a rookie wage scale tied to their draft position. After a rookie contract expires, the player becomes a free agent and can sign with any team. In addition to 32 regular picks in each of the seven rounds, the NFL awards about 32 "compensatory picks" to teams based on players lost and gained in free agency. Compensatory picks are inserted in the draft at the end of rounds three through seven. Thus, the draft has about 256 picks. Teams can trade their assigned draft picks for other picks and/or players. From 2002 to 2021, only 61% of all draft picks were used by teams according to their assigned draft position. For the remaining 39% of draft picks, a different team selected a player because the picks were traded.

The NFL draft's goal of promoting competitive balance remains empirically ambiguous (Maxcy, 2012). Few prior papers have studied whether the draft improves competitive balance. Grier and Tollison (1994) find that a later average draft position in the last 5, 4, and 3 years has a negative relation with a team's win percentage controlling for last year's win percentage. While this finding is promising, there are several issues with the research design. First, win percentage is a problematic dependent variable as teams have different schedules facing opponents with different strengths. The standings at the end of the regular season determine which teams advance to the playoffs—the single-elimination tournament that culminates with the Super Bowl to determine the NFL champion. Teams might temporarily improve win percentage yet still miss the playoffs. Second, there might be a performance spillover effect longer than one year ago. Third, by design the model can only pick up a draft effect 5, 4, and 3 years ago and assumes the effect of each of these three years is equal. Fourth, using draft position assumes that the value of draft picks follows a linear decreasing function of draft position. Fifth, the model only considers original draft position ignoring draft-pick trades. We address all five issues in this paper.

Caporale and Collier (2015) build on Grier and Tollison (1994). The authors find that a later average draft position over the last five years has a negative relation with a team's win percentage controlling for last year's win percentage and strength of schedule computed by looking at a team's opponents win percentages from last year. The same concerns apply for win percentage as a dependent variable, only considering a performance spillover effect one year back, assuming draft-pick value follows a linear decreasing function of draft position, and only considering original draft position ignoring draft-pick trades. The different draft position variable (including all five last years) still assumes equal contribution from each draft year. Caporale and Collier (2015) do not find a significant effect for strength of schedule. Measuring opponents' strength with last year's performance (as opposed to this year's performance) could explain the insignificance finding. In our analysis, we base strength of schedule on the current year.

In related work, Fort and Maxcy (2003) review prior literature on competitive balance. Papers have used measures summarizing competitive balance with a single number for a sports league in a single season such as the standard deviation of win percentages. For example, Larsen et al. (2006) find that free agency and the salary cap in the NFL promote competitive balance measured by Gini coefficients and deviations of the Herfindahl–Hirschman Index. With a different approach, Lee (2010) studies the impact of the 1993 collective bargaining agreement (CBA) between the NFL owners and players and competitive balance. In regressions for team win percentage, the author finds that the estimated coefficient for lagged win percentage is lower after the 1993 CBA. As we study the impact of the draft on competitive balance during the 2002–2021 period, our dataset naturally controls for the introduction of free agency, the salary cap, and the CBA.

In this paper, we empirically investigate whether the NFL draft promotes competitive balance. First, we review market valuations of NFL draft picks. Market valuations fall in three buckets: industry practice, empirical estimations based on observed trades, and evaluations of players picked at different draft positions. For each valuation scheme, we define (i) original draft currency as the total value of picks available before any draft trades, and (ii) final draft currency as the total value of picks used after all draft trades. To assess whether the draft promotes competitive balance, we address the following questions.

Does higher original draft currency (before trading picks) lead to increased probability of reaching the playoffs? If so, after how many years? How does final draft currency (after trading picks) affect the probability of reaching the playoffs? What market valuation of draft picks best captures any reduction in competitive imbalance?

Market Value for NFL Draft Picks

In 1991, Mike McCoy, a petroleum engineer and minority owner of the Dallas Cowboys, used a subset of draft-pick trades from 1987 to 1990 to assign values to each draft pick (Massey & Thaler, 2013). McCoy's objective was to characterize past trading behavior rather than create a price list. However, McCoy's draft pick value chart (PVC), or "the Chart," would revolutionize the NFL draft. Initially, owner Jerry Jones and coach Jimmy Johnson used the PVC extensively in the early 1990s, explaining why the PVC is frequently misattributed to Jimmy Johnson (Fortier, 2022). Subsequently, personnel from the Dallas Cowboys moved to other teams taking the PVC with them. Soon the PVC became the norm for negotiating draft-pick trades. In 2004, ESPN reported that "Before NFL general managers consider trading draft picks, they more often than not consult this value chart. The chart assigns each pick in the draft a point value, giving GMs an easy reference to compare the relative value of draft picks in different rounds." (ESPN Insider, 2004). In Figure 1, the PVC graph is McCoy's chart rescaled relative to the number 1 pick.

Massey and Thaler (2013) empirically estimate the value of draft picks using all trades involving only same-year draft picks. Let $v(n)$ denote the value of the n-th pick relative to the number 1 pick ($v(1) = 1$). As an example, if pick 7 is traded for picks 18 and 31, the squared difference between the pick values on both sides of the trade is $(v(7) - (v(18) + v(31)))^2$. The authors fit a Weibull function for $v(n)$ by minimizing the sum over all observed trades of the squared differences between the estimated pick values on both sides of the trade. Graph MT1 in Figure 1 is the estimation using data from 1983 to 2008, graph MT2 is the estimation using data from 2001 to 2008. Note the very steep decline for PVC. Both MT1 and MT2 resemble PVC indicating that teams did indeed use PVC for negotiating draft-pick trades. MT1 and MT2 have a slightly less steep decline suggesting that PVC overvalues early picks.

Instead of assigning draft-pick values based on observed draft-pick trades, others have assigned values to $v(n)$ by studying the average performance of players drafted with the n-th pick. The founder of Pro Football Reference (PFR), Doug Drinen, created the Approximate Value (AV) method to assign a single number to the on-field value of a player (Winston et al., 2022). Thus, AV is a more comprehensive measure than simpler metrics such as number of starts, or number of times making it to the Pro Bowl (an all-star game played toward the end of the season). Using draft data from 1970 to 1999, Stuart (2008) estimated a formula linking career AV of each player to his rookie draft slot. PFRAV in Figure 1 is Stuart's draft-value curve rescaled relative to the number 1 pick. After analyzing games played, games

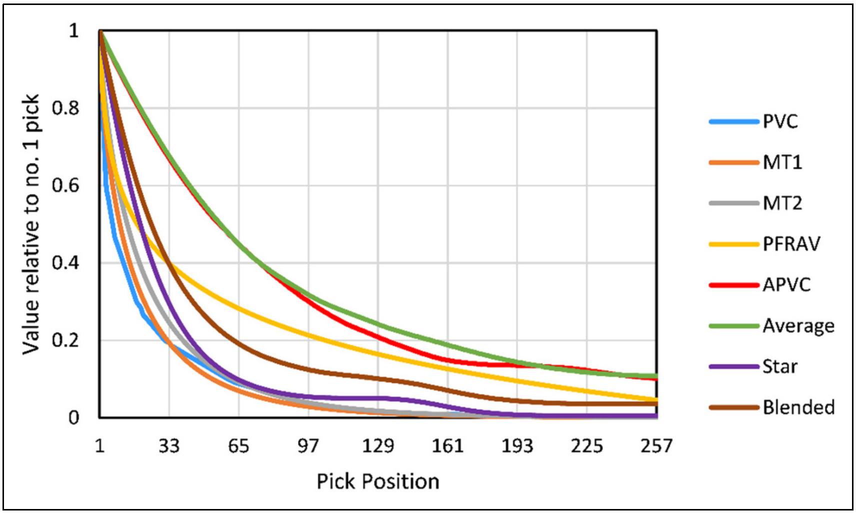

Figure 1. Draft-value curves. PVC: Original Pick Value Chart (PVC) introduced by McKoy which became the standard for NFL teams to use in negotiating draft trades. MT1: Implied draft position value estimated by Massey and Thaler (2013) using 1983–2008 data. MT2: Implied draft position value estimated by Massey and Thaler (2013) using 2001–2008 data. PFRAV: Draft curve from Pro Football Reference (PFR) based on the Approximate Value (AV) of players. APVC: Alternative Pick Value Chart (APVC) proposed by Schuckers (2011). Average, Star, Blended: Draft curves proposed by Lopez (2018).

started, career AV, and Pro Bowls using the drafts from 1991 to 2001, Schuckers (2011) proposed and Alternative PVC (APVC). We rescale Schuckers' chart relative to the number 1 pick to obtain graph APVC in Figure 1.

Michael Lopez, Senior Director of Football Data and Analytics at the NFL, suggested that teams might not be interested in drafting for average player performance, but instead prefer a shot at a superstar (Lopez, 2018). Figure 1 depicts three rescaled charts proposed by Lopez. Average is based on average career AV. Star is based on the probability of landing a superstar. Blended is a weighted average of the Average and Star curves. In the remainder of this paper, we investigate our research questions for each of the curves in Figure 1.

Data and Method

We collected and cross-checked data on the NFL drafts, and all NFL games played for the 1998 through 2021 seasons. Our primary data source, pro-football-reference.com, documents for each draft pick which team made the pick as well as any trade history for the pick. Pro-football-reference.com also documents the final score for each game as well as which teams reached the playoffs. We cross-checked our data with

Wikipedia. NFL teams are assigned to either the American Football Conference or the National Football Conference. In each conference, teams are assigned to divisions. In 2002, the NFL expanded to 32 teams and realigned the divisions to its current organization. Instead of having three divisions with an unequal number of teams, each conference realigned to four divisions (East, North, South, and West) of four teams each. From 2002 onward, in each conference, all four division winners qualified for the playoffs as well as two wildcard teams (nondivision winners with the best record). So, 12 out of 32 NFL teams qualify for the playoffs. Starting in 2021, a third wildcard team also qualified in each conference. The 2002 realignment provides an opportunity to study the same set of 32 teams. Therefore, we focus on the 2002–2021 period. To include lagged variables of interest, we collect data back to 1998.

Variables

Our dependent variable is $PO_{it} = 1$ if team i qualified for the playoffs at the conclusion of regular season t, 0 otherwise. Let OS_{it} be the original set of draft picks for team i in year t before any draft trades. Similarly, with FS_{it} we denote the final set of draft picks used by team i in year t after all draft trades. We use $v(n)$ to denote the value of the n-th draft pick. We calculate the original draft currency for team i in year t as $ODC_{it} = \sum_{n \in OS_{it}} v(n)$. Analogously, we calculate final draft currency as $FDC_{it} = \sum_{n \in FS_{it}} v(n)$.

To control for the strength of the teams each season, we use the least squares method to determine team ratings. The least squares method is commonly used to assess team strength when teams do not play all other teams (Albert et al., 2017; Lapré & Palazzolo, 2022; Winston et al., 2022). Because each NFL team plays a different subset of opponents, least squares ratings are better control variables for team strength compared to win percentages. A major advantage of least squares is the clear interpretation of the difference in ratings (Groll et al., 2020). Let r_{it} be the rating for team i in season t. The rating represents the expected scoring margin on a neutral field against an average team in season t. If $r_{it} > 0$, then team i is expected to beat an average team by r_{it} points in season t. If $r_{it} < 0$, then team i is expected to lose to an average team by r_{it} points in season t. We use the actual game results to calculate the scoring margin m_{ijt} as the difference between the number of points scored by home team i and the number of points scored by away team j in season t. Let h_t be the home advantage in season t and N_t the number of teams in season t. For 2002 through 2021, $N_t = 32$. Lastly, let $G(t)$ be the set of all regular season games played in season t.

