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Discriminant Function Analysis Reveals Which Combination of Measures from the NFL Scouting Combine Predict NFL Performance

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Abstract

The National Football League (NFL) Scouting Combine (the Combine), is an annual track-meet style event where NFL scouts and general managers evaluate newly-eligible players before the upcoming draft. During the Combine, players' height, weight, speed, agility, acceleration, jumping, explosive movement, and strength are measured through their participation in multiple drills such as the 40-yard dash, vertical jump, and bench press. Although numerous studies have tested which individual drills predict NFL success for different positions, the results are often inconsistent across studies. These previous studies rely largely on individual predictors without considering how the various abilities measured at the Combine work together to predict performance. In this study, using discriminate function analysis, we analyze 20 years of data to identify the best *combination* of skills necessary to achieve varying levels of success for each player position. To date, this study represents the largest, most comprehensive study on the topic. We found that for offensive positions, single measures were often the best predictors of success. By contrast, for defensive positions, we found significant discriminant functions identifying unique combinations of traits that predicted success. We examined success using multiple benchmarks: draft status, number of games played, number of games started, and honors received. All significance tests were two-tailed, alpha = .05. These results indicate that, at least for some NFL positions, scouts and general managers should consider relative performance across multiple drills. Differences between the predictors presumably used by scouts and general managers when drafting players and those which predict actual NFL success are discussed.

Keywords

sprint, jump, change of direction, bench press, performance, NFL

Introduction

Identifying new talent is a key to success for many businesses, and for sports franchises in particular. With the largest revenue of all sports in the United States, the National Football League (NFL) is no exception (Amoros, 2016). The issue of identifying talent in the NFL is arguably particularly critical given the large roster size and often-times short careers of American football[1] players.

The need to identify new talent is further exacerbated by the NFL salary cap. Veteran players require contracts larger than recent draftees, and teams are limited in their maximum allotted spending (National Football League's Players Association, 2020). As a result, acquiring good players via the draft is necessary for remaining competitive in the NFL (Carey, 2008). Nevertheless, draft "busts"—players who do not live up to their pre-draft expectations—are common (Boulier et al, 2010). As a recent example three of the top four quarterbacks drafted in 2018 had been traded away by 2022.

Draft busts are likely common for several reasons. One reