

Initial Match and Career Outcomes: Evidence from the NFL Draft

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Abstract

In this study, we investigate the impact of the initial employer-employee match on future career outcomes. To avoid potential endogeneity problems due to the matching process, we exploit the NFL draft, which is the mechanism used to allocate new players to teams in professional football. The draft rules create exogenous variation in team quality among similar ability players. By leveraging these discontinuities, we can identify the effects of the initial match on the career outcomes of drafted players. We examine multiple performance measures and find no substantial effect of the quality of the team drafting the player on their career outcomes. Our findings suggest that the market is able to correct any inefficiency in the initial match, resulting in no discernible effects on long-run player performance.

Keywords: matching, career outcomes.

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1 Introduction

Economics has long recognized that initial conditions can have an impact on long-run outcomes. There is a large literature on the scarring effects of unemployment, showing that unemployment spells have long-lasting detrimental effects on future employment prospects (Arulampalam et al., 2000; Gregg, 2001). Adverse economic conditions at the time of graduation are also linked with enduring negative effects on earnings and employment (Kahn, 2010; Oreopoulos et al., 2012; Oyer, 2006, 2008; Raaum and Røed, 2006). Furthermore, interventions during early life can have persistent effects on labor market outcomes well into adulthood (Heckman et al., 2010). Several factors may contribute to observing such hysteresis in labor markets. Employment history can serve as a signal of productivity to potential employers. In addition, learning and skill acquisition can be hindered by unemployment or underemployment.

Nonetheless, markets possess inherent self-regulating mechanisms that foster the efficient allocation of resources. They achieve this through various means, such as establishing and transferring property rights (Coase, 1960), creating incentives for information acquisition and dissemination (Hayek, 1945), rewarding skill acquisition by paying employees for their productive contributions (Becker, 1994), and fostering competitive forces that drive talent to the firms that can make the most efficient use of it. As a result of these market forces, any short-term inefficiency would tend to be corrected in the long run.

In this paper, we test whether well-functioning markets do indeed correct such initial inefficiencies, leading to no observable long-run effects. We do so by studying the effects of the initial match between football players and NFL teams on the subsequent performance of players throughout their career. This is a labor market in which there are significant inefficiencies at the time employees enter, but the market is very competitive, performance is observable to all parties, and property rights over the employee's time are very well established and easily tradeable. We exploit the fact that players enter professional football through the NFL draft, rather than a competitive bidding process. In the draft,

teams take turns to select players among prospective candidates. The draft takes place in several rounds and, within each round, teams pick players in reverse order to their standing in the league. As a result, the draft creates a discontinuity in the quality of the team around the change in rounds: the top team selects a player in the last pick of a round, followed by the worst team selecting a player in the first pick of the next round. Nevertheless, because teams will want to select the best player among the pool of remaining candidates, players in subsequent picks are likely very similar in skill. The round discontinuity in team quality, therefore, allows us to compare the performance of similar players that start their professional career in very different teams, and observe whether their subsequent career outcomes converge or diverge.¹

The results show no discernible difference in career outcomes among players based on their initial match. We show this to be the case across multiple performance measures: number of games played throughout the career, number of pro-bowl appearances, as well as total career earnings, among others. Regardless of the measure used, we see no difference among similar players that start their career in very different teams. Exploiting the round discontinuity, we compare players that were selected at the end of one round (who end up playing for the top teams of the league) to players selected at the beginning of the next one (who start playing for the teams at the bottom of the league). Those players, on average, played the same number of games, were equally likely to be selected to play the Pro Bowl, and earned similar total compensation throughout their careers.

We also exploit the fact that teams are allowed to trade their draft picks. Although some of these trades are negotiated during the draft, many take place as part of compensation for player transfers. As such, the latter trades are typically recorded in the transfer contracts and negotiated well in advance of the draft (sometimes even years in advance). They can therefore be assumed to be exogenous to the characteristics of the player being selected. We also used the variation in team quality created by such exogenous trades

¹The difference in team quality can be quite sizeable. To get a sense of the magnitude, consider the value of the NFL franchises. In 2021, Forbes estimated that the most valuable team (Dallas Cowboys) was worth \$6.5 billion, whereas the least valuable team (Buffalo Bills) was worth \$2.27 billion, just over a third as much.

in our identification strategy. The results, again, show no economically nor statistically meaningful differences in career outcomes.

There is prior evidence of an effect of initial labor market conditions on future performance. Baker et al. (1994), using detailed evidence from one firm, find that cohorts of employees that earn more upon entry into the firm keep earning more through time. In the market for academic economists (Oyer, 2006), or financial professionals (Oyer, 2008), graduates that enter the market during a recession show decreased earnings years after graduation. Kahn (2010) documents similar findings for a broad sample of college graduates. Instead, our evidence comes from comparing players that enter the NFL in the same year, and hence under the same economic environment, but end up in different teams. Our results suggest that, despite the initial allocation of players to teams not being done in a competitive fashion, the initial match does not have any discernible effect on the future career outcomes of the players. They suggest that the earlier documented effects of recessions are unlikely to come from simply an initial misallocation of employees to firms within an industry.

There is also a large literature on the scarring effects of unemployment in recessions (Arulampalam et al., 2000; Gregg, 2001). Recent evidence points to the importance of job displacement in explaining the scarring, and thereby creating a sizeable cost of business cycles. Huckfeldt (2022) shows that most of the fall in earnings caused by unemployment is explained by workers moving to lower occupation jobs. Our results support this conclusion, as we do not seem to find any long-run effect of initial employment in a setting in which the initial employment does not cause any industry or occupation displacement.

2 NFL Background

The National Football League (NFL) started in its current form in 1970, after the merger between the two major professional leagues existing at the time, the American Football League (AFL) and the NFL. As a result of that merger, 28 teams competed in the league,

with that number later expanded to reach the current number of 32 teams. In our study, we restrict attention to the drafts taking place after 1970.

The NFL draft is the mechanism used for player recruitment into professional football. Although it is not the only way to enter the NFL league, it is by far the most common. Every year, each team is allotted a position in the draft in reverse order to their record in the league during the previous season. This way, in each round, the team that finished in last place picks first, and the Super Bowl winner goes last. Since 1994, there are seven rounds and 32 teams, although earlier drafts had more rounds with fewer teams. All teams select one player in the order allocated, or trade their pick to another team. Such trades are commonplace. Sometimes they happen during the draft, but it is also common for teams to trade draft picks as partial compensation in contract negotiations for the transfer of players. When that happens, a team might “sell” some of its future draft picks months or even years in advance.

In addition to the regular draft picks, there are compensatory picks awarded to teams based on the number of free-agent players lost or gained. These compensatory picks are selected at the end of rounds three to seven (there is no compensatory pick between rounds one and two). For the purpose of this study, we ignore these picks.

Contracts signed during the draft are governed by the collective bargaining agreement between players and teams. Every rookie player signs a four-year contract. After those four years, the player becomes a free agent (unrestricted free agency was introduced in 1992). In addition, for first-round picks, the team has an option to extend the contract for a fifth year. However, it is not uncommon for teams to renegotiate the initial agreement after the third season, extending the contract to prevent losing the player to free agency later on.

The league and collective bargaining agreement also impose limitations on salaries. In 1994, a salary cap was introduced, with the objective of maintaining competitive balance. There is an additional salary cap for rookies and the collective agreement establishes specific salary parameters for each draft slot, effectively tying compensation to the pick

of the draft. Because salaries are not determined competitively until the player reaches free-agent status (and even then, the salary cap restricts the ability of teams to pay market salaries), we need to be cautious with the interpretation of any career outcome that is based on compensation numbers. However, despite these constraints on salaries, we still expect total career earnings to be highly correlated with a player's productive value.

3 Data

3.1 Data Sources and Descriptive Statistics

We use data from three different sources for our analysis (see Table 1 for variable definitions and sources). First, we obtain draft information from Pro-Football Reference.² The sample covers all players drafted between the years of 1970 and 2014, and includes player information for each draft pick (such as name, position, and team drafting the player), as well as all their performance statistics. However, we limit the analysis to the first seven rounds of each year's draft, to have a consistent sample throughout all the years.