The forecasted margin for a game between home team i and away team j in season t is $h_t + r_{it} - r_{jt}$. Consequently, the forecasted error for this game is $(h_t + r_{it} - r_{jt}) - m_{ijt}$. For each regular season t, we solve for the team ratings (r_{it}) and the home advantage (h_t) by minimizing the sum of squared errors subject to the average rating being equal to zero:

$$\min \sum_{(i,j) \in G(t)} ((h_t + r_{it} - r_{jt}) - m_{ijt})^2$$

$$\text{s.t.} \quad \frac{1}{N_t}\sum_{i=1}^{N_t} r_{it} = 0$$

For each regular season t, we use Excel Solver to solve this quadratic programming problem. Solver is guaranteed to find the global minimum, since we minimize a convex quadratic function subject to a linear constraint (Winston & Albright, 1997). Next, we calculate the strength of schedule SoS_{it} by averaging the ratings of the opponents faced by team i in all regular season games in season t.

Teams could perform worse when they have a new head coach. To control for a team changing head coaches, we define $nhc_{it} = 1$ if team i had a new head coach in season t, 0 otherwise. Since a team with a new head coach might change their subsequent draft strategy, we also include a lag for a new head coach in the prior season: nhc_{it-1}. There are 22 starting positions on an NFL team—11 on offense and 11 on defense. So, if teams used draft picks proportional to each starting position, then 4.5% (1/22) of first-round picks would be used for each starting position. However, teams use a disproportionate share of first-round picks for quarterbacks (QBs). During 2002–2021, 9.4% of first-round picks were used for QBs, by far the highest percentage among all starting positions. This is no surprise given the importance of the QB in the NFL. It typically takes a few years for a new QB to develop. While we cannot control for all possible player positions in terms of team needs and picks, we control for QBs picked in the first round given their importance. We define $r1qb_{it} = 1$ if team i used a first-round pick for a QB in season t, 0 otherwise. Given the time for QBs to develop, we also control for $r1qb_{it-1}$ and $r1qb_{it-2}$. Not only do these QB variables control for teams picking QBs but they also control for teams with a good QB who rarely draft a first-round QB. Since the division in which a team is playing can impact the probability of reaching the playoffs, we control for any division effects with division dummies $D_{ij} = 1$ if team i plays in division j, 0 otherwise.

Methodology

We use logistic regression to estimate the probability of reaching the playoffs as follows:

$$\begin{aligned}\ln\frac{\Pr(\mathrm{PO}_{it}=1)}{1-\Pr(\mathrm{PO}_{it}=1)} =& \alpha_0 + \alpha_1 r_{it-1} + \alpha_2 r_{it-2} + \alpha_3 r_{it-3} + \alpha_4 r_{it-4} + \alpha_5 SoS_{it} \\ &+ \alpha_6 nhc_{it} + \alpha_7 nhc_{it-1} + \alpha_8 r1qb_{it} + \alpha_9 r1qb_{it-1} \\ &+ \alpha_{10} r1qb_{it-2} + \sum_{j>1}\alpha_{11j} D_{ij} + \beta_1 ODC_{it} + \beta_2 ODC_{it-1} \\ &+ \beta_3 ODC_{it-2} + \beta_4 ODC_{it-3} + e_{it}\end{aligned} \tag{1}$$

A positive value for α_1 means that a team has a higher probability of reaching the playoffs if they were a stronger team last year. Similarly, with α_2, α_3, and α_4 we estimate any persistence of team strength two, three, and four years back. A negative value for α_5 means that a team with a tougher strength of schedule has a lower probability of reaching the playoffs. So, in contrast to Grier and Tollison (1994) and Caporale and Collier (2015), we (i) allow for performance spillover beyond one year, and (ii) control for strength of schedule in the current year rather than the previous year. A positive value for β_1 means that higher original draft currency in the draft immediately preceding the regular season increases the probability of reaching the playoffs. With β_2, β_3, and β_4 we assess delayed effects of original draft currency as it can take time for draft picks to make an impact. We estimate equation (1) for each of the draft-value curves in Figure 1, that is, for each curve, we use the plotted $v(n)$ values in Figure 1 to calculate original draft currency. We also estimate equation (1) with original draft currency based on a linear draft-value curve implied by Grier and Tollison (1994) and Caporale and Collier (2015). To assess the impact of final draft currency, we replace the original draft currency variables with final draft currency variables in equation (1).

In the estimation, we fit random-effects models adjusting the standard errors for clustering observations by team. For the Cleveland Browns, we can calculate all lagged variables starting in 2003. For the Houston Texans, we can calculate all lagged variables starting in 2005. For the other 30 teams, we have all 20 observations for 2002–2021. Thus, the final dataset contains 635 observations. For logistic regression, Hosmer et al. (2013) recommend at least 10 events per independent variable to avoid overfitting. Thus, with 244 playoff appearances in our dataset, we should not include more than 24 independent variables. Equation (1) has 21 independent variables. So, overfitting is not a concern. The ultimate dependent variable would be winning the Superbowl, but with only 20 Superbowl champions in the dataset, we could have only 2 independent variables to avoid overfitting. Similarly, for any intermediate playoff success measures, the number of independent variables would be too small: conference champions (4), playing in the conference championship game (8), playing in the divisional round (16). In robustness tests, we also use win percentage in the regular season as a dependent variable.

Empirical Results

Table 1 shows the logistic regression estimates for reaching the playoffs with original draft currency. Model (1) is the base model with control variables only. The positive and statistically significant coefficients for ratings from the past two years indicate that higher team strength in the past two years enhances the probability of reaching the playoffs. Further back in time, the effect of team strength drops off. Ratings from three or four years ago are not statistically significant. The negative and statistically significant coefficient for strength of schedule indicates that playing tougher opponents reduces the probability of reaching the playoffs. The control variables for teams changing head coaches are not statistically significant, similar to prior findings in the literature (De Paola & Scoppa, 2012; Koning, 2003; Van Ours & Van Tuijl, 2016). First-round QBs contribute to reaching the playoffs in their second and third years, but not in their first year. None of the division dummies are significant. These significance findings are consistent across all models in Table 1.

