MGT 817 - Sports Analytics

The Signaling Power of the NFL Combine

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December 7, 2020

Abstract

National Football League (NFL) teams rely heavily on selecting top talent from the college draft to build competitive programs. The front office commits considerable resources each year to scouting, vetting, and understanding the incoming draft class. Scouts use the NFL Combine, a showcase of isolated player athleticism, as a fountain of collegiate player data. Our paper investigates whether the NFL combine conveys information to scouts and NFL teams that affects draft position for the offensive skill positions of Running Back (RB) and Wide Receiver (WR). More specifically, we examine whether high-ability college players at RB and WR successfully signal their ability through the Combine and whether NFL teams take note. Our analysis finds that the Combine does reveal a statistically significant signal, but that not all events are created equal: the 40-yard dash, followed by the broad jump, convey much of the Combine information. We further conclude that, controlling for collegiate performance, high-ability players perform better at the NFL Combine than low-ability players and are rewarded with a lower draft selection.

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Introduction

There are diverging results in the literature on correlations between college statistics, combine performance, draft pick and future performance in the NFL. Various authors have studied this subject for different football positions. We tackle a different angle : we study whether the NFL Draft is a signaling game in which players can signal their ability by the NFL Combine, get drafted earlier and earn more money. The average salary for a first-round pick is $17 million; for a second round pick, $3 million; and continuing drop-offs. So getting drafted earlier has a huge impact. Yet, a player's free time is a constrained variable and players face inherent trade-offs between physical training, academics, and leisure. The NFL combine is an artificial training environment where collegiate players perform physical and mental tests two months before the Draft.

We divided our data into high and low ability players; If the combine works as a signaling device, high ability players should (a) perform better at the combine, and (b) be picked earlier because of it. We examine the quantitative factors of collegiate performance, combine performance, and physical attributes and how they are linked to draft position for the offensive skill positions Running Back, and Wide Receiver. Our results will illuminate the elements of performance most important to NFL scouts, and provide players with an understanding of how to direct their time to secure a coveted draft pick.

We want to know what determines a draft pick, which skills NFL teams consider to be the most important in their choices, which skills and which events are good predictors of future performance. Can NFL teams even really rationally identify future performers or does the inherent random variability of individual performance prevent it? Is it right that the combine which is an artificial training environment influences draft picks? Does it even? Which pre-draft information and skills are good predictors of the ability of a player in the NFL? These are the kind of questions that lead us through our study.

1.1 Research setup

Research question: Does the NFL combine work as a signal for a player's ability?

Below our theoretical setup is shown. Players are either of high- or low-ability and can choose how they perform at the NFL Combine. Teams assess all information they have about a Player and draft accordingly. In a working Signaling Game, if only high-ability Player overperform at the Combine relative to the value Teams assessed value of the Player it will be optimal to draft them earlier to maximize the Team's utility. Players have then an incentive to overperform since this would maximize their utility (salary). The signal would only be separating if low-ability players are not able to "fake" their ability by overperforming at the Combine.

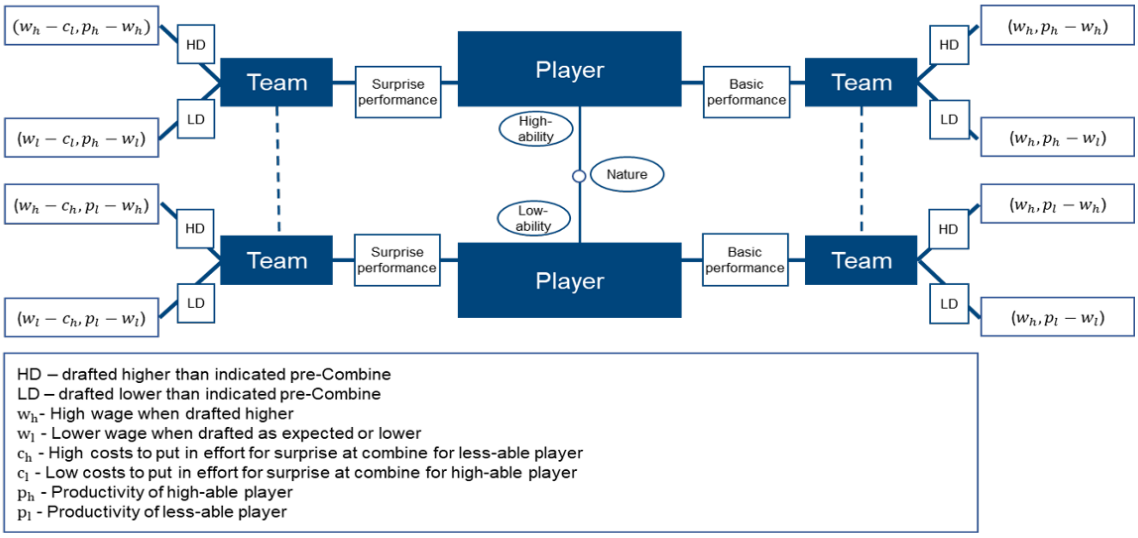

Figure 1.1: **Theoretical model.**

This figure shows our theoretical frame work based on a classical Game Theory diagram in dynamic Bayesian games.

Hypotheses

1. High-ability players are picked before low-ability players in the NFL draft.
2. High-ability players perform better at the NFL Combine.
3. High-ability players perform better than players with the same pre-Combine draft stock which turn out to be of low-ability.
4. Teams pick up the higher performance as a signal relative to a player's College career and draft them earlier because of it.

Literature Review

The challenge of identifying college football players who are most likely to succeed in the NFL has been studied by various authors with a focus on each position. The challenge generally relates to whether NFL teams aggregate available information optimally and if they base their judgement on the right attributes - those with predictive power of future performance. Authors examine how pre-draft information - from college performance, combine measures and physical attributes to injury data and qualitative information - can explain draft positions and NFL career success.

Schatz (2005) depicts the quarterback prediction problem as one of the "Hilbert Problems" for football. In a 2008 New Yorker article, Malcom Gladwell (2008) cited Berri and Simmons (2009) who find that a quarterback's draft position impacts playing time but not performance in the NFL. Quinn, Geier, and Berkovitz (2007) arrive at similar conclusions. Massey and Thaler (2010) find that early first-round draft picks are being overpaid compared to their future performance.

To avoid selection bias, Wolfson, Addona and Schmicker (2011) base their analysis on all drafted quarterbacks since 1997, including those who haven't played a professional game. They find similar evidence that early picked quarterbacks with higher college YPA are more likely to produce fewer Net Points in the NFL. However, they also find that draft position is an important predictor of future success in the NFL, contrary to college and combine statistics. They underline that draft position provides information that college and combine data do not (scouts' reports, "Pro Days" observations, injury status, personal interactions, etc). They also conclude that NFL teams make an effective use of pre-draft quantitative and qualitative information, and that their difficulty to identify future performers simply derives from the inherent random variability in individual performance. Pitts and Evans (2018) find that quarterbacks with higher Wonderlic scores have more productive NFL careers but are not selected earlier in the draft. However, in studies that focus solely on the quarterback position, Berri and Simmons (2011) and Welter (2013) arrive at opposite conclusion. Berri and Simmons (2011) find that height, Wonderlic score and forty-yard dash times are good predictors of draft positions but not of NFL performance. Mirabile

(2005) finds no predictive power to Wonderlic scores on either output. Sample selection, methodology and measurements of NFL productivity explain these diverging results.

Berri and Simmons (2011) cite the work of Hendricks (2003) on how draft choices can reflect the uncertainty about a player's future productivity given the heterogeneity of resources between college divisions. Players from lower divisions may either be disadvantaged in the draft pick because their measures are less reliable (statistical discrimination) or advantaged in the draft pick by teams willing to try their luck on potential hidden gems (option value, following Lazear (1986)). For this reason, our analysis will include a variable to separate players depending on how well their conference is ranked.

Some authors have also analyzed these relationships on other positions. Since running backs and offensive line players have more precise roles on the field, it seems easier to predict their future performance. Treme and Allen (2009) examine predictors of draft positions for wide receivers and find the following to be significant: amount of media coverage, pre-draft ranking, forty-yard dash time and number of touchdowns in college. However, the study's scope is limited to players' rookie season rather than their entire careers. Kitchens (2015) examines the relationship between all offensive and defensive players' draft position and final collegiate season performance. His findings show that players from better ranked college teams are selected earlier but there is no evidence of correlation between the ranking of their school and their future performance. These findings support statistical discrimination in the NFL. Hendricks, DeBrock and Koenker (2003) find similar evidence.