Second, we obtain the information on the trade of draft picks and the dates at which they took place from Pro Sport Transactions.³ Finally, we collected salary information from Spotrac.⁴ This sample is more limited, and covers only players drafted between 2005 and 2018. We collected information on the contracts signed by these players, including the yearly salary and bonuses, as well as the total amount earned through 2018. This represents the total career earnings for players that retired prior to that year. But for players that were still active as of 2018, our measure of career earnings is truncated, and only captures their earnings up to that year. Because we are only able to capture the first few years of earnings (often only the first signed contract) for players drafted in the later years of our sample, we limit the analyses to the players that were drafted before 2015. This way, even if some players are still active at the point the data is truncated,

²www.pro-football-reference.com

³<https://www.prosportstransactions.com/football/>

⁴<https://www.spotrac.com/nfl/draft/>

at least we capture a reasonably large portion of their career earnings.⁵

Table 2 provides some basic descriptive statistics of our data. The length of the career of a player has been used in the past as a proxy for the performance of a player. The table shows that the average number of total career games is 68, which implies 4 regular seasons of 17 games each. It is in line with a duration of the average career of 4.7 years. However, we observe that players get to be starters in their main position only 2.3 of those years on average.

We also consider alternative measures of performance. Our data contains information on players' appearances in the pro-bowl and the all-pro first teams. The pro-bowl is an exhibition game, in which the best players of the American Football Conference (AFC) play against the best of the National Football Conference (NFC). It takes place once a year (usually mid-way of their regular season) since 1970. On the other hand, the all-pro first team includes only the best players of the season in each position. As we can see in Table 1, it is much harder to be selected for the all-pro team than the pro-bowl. However, both are measures of overall player quality.

In addition, Pro-Football Reference calculates a measure of approximate value for each individual player and each active year of his career based on performance statics (such as passing or rushing yards). This measure captures the contribution of the player to the performance of either the offensive or defensive lines of his team, depending on his position, in a given year. We use this variable as an alternative measure of player's productivity.⁶ This measure is then aggregated into two other measures of career productivity. The career approximate value measure is a weighted average of the highest approximate value per year of a player. This measure assigns a 100% weight to the player best season approximate value, 95% to the player second-best season and so on.

⁵The results are robust to using earlier cutoff dates. But the sample gets progressively smaller, with the corresponding loss of power.

⁶The approximate value measure was developed by the mathematician and founder of the sport reference web page Doug Drinen with the objective of being able to compare players of different positions and different periods. The main idea of these methodology is to assign a total number of points to each offensive and defensive lines of each team on the league based on team performance. Then, the methodology assigns those points among the players belonging to each line, depending on their individual contribution to the team performance.

On the other hand, the draft approximate value is the approximate value accumulated by the player on the team that drafted him. As expected, the average value of the career approximate value is higher than the draft approximate value.

Finally, we can also see that career earnings are quite sizeable, amounting to about \$12 million, on average. We report as well the statistics for the logarithm of career earnings, as this is what we use in our analyses. Notice, however, that the sample size for this measure drops quite considerably.

Table 2 also shows that it is common for teams to trade their draft picks. In our sample, 33.5% of the picks between 1970 and 2014 were traded. The percentage of transactions per year varies from 21 to 50% of the picks, implying between 40 and 111 trades per draft. Some of these trades can take place during the draft itself and are motivated by the desire of a team to select a particular player. However, other trades are negotiated a long time in advance of the draft and, hence, are unlikely to respond to a bid for a specific player. We classify a trade as exogenous if it takes place at least one month prior to the draft. In our sample almost half of all trades are exogenous.

3.2 Measuring Output

As described earlier, we have seven measures of player performance or output. *Games* and *Starter* measure the duration of a player's career in the league. *All-pro* and *Pro-bowl* are subjective evaluations of player quality. *C-value* and *D-value* are constructed measures of value based on objective performance statistics. Finally, *Earnings* is the market's reflection of the value of the player. Having multiple measures, which capture different aspects of player performance, allows us to address the robustness of our results. However, to present our results in a more parsimonious way, we will reduce the dimensionality of our measures of performance.

Table 8 presents the principal components analysis of our measures. Because *Earnings* is only available for a limited number of years, this table looks at the first six measures for our entire sample. The results show we only have one component with an eigenvalue

above 1, in which all six measures load with a similar weight. However, because the second component has an eigenvalue close to 1, we include it as well. The orthogonal rotation of the two main components, presented in Panel B, shows that *Games*, *Starter*, *C-value*, and *D-value* load in the first factor, whereas *All-pro* and *Pro-bowl* load in the second.

Table 9 looks at all seven measures, but limiting the sample to those observations for which we have the player's earnings. Again, we have one factor with an eigenvalue clearly above 1, and a second marginal factor, albeit this time the eigenvalue is slightly above 1. Rotating the components gives us an analogous picture to the one obtained from the whole sample: Panel B shows that we have one factor with loadings on *All-pro* and *Pro-bowl*, and a main factor with loadings on all other measures, including *Ln Earnings*.

These results allow us to greatly reduce the dimensionality of the performance measures. However, instead of aggregating these measures into two factors, we will simply use the number of games and pro-bowl appearances as our main measures of productivity. This makes our results easier to interpret. The number of games played has been used in the past to measure a player's career performance (Massey and Thaler, 2013), and is more granular than the number of seasons played as a starter. In addition, *Games* is arguably more objective than *C-value* and *D-value*, both of which involve some subjective choices in their construction (such as the weighting of each season's score). With regards to the second score, we chose *Pro-bowl*, as being selected for the all-pro team is a much rarer event, reducing the power of our tests. Nonetheless, untabulated results for the excluded measures are consistent with those for *Games* and *Pro-bowl*.

Finally, notice that the limited data we have for career earnings, together with the institutional constraints on the competitive bidding process during player recruitment, may render this measure less informative. In addition, it seems to capture the same underlying factor as *Games*. However, because earnings is, arguably, the most economically meaningful measure of career performance, and the measure used in most prior studies, we also include *Ln Earnings* in our reported analyses.

4 Initial Match and Career Outcomes

4.1 The NFL Draft: Discontinuities in Team Quality

Because teams are selecting players in reverse order to their league record in each round, there should be a clear relationship between team quality, pick and round, satisfying:

$$Q_i = P_i - R_i + 1, \tag{1}$$

where Q_i is the quality of the team (scaled, so that $Q_i = 1$ for the top team and $Q_i = 0$ for the bottom team), R_i is the draft round, and P_i is the draft pick normalized by the number of teams T , so that $P_i \in [R_i - 1, R_i]$ for all picks in round R_i , with $P_i = R_i - 1 + 1/T$ for the first pick of round R_i , and $P_i = R_i$ for the last pick of round R_i .⁷

Table 3 describes the change in team quality over the NFL draft. Column (1) estimates equation 1 using all the observations. The estimates show that there is a clear upward trend within round, reflecting the draft rules calling for teams to select players sequentially in increasing rank, and resetting after each round. In addition, there is a sizeable jump down in team quality at each round change. However, the figure also shows substantial noise, due to the fact that a significant number of teams trade their draft picks to other teams. Such trades effectively flatten the curve within round, as teams that select early in the round will inevitably trade to better teams, while teams selecting at the end of the round will trade to lower quality teams. As a result, the average team selecting at the beginning of the round is in the 20th percentile of the ranking, and the average team selecting at the end of the round is in the 80th percentile.

Column (2) estimates the same relationship dropping all observations that involve a trade. We can now see that the relationship in equation (1) clearly holds. The first team selecting a player in each round is (close to) the worst team, and the last team selecting

⁷Technically, for 1 to hold, we need to define Q_i as $T + 1$ minus the team ranking divided by T , so that $Q_i = 1/T$ for the worst team. However, to simplify the interpretation of our results later, we define Q_i as T minus the ranking divided by $T - 1$.

within a round is the best team. In addition, the slope of the relationship between team quality and pick is close to 1, with the drop in quality after each round also being close to 1. Figure 1 shows graphically how the quality of the team changes over the first three rounds of the draft using only the observations that do not involve a trade.