In Model (2), we add the original draft currency variables calculated with $v(n)$ values for McCoy's PVC. None of the draft currency variables are statistically significant. Thus, higher original draft currency measured according to the PVC does not lead to a higher probability of reaching the playoffs. We find the same in Models (3) through (10). For all pick valuations in Figure 1, original draft currency does not affect the probability of reaching the playoffs.

Table 2 shows the logistic regression estimates for reaching the playoffs with final draft currency reflecting actual picks made after all draft trades. Again, the significant estimates for team ratings from the past two years and strength of schedule are consistent across all models. In Model (2) with the final draft currency variables calculated with $v(n)$ values for McCoy's PVC, none of the draft currency variables are statistically significant. We find the same pattern in Models (3) and (4) when we calculate final draft currency with the implied draft position value estimated by Massey and Thaler (2013) for both MT1 and MT2 draft-value curves. However, in Model (5), final draft currency for the Star draft-value curve from three years ago is positive and statistically significant. Moreover, in Models (6) through (10) for the Blended, PFRAV, APVC, Average, and Linear draft-value curves, both final draft currency from two years ago and three years ago are positive and statistically significant. Furthermore, the higher log pseudolikelihood values indicate better model fit for Models (7) through (10) compared to Models (1) through (6). These results suggest that draft-value curves PFRAV, APVC, Average, and Linear better capture how final draft currency from two and three years ago increases the probability of reaching the playoffs.

Teams can trade their original draft picks for other draft picks and/or veteran players. So, teams that end up with higher final draft currency compared to their original draft currency, might not only have traded picks but also traded away veteran players. While we fully incorporate gaining or losing draft picks, it is difficult to model gaining or losing veteran players. According to models with better model fit in Table 2, a team with a higher final draft currency has a higher probability of reaching the playoffs (with a delay). The benefit could be a combination of trading picks and trading away veteran talent. As a result, the coefficient estimates for final draft currency in Table 2 could be biased down, as the estimates might represent the net benefit of gaining draft currency and losing veteran talent. Therefore, it is possible that our results are understating the dynamics in the NFL, and the impact of final draft currency could be even bigger. Consequently, our finding—that final draft currency increases the probability of reaching the playoffs whereas original draft currency does not—is possibly even stronger.

Table 1. Logistic Regression Models for Making the Playoffs in 2002–2021: Original Draft Currency.

Original draft currency	(1) —	(2) PVC	(3) MT1	(4) MT2	(5) Star	(6) Blended	(7) PFRAV	(8) APVC	(9) Average	(10) Linear
Rating, lag 1	0.082***	0.098***	0.097***	0.097***	0.098***	0.104***	0.105***	0.104***	0.103***	0.098***
	(0.017)	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)	(0.022)	(0.021)	(0.021)	(0.018)
Rating, lag 2	0.075***	0.090***	0.093***	0.095***	0.090**	0.075**	0.061**	0.058**	0.056**	0.058***
	(0.016)	(0.025)	(0.027)	(0.028)	(0.029)	(0.026)	(0.021)	(0.019)	(0.019)	(0.017)
Rating, lag 3	−0.010	0.001	−0.001	−0.003	−0.007	−0.010	−0.007	−0.011	−0.012	−0.008
	(0.016)	(0.025)	(0.028)	(0.028)	(0.027)	(0.025)	(0.021)	(0.020)	(0.020)	(0.017)
Rating, lag 4	0.015	0.005	0.003	0.003	0.007	0.017	0.025	0.027	0.029	0.026
	(0.017)	(0.026)	(0.028)	(0.029)	(0.030)	(0.028)	(0.023)	(0.022)	(0.022)	(0.019)
Strength of schedule	−0.320***	−0.324***	−0.324***	−0.323***	−0.322***	−0.319***	−0.319***	−0.319***	−0.318***	−0.317***
	(0.068)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)	(0.069)
New head coach	−0.078	−0.128	−0.128	−0.129	−0.127	−0.121	−0.113	−0.083	−0.077	−0.047
	(0.273)	(0.268)	(0.273)	(0.275)	(0.279)	(0.277)	(0.273)	(0.275)	(0.276)	(0.278)
New head coach, lag 1	−0.049	−0.083	−0.095	−0.096	−0.082	−0.042	−0.026	−0.022	−0.022	−0.040
	(0.254)	(0.254)	(0.251)	(0.248)	(0.247)	(0.253)	(0.260)	(0.262)	(0.264)	(0.266)
Round 1 QB in 1st year	−0.254	−0.313	−0.299	−0.293	−0.280	−0.275	−0.286	−0.244	−0.239	−0.233
	(0.385)	(0.392)	(0.387)	(0.385)	(0.384)	(0.388)	(0.396)	(0.397)	(0.397)	(0.401)
Round 1 QB in 2nd year	0.616*	0.566	0.568	0.575*	0.592*	0.598*	0.600*	0.593*	0.591*	0.583*
	(0.286)	(0.297)	(0.294)	(0.293)	(0.291)	(0.288)	(0.284)	(0.283)	(0.282)	(0.276)
Round 1 QB in 3rd year	0.771**	0.732**	0.743**	0.751**	0.768**	0.784**	0.789**	0.805**	0.806**	0.784**
	(0.282)	(0.275)	(0.275)	(0.275)	(0.277)	(0.276)	(0.278)	(0.281)	(0.282)	(0.286)
Draft currency		0.615	0.519	0.509	0.462	0.610	0.745	0.575	0.553	0.373
		(0.720)	(0.706)	(0.682)	(0.651)	(0.624)	(0.535)	(0.423)	(0.407)	(0.241)
Draft currency, lag 1		0.529	0.594	0.596	0.435	0.078	−0.261	−0.296	−0.341	−0.243
		(0.569)	(0.561)	(0.565)	(0.564)	(0.538)	(0.483)	(0.364)	(0.355)	(0.248)
Draft currency, lag 2		0.392	0.310	0.250	0.119	0.047	0.118	−0.042	−0.067	0.027
		(0.585)	(0.637)	(0.636)	(0.597)	(0.539)	(0.423)	(0.371)	(0.347)	(0.194)