Pitts and Evans (2018) have focused on tight ends, running backs and wide receivers. They identify the following factors as related to better draft positions and NFL productivity: College Sports Expense, BMI, Height and All-American selection for running backs, Height for tight ends, Vertical Leaps for wide receivers. They find that players with injuries during their final collegiate season are more likely to be selected later in the draft, up to one or two rounds later. Also, faster players who exit college early and are more productive in college tend to have better draft positions and NFL productivity. They find that tight ends with higher BMI's are selected earlier in the draft but are not more productive in the NFL, contrary to Mulholland and Jensen's (2014) findings. These findings also contrast with previous findings on quarterbacks. However, the authors argue that Mulholland and Jensen's study did not take into account qualitative data like they did (injuries, personal issues, Human Resource Tactics' psychological analyses, football intelligence). They also insist on how some positions like tight ends are used to playing other college sports too, and players face different available opportunities in college as well as different playing environments with more or less surrounding talented players.

For wide receivers and tight ends, Mulholland and Jensen (2016) find that predictors of draft positions differ from predictors of NFL career success. Their study includes physical variables (size), college performance and NFL combine results (speed, athletic ability, strength). While the measure of combine bench press repetitions is a good predictor of draft results, it has no significant correlation to NFL performance. Good predictors of draft results also include SEC dummy, ACC dummy, forty-year-dash time, height, receiving yards in college and BCS (Bowl Championship Series) college indicator. Vice versa, the combine broad jump and physical variables (height, weight, BMI) have significant predictive power on NFL career success but not on draft results. Yet, the authors warn on multicollinearity issues to their analysis.

Kuzmits and Adams (2008) do not find evidence of combine performance predicting future NFL performance, probably due to the artificial training environment of the combine. However, they do find a significant correlation between a running back's performance in sprint drills and his expected NFL productivity.

Overall, the question of draft positions being a predictor of NFL performance is strongly debated. Draft results also derive from what teams need at a given moment - and this explains certain early college exits. Similar analyses on National Basketball Association (NBA) typically show that collegiate productivity and draft positions are significantly correlated, so as draft position and career success, but not collegiate productivity and NBA productivity. Also, similar to Kim (2015) in the NFL, it seems that players who enter the NBA at a younger age are more likely to have a more productive careers later on. These studies highlight the potential to improve drafting strategies by combining traditional and analytical approaches in order to better identify future performance of college football players. The literature on tying collegiate performance to draft position is filled with a litany of explanatory variables, often with mixed results. We will use past studies to inform our variable selection while also being more perceptive about our choices.

Methodology

A player's draft position should be determined by the information teams have about a particular player i. We divide this information space into three categories:

1. Performance during college career: pre-Combine draft stock (DS_i),
2. Performance at the NFL Combine ($COMB_i$),
3. Physical player characteristics (Z_i).

The categories of points 1. and 2. are to a certain degree quantifiable. The draft stock variable attempts to capture all information a team has about a player from his College career. The Combine should be the only significant source of new information we can quantify between the end of a player's College career and the Draft for teams to consider. Category 3 consists of more qualitative measures and is harder to assess. The resulting linear model for a player's draft position Y_i is:

$$Y_i = \beta_0 + \beta_1 DS_i + \beta_{2j} Z_{ij} + \beta_3 COMB_i + \epsilon_i \tag{1}$$

Our research is based on the signaling model shown in Figure 1.1. Other studies have looked at the development of NFL players. They have contrasted a player's performance in college, performance at the NFL Combine, and draft position with his NFL performance. For our research, we bifurcate players into high- and low- ability groups using empirical measures with the objective of detecting patterns in college and combine performance specific to each group. We aim to isolate the information of the NFL Combine as a signal for teams this way. We focus on two offensive skill positions - Running Back and Wide Receiver - as we believe these players are most likely to reveal their skills in a quantifiable way.

First, we classify the ability of a player using two methods. To circumvent the issue of finding a robust measure for ability out of the abundance of NFL player career statistics, we use annual Madden ratings (from the eponymous video game), which are modeled on a player's holistic performance. We use data from Madden to differentiate between players that turned out to be above and below average performers. To a certain degree, this measure is biased. In the first years of a player's professional career his Madden rating are most likely influenced by his collegiate performance and when he was drafted. To increase robustness we employ a second ability measure which is based on the number of seasons a player was active in the NFL and whether he was ever selected to an All-Star team. Second, we derive player's performance $COMB_i$ at the NFL Combine using the 40 Yard dash as a proxy, as previous research (e.g. Park (2016)) showed it to be the most reliable determinant of the Combine's influence on a player's draft position. Further, we construct a proprietary Combine performance measure which is a linear combination of the individual events. The weights are found by using Principal Component Analysis.

We next construct a model for assessing a college player's pre-combine attributes (i.e., his college performance). Our final model will assess the influence of the Combine on draft position conditional on high- or low-ability, but this requires we control for the other relevant information available to teams about pre-draft players. We considered a litany of potential explanatory variables based on prior work done by Berri and Simmons (2011), Mulholland and Jensen (2016), and Pitts and Evans (2018) before deciding on a set of 16 (see Table 7.1 for the full list). These variables capture several facets of career college performance (e.g. yards, touchdowns, plays, Bowl appearances), comparative ability (e.g. yards compared to max yards of any player at same position, team wins, conference), and improvement (e.g. final year performance compared to career performance). We then split our college player database into two groups, a testing period covering 2000-2008, and a training period covering 2009-2020. This was a natural breaking point, as the data was divided approximately in half and we did not have Madden ratings pre-2008. We further split our data between WRs and RBs so each group will be evaluated separately. We fit a linear regression model to the WR and RB testing sets, with a y-variable equal to the square root of eventual draft position (discussed more below). This yielded our pre-combine draft stock variables DS_i. Players who were not drafted during this timeframe were excluded. The resulting model will then be used on the testing set (post-2008) as part of the final regression to control for pre-Combine college performance.

In comparison to other studies such as Berri and Simmons (2011), we believe that the absolute pick number (in the NFL typically ranging from 1-256) is not a good evaluation of the dependent variable Y_i as it is highly dependent on individual team needs and how many players of each position are in the draft. For example, a team will choose an equally capable Defensive End over a running back if it fills that team's needs. Within a given position, however, the best available player will always be chosen earlier. As in Park (2016), we use the square root of the draft pick as our Y_i variable to minimize these effects. For robustness, we created another dependent variable, a relative ranking, that divides a player's positional pick by the total number of players at that position in the draft (e.g.

2nd RB drafted of 10 total RBs in the draft = 0.2). That way, the measure is independent of team needs and assigns a lower (i.e. better) value for earlier picked players in a draft despite any variations in draft class strength. The last picked player of a position's relative draft pick equals to 1, undrafted players get the relative value of 1.01 and 16.03 for the square-root of his pick assigned.

3.1 Hypothesis testing

After obtaining all necessary data detailed above (further described in the Data Description section), we start testing our hypotheses. Hypotheses 1 (high-ability players are picked before low-ability players in the draft) and 2 (high-ability players perform better at the NFL Combine) are straightforward and will be assessed by comparing the descriptive statistics of high- versus low-ability players and assessing significance with a t-test. The central question of this paper, captured by Hypotheses 3 and 4, is whether future high-ability players perform better at the Combine than low-ability players conditional on similar collegiate performance, and whether NFL teams factor this signal into their draft decisions. To test this, we create "portfolios" of players by dividing them into quintiles based on the DS_i variable. Using these portfolios we can compare the Combine performance of players of similar pre-Combine status. Finally, we use the regression detailed in Formula (1) to test whether teams are able to use the Combine to differentiate between high- and low-ability players.

Data and Description

4.1 Data sets

We gathered seven primary data sources which were sourced from *pro-football-reference.com*, *sports-reference.com/cfb*, and *nflcombineresults.com*. The NFL Madden ratings were downloaded from a GitHub project projecting draft positions using Random Forests. Each dataset was randomly spot-tested for data accuracy verification.

1. College performance data for RB, WR (2000-2019)
2. College Bowls & All-American selections (2000-2019)
3. Combine performance data (2000-2019)
4. Draft position data (2000-2019)
5. Madden NFL ratings (2008-2019)
6. NFL Receiving & Rushing data (2000-2019)
7. Pro Bowl/All Pro data (1995-2019)

4.2 Data transformation

As illustrated in the Methodology, we began by using the draft position data to calibrate a linear regression to forecast the square-root and relative draft position only based on a player's college statistics. The full selection of variables used in the draft stock model appears in Table 7.1 of the Appendix.

After that, we applied Principal Component Analysis on the most available Combine performances for Running Backs and Wide Receivers. The resulting weights of each discipline to build the first component which we are using as a Combine performance measure are detailed in Table 4.1. The fifth column of the Table depicts the explained variance by the first component of the PCA which is used as the Combine performance measure. The results show that each discipline's influence has the right sign and about 50% of the Combine data's variation was explained by the linear combination based on PCA.