Having established that there is a sizeable change in team quality around round changes, Figure 1 provide a visual representation of our main result. They plot our measures of career performance over the first four draft rounds. The figures also provide a non-parametric estimate of the relationship between draft pick and performance, estimated separately for each round. All three figures show a decreasing relationship, reflecting the fact that better players are picked earlier in the draft. We also see no discernible jumps in career performance at any of the round changes. Regardless of whether we use *Games*, *Pro-bowl*, or *Ln Earnings*, performance of players selected at the end of one round is very close to performance of those selected at the beginning of the next round. The figures suggest that the quality of the team drafting an NFL player has no impact on the career outcomes of that player.

4.2 Performance Around Round Changes

Next, we extend the earlier visual intuition with several formal tests. To estimate the effect of team quality on career outcomes, we first start by using a regression discontinuity design. Assuming that players selected in contiguous picks in the draft are of comparable skill (i.e. player skill only falls continuously with the draft pick), we can compare players that are picked at the end of a round with players picked at the beginning of the next round, as the former end up in discontinuously better teams than the latter. Because player skill differences are likely minor, we can attribute any differences in performance to differences in team quality on both sides of the round discontinuity. Using players from two consecutive rounds, we estimate:

$$Y_i = \alpha + \beta_{round}D_{Ri} + \epsilon_i, \tag{2}$$

where $i = (p, t)$ denotes a player selected in pick p in draft year t , Y_i is the outcome of interest for player i , and D_{Ri} is a dummy that takes value of 1 if the player is selected in the higher of the two draft rounds. The round effect β_{round} measures the effect of starting your career in a better team, represented by the quality difference between teams to the left and right of the round discontinuity. Because we want the players to be similar, we limit the sample to a bandwidth around the round discontinuity. A wider bandwidth increases the number of observations, and hence the precision of the estimate. However, it also potentially increases the skill difference among the players on both sides of the discontinuity. Because better players are picked earlier, if players in the later round are less skilled, our estimate of β_{round} would be biased downwards. To minimize that possibility, we estimate this regression with a narrow bandwidth of 5 players on each side of the round discontinuity. However, our results are robust to using alternative bandwidths. Untabulated regressions using 1, 2, and 3 players on each side of the discontinuity yield the same results.

Table 4 provides estimates of the round effects on career performance by estimating model (2) around two consecutive rounds using OLS. Panel A presents the estimates for the number of games played. It shows that the top five players of the second round (who end up in a worse team) play, on average, four fewer games than the last five players of the first round (column (1)). This estimate is not only statistically insignificant, but its economic size is also small, relative to the 95 games that the average player at the bottom of round 1 plays throughout their career. The estimate for the change between rounds 2 and 3 (column (2)) is equally small in size and statistically insignificant, as is the change between rounds 3 and 4 (column (3)).⁸ In columns (4) to (6) we restrict the sample to those players that were selected by a team without involving a trade of that draft pick. The estimates are similarly small and insignificant.

The same pattern repeats when considering the number of Pro-Bowl appearances in Panel B. The effect of the round change has inconsistent signs, is generally small, and insignificant.

⁸The same is true if we consider all other round pairs. We do not report the results for brevity.

Finally, Panel C compares the total career earnings of players around round changes. Some of the differences are larger (37 log points between rounds 2 and 3). However, the estimates vary quite significantly in size and even sign throughout our specifications, and there is a large uncertainty in those estimates. In general, the estimates are statistically insignificant. However, we need to consider these results with caution. First, the number of observations is greatly reduced, compared to the other performance measures, due to data availability. Second, there is a large variation in compensation, making the identification of any effect difficult with our limited data. In any case, the results suggest that there is no clear effect of initial team quality on career earnings throughout a player’s career.

Across all our measures, we do not see a significant impact of the round changes on the overall career performance of NFL players.

4.3 Team Quality and Player Career Performance Around Round Changes

Model 2 estimates the effect of a round change arising from the discontinuity in team quality created by the draft. To interpret our results in terms of the effect of the quality of the team on player outcomes, we can derive the Wald estimator by dividing the estimated round effect by the difference in average team quality on both sides of the round discontinuity. That is, the Wald estimator is $\beta_{round}/\Delta Q_R$, where β_{round} is the estimated round effect on performance (reported on Table 4) and ΔQ_R denotes the average difference in team quality on both sides of the round discontinuity. To implement it, we estimate the following model using the same sample around the changes in draft rounds:

$$Y_i = \alpha + \beta Q_i + \epsilon_i, \tag{3}$$

where Q_i denotes the quality of the team that drafts player i , and we instrument Q_i with the dummy for the later draft round, D_{Ri} . This IV approach yields the Wald estimator

for the treatment effect of changing a player’s team quality. Because Q_i takes values between 0 and 1, β measures the effect on the outcome variable Y of moving a given player from the worst team to the best team in the NFL league.

Table 5 provides the estimate of the corresponding effects of team quality on career performance using the same bandwidth of 5 players around two consecutive draft rounds.⁹ Naturally, the estimates are somewhat larger, as $\Delta Q_R < 1$. For instance, for players drafted around the change between rounds 1 and 2, going from the worst team in the league to the best team results in an increase in 8 games played throughout the career. The effect is still statistically insignificant, and remains so throughout all the specifications (for all round pairs, and regardless of whether we limit the sample to those picks that did not involve a trade) and for all performance measures.

4.4 Team Quality and Player Career Performance in the Entire Sample

4.4.1 Exploiting Round Changes

Next, we expand the previous results by considering the entire sample of draft picks, including all rounds and all the draft players. While restricting the sample to a bandwidth around the round changes allows us to cleanly identify any round effects, using our whole sample of draft picks makes it possible to control for other characteristics that may affect a player’s career, such as the position he plays in. In this case, it becomes important to control for the pick, as the quality of the players is going to vary widely along the entire draft sample. We estimate:

$$Y_i = \alpha + \beta Q_i + m(\gamma', P_i) + \delta X_i \epsilon_i, \quad (4)$$

where P_i denotes the player’s draft pick (i.e., $P_i = p$ if $i = (p, t)$) and m is a polynomial with a vector of parameters γ' that captures in a flexible way the fact that player skill

⁹We only report the second-stage results, but the effective first-stage F-statistic is well above 10, suggesting we do not have a weak instrument problem.

is decreasing in draft pick. In our specifications, we use a linear polynomial with slopes that are allowed to vary for each round of the draft. Because the quality of the team changes discontinuously between draft rounds, we instrument Q_i with R_i , denoting the round in which player i is selected. The first stage, therefore, is:

$$Q_i = a + bR_i + cP_i + u_i. \quad (5)$$

Because teams draft players in reverse order to their quality, the draft pick and the round would perfectly predict the quality of the team in the absence of trades. Furthermore, because we normalize the team quality to equal 0 for the worst team and 1 for the best team, we should get $b = -1$ and $c = 1/(T - 1)$, where T is the number of teams. Effectively, the first round of the IV regression is the estimate of model 1 presented in Table 3. By instrumenting team quality with the round, we are only exploiting the variation in team quality that arises from the discontinuity caused by the change in draft rounds. We do not use the continuous change in quality due to the sequential selections within a round, or the variation caused by teams trading their draft picks. This model is simply a generalization of the Wald estimates obtained from model (3) above.

Table 6 presents the IV estimates for model (4). The results in Panel A show that the effect of team quality on the total number of games played throughout the career is small and insignificant: column (1) shows that going from the worst to the best team in the league increases the number of games played by 1.5. Adding position and year fixed effects in column (2) does not change the results. In addition, the estimate in columns (3) and (4) becomes even smaller in absolute value when we restrict the sample to those players whose draft pick was not traded, or that were selected in the first three rounds of the draft (because player quality is highest in the top rounds, we would expect to find the strongest effects of team quality matching on career outcomes for players drafted in those top rounds).