(continued)

Table 1. (continued)

Original draft currency	(1) —	(2) PVC	(3) MT1	(4) MT2	(5) Star	(6) Blended	(7) PFRAV	(8) APVC	(9) Average	(10) Linear
Draft currency, lag 3		−0.261	−0.296	−0.282	−0.143	0.144	0.401	0.368	0.400	0.338
		(0.673)	(0.651)	(0.641)	(0.610)	(0.573)	(0.497)	(0.384)	(0.366)	(0.236)
Division dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.503	−1.271	−1.180	−1.283	−1.314	−1.745	−2.238	−2.079	−1.979	−2.564
	(0.302)	(0.983)	(1.018)	(1.214)	(1.482)	(2.045)	(1.899)	(2.357)	(2.273)	(1.988)
Wald χ^2	550.84***	579.28***	574.83***	581.60***	605.26***	642.50***	614.38***	614.96***	603.64***	581.26***
Log pseudolikelihood	−365.65	−364.81	−364.82	−364.83	−365.10	−365.08	−364.18	−363.98	−363.73	−363.03
Number of observations	635	635	635	635	635	635	635	635	635	635

Dependent variable: Reach the Playoffs. Standard errors clustered by team in parentheses. * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Table 2. Logistic Regression Models for Making the Playoffs in 2002–2021: Final Draft Currency.

Final draft currency	(1) —	(2) PVC	(3) MT1	(4) MT2	(5) Star	(6) Blended	(7) PFRAV	(8) APVC	(9) Average	(10) Linear
Rating, lag 1	0.082***	0.069***	0.067***	0.066***	0.065***	0.069***	0.076***	0.076***	0.076***	0.078***
	(0.017)	(0.020)	(0.020)	(0.020)	(0.019)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)
Rating, lag 2	0.075***	0.078**	0.079**	0.078**	0.076**	0.073**	0.070***	0.071***	0.071***	0.072***
	(0.016)	(0.026)	(0.025)	(0.025)	(0.024)	(0.023)	(0.021)	(0.020)	(0.020)	(0.018)
Rating, lag 3	−0.010	0.015	0.015	0.015	0.015	0.018	0.019	0.015	0.015	0.011
	(0.016)	(0.021)	(0.021)	(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)	(0.019)
Rating, lag 4	0.015	0.035	0.035	0.036	0.037	0.037	0.033	0.029	0.028	0.023
	(0.017)	(0.022)	(0.021)	(0.021)	(0.020)	(0.020)	(0.020)	(0.019)	(0.019)	(0.018)
Strength of schedule	−0.320***	−0.321***	−0.323***	−0.322***	−0.321***	−0.317***	−0.316***	−0.317***	−0.316***	−0.315***
	(0.068)	(0.069)	(0.069)	(0.069)	(0.068)	(0.068)	(0.069)	(0.068)	(0.068)	(0.069)
New head coach	−0.078	−0.063	−0.055	−0.056	−0.062	−0.079	−0.092	−0.097	−0.099	−0.095
	(0.273)	(0.300)	(0.301)	(0.301)	(0.300)	(0.300)	(0.301)	(0.297)	(0.297)	(0.297)
New head coach, lag 1	−0.049	−0.057	−0.064	−0.062	−0.065	−0.059	−0.046	−0.053	−0.054	−0.050
	(0.254)	(0.253)	(0.251)	(0.252)	(0.253)	(0.259)	(0.264)	(0.263)	(0.263)	(0.263)
Round 1 QB in 1st year	−0.254	−0.259	−0.255	−0.253	−0.252	−0.264	−0.270	−0.260	−0.261	−0.236
	(0.385)	(0.395)	(0.389)	(0.386)	(0.382)	(0.388)	(0.393)	(0.394)	(0.394)	(0.389)
Round 1 QB in 2nd year	0.616*	0.562	0.552	0.560	0.573	0.609*	0.666*	0.643*	0.650*	0.676*
	(0.286)	(0.312)	(0.312)	(0.308)	(0.310)	(0.311)	(0.313)	(0.304)	(0.306)	(0.303)
Round 1 QB in 3rd year	0.771**	0.609*	0.618*	0.626*	0.634*	0.648*	0.674*	0.714*	0.715*	0.761*
	(0.282)	(0.294)	(0.292)	(0.295)	(0.297)	(0.301)	(0.301)	(0.305)	(0.304)	(0.300)
Draft currency		−0.320	−0.362	−0.373	−0.348	−0.207	−0.023	−0.037	−0.032	0.011
		(0.488)	(0.458)	(0.391)	(0.336)	(0.246)	(0.200)	(0.130)	(0.127)	(0.083)
Draft currency, lag 1		0.152	0.184	0.110	0.027	−0.101	−0.216	−0.158	−0.165	−0.139
		(0.530)	(0.483)	(0.439)	(0.372)	(0.319)	(0.285)	(0.191)	(0.181)	(0.107)
Draft currency, lag 2		0.833	0.759	0.712	0.630	0.630*	0.665*	0.434*	0.420*	0.281*
		(0.438)	(0.405)	(0.372)	(0.326)	(0.301)	(0.312)	(0.212)	(0.206)	(0.135)

(continued)

Table 2. (continued)

Final draft currency	(1) —	(2) PVC	(3) MT1	(4) MT2	(5) Star	(6) Blended	(7) PFRAV	(8) APVC	(9) Average	(10) Linear
Draft currency, lag 3		0.779	0.705	0.698	0.651*	0.665*	0.675*	0.468*	0.456*	0.301**
		(0.484)	(0.441)	(0.393)	(0.329)	(0.290)	(0.294)	(0.184)	(0.180)	(0.115)
Division dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.503	−1.434*	−1.341*	−1.407*	−1.468*	−1.969*	−2.494**	−2.404**	−2.404**	−2.479**
	(0.302)	(0.703)	(0.663)	(0.684)	(0.698)	(0.824)	(0.913)	(0.905)	(0.901)	(0.862)
Wald χ^2	550.84***	758.98***	752.48***	792.07***	780.93***	723.19***	506.51***	569.06***	549.55***	578.83***
Log pseudolikelihood	−365.65	−361.75	−361.89	−361.31	−360.71	−359.13	−358.01	−357.89	−357.85	−357.35
Number of observations	635	635	635	635	635	635	635	635	635	635