Table 4.1: **Discipline weights for the PCA measure.**

This table shows the component weights for each Combine discipline on the PCA measure as well as the explained variance of the Combine data by the first component.

	40 Yard	Leap	Broad Jump	Shuttle	expl. variance
Running Back	-0.47	0.57	0.56	-0.37	52.21%
Wide Receiver	-0.48	0.60	0.57	-0.28	49.39%

To further illustrate this point, we are depicting the relationship between the normalized combine results for each discipline of every player and his assigned first component in Figure 7.1 in the Appendix. The disciplines that are measured in time have a negative relationship and the measures based on distance have a positive relationship. Thus, the first component represents a valid measure for the evaluation of a player's Combine performance and is used in subsequent analyses. Our alternative measure for Combine performance is each player's results for the 40 Yard dash.

After constructing the Combine measure, we have divided the sample in high- and low-ability players by using Madden NFL ratings. The ratings of Madden players range from 35 to 99. Furthermore, we have found out that the average rating of a player in the Madden database between 2008 and 2019 is 70.43 while the median is 69.33. Given those two measures we have defined a high ability player as a player that has had a rating above 71 at least once. This evaluation method is somehow arbitrary, however, which is why we are also using an ability measure based on NFL seasons, Pro Bowl, and All-Pro data. We use the Receiving and Rushing data to extract the career length of each player and if he was selected for the Pro Bowl or as an All-Pro at some point in his career. The average career length in our NFL data is roughly 3.5 year. We classified high-ability players as players that have either been selected to be an All-Pro, to the Pro Bowl or that have had a career that is longer than 4 years. There is some bias in thin measure as some players that are high-ability are newly or still active with less than 4 seasons.

4.3 Data linkage and description

Lastly, we have to combine the different data sets into one data set to use in our empirical considerations. The problem is that for the same name different spelling structures were used. Players with special characters or name suffixes in their name like D'Andre Swift or Lynn Bowden Jr. are not consistently spelled throughout the data sets. Another problem is the multiple occurrence of certain player names for the same position like Steve Smith. Thus, we created a proprietary ID to link the data tables. For the creation of the final data set we first dropped all players that had duplicate names. The amount of players is not high enough to cause biases in our results. Then we deleted all special characters and suffixes of each name and merged first and last name - in lower case letters - together to get the ID we used to link the Combine performances, draft position, Madden ratings, NFL data, and Collegiate data. A descriptive table of our dataset can be seen in Table 7.3. The data set consists out of Running Backs and Wide Receivers. The statistical measures for the combine as well as draft pick data show that the two positions are quite comparable. There are more Wide Receivers than Running Backs in the data set and less players classified as high-ability for measure 2 than for measure 1.

Results and Discussion

Our descriptive results for players of high- and low-ability of similar pre-Combine evaluation are detailed in Table 7.4. The tables group players into quintiles based on their ability and describe players' performance and characteristics. We used two measures to distinguish high ability players from low ability players: (1) based on Madden ratings, (2) based on seasons played, Pro Bowls, and All-Pros (see Methodology). We grouped players based on two measures: (1) draft stock (variable Predicted_sqrt), (2) scrimmage yards (variable scrim_yards). The tables detail the similarity between high- and low-ability Quintile to show their comparability based on the information about them revealed before the Combine. The Table further shows that players who are of high-ability get drafted with a lower pick (i.e. higher) than players of low-ability (also see Figure 7.2). This supports Hypothesis 1 while it also implies that teams are generally able to differentiate players along ability. The higher Combine performance accompanied with a lower time at the 40 Yard dash (see Figure 5.1) is supporting our second Hypothesis and also indicates that Hypothesis 3 is true.

The difference in mean and median for each quintile is visualized in Figure 5.1. To

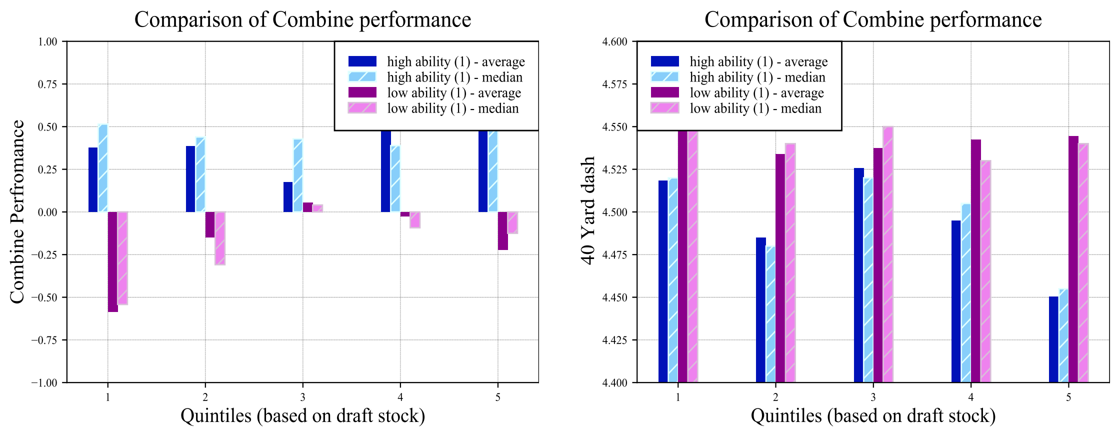

Figure 5.1: **Combine performance among draft-stock and high- & low-ability players.**

This figure shows the mean and median Combine performance of high- and low-ability players (Madden ratings used) sorted among their pre-Combine draft stock rating.

further test Hypothesis 3 we have conducted a t-test of difference in mean for each quintile's Combine performance and 40 Yard time (see Table 5.1). The test suggests significant differences in Combine performance between high-ability players relative to low-ability players who have similar information revealed about themselves before the Combine. The t-tests reveal that for 4 of the 5 quintiles the average performance of a high-ability player was relatively higher than for their low-ability comparable players which supports Hypotheses 2 and 3. This holds also true for using the 40 Yard dash time as a measure for Combine performance. It is questionable, however, whether players perform better at the Combine because they want to signal their ability or because they are just better athletes which has just not materialized during their college performance or was not picked up correctly by our draft stock model to form the portfolios.

Table 5.1: **Combine performance t-tests.**

This table depicts the t-tests done between the average Combine performance and 40 Yard dash between high-ability and low-ability players that are in the same draft stock quintile.

	Player draft stock quintile				
	(1)	(2)	(3)	(4)	(5)
mean performance - high-ability	0.378	0.386	0.174	0.529	1.077
mean performance - low-ability	-0.584	-0.149	0.053	-0.025	-0.221
t-test statistic	2.7468	2.0286	0.3847	1.9731	4.7247
p-value	0.0085	0.0459	0.7023	0.0525	0.0000
mean 40 dash time - high-ability	4.518	4.485	4.526	4.495	4.450
mean 40 dash time - low-ability	4.569	4.534	4.537	4.542	4.544
t-test statistic	-2.0607	-2.3347	-0.5556	-1.9930	-4.1299
p-value	0.0458	0.0219	0.5808	0.0508	0.0002

We have already established that teams are generally able to differentiate between the ability levels of players (see Figure 7.2). To further investigate the teams' draft pick behavior we observe on Figure 5.2 the relationship between a player's Combine performance and his draft position. The slope of the relationship is negative for high- and low-ability players which suggests that the better a players performs at the Combine the higher he gets picked in the NFL draft. This fact has been established in earlier studies as well (e.g. Park (2016)). We investigate what drives the difference in where the designated players are drafted. The Figure also shows that this relationship seems to be more pronounced for high-ability players (left) than for players than turn out to be of low-ability (right). To further investigate this fact we ran the regression from Formula (1) and show the results in Table 5.2. The results confirm that the influence of the NFL Combine performance of a player is more pronounced for high-ability players. This is true for our combine measure as well as when all Combine disciplines are included. We ran both regressions as our combine measure does not include all the variation in Combine performance of the four individual disciplines but only 50% (see Table 4.1). If a team knows that high-ability players perform on average better than similar players of similar collegiate performance at the combine (Hypothesis 3) they ought to use it as a way to differentiate player ability. The higher influence of the Combine for high-ability players present weak evidence that teams are able to use the NFL Combine performance to differentiate between player ability and give indication that Hypothesis 4 is true. Further, the regression shows 2 other drivers of the lower draft pick used for high-ability players. The draft stock variable (so a player's college career) and the Intercept are largely different as well. This means that teams (a) use the college career to differentiate between a player's ability and (b) that there are also factors that drive different draft position which our model is not able to pick up.

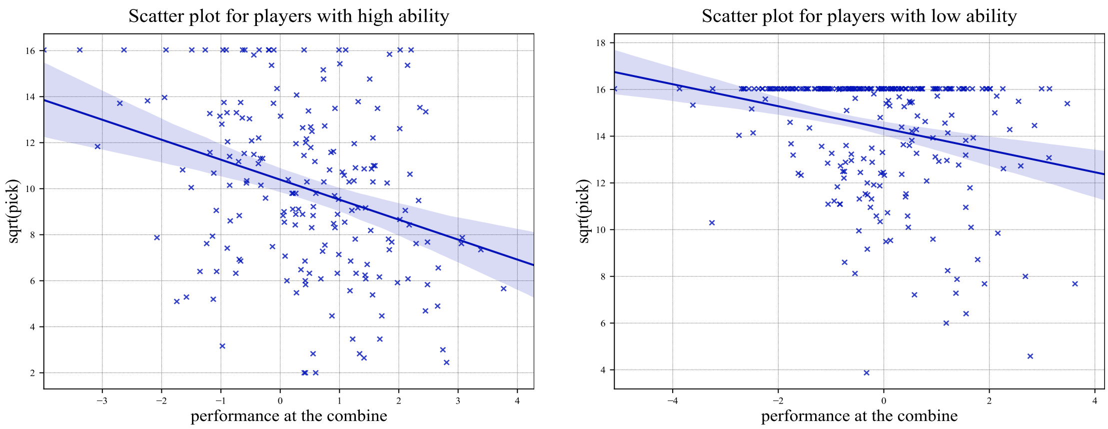

Figure 5.2: **Relation between Combine performance and sqrt(pick).**

All parameters are estimated upon daily S&P 500 Log-returns R_t during the parameter estimation window. The given model combination uses the relevant log-likelihood given in equation (5) and (6) that are maximized to estimated each parameter.

5.1 Signal discussion

We discuss now how the differences in Combine performances can be explained. In Figure 7.3 we further depict the differences in Combine performance in each player Quintile and differentiate between the conference player played in. In the literature, players from lower divisions seem to have been both disadvantaged in the draft pick because of less reliable data (statistical discrimination) and advantaged because it gives them more potential

Table 5.2: **Regression sqrt(pick) on Draft-Stock & Combine Measures.**

This table shows the results of regressing the square-root of a player's draft pick on his pre-combine Draft-Stock as well as his Combine performance and his BMI as a control variable for high- and low-ability players separately. Regressions (1) and (3) are for high-ability players while regressions (2) and (4) are done for low-ability players. The high-ability measure is based on Madden NFL ratings (see Methodology) and the Combine Measure (β_3) represents the PCA Combine measure.

	Dependent Variable: sqrt(draft pick)			
Expl. variables	High-ability	Low-ability	High-ability	Low-ability
	(1)	(2)	(3)	(4)
Draft-Stock (β_1)	0.36***	0.12	0.40***	0.14*
	(-2.88)	(-1.58)	(-3.45)	(-1.84)
BMI (β_2)	0.28***	-0.04	0.09	-0.15**
	(-2.67)	(-0.60)	(0.81)	(-2.15)
Combine Measure (β_3)	-0.90***	-0.47***		
	(-5.64)	(-4.09)		
40 Yard dash (β_4)			11.51***	8.36***
			(-4.66)	(-5.45)
Vertical Jump (β_5)			-0.13	0.02
			(-1.13)	(-0.4)
Broad Jump (β_6)			-0.07	-0.07**
			(-1.61)	(-2.11)
Shuttle (β_7)			-0.26	-1.07
			(-0.17)	(-0.99)
Intercept (β_0)	-1.02	14.04***	-33.60**	-8.77
	(-0.29)	(-6.96)	(-2.18)	(-0.97)
R^2	16.75%	8.22%	21.82%	17.46%
N	196	272	196	272

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, t-test statistics in parentheses

(option value). This could mean that it is much more important for some players to signal themselves through certain events. One could hypothesize that if players deliberately signal their ability through the Combine then players from minor conferences have more incentive to do so since their college career may have less value (statistical discrimination - compare Berri & Simmons 2011). The Figure shows that there is no clear differentiating trend. It seems to be that players from minor colleges perform worse than their counterparts from major conferences. This would suggest that the difference in Combine performance in our analysis between high- and low-ability players is primarily driven by their ability rather than their decision to signal their ability.

The differences in Combine performance differences between the quintiles give us also clues about what could drive the signal. The lower quintiles have a better predicted draft position. Thus, they ought to have less incentive to perform well at the draft. As observable in Table 7.4 and Figures 5.1 & 7.3 players with worse pre-Combine draft stocks tend to perform better at the Combine (for high- and low ability player). As high-ability players with worse college careers do perform better at the Combine, low-ability players do it as well. This would indicate that players do decide to perform better at the Combine when they have had worse college careers. To further investigate this phenomenon we depict the performance differences between high- and low-ability players (mean and median) in Figure 7.5. One can observe that the differences are highest for players with a high and low draft stock which is also observable in the t-tests from Table 7.5. This implies that the signaling is strongest for players with very good and relatively bad College careers (seems to roughly also hold for our alternative measures - Table 7.5). An explanation for that could be that players that are on the brink of being drafted or go into an early round have extra incentive to signal their ability and do so compared to others of low-ability. The average NFL guaranteed Rookie salary for players picked in the first round was around 16 times higher in 2020 (see Football Next level) than for an average round 3 pick. The differences in average Rookie salary drastically drop off after then for the later rounds. For players who are not that likely to be drafted the possibility to be drafted provides a possibility for financial stability. This could explain why the signaling is more pronounced in the quintiles of players with good and bad College careers. These results indicate that the signal is behavioral and not purely driven by ability. Thus, our approach yields an ambiguous answer and the Tables & Figures presents no ultimate proof for what drives the Combine signal and constitutes opportunity for further research.

5.2 Robustness tests

To test the robustness of our results we depict the same tables and tests for players ranked by their Scrimmage Yards in college and also applied our second measure for ability for both portfolio selections as part of Table 7.4. The results largely support our aforementioned conclusions. When moving to our second ability measure the results become ambiguous. In general, they are still favoring our Hypotheses 1-3. Hypothesis 4 is still supported when you look at the influence of our Combine measure or take all Combine disciplines and their direction disregarding their significance into account. Specifically, the Broad Jump seems to be more influential in these alternative regressions. It can be seen in Table 7.3 that there are less players designated as high-ability for our second approach using the player's career length and Pro Bowl/All-Pro selections than for the first approach using Madden ratings. We believe this measure is somewhat biased because players that are relatively new in the NFL and have not made any selection cannot be considered high-ability per definition. This is the case for the Green Bay Packers Running Back Aaron Jones for example. He is considered high-ability by our first, but not by the second measure. He is in the league for 3 full years now and has no Pro Bowl or All-Pro selection but has had the most Touchdowns in 2019 and an Yards per Run well above 5. These problems are bound to occur when you have subjective thresholds to classify skill. The direction of our robustness tests broadly supports the initial research question, however.

Conclusion

Challenges & Solutions

We investigated the influence of the NFL Combine on a player's draft position from a new perspective. By using ex-post NFL Madden ratings and players' eventual career statistics, we divided players into two ability categories and assessed their Combine performances and subsequent influence on the NFL draft.

We found strong evidence that players of high ability perform better at the Combine and that teams, generally, are able to differentiate between the ability of players. The main drivers of this differentiation are the college career and the Combine performance of the player as well as some qualitative factors which could not be fully captured by our model. Our research indicates that the signaling power is mainly driven by the natural ability of a player and not the incentive to overperform at the draft to get picked higher. Thus, we conclude that the NFL Combine does work as a separating signal for teams to assess a player's ability and is already used as such in the drafting process.

<u>Study limitations</u>

Our study's main limitation is available data. As we used multiple data sources with ambiguous names and keys, and not every player was in each dataset (e.g., not every player attends the Combine), we were forced to drop some players. We also excluded some features that were used in earlier studies to assess a player's College career, such as injuries (see Berri and Simmons 2011). Furthermore, there are Pro-Days at bigger Colleges before the Combine which constitute pre-Combine information our draft stock does not capture.

<u>Further Research</u>

Our approach to use Madden data to assess the ability and NFL career of players is highly relevant. Further research could investigate what drives Madden Ratings (i.e. a player's career performance) and what college performance characteristics lead to a successful professional career. Other research built on our approach could assess our findings for other positions by using alternative statistics (QBR, defensive impact measures) to assess their college career. Another interesting approach is to further examine descriptively what drives the signaling power of the NFL Combine in addition to what we did in this study.