We find similarly small and insignificant effects in Panel B of Table 6, when considering

the number of Pro-bowl appearances. Panel C presents the results for career earnings (in logs). Column (1), using the full sample, shows a positive effect of 20 log points. However, this result is not statistically significant. Moreover, when we control for position and year fixed effects in column (2), the effect becomes smaller, at 13 log points. Dropping the observations that involve a trade in column (3), the effect becomes smaller still. It remains so in column (4) when we look only at the first three rounds of the draft, for which the effect of team quality should be strongest. Regardless of the measure of performance, or the specification used, none of the estimates are statistically significant.

4.4.2 Exploiting Draft Trades

Finally, notice that pick trades create jumps in team quality among contiguous picks. When using the entire sample, we can also exploit such discontinuities in team quality caused by draft pick trades. We can write equation 5 as:

$$Q_i = a + bR_i + cP_i + \Delta Q_i, \tag{6}$$

where $\Delta Q_i = Q_i - Q_i^{NT}$ and Q_i^{NT} measures the quality of the team that would have drafted player i if no draft trade had occurred. Hence, ΔQ_i measures the change in team quality caused by the trade of player i .¹⁰ Many of these trades are the result of contractual agreements signed prior to the draft (sometimes even years in the past), and hence, the team quality differences that they create are likely exogenous. To mitigate any potential concern about the endogeneity of pick trades, we exclude all trades that took place within less than a month of the draft. We exploit the variation created by those trades by estimating equation 4 instrumenting Q_i with $D_{i,ET}\Delta Q_i$, where $D_{i,ET}$ is a dummy that equals 1 when player i is drafted in an exogenous traded pick, that is, a trade that was agreed at least one month prior to the draft. Effectively, we are only exploiting team quality differences that arise from these exogenous trades to estimate the effect of team quality on player outcomes.

¹⁰Notice that equation 6 is really an identity, as the right-hand side simplifies to $a + bR_i + cP_i$ if there is no trade and to Q_i when a trade occurred, as $Q_i^{NT} = a + bR_i + cP_i$.

Table 7 presents the estimates for model (4) using the exogenous draft trades as an instrument for team quality. Interestingly, the results are analogous to using the round changes as an instrument. Although the estimated effects of team quality on the number of games played in Panel A are slightly larger (an increase of 4 to 5 games when going from the worst to the best team), the estimates are still small and insignificant. The estimates are also insignificant for the number of Pro-Bowl appearances (Panel B) and earnings (Panel C). In the latter case, using trades as an instrument yields effects that are even of inconsistent sign.

Overall, the results show that the initial matching has no effect on career outcomes for drafted players. Those players that start their career in a top team have equally lasting and productive careers as those starting playing for a team at the bottom of the league.

4.5 Robustness tests

In this section, we present two additional tests to assess the robustness of our results.

4.5.1 Survival Analysis

An alternative way to think about career success is in terms of survival in the NFL. In this section, we estimate the probability that a player exits the NFL. We then check the extent to which that probability differs based on the quality of the team in the initial match.

We start by estimating a proportional hazard model in Table 10, in which we allow the hazard rate to vary with the draft round. For simplicity, we limit the sample to the first five rounds. The objective of this is to show that the hazard rate varies with the quality of the player, as those selected in higher rounds will on average be of lower ability. Moreover, we should not expect big differences in team quality across rounds because the average player in each round ends up matched to an average team (each team picks one player in each round, except for perhaps the effect of trades). The round, therefore, captures the effect of player ability (for a similar team quality) on the probability of

exiting the league. The table shows that the rate increases as we move to higher rounds, suggesting that players picked later in the draft exit the league at a higher rate. This is consistent with the results we had for the number of games played over the career, which decreases in the draft pick.

Next, we want to estimate the influence that team quality has on that hazard rate. Table 11 exploits the discontinuity in team quality in an analogous way to Table 4. We consider the last 5 picks of a round together with the first 5 picks of the following round. We then estimate a hazard model using a dummy for the higher round. To the extent that the players are similar, they should exit the league at similar rates if the initial team has no impact on their careers. However, if team quality has an impact on the player's career, the dummy for higher round will pick up the differential hazard rate for players matched to a top team. Overall, Table 11 fails to find any significant difference among players selected on both sides of the discontinuity between rounds 1 and 2, 2 and 3, or 3 and 4, and regardless of whether we consider all players, or only those that did not involve a traded pick. For consistency with our estimates in 4, we do the analyses for our two sample periods: our full sample, and the reduced sample for career earnings. Although the estimates are larger in the later case, they are less precisely estimated, due to the smaller sample size. The results show that team quality of the initial match has no effect on the probability of survival of a player in the NFL.

4.5.2 Team Quality

One concern with our results is that the institutions and regulations (such as the draft) imposed by the league to have a competitive balance are indeed effective and, as a result, the ranking of teams in a given year is random. In that case, our measure of team quality may not capture meaningful differences among the teams that would impact a player's performance.

In practice, though, although the existence of these institutions may indeed lower the differences among teams, they are unlikely to completely eliminate them. In fact, There

is often talk of franchise dynasties, suggesting that there is some persistence in team quality.¹¹ And, in fact, some teams consistently over-perform for extended periods of time.

To check the robustness of our results, Table 12 estimates analogous regression discontinuity models to Table 4, exploiting the differences in team quality generated by round changes.¹² We still consider only the last 5 picks of a round and the first 5 picks of the consecutive round. However, among those picks, we restrict the sample to the teams with consistent league rankings over multiple years. In column (1), teams at the end of a round must rank in the top tercile for all of the previous 3 years, while teams at the beginning of the higher round must rank in the bottom tercile for the previous 3 years. There is still no difference in performance, neither on the number of games played, nor on the number of Pro-Bowl appearances. Column (2) increases the requirement to 5 years with similarly negligible effects.

Columns (3) and (4) now require that teams at the end of a round rank in the top tercile for the following 3 or 5 years, while teams at the beginning of the higher round rank in the bottom tercile for the same period.¹³ This alternative requirement is potentially more problematic, as it can be affected by the drafted players. However, it is also more meaningfully related to the actual quality of the team that the drafted players will play for. The results are still insignificant, except for the effect on *Pro-bowl* in column (4).

Finally, columns (5) to (8) repeat the same exercise for the discontinuity between rounds 2 and 3. We still fail to find any significant result. Players that land in a team that consistently ranks poorly have equally successful careers as players that start playing for a team that consistently ranks highly.

¹¹<https://fivethirtyeight.com/features/the-patriots-are-the-nfls-greatest-dynasty/>

¹²Due to the limited sample, we exclude earnings from this analysis.

¹³More precisely, we require the teams be in the top or bottom terciles on the year of the draft plus the following 2 or 4 years.

5 Conclusion

This paper exploits the discontinuity in team quality caused by NFL draft to study how the initial matching affects the career outcome of NFL players. The results clearly show that the initial match has no sizeable effect on career performance, regardless of the measure used. Players matched to a top team seem to have equally lengthy, productive, and successful careers as those starting out with a bottom team. They also earn similar amounts over the course of their careers.

There has been some evidence contrary to our results in other contexts. Our setting has some interesting features that help illuminate the discussion in the literature. In particular, performance in this market is readily observable. Pundits track a large number of metrics for players and teams. Although measuring performance is by no means simple, there are a multitude of measures available for each player and each game played. Teams can readily observe game performance each week and assess the value of a player in any other team. This transparency, we believe, is at the heart of our differing results. When a player is matched to a team, even though a contract may bind them together, and the player cannot freely negotiate with other teams for an extended part of their career, the lack of information asymmetry facilitates efficient contract renegotiations. As a result, the initial match does not seem to affect the chances of a player remaining in the NFL. This is in contrast to earlier evidence suggesting that the negative long-run effects of a poor initial match are driven by employees being driven into lower-paying occupations. Our results, therefore, suggest that it is the lack of information, and the potential asymmetry of information between current and potential employers, that may be at the heart of this earlier evidence.