Dependent variable: Reach the Playoffs. Standard errors clustered by team in parentheses. * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

We perform several robustness tests. First, we add an additional draft currency variable for the draft four years ago (ODC_{it-4} or FDC_{it-4}). The results reported in Supplementary appendix Tables S1 and S2 show that this variable is not significant in any of the models. None of our conclusions change. When we include team dummies (instead of division dummies) in equation (1), we find the same patterns as in Table 1 (Supplementary appendix Table S3). The same control variables are significant and none of the original draft currency variables are significant. When we include team dummies (instead of division dummies) in the models with final draft currency, the models with better model fit are PFRAV, APCV, Average, and Linear just like in Table 2 (Supplementary appendix Table S4). For these models, the same control variables are significant, and final draft currency from three years ago is positive and significant.

The results strongly suggest that original draft currency does not affect the probability of reaching the playoffs, but final draft currency does after a few years. So, it boils down to successfully trading draft picks rather than just picking in the original order. We formally verify this in a set of robustness tests. Let $\Delta DC_{it-k} = FDC_{it-k} - ODC_{it-k}$ be the change in draft currency for team i in draft $t - k$ ($k = 0, 1, 2, 3$). Supplementary appendix Table S5 shows the results when we add ΔDC_{it-k} for $k = 0, 1, 2, 3$ to equation (1). Again, model fit is higher for Models (7) through (10). Consistent with Tables 1 and 2, in the models for draft-value curves PFRAV, APVC, Average, and Linear none of the original draft currency variables are significant and the coefficient estimates for change in draft currency variables two and three years ago are positive and significant.

Prior to 2017, teams were not allowed to trade compensatory picks. Starting in 2017, however, compensatory picks could be traded just like regular picks. We create alternative draft currency variables focusing on tradable picks only, that is, we omit compensatory picks prior to 2017. The results in Supplementary appendix Tables S6 and S7 show that (i) model fit is higher for PFRAV, APVC, Average, and Linear, and (ii) final draft currency from three years ago is positive and significant. These results further support our conclusion that final draft currency with a less steep decline increases the probability of reaching the playoffs with a delay.

Next, we investigate whether sample selection bias is a concern as it relates to the New England Patriots. The Patriots are by far the most successful team during the 2002–2021 period. They have 17 playoff appearances (compared to 7.6 for an average team), 8 Super Bowl appearances (compared to 3, 2, 1, or 0 for each of the other teams), and 5 Super Bowl wins (compared to just 2, 1, or 0 for each of the other teams). The Patriots also trade more of their draft picks (58%) compared to the league average (39%). Moreover, they tend to amass picks which are worth more in the APVC, Average, and Linear draft-value curves compared to the draft curves typically used by teams (PVC, MT1, MT2) in draft trades. So, the question arises whether the results are merely a Patriots effect. When we run our analysis omitting the Patriots observations, the results are similar to the results when we omit non-tradable compensatory picks. None of the original draft currency variables are significant (Supplementary appendix Table S8), model fit is highest for final draft currency with APVC, Average, and Linear, and final draft currency from three years ago is positive and significant (Supplementary appendix Table S9). So, it is not merely a Patriots driven finding that final draft currency with a less steep decline increases the probability of reaching the playoffs with a delay. Appendix A shows that our findings are robust for other draft-value curves as well.

In a final set of robustness tests, we use win percentage in the regular season as an alternative dependent variable. Supplementary appendix Tables S10 and S11 report the results. The only significant (and positive) original draft currency variables are from one year ago for MT1 and MT2. However, the R^2 for these two models is lower than for the base model and most other models. The only significant (and positive) final draft currency variables are from three years ago for PFRAV, APVC, Average, and Linear. These four models also have the highest R^2 values among all models for win percentage in Supplementary appendix Tables S10 and S11. So, again, model fit is better for models with final draft currency with less steep decline in draft-pick value, and final draft currency contributes to success with a delay.

Discussion

The empirical results show that original draft currency does not affect the probability of reaching the playoffs. However, final draft currency does increase the probability of reaching the playoffs with a delay, and model fit is better for draft-value curves with a less steep decline, notably APVC, Average, and Linear. So, which teams end up with more final draft currency?

In Figure 2, we plot final draft currency against original draft currency. The horizontal (vertical) axis represents a team's original (final) draft currency averaged over 2002–2021. On the 45-degree line, the potential for promoting competitive balance is the highest as final draft currency equals original draft currency determined by the draft order. More deviation from the 45-degree line means more deviation from the perfect potential of promoting competitive balance. So, on average, a team above (below) the 45-degree line gained (lost) draft currency in trading picks. The scatterplot on the left based on PVC draft currency shows that teams are close to the 45-degree line suggesting that teams did indeed use the PVC when negotiating draft-pick trades. The scatterplot on the right based on APVC draft currency shows more variation around the 45-degree line. So, on average, teams with higher original draft currency (and thus earlier draft position) end up with higher final draft currency, but there is significant variation above and below the 45-degree line.