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Appendix

Data

Table 7.1: **Used variables for creation of the draft stock model.**

Variable	Running Back	Wide Receiver
X1	Team wins in final year	Team wins in final year
X2	Conference	Conference
X3	Receiving yards in final year	Receiving yards in final year
X4	Rushing yards in final year	Rushing yards in final year
X5	Rushing yards per game in final year	Receiving yards per game in final year
X6	Total touchdowns in final year	Total touchdowns in final year
X7	Total touchdowns per game in final year	Total touchdowns per game in final year
X14	Career total touchdowns	Career total touchdowns
X15	Career receiving yards	Career receiving yards
X16	Career rushing yards	Career rushing yards
X17	Career plays	Career plays
X18	Touchdowns final year/Career touchdowns	Touchdowns final year/Career touchdowns
X19	Total yards in final year/Career total yards	Total yards in final year/Career total yards
X20	Final year yards/Max yards of any RB that year	Final year yards/Max yards of any WR that year
X21	Appearance in a BCS bowl	Appearance in a BCS bowl
X22	All-American selection	All-American selection

Table 7.2: **Regression of sqrt(pick) and relative(pick) on Full Draft-Stock Model.**

Explanatory variables	Sqrt Pick		Relative Pick	
	RBs	WRs	RBs	WRs
	(1)	(2)	(3)	(4)
X1	-5.24***	-6.56***	-0.37**	-0.46***
	(-2.66)	(-4.84)	(-2.56)	(-4.49)
X2	0.01	-0.65	0.23	-0.04
	(0.01)	(-1.26)	(0.54)	(-1.04)
X3	0.00	0.00	0.00	0.00
	(0.26)	(0.45)	(1.054)	(-0.38)
X4	0.00	-0.01	0.00	0.00
	(0.07)	(-0.59)	(0.28)	(-1.05)
X5	-0.04	-0.08	0.00	0.00
	(-0.31)	(-0.87)	(-0.23)	(-0.43)
X6	-0.48	0.23	-0.04	0.05
	(-0.57)	(0.26)	(-0.70)	(0.83)
X7	5.13	-1.17	0.34	-0.45
	(0.55)	(-0.12)	(0.49)	(-0.60)
X14	0.06	-0.17	0.01	-0.01
	(0.51)	(-1.57)	(1.13)	(-1.69)
X15	0.00	0.00	0.00	0.00
	(-0.35)	(0.00)	(-0.85)	(0.32)
X16	0.00	0.00	0.00	0.00
	(-0.52)	(0.18)	(-0.84)	(0.6)
X17	-0.12	0.04	0.01	0.00
	(-1.29)	(0.59)	(-0.91)	(0.32)
X18	3.85	-5.27	0.56	-0.43
	(0.72)	(-1.5)	(1.43)	(-1.63)
X19	-7.64	4.32	-0.66	0.37
	(-1.27)	(0.94)	(-1.44)	(1.08)
X20	0.02	-1.63	-0.29	0.10
	(0.00)	(-0.42)	(-0.92)	(0.34)
X21	0.16	0.41	-0.06	0.01
	(0.08)	(0.23)	(-0.43)	(0.01)
X22	1.30	1.13	0.085	0.08
	(1.33)	(1.61)	(1.18)	(1.49)
Intercept	21.95***	19.50***	3.86***	1.16***
	(5.30)	(7.56)	(3.859)	(6.016)
R^2	30.3%	33.8%	29.0%	31.5%
N	117	194	117	194

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, t-test statistics in parentheses

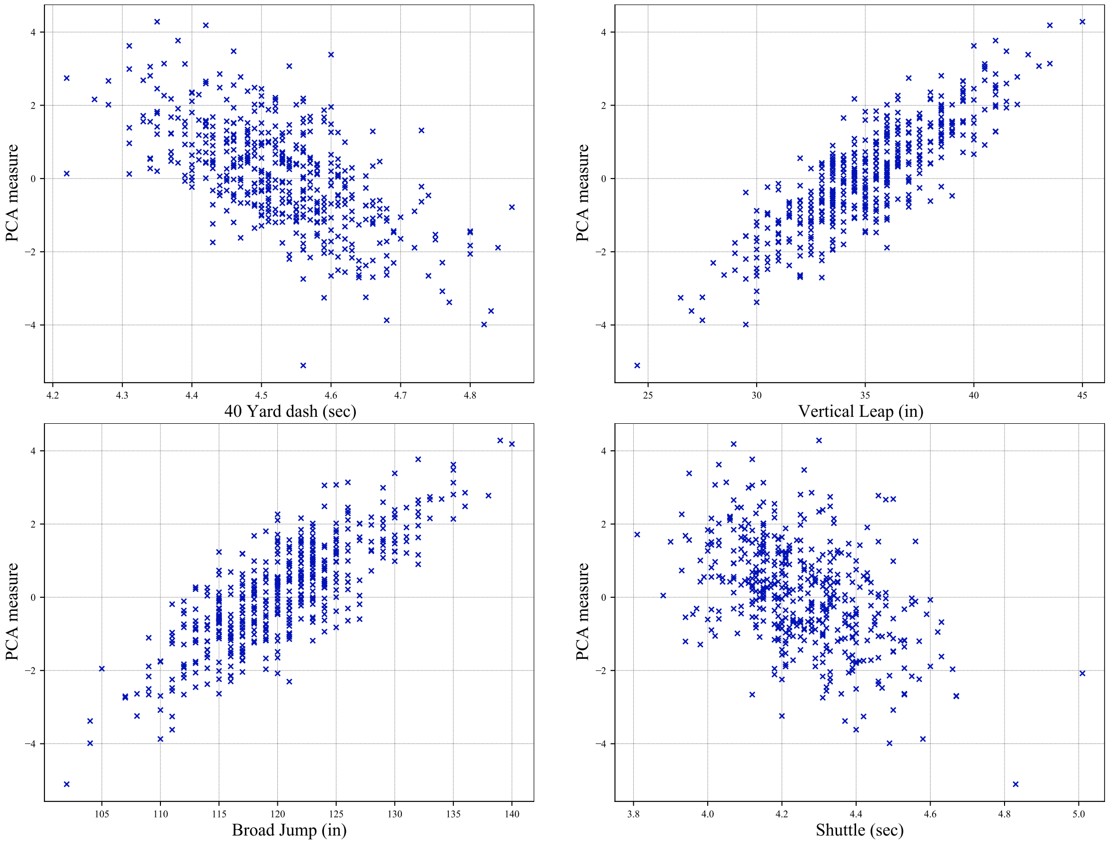

Figure 7.1: **Combine and PCA measure scatter plots.**

This figure shows the relationship of each player's normalized discipline performance and his assigned first component value for each Combine discipline used in our analyses.

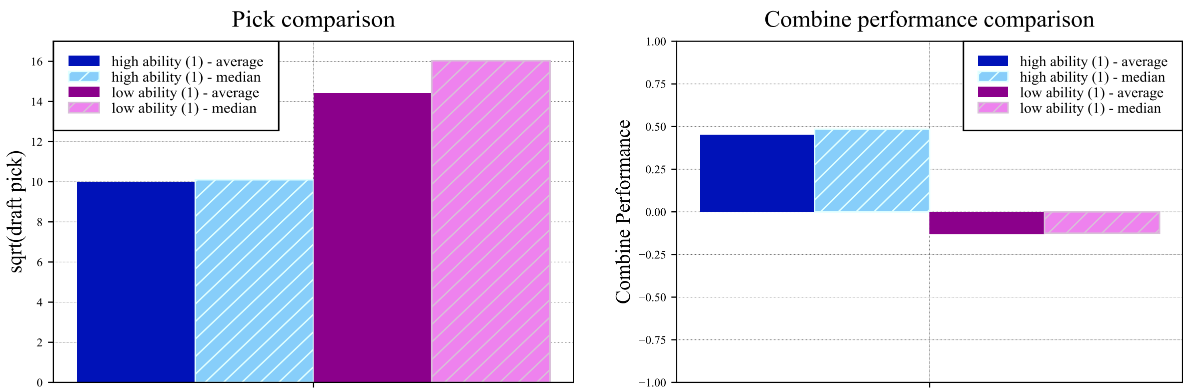

Figure 7.2: **Draft pick and Combine performance.**

This figure shows the mean and median sqrt(draft pick) and the Combine performance of all high- and low-ability players. Both differences in mean are significant with a p-value of 0.00.

Table 7.3: **Descriptive Table.**

This table shows the minimum, maximum and the average of each measure fro Running Backs and Wide Receivers. Also, the number of players of each position and the number of highly-able players under measure 1 (Madden ratings) and measure 2 (seasons, Pro Bowl & All Pro) are depicted.