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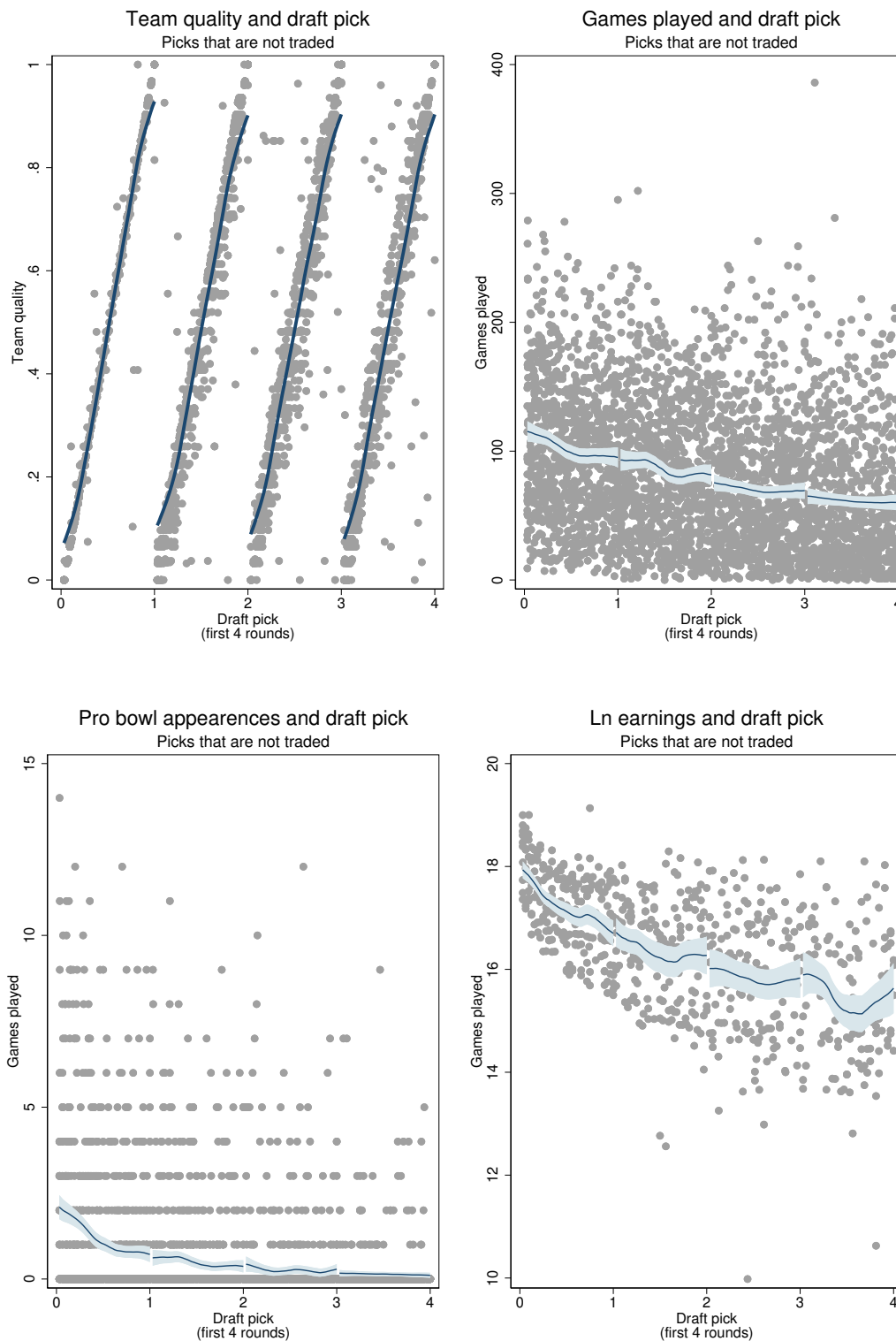
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FIGURE 1: NON-PARAMETRIC ANALYSIS AT THE DISCONTINUITY: TEAM QUALITY AND CAREER PERFORMANCE



Notes. The figure plots the smoothed local polynomial (per round) of the team quality and career outcomes of players drafted in the first 4 rounds. Team quality, games played, and Pro-bowl appearances use data from 1970 to 2014. Log earnings is for the period 2005 to 2014.

Table 1: Variable Description

Panel A:	Output Variable Description	Data Source
Games	Total career games.	Pro-Football Reference
Starter	Years as starter during the career.	Pro-Football Reference
All-pro	Number of times the player was selected for the yearly all-pro team.	Pro-Football Reference
Pro-bowl	Number of times the player was selected for the yearly pro-bowl game.	Pro-Football Reference
C-Value	Weighted career approximate value contribution of the player.	Pro-Football Reference
D-Value	Approximate value of the player while on the team that drafted him.	Pro-Football Reference
Earnings	Total career earnings.	Spotrac
Panel B:	Control Variable Description	Data Source
Round	Round of the draft in which the player was selected	Pro-Football Reference
D(higher round)	Dummy with value 1 for the higher round on the comparison between adjacent rounds	Calculated
Pick	Pick of the draft in which the player was selected	Pro-Football Reference
Pick_adj	Normalized pick: $P = R - 1 + (pick - pick_R)/N$, where R is the $pick$'s round, $pick_R$ is the first pick of the round, and N is the number of teams.	Calculated
Ranking	Ranking of the team drafting the player.	Pro-Football Reference
Team quality (Q)	Normalized team ranking: $Q = (N - Ranking)/(N - 1)$, where N is the number of teams. $Tq \in [0, 1]$, with 0 being the bottom team and 1 the top team.	Calculated
Trade	Dummy with value 1 if there was a transaction for that pick of the draft.	Pro Sport Transactions
Ex. Trade	Dummy with value 1 if there was an exogenous transaction (taking place at least one month before the draft) for that pick.	Pro Sport Transactions
End. Trade	Dummy with value 1 if there was an endogenous transaction (taking place at most one month before the draft) for that pick.	Pro Sport Transactions

Panel C:	Player Variable Description	Data Source
Position	Player position.	Pro-Football Reference
Team	Team drafting the player.	Pro-Football Reference
Age	Age of the player in his draft year.	Pro-Football Reference
Experience	Years of experience in the NFL up to 2014.	Pro-Football Reference
College	College of the player before the draft.	Pro-Football Reference
Draft Year	Year the player was drafted.	Pro-Football Reference

Table 2: Summary Statistics

Variables	(1) N	(2) mean	(3) sd	(4) min	(5) max
Output Variables					
Games	8,036	68.450	55.31	0	386
Starter	9,162	2.287	3.308	0	19
All-pro	9,162	0.095	0.533	0	10
Pro-bowl	9,162	0.342	1.224	0	14
C-value	8,042	19.759	23.460	-4	176
D-value	7,241	16.010	20.469	-4	160
Earnings	2,562	1.17e+07	1.85e+07	21,600	2.04e+08
Earnings (Ln)	2,562	15.237	1.552	9.980	19.134
Control Variables					
Trade	10,051	0.347	0.476	0	1
Exogenous Trade	10,051	0.181	0.385	0	1
Endogenous Trade	10,051	0.167	0.373	0	1
Player Variables					
Experience	9,162	4.732	4.141	1	25
Age	8,080	22.469	0.839	20	29

Notes. Summary statistics for output and player variables are calculated for the sample of players drafted between 1970 and 2014, except for Earnings, which include players drafted between 2005 and 2014. Summary statistics for control variables are calculated for players drafted between 1970 and 2018.