We formally test the observations in Figure 2 by regressing final draft currency on original draft currency in Table 3: $FDC_{it} = \alpha + \beta ODC_{it} + e_{it}$. In Models (1) through (8) for draft curves PVC through Average, the estimate for α is 0 and not statistically significant, whereas the estimate for β is 1 and statistically significant (moreover, 1 is

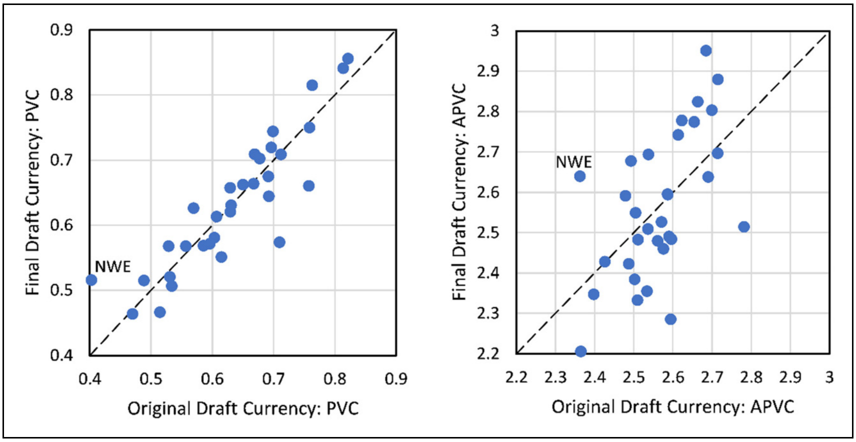

Figure 2. Team average draft currency comparisons 2002–2021: PVC and APVC. Each point represents a team's original draft currency and final draft currency averaged over 2002–2021. Points above (below) the dashed line are teams that ended up with more (less) currency because of their trades. In both charts, the New England Patriots (NWE) are the team on the far left with the least original draft currency. According to the PVC (APVC) valuation, the Patriots ended up with more currency than 4 (21) other teams on average.

contained in the 95% confidence interval around the estimate). So, on average, teams with higher original draft currency end up with higher final draft currency. However, the R^2 decreases from 0.67 for PVC (the steepest draft curve) to 0.29 for APVC and 0.28 for Average (the least steep draft curves depicted in Figure 1), meaning there is more variation around the 45-degree line in Figure 2. Yet, for APVC and Average, the model fit for the probability of reaching the playoffs is higher. So, less steep draft-value curves matter more for reaching the playoffs, but there is more variation away from the 45-degree line in Figure 2, meaning that some teams gain more draft currency than others, while other teams lose more draft currency (Appendix B shows the change in draft currency by team). Hence, some teams better understand the value of out-trading other teams using a less steep draft-value curve. The prime example of this phenomenon is New England.

In Figure 2, the New England Patriots are the team farthest to the left. As the strongest team on average, they had the least original draft currency. Trading picks they ended up with more final draft currency—measured by PVC—than four other teams. Measured by APVC, the Patriots ended up with more final draft currency than 21 other teams. By cleverly trading picks, the Patriots acquired draft picks undervalued by other teams which allowed the Patriots to remain among the strongest teams over a 20-year period thereby negating the intent of the draft. The mechanism of the draft is not necessarily flawed. Instead, other teams' perceived value of draft picks perpetuates competitive imbalance.

Table 3. Linear Regression Models for Final Draft Currency: 2002–2021.

Final draft currency	(1) PVC	(2) MT1	(3) MT2	(4) Star	(5) Blended	(6) PFRAV	(7) APVC	(8) Average	(9) Linear
Original draft currency	1.004***	1.001***	1.016***	1.024***	1.051***	1.003***	0.997***	0.977***	0.813***
	(0.036)	(0.035)	(0.040)	(0.043)	(0.054)	(0.056)	(0.072)	(0.070)	(0.068)
Team fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	−0.003	−0.000	−0.012	−0.024	−0.072	−0.006	0.007	0.060	0.769**
	(0.023)	(0.023)	(0.030)	(0.041)	(0.077)	(0.097)	(0.184)	(0.188)	(0.279)
R^2	0.6742	0.6608	0.6163	0.5619	0.4752	0.4053	0.2879	0.2801	0.1930
Number of observations	640	640	640	640	640	640	640	640	640

Dependent variable: Final Draft Currency. Standard errors clustered by team in parentheses. * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$.

Bill Belichick, head coach and de facto general manager of the New England Patriots since 2000, commented on the rule change in 2017 allowing teams to trade compensatory picks:

> "In the past [compensatory] picks really, I wouldn't say don't have any value, but they didn't have much value because you couldn't do anything with them other than pick a player at that spot. Now that those picks are tradeable, that changes things a little bit because they are capital to move up, move back, or you could move into those spots or trade them for other players." (Hill, 2018).

Clearly, the Patriots view a draft pick as draft currency rather than merely a spot to pick a player. For the draft to reach its intended full potential of promoting competitive balance, teams will need to agree on a draft-value curve that better reflects (i) the contribution of players picked at their draft positions and (ii) the relation between draft currency and access to the playoffs.

To quantify the impact of improving final draft currency on the probability of making the playoffs, consider an average team (with a rating of 0 by construction) playing an average schedule (with a strength of schedule of 0) which has not drafted a QB in the first round in the past three years, with an average final draft currency according to the APVC of 2.6. We reestimated the logistic-regression model from Table 2 for final draft currency with the APVC leaving out nonsignificant variables. With these estimates, we determine that the estimated probability of making the playoffs for this average team is 0.338. If this average team were to make the draft trades the New England Patriots made, the improved final draft currency of 2.9 would change the estimated probability of making the playoffs to 0.389, an increase of 15%.

Conclusion

The intent of the NFL draft is to enhance competitive balance, yet empirical evidence to that effect has been empirically ambiguous (Maxcy, 2012). Our results provide novel insights by studying the probability of reaching the playoffs since the NFL realigned itself in 2002. We study a wide range of draft-value curves covering the highly nonlinear decline in draft-pick value of McCoy's PVC to a linear decline in draft value. Regardless of the draft-value curve we use to calculate original draft currency before any trades, we consistently find that original draft currency does not affect the probability of reaching the playoffs. Interestingly, after a few years, final draft currency after trades does increase the probability of reaching the playoffs. Since the total amount of original draft currency is a fixed pie each year, some teams gain draft currency at the expense of other teams. We find that teams that "out-trade" other teams increase their chances of reaching the playoffs. The impact of final draft currency happens with a delay; it takes at least until the third season after a draft before the impact on access to the playoffs can be expected. We find that model fit is better for draft curves with a less steep decline in draft-pick value than McCoy's PVC. Draft curves such as APVC, Average, and Linear provide better model fit. Some teams gained more draft currency valued by these less steep draft curves than other teams. In particular, the New England Patriots with the least original draft currency ended up with more draft currency valued by the APVC than 21 other teams allowing the Patriots to remain among the strongest teams over a 20-year period.