	Running Back			Wide Receiver		
	avg.	min.	max.	avg.	min.	max.
Height	70.44	65.75	75.00	72.73	66.13	77.63
Weight	213.71	176.00	247.00	201.80	149.00	243.00
BMI	30.49	26.75	34.17	26.99	22.24	30.63
Draft stock						
predicted sqrt(pick)	9.84	3.67	15.57	10.95	3.09	16.43
predicted rel pick	0.45	0.10	0.95	0.44	0.05	1.12
Combine performance						
40 Yard	4.56	4.34	4.86	4.51	4.22	4.75
Vert. Leap	34.89	27.00	43.00	35.32	24.50	45.00
Broad Jump	118.95	104.00	135.00	121.04	102.00	140.00
Shuttle	4.28	3.93	4.67	4.24	3.81	5.01
PCA-measure	0.17	-3.99	3.77	0.08	-5.11	4.28
pick	173.26	8.00	257.00	170.81	4.00	257.00
sqrt-pick	12.69	2.83	16.03	12.48	2.00	16.03
real pick	0.67	0.04	1.01	0.68	0.03	1.01

	Running Back	Wide Receiver
N	165	303
high-ability - 1	84	112
high-ability - 2	51	75

Quintile comparisons

Table 7.4: **Collegiate performance quintiles for high and low-ability players**

These tables group players into quintiles based on their ability and describe players' performance. We used two measures to distinguish high ability players from low ability players: (1) based on Madden ratings, (2) based on Pro Bowls and All-Pros (see Methodology). We grouped players based on two measures: (1) draft stock (variable Predicted_sqrt), (2) scrimmage yards (variable scrim_yards). So this leaves us with eight tables of collegiate performance quintiles. The Combine Measure (β_3) represents the PCA Combine measure (see Data). The Relative Pick adjusts for the scarcity of the player's position in the draft (number of players of the same position selected before the player divided by total amount of players of that position in the draft).

Panel A. Collegiate performance quintile based on draft stock

Table 7.4.1. Collegiate performance quintiles (draft stock) for high-ability players (ha_flag=1)

Variables	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Pick (min)	4	8	34	7	4
Pick (avg)	102.130	102.604	119.720	126.677	147.150
Relative Pick (min)	0.029	0.036	0.088	0.029	0.036
Relative Pick (avg)	0.398	0.404	0.454	0.509	0.582
SQRT(pick) (min)	2.000	2.828	5.831	2.646	2.000
SQRT(pick) (avg)	9.360	9.648	10.424	10.725	11.290
Draft Stock (min)	3.093	8.788	10.250	11.329	12.409
Draft Stock (avg)	7.256	9.340	10.685	11.718	13.694
Scrimmage Yards (max)	7444	6435	5452	4933	3401
Scrimmage Yards (avg)	4004	3145	2392	2156	2103
Combine (max)	3.768	2.743	2.334	4.283	3.071
Combine (avg)	0.378	0.386	0.174	0.529	1.077
40 Yard Dash (min)	4.33	4.22	4.39	4.22	4.28
40 Yard Dash (max)	4.82	4.67	4.77	4.73	4.60
40 Yard Dash (avg)	4.518	4.485	4.526	4.495	4.450
N	69	48	25	34	20

Table 7.4.2. Collegiate performance quintiles (draft stock) for low-ability players (ha_flag=0)

Variables	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Pick (min)	41	53	15	52	21
Pick (avg)	198.440	203.200	213.188	222.000	219.135
Relative Pick (min)	0.167	0.080	0.057	0.222	0.107
Relative Pick (avg)	0.788	0.804	0.837	0.887	0.875
SQRT(pick) (min)	6.403	7.280	3.873	7.211	4.583
SQRT(pick) (avg)	13.824	14.056	14.354	14.751	14.574
Draft Stock (min)	5.250	8.855	10.228	11.240	12.376
Draft Stock (avg)	7.705	9.499	10.744	11.788	13.459
Scrimmage Yards (max)	6581	5788	5085	3473	3803
Scrimmage Yards (avg)	3446	2519	2344	1720	1691
Combine (max)	2.161	4.186	3.624	3.477	3.139
Combine (avg)	-0.584	-0.149	0.053	-0.025	-0.221
40 Yard Dash (min)	4.26	4.31	4.31	4.31	4.33
40 Yard Dash (max)	4.80	4.86	4.80	4.75	4.84
40 Yard Dash (avg)	4.569	4.534	4.537	4.542	4.544
N	25	45	69	59	74

Table 7.4.3. Collegiate performance quintiles (draft stock) for high-ability players (ha_flag_2=1)

Variables	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Pick (min)	4	8	34	34	4
Pick (avg)	88.511	109.517	118.357	141.435	140.800
Relative Pick (min)	0.029	0.036	0.088	0.040	0.036
Relative Pick (avg)	0.349	0.447	0.470	0.571	0.546
SQRT(pick) (min)	2.000	2.828	5.831	5.831	2.000
SQRT(pick) (avg)	8.644	9.862	10.259	11.449	10.943
Draft Stock (min)	3.093	8.788	10.250	11.329	12.409
Draft Stock (avg)	7.215	9.357	10.717	11.738	13.688
Scrimmage Yards (max)	7042	4577	3801	4933	3401
Scrimmage Yards (avg)	3945	3087	2431	2230	2047
Combine (max)	3.384	2.454	2.334	4.283	3.070
Combine (avg)	0.368	0.200	0.360	0.640	0.865
40 Yard Dash (min)	4.33	4.34	4.39	4.31	4.28
40 Yard Dash (max)	4.76	4.67	4.77	4.73	4.62
40 Yard Dash (avg)	4.508	4.496	4.539	4.514	4.459
N	45	29	14	23	15

Table 7.4.4. Collegiate performance quintiles (draft stock) for low-ability players (ha_flag_2=0)

Variables	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Pick (min)	22	9	15	7	21
Pick (avg)	163.776	170.203	200.575	202.171	215.785
Relative Pick (min)	0.053	0.059	0.057	0.029	0.107
Relative Pick (avg)	0.642	0.666	0.782	0.807	0.863
SQRT(pick) (min)	4.690	3.000	3.873	2.646	4.583
SQRT(pick) (avg)	12.296	12.650	13.842	13.880	14.432
Draft Stock (min)	3.675	8.793	10.228	11.240	12.376
Draft Stock (avg)	7.522	9.444	10.730	11.770	13.475
Scrimmage Yards (max)	7444	6435	5452	4468	3803
Scrimmage Yards (avg)	3773	2731	2344	1764	1727
Combine (max)	3.768	4.186	3.624	3.477	3.139
Combine (avg)	-0.104	0.094	0.037	0.026	-0.099
40 Yard Dash (min)	4.26	4.22	4.31	4.22	4.33
40 Yard Dash (max)	4.82	4.86	4.80	4.75	4.84
40 Yard Dash (avg)	4.553	4.515	4.534	4.529	4.537
N	49	64	80	70	79

Panel B. Collegiate performance quintile based on scrimmage yards

Table 7.4.5. Collegiate performance quintiles (scrimmage yards) for high-ability players (ha_flag=1)

Variables	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Pick (min)	9	7	12	4	4
Pick (avg)	131.200	135.190	126.781	100.312	103.200
Relative Pick (min)	0.094	0.059	0.029	0.036	0.029
Relative Pick (avg)	0.531	0.536	0.495	0.398	0.395
SQRT(pick) (min)	3.000	2.646	3.464	2.000	2.000
SQRT(pick) (avg)	10.819	10.894	10.772	9.373	9.516
Draft Stock (min)	8.790	8.534	6.757	3.930	3.093
Draft Stock (avg)	11.552	11.948	10.351	9.666	7.908
Scrimmage Yards (max)	1461	1997	2705	3457	7444
Scrimmage Yards (avg)	1163	1764	2375	3058	4478
Combine (max)	4.283	2.292	3.768	3.071	3.384
Combine (avg)	0.740	0.505	0.532	0.493	0.266
40 Yard Dash (min)	4.22	4.22	4.37	4;34	4.33
40 Yard Dash (max)	4.65	4.77	4.73	4.73	4.82
40 Yard Dash (avg)	4.473	4.462	4.484	4.513	4.520
N	25	21	32	48	70

Table 7.4.6. Collegiate performance quintiles (scrimmage yards) for low-ability players (ha_flag=0)

Variables	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Pick (min)	53	36	15	52	41
Pick (avg)	219.101	214.458	210.532	209.867	211.375
Relative Pick (min)	0.080	0.107	0.057	0.222	0.167
Relative Pick (avg)	0.866	0.859	0.832	0.835	0.832
SQRT(pick) (min)	7.280	6.000	3.873	7.211	6.403
SQRT(pick) (avg)	14.615	14.456	14.252	14.283	14.238
Draft Stock (min)	8.855	8.196	7.537	8.066	5.250
Draft Stock (avg)	12.003	11.847	10.982	10.540	9.020
Scrimmage Yards (max)	1471	2022	2703	3480	6581
Scrimmage Yards (avg)	1048	1766	2338	3059	4409
Combine (max)	4.186	3.624	2.775	2.855	1.559
Combine (avg)	0.286	-0.304	-0.319	0.115	-0.780
40 Yard Dash (min)	4.33	4.26	4.35	4.31	4.31
40 Yard Dash (max)	4.86	4.75	4.84	4.75	4.80
40 Yard Dash (avg)	4.532	4.533	4.552	4.537	4.588
N	69	72	62	45	24