Table 3: Round Effect on Team Quality

	(1)	(2)
	Team quality	Team quality
Pick_adj	0.638*** (0.010)	0.982*** (0.004)
D(higher round)	-0.636*** (0.010)	-0.982*** (0.004)
Constant	0.792*** (0.007)	0.974*** (0.003)
Observations	9,162	6,097
R-squared	0.377	0.903
Sample	All	No trades

Notes. This table reports OLS regressions estimating model (1). Column (1) uses the entire sample of draft picks between 1970 and 2014. Column (2) drops observations involving a trade. Robust standard errors in parentheses. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

Table 4: Exploiting Round Changes: OLS

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Games						
D(higher round)	-4,282 (5.331)	-2,524 (5.219)	-2,733 (5.778)	-3,265 (6.656)	-6,428 (6.342)	-3,137 (7.243)
Constant	95.192*** (3,714)	78.061*** (3,527)	69.605*** (3,681)	96.683*** (4,560)	81.040*** (4,224)	70.930*** (4,649)
Observations	440	414	384	298	279	250
R-squared	0.001	0.001	0.001	0.001	0.004	0.001
Panel B: Pro-bowl						
D(higher round)	-0.131 (0.163)	0.054 (0.107)	-0.154 (0.097)	-0.126 (0.189)	0.042 (0.148)	-0.098 (0.117)
Constant	0.758*** (0.123)	0.283*** (0.061)	0.316*** (0.078)	0.738*** (0.133)	0.344*** (0.087)	0.278*** (0.084)
Observations	441	427	417	298	289	272
R-squared	0.001	0.001	0.006	0.001	0.000	0.003
Panel C: Earnings(Ln)						
D(higher round)	0.053 (0.171)	-0.370 (0.253)	-0.027 (0.291)	0.162 (0.214)	-0.436 (0.318)	-0.074 (0.372)
Constant	16.742*** (0.107)	16.254*** (0.171)	15.912*** (0.198)	16.667*** (0.135)	16.293*** (0.221)	16.021*** (0.243)
Observations	90	76	72	56	52	35
R-squared	0.001	0.028	0.000	0.010	0.036	0.001
Sample	All	All	All	No trades	No trades	No trades
Rounds	1-2	2-3	3-4	1-2	2-3	3-4

Notes. This table estimates model (2). It reports OLS regressions of player outcomes on a dummy that takes value 1 for the higher round, $D(\text{higherround})$. Each panel considers a different outcome as the dependent variable. Panels A and B include players drafted between 1970 and 2014, Panel C includes players drafted between 2005 and 2014. The sample includes, for each year, the last five players of a round and the first five players of the following round. Each regression considers only two consecutive rounds, exploiting the discontinuity between the first and second, between the second and third, and between the third and fourth rounds. Columns (1) to (3) use all available observations, whereas columns (4) to (6) restrict each sample to picks that do not involve a trade. Robust standard errors in parentheses. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

Table 5: Exploiting Round Changes: Wald Estimator, IV(Round)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Games						
Team quality (Instrumented)	8,217 (10.240)	4,526 (9.328)	5,163 (10.894)	3,872 (7.868)	7,575 (7.454)	3,731 (8.580)
Constant	89.003*** (5.787)	74.630*** (5.370)	65.757*** (6.436)	93.123*** (5.284)	74.089*** (5.115)	67.545*** (5.978)
Observations	440	414	384	298	279	250
R-squared		0.003		0.000	0.002	0.001
Effective F-Statistics	343.9	433.5	321.3	6877	10311	4605
Panel B: Pro-bowl						
Team quality (Instrumented)	0.254 (0.315)	-0.096 (0.189)	0.292 (0.185)	0.149 (0.224)	-0.050 (0.173)	0.116 (0.138)
Constant	0.567*** (0.166)	0.356*** (0.120)	0.096 (0.089)	0.601*** (0.147)	0.390*** (0.129)	0.172** (0.087)
Observations	441	427	417	298	289	272
R-squared				0.001		0.002
Effective F-Statistics	335.3	453.7	340	6877	10645	5484
Panel C: Earnings(Ln)						
Team quality (Instrumented)	-0.123 (0.388)	0.620 (0.431)	0.089 (0.934)	-0.187 (0.242)	0.508 (0.366)	0.085 (0.415)
Constant	16.834*** (0.243)	15.776*** (0.253)	15.855*** (0.484)	16.842*** (0.176)	15.822*** (0.246)	15.942*** (0.296)
Observations	90	76	72	56	52	35
R-squared	0.011			0.012	0.021	0.003
Effective F-Statistics	39.84	106.4	13.95	3384	2929	1955
Sample	All	All	All	No trades	No trades	No trades
Rounds	1-2	2-3	3-4	1-2	2-3	3-4

Notes. This table estimates model (3). It reports the second stage of IV regressions of player outcomes on team quality (Q), instrumented with a dummy that takes value 1 for the higher round, $D(\text{higherround})$ (as well as the Effective first-stage F-statistic). Each panel considers a different outcome as the dependent variable. Panels A and B include players drafted between 1970 and 2014, Panel C includes players drafted between 2005 and 2014. The sample includes, for each year, the last five players of a round and the first five players of the following round. Each regression considers only two consecutive rounds, exploiting the discontinuity between the first and second, between the second and third, and between the third and fourth rounds. Columns (1) to (3) use all available observations, whereas columns (4) to (6) restrict each sample to picks that do not involve a trade. Robust standard errors in parentheses. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

Table 6: Instrumental Variables Regressions: Rounds as Instruments

	(1)	(2)	(3)	(4)
Panel A: Games				
Team quality (Instrumented)	1.467 (3.414)	1.652 (3.196)	0.806 (2.542)	-0.224 (4.808)
Constant	115.476*** (3.184)	133.788*** (6.371)	139.473*** (7.489)	132.627*** (9.184)
Observations	8,036	8,036	5,312	3,833
R-squared	0.130	0.245	0.243	0.223
Effective F-Statistic	3198.6	3183.5	41776.3	1500.3
Panel B: Pro-bowl				
Team quality (Instrumented)	-0.074 (0.062)	-0.070 (0.062)	-0.053 (0.049)	-0.170 (0.137)
Constant	2.077*** (0.143)	2.261*** (0.179)	2.347*** (0.221)	2.264*** (0.262)
Observations	9,162	9,162	6,097	3,922
R-squared	0.123	0.137	0.142	0.121
Effective F-Statistic	3697.8	3697.2	45353.5	1539.6
Panel C: Earnings(Ln)				
Team quality (Instrumented)	0.195 (0.196)	0.130 (0.186)	0.039 (0.133)	0.143 (0.204)
Constant	17.714*** (0.140)	18.198*** (0.243)	18.219*** (0.287)	18.130*** (0.257)
Observations	1,687	1,687	982	804
R-squared	0.409	0.474	0.536	0.352
Effective F-Statistic	664.6	657.5	34358.2	401.4
Sample	All	All	No Trades	Rounds 1-3
Position FE	No	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes

Notes. This table estimates model (4), using model (5) as the first stage. It reports the second stage of IV regressions of player outcomes on team quality (Q), instrumented with the draft round (as well as the Effective first-stage F-statistic). Each panel considers a different outcome as the dependent variable. All regressions also include a linear polynomial on $Pick_{adj}$, with slopes that are allowed to vary by round. The sample includes all players drafted between 1970 and 2014 for Panels A and B, and between 2005 and 2014 for Panel C. Columns (1) and (2) use all available observations, column (3) restrict the sample to picks that do not involve a trade, and column (4) restricts the sample to the first three rounds of each year. Robust standard errors in parentheses. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