In our analysis, we could not control for different player positions. Future research should investigate how teams adjust their positional priorities based on recent success. Another fruitful avenue for future research would be to extend our analysis to include player-roster management considering both the depth in the draft for specific player positions and alternatives in free agency.

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Supplemental Material

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Appendix

Appendix A—Additional Draft-Value Curves

In addition to the estimated draft-value curves, MT1 and MT2 in Figure 1, Massey and Thaler (2013) introduce a surplus value for each draft pick. First, the authors use performance categories based on number of starts and Pro Bowl selections to estimate performance value by draft pick. Next, the authors use player salary data from

1994–2008 to determine compensation cost by draft pick. Finally, they calculate surplus value as the difference between performance value and compensation cost. Because compensation declines more quickly than performance value at the beginning of the draft, surplus value initially increases to its maximum at the beginning of the second round and then decreases through the rest of the draft.

We took the surplus graph from Figure 3, Panel B in (Massey & Thaler, 2013, p. 1489) which shows surplus value for picks 1 through 161. We used graphreader.com to create numerical values for these picks. Surplus value is linear for the last part of the graph—picks 139 through 161. We used linear regression on these last picks to extrapolate the graph for picks 162 through 262.

Estimating Model (1) using surplus value for original draft currency gives the same results as all the other draft curves (see Supplementary appendix Table S12). The same control variables in Table 1 are significant, and none of the original draft currency variables are significant. When we use surplus value for final draft currency, again, the same control variables in Table 2 are significant (see Supplementary appendix Table S13). Final draft currency from two years ago is weakly significant ($p = 0.054$) and from three years ago is significant ($p = 0.010$). These findings are consistent with the results in Table 2. The model fit for final draft currency based on surplus value is slightly worse than for the APVC, Average, and Linear draft curves.

While these findings show further robustness of our conclusions, surplus value has several caveats. First, Massey and Thaler (2013, p. 1489) mention: "Clearly, we should be cautious in interpreting this surplus curve; it is meant to summarize the results simply. Whereas the general shape is robust to a wide range of modeling decisions, the precise values are not."

Second, Winston et al. (2022, p. 225) mention: "As pointed out by Birnbaum, there is a major flaw in the [Massey & Thaler (2013)] analysis. [Massey and Thaler] assume that all players who play the same position and are in the same performance category are equally valuable. However, these categories are arbitrarily defined and they can include large variability in player quality. For example, a player who has a single start at a meaningless week 17 game will be in the same category with someone who has eight starts in the season. In order for [Massey and Thaler] to nail down their conclusion that the NFL draft is inefficient, they needed a better measure of player performance."

Third, Massey and Thaler's surplus value critically depends on observed compensation for drafted players between 1994 and 2008. The 2011 Collective Bargaining Agreement drastically reduced salaries for early first-round picks by implementing a rookie wage scale (Corry, 2019). So, for the second half of our data, the surplus curve would look very different.

Rich Hill (RH) of SBNation updated the PVC based on recently observed draft trades since 2012 (Hill, 2017). Compared to the curves in Figure 1, the RH draft-value curve is very similar to the original PVC in Figure 1. When we run our analysis with draft currency based on the RH value curve, we obtain estimates and model fit that are very similar to the results for PVC (Supplementary appendix Tables S12 and S13). Spielberger and Fitzgerald (2020) proposed a draft-value curve using salary data. The Fitzgerald–Spielberger draft-value chart (FS) grades draft picks from 2011 to 2015 based on salary data after players' initial rookie contracts. The FS curve is very similar to the PFRAV curve in Figure 1. Our results in Supplementary appendix Tables S12 and S13 with the FS draft-value curve are very similar to the results for PFRAV. The results for these additional draft-value curves—Surplus Value, RH, and FS—confirm the findings and conclusions obtained with the draft-value curves in Figure 1.

Appendix B—Change in Draft Currency

See Figure B.1.

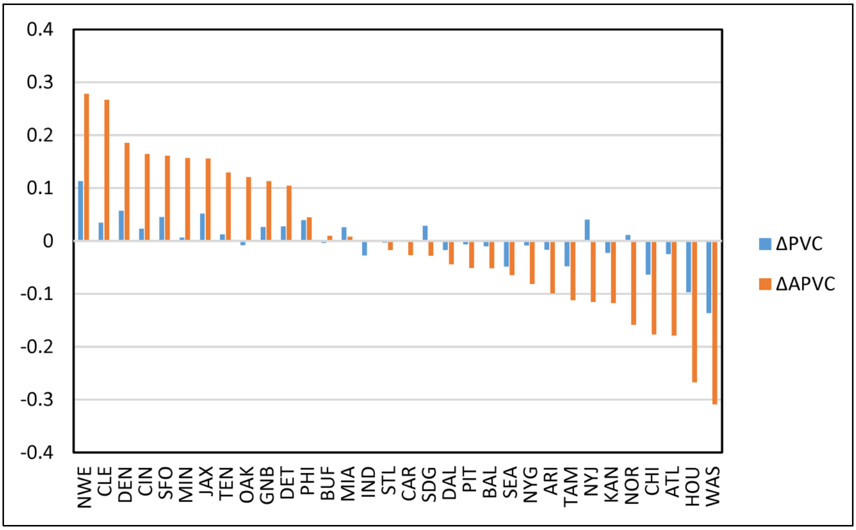

Figure B1. Team average change in draft currency 2002–2021: ΔPVC and ΔAPVC.