Table 7.4.7. Collegiate performance quintiles (scrimmage yards) for high-ability players (ha_flag_2=1)

Variables	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Pick (min)	34	28	12	4	4
Pick (avg)	133.688	159.813	120.067	113.406	86.277
Relative Pick (min)	0.143	0.147	0.088	0.036	0.029
Relative Pick (avg)	0.543	0.623	0.490	0.455	0.340
SQRT(pick) (min)	5.831	5.292	3.464	2.000	2.000
SQRT(pick) (avg)	11.069	11.990	10.453	9.891	8.592
Draft Stock (min)	8.790	8.534	8.894	3.930	3.093
Draft Stock (avg)	11.829	11.801	10.668	9.831	7.845
Scrimmage Yards (max)	1461	1992	2631	3457	7042
Scrimmage Yards (avg)	1161	1770	2417	3094	4276
Combine (max)	4.283	2.990	2.334	3.071	3.384
Combine (avg)	0.623	0.330	0.502	0.464	0.371
40 Yard Dash (min)	4.34	4.28	4.38	4.34	4.33
40 Yard Dash (max)	4.65	4.77	4.73	4.73	4.76
40 Yard Dash (avg)	4.492	4.491	4.497	4.520	4.504
N	16	16	15	32	47

Table 7.4.8. Collegiate performance quintiles (scrimmage yards) for low-ability players (ha_flag_2=0)

Variables	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
Pick (min)	9	7	15	22	37
Pick (avg)	208.449	204.195	193.785	174.262	175.362
Relative Pick (min)	0.080	0.059	0.029	0.059	0.053
Relative Pick (avg)	0.825	0.820	0.761	0.690	0.674
SQRT(pick) (min)	3.000	2.646	3.873	4.690	6.083
SQRT(pick) (avg)	14.126	13.997	13.564	12.724	12.851
Draft Stock (min)	8.855	8.196	6.757	6.450	3.675
Draft Stock (avg)	11.895	11.884	10.786	10.224	8.538
Scrimmage Yards (max)	1471	2022	2705	3480	7444
Scrimmage Yards (avg)	1062	1765	2338	3041	4645
Combine (max)	4.186	3.624	3.768	2.855	2.155
Combine (avg)	0.363	-0.216	-0.130	0.230	-0.373
40 Yard Dash (min)	4.22	4.22	4.35	4.31	4.31
40 Yard Dash (max)	4.86	4.75	4.84	4.75	4.82
40 Yard Dash (avg)	4.521	4.523	4.535	4.527	4.570
N	78	77	79	61	47

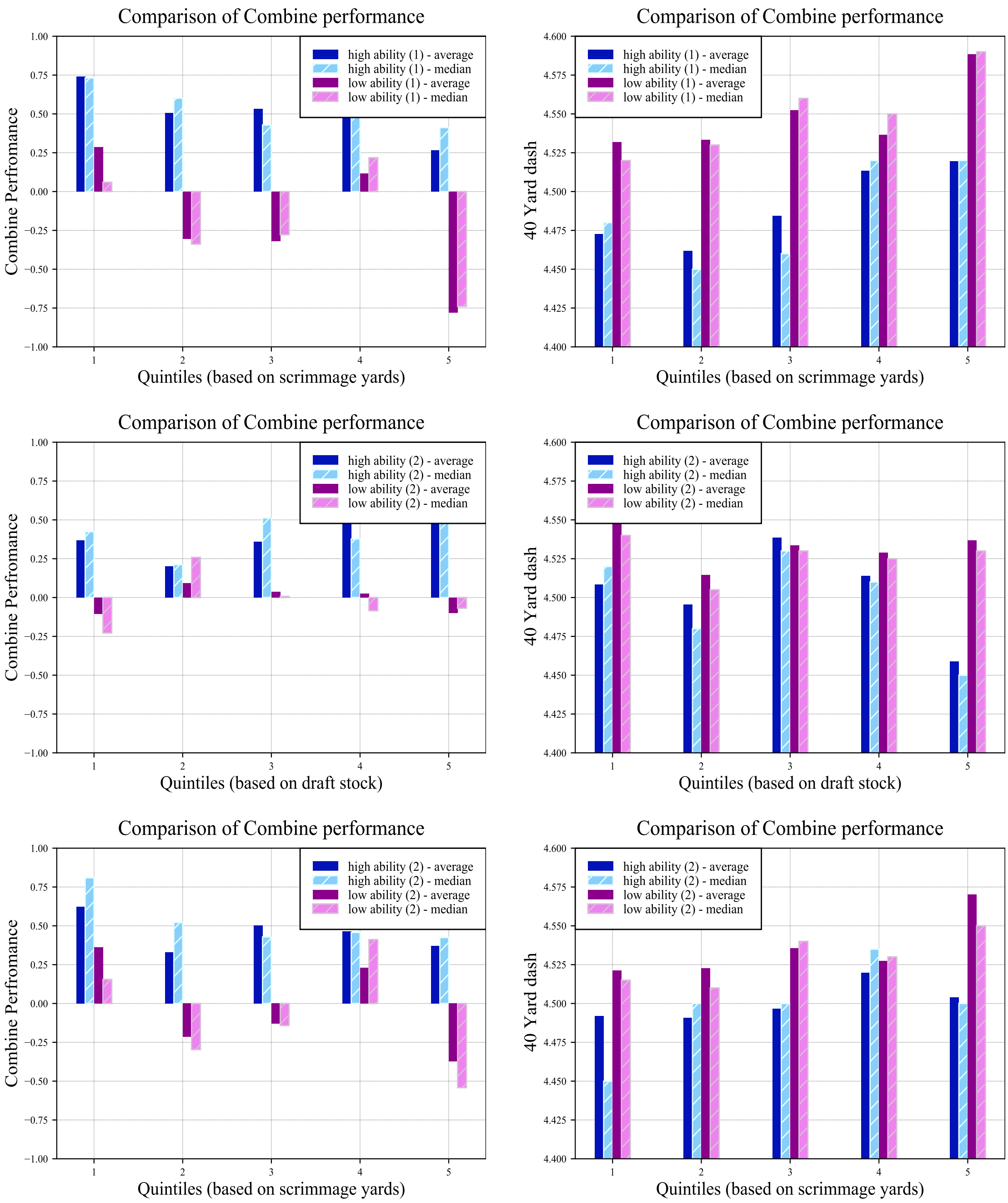

Figure 7.3: **Combine performance among draft-stock and high- & low-ability players - robustness test.**

This figure shows the mean and median Combine performance of high- and low-ability players sorted among their pre-Combine draft-stock rating.

Table 7.5: **Combine performance t-tests.**

Table of t-tests to test robustness of Table 5.1. The first table depicts the t-tests based on draft stock quintiles and the alternative high-ability measure (seasons & All-Pro/Pro Bowl). The second and third table have quintiles based on a player's Scrimmage Yards in college and the two ability measures.

NFL career ability	Player draft stock quintile				
	(1)	(2)	(3)	(4)	(5)
mean performance - high-ability	0.368	0.200	0.360	0.640	0.865
mean performance - low-ability	-0.104	0.094	0.037	0.026	-0.099
t-test statistic	1.4078	0.4126	0.7761	1.8948	2.5627
p-value	0.1626	0.6811	0.4482	0.0664	0.0178
mean 40 dash time - high-ability	4.473	4.462	4.484	4.513	4.520
mean 40 dash time - low-ability	4.508	4.496	4.539	4.514	4.459
t-test statistic	-2.1393	-0.8836	0.1705	-0.5623	-2.6931
p-value	0.0351	0.3802	0.8665	0.5773	0.0143

Madden ability	Player Scrimmage Yards quintile				
	(1)	(2)	(3)	(4)	(5)
mean performance - high-ability	0.740	0.505	0.532	0.493	0.266
mean performance - low-ability	0.286	-0.304	-0.319	0.115	-0.780
t-test statistic	1.3041	2.3115	3.1149	1.3592	3.0716
p-value	0.1992	0.0272	0.0027	0.1775	0.0039
mean 40 dash time - high-ability	4.473	4.462	4.484	4.513	4.520
mean 40 dash time - low-ability	4.532	4.533	4.552	4.537	4.588
t-test statistic	-2.3358	-2.2885	-3.5453	-1.2176	-2.5021
p-value	0.0239	0.0304	0.0007	0.2267	0.0174