Table 7: Instrumental Variables Regressions: Trades as Instruments

	(1)	(2)	(3)	(4)	(5)
Panel A: IV- trades					
Team quality (Instrumented)	4.356 (7.650)	5.329 (7.426)	5.378 (7.441)	4.748 (7.834)	4.503 (10.756)
Constant	114.826*** (3.503)	132.901*** (6.516)	132.625*** (6.923)	133.163*** (6.626)	131.521*** (9.304)
Observations	8,036	8,036	6,539	7,677	3,833
R-squared	0.130	0.244	0.228	0.245	0.222
Effective F-Statistic	2794.1	2699.6	2622.5	2260.5	1083.7
Panel B: Pro-bowl					
Team quality (Instrumented)	0.123 (0.171)	0.134 (0.172)	0.130 (0.172)	0.136 (0.168)	0.022 (0.380)
Constant	2.033*** (0.143)	2.217*** (0.179)	2.230*** (0.198)	2.191*** (0.182)	2.220*** (0.267)
Observations	9,162	9,162	7,561	8,768	3,922
R-squared	0.122	0.136	0.135	0.137	0.121
Effective F-Statistic	3172.6	3069.5	2983.6	2575.2	1127.5
Panel C: Earnings(ln)					
Team quality (Instrumented)	0.147 (0.458)	0.302 (0.434)	0.298 (0.426)	-0.101 (0.485)	-0.640 (0.580)
Constant	17.723*** (0.160)	18.153*** (0.264)	17.991*** (0.292)	18.319*** (0.269)	18.170*** (0.262)
Observations	1,687	1,687	1,192	1,559	804
R-squared	0.409	0.472	0.488	0.482	0.333
Effective F-Statistic	92.15	90.80	102.3	71.08	35.05
Bandwidth	All	All	No endog trades	No seq trades	Rounds 1-3
Position FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes

Notes. This table estimates model (4), using model (6) as the first stage. It reports the second stage of IV regressions of player outcomes on team quality (Q), instrumented with the difference in team quality between the team drafting the player after a trade and the team allocated the pick before the trade (as well as the Effective first-stage F-statistic). Each panel considers a different outcome as the dependent variable. All regressions also include a linear polynomial on $Pick_{adj}$, with slopes that are allowed to vary by round. The sample includes all players drafted between 1970 and 2014 for Panels A and B, and between 2005 and 2014 for Panel C. Columns (1) and (2) use all available observations, column (3) restrict the sample to picks that do not involve a trade, and column (4) restricts the sample to the first three rounds of each year. Robust standard errors in parentheses. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

6 Appendix: Supporting Tables and Figures

Table 8: Principal Component Analysis for Outcome Variables I: 1970-2014

	(1)	(2)	(3)
Panel A: Unrotated principal component analysis			
	Comp1 (4.406)	Comp2 (0.973)	Unexplained
Games	0.401	-0.410	0.129
Starter	0.431	-0.332	0.076
Pro-bowl	0.389	0.472	0.115
All-pro	0.321	0.685	0.089
C-value	0.460	-0.166	0.043
D-value	0.434	-0.047	0.170
Panel B: Rotated Components			
Games	0.555	-0.144	0.129
Starter	0.540	-0.062	0.076
Pro-bowl	0.090	0.605	0.115
All-pro	-0.079	0.753	0.089
C-value	0.47	0.095	0.043
D-value	0.396	0.183	0.170
Panel C: Component rotation matrix			
	Comp1	Comp2	
Comp1	0.857	0.516	
Comp2	-0.516	0.857	

Notes. Principal component analysis including all the available productivity measures from 1970 to 2014. Eigenvalues of the components in parentheses. Panels B and C use an orthogonal rotation.

Table 9: Principal Component Analysis for Outcome Variables II: 2005-2014

	(1)	(2)	(3)
Panel A: Unrotated principal component analysis			
	Comp1 (4.775)	Comp2 (1.145)	Unexplained
Games	0.3783	-0.3427	0.182
Starter	0.406	-0.2679	0.131
Pro-bowl	0.3486	0.5006	0.133
All-pro	0.2703	0.6905	0.105
C-value	0.4444	-0.0794	0.050
D-value	0.4279	0.0171	0.125
Earnings (Ln)	0.342	-0.2771	0.354
Panel B: Rotated Components			
Games	0.493	-0.134	0.18240
Starter	0.483	-0.055	0.13090
Pro-bowl	0.084	0.604	0.13300
All-pro	-0.073	0.738	0.10530
C-value	0.432	0.131	0.04994
D-value	0.374	0.209	0.12530
Earnings (Ln)	0.431	-0.092	0.35360
Panel C: Component rotation matrix			
	Comp1	Comp2	
Comp1	0.8911	0.4538	
Comp2	-0.4538	0.8911	

Notes. Principal component analysis including all the available productivity measures from 2005 to 2014. Eigenvalues of the components in parentheses. Panels B and C use an orthogonal rotation.

Table 10: Survival Analysis by Round

	1970-2014		2005-2018	
	(1)	(2)	(3)	(4)
Round 2	0.327*** (0.043)	0.302*** (0.053)	0.230** (0.095)	0.277** (0.122)
Round 3	0.484*** (0.044)	0.466*** (0.053)	0.476*** (0.094)	0.547*** (0.117)
Round 4	0.635*** (0.044)	0.655*** (0.054)	0.605*** (0.091)	0.651*** (0.121)
Round 5	0.782*** (0.045)	0.782*** (0.055)	0.796*** (0.092)	0.919*** (0.122)
Observations	6,102	3,979	1,865	1,085
Sample	All	No trades	All	No trades

Notes. This table reports the coefficient estimates a Cox proportional hazard model that allows for censoring on the last year of the sample. The sample includes all players drafted between 1970 and 2014 and between 2005 and 2014, using the first 5 rounds of each year's draft. *Round 'n'* is dummy taking value 1 for round '*n*' and 0 otherwise. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

Table 11: Survival Analysis around the Discontinuity

	(1)	(2)	(3)	(4)	(5)	(6)
Period: 1970-2014						
<i>D(higher round)</i>	0.067 (0.104)	0.048 (0.126)	0.012 (0.106)	0.003 (0.131)	0.007 (0.110)	0.055 (0.133)
Observations	440	298	414	279	384	250
Period: 2005-2018						
<i>D(higher round)</i>	-0.154 (0.234)	-0.328 (0.310)	0.297 (0.239)	0.295 (0.287)	0.121 (0.234)	0.048 (0.335)
Observations	130	79	113	77	110	54
Sample Rounds	All 1-2	No trades 1-2	All 2-3	No trades 2-3	All 3-4	No trades 3-4

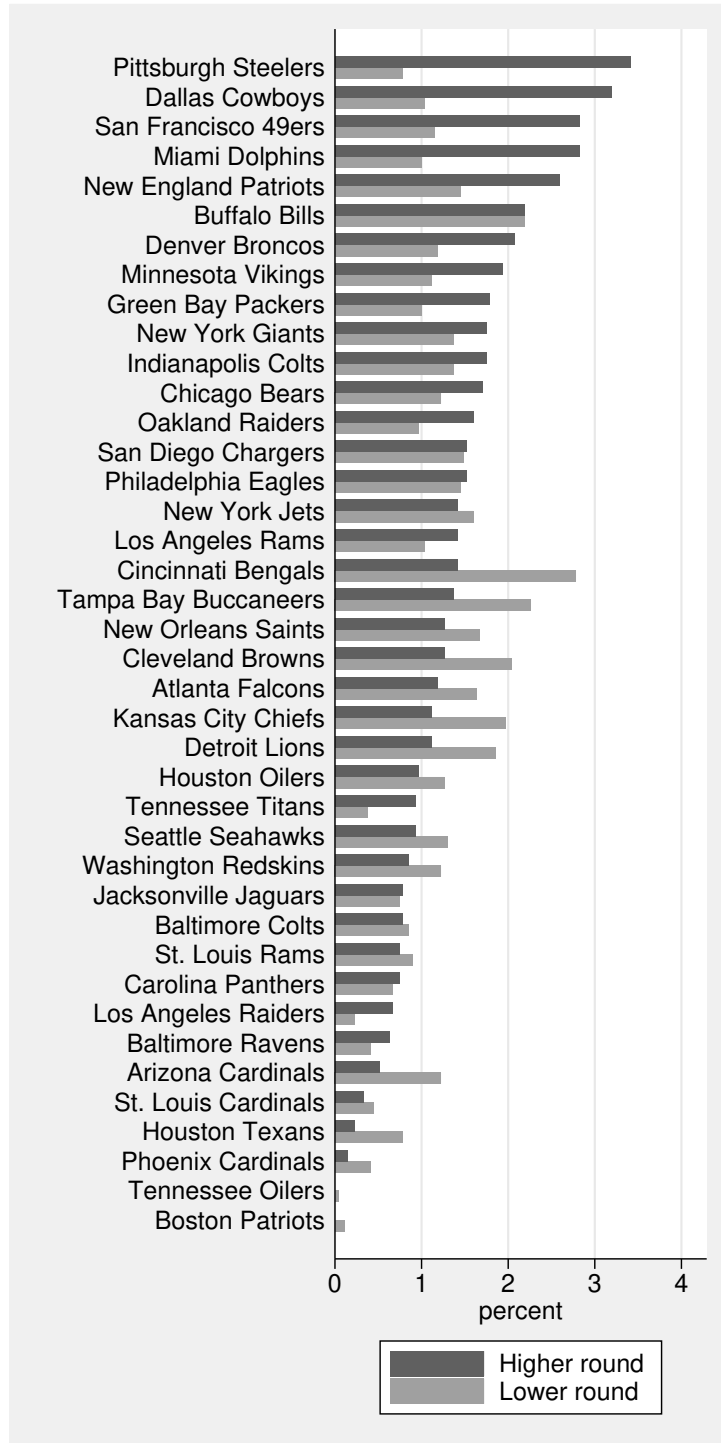
Notes. This table reports the coefficient estimates a Cox proportional hazard model that allows for censoring on the last year of the sample. The sample includes players drafted between 1970 and 2014 and between 2005 and 2014. It compares the survival around the round discontinuity on the first three rounds. The sample includes, for each year, the last five players of a round and the first five players of the following round. Each regression considers only two consecutive rounds, exploiting the discontinuity between the first and second, between the second and third, and between the third and fourth rounds. Odd columns use all available observations, whereas even columns restrict each sample to picks that do not involve a trade. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