NFL career ability	Player Scrimmage Yards quintile				
	(1)	(2)	(3)	(4)	(5)
mean performance - high-ability	0.623	0.330	0.502	0.464	0.371
mean performance - low-ability	0.363	-0.216	-0.130	0.230	-0.373
t-test statistic	0.5759	1.2249	2.1198	0.8036	2.5521
p-value	0.5711	0.2351	0.0440	0.4246	0.0124
mean 40 dash time - high-ability	4.492	4.491	4.497	4.520	4.504
mean 40 dash time - low-ability	4.521	4.523	4.535	4.527	4.570
t-test statistic	-1.0389	-0.8722	-1.4755	-0.3739	-3.1041
p-value	0.3089	0.3943	0.1557	0.7098	0.0026

Regressions

Table 7.6: **Regression sqrt(pick) on Draft-Stock & Combine Measures.**

This table shows the results of regressing the square-root of a player's draft pick on his pre-combine Draft-Stock as well as his Combine performance and his BMI for high- and low-ability players separately. Regressions (1) & (3) are for high-ability players while regressions (2) & (4) are done for low-ability players. The high-ability measure is based on a player's NFL seasons and selections to Pro Bowls & All-Pros (see Methodology) and the Combine Measure (β_3) represents the PCA Combine measure (see Data).

Explanatory variables	Dependent Variable: Sqrt(Draft pick)			
	High-ability	Low-ability	High-ability	Low-ability
	(1)	(2)	(3)	(4)
Draft-Stock	0.50***	0.32***	0.52***	0.33***
	-3.65	-3.9	-4.12	-4.24
BMI	0.31**	-0.05	0.13	-0.21***
	-2.18	(-0.78)	-0.89	(-3.05)
Combine Measure	-0.92***	-0.72***		
	(-4.12)	(-6.08)		
40 Yard dash			8.47**	12.44***
			-2.45	-7.86
Vertical Jump			-0.09	0.03
			(-0.59)	-0.46
Broad Jump			-0.15**	-0.08**
			(-2.29)	(-2.49)
Shuttle			-0.94	-0.57
			(-0.51)	(-0.54)
Intercept	-3.3	11.53***	-11.62	-29.19***
	(-0.73)	-5.08	(-0.64)	(-3.00)
R^2	19.72%	15.73%	24.34%	26.37%
N	126	342	126	342

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, t-test statistics in parentheses

Table 7.7: **Regression relative pick on Draft-Stock & Combine Measures.**

This table shows the results of regressing the square-root of a player's draft pick on his pre-combine Draft-Stock as well as his Combine performance and his BMI as a control variable for high- and low-ability players separately. Regressions (1) & (3) are for high-ability players while regressions (2) & (4) are done for low-ability players (Madden classification). The same logic applies for regressions (5) & (7) and/ (6) & (8) (NFL seasons/ Pro Bowl/ All-Pro classification).

Explanatory variables	Dependent Variable: relative draft pick							
	Madden ability measure				NFL career ability measure			
	High-ability	Low-ability	High-ability	Low-ability	High-ability	Low-ability	High-ability	Low-ability
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Draft-Stock	0.56***	0.19*	0.60***	0.18	0.78***	0.39***	0.80***	0.37***
	(-4.12)	(-1.78)	(-4.46)	(-1.63)	(-4.96)	(-3.68)	(-5.54)	(-3.48)
BMI	0.01	-0.01	-0.01	-0.02**	0	-0.01*	-0.01	-0.03***
	(-0.72)	(-0.89)	(-0.99)	(-2.25)	(-0.22)	(-1.87)	(-0.91)	(-3.82)
Combine Measure	-0.06***	-0.04***			-0.07***	-0.06***		
	(-4.54)	(-4.44)			(-3.63)	(-6.29)		
40 Yard dash			0.83***	0.74***			0.61**	1.05***
			(-4.11)	(-5.1)			(-2.27)	(-7.79)
Vertical Jump			0	0			0	0
			(-0.32)	(-0.3)			(-0.03)	(-0.57)
Broad Jump			-0.01**	-0.01*			-0.01***	-0.01**
			(-2.28)	(-1.85)			(-3.14)	(-2.34)
Shuttle			-0.08	-0.08			-0.16	-0.04
			(-0.63)	(-0.80)			(-1.19)	(-0.42)
Intercept	0.09	0.91***	-1.85	-1.19	0.12	0.93***	0.21	-2.50***
	(-0.36)	(-5.18)	(-1.56)	(-1.30)	(-0.38)	(-4.84)	(-0.17)	(-2.76)
R^2	18.69%	8.77%	23.02%	16.38%	26.51%	16.05%	31.87%	24.46%
N	196	272	196	272	126	342	126	342

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$, t-test statistics in parentheses

Results discussion

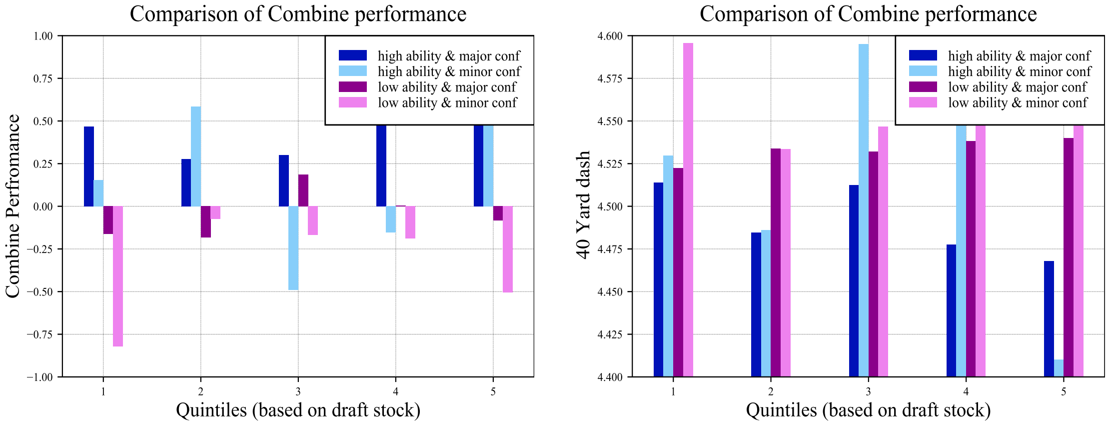

Figure 7.4: **Combine performance among major and minor conference players.**

The Figure depicts the average performance at the average PCA-measure (left) and 40 the Yard dash (right) for players of high-.ability (blue) and low-ability (violet) that attended major (dark) or minor (bright) colleges. There are 142 players from major conference colleges that are of high-ability, 54 from minor colleges that are of high-ability, 183 players of low-ability and major colleges, and 89 players from minor colleges that turn out to be of low-ability.

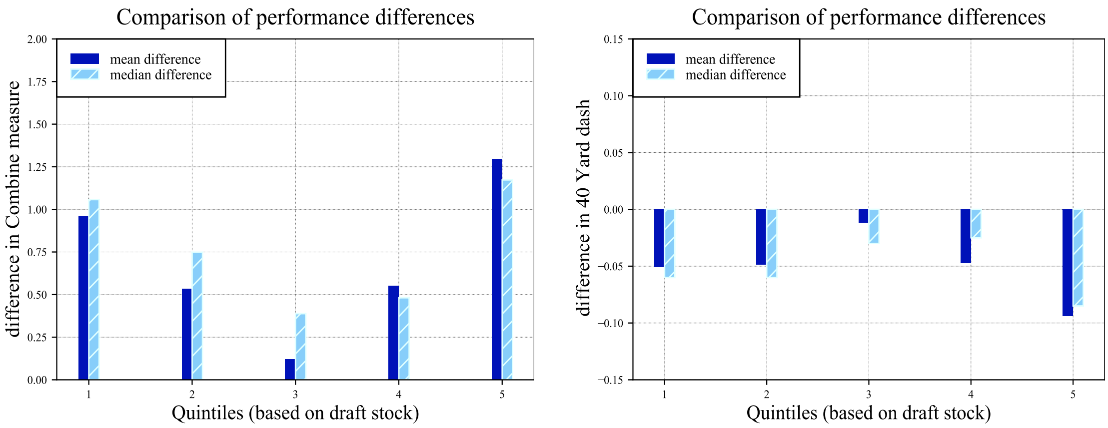

Figure 7.5: **Differences in Combine performance.**

The Figure shows the differences between Combine performances for each draft stock quintile. The right side the the differences in average and median of the PCA-measure for Combine performance. The left side shows the difference in average and mean 40 Yard dash time.