Table 12: Team Quality Stability over Time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable: Games								
<i>D(higher round)</i>	0.165 (9.567)	-3.336 (10.324)	4.585 (10.414)	4.911 (10.287)	4.462 (10.281)	-3.598 (10.150)	12.414 (9.481)	13.275 (10.168)
Constant	97.747*** (5.956)	98.434*** (6.669)	96.165*** (6.864)	89.326*** (6.433)	77.693*** (5.627)	73.022*** (5.192)	71.566*** (5.888)	70.022*** (5.581)
R-squared	0.000	0.001	0.001	0.001	0.002	0.001	0.013	0.013
Variable: Pro-Bowl								
<i>D(higher round)</i>	0.025 (0.330)	-0.306 (0.359)	-0.022 (0.307)	-0.487** (0.214)	-0.057 (0.237)	0.000 (0.224)	-0.025 (0.230)	-0.122 (0.225)
Constant	0.800*** (0.215)	0.892*** (0.255)	0.714*** (0.181)	0.750*** (0.188)	0.457*** (0.134)	0.394*** (0.122)	0.425*** (0.132)	0.419*** (0.124)
R-squared	0.000	0.005	0.000	0.020	0.000	0.000	0.000	0.002
Observations	152	124	143	130	137	127	137	130
Stable team quality	Last 3 years	Last 5 years	Next 3 years	Next 5 years	Last 3 years	Last 5 years	Next 3 years	Next 5 years
Rounds	1-2	1-2	1-2	1-2	2-3	2-3	2-3	2-3

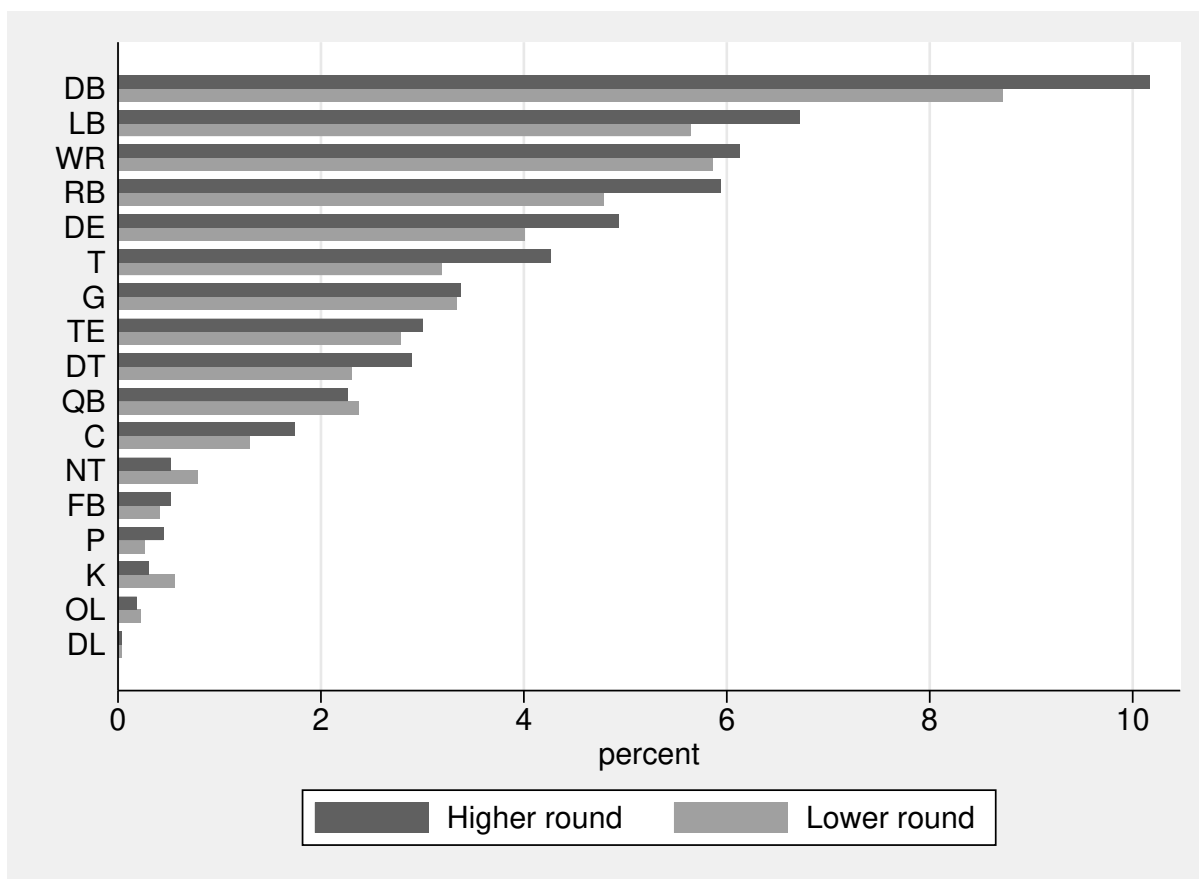
Notes. This table estimates model (2). It reports OLS regressions of player outcomes on a dummy that takes value 1 for the higher round, $D(\text{higherround})$. Each panel considers a different outcome as the dependent variable. The sample includes players drafted between 1970 and 2014. For each year, we consider the last five players of a round and the first five players of the following round. We further limit the sample to players drafted by a team with a stable team quality: top teams that rank in the top tercile or bottom teams that rank in the bottom tercile for each of the last 3 or 5 years, or the next 3 or 5 years). Each regression considers only two consecutive rounds, exploiting the discontinuity between the first and second, between the second and third, and between the third and fourth rounds. Robust standard errors in parentheses. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

FIGURE 2: TEAM DISTRIBUTION AT THE DISCONTINUITY



Notes. The figure plots the distribution of teams on each side of the round discontinuity, using the last five players of a round (higher round) and the first five players of the following round (lower round).

FIGURE 3: POSITION DISTRIBUTION AT THE DISCONTINUITY



Notes. The figure plots the distribution of player positions on each side of the round discontinuity, using the last five players of a round (higher round) and the first five players of the following round (lower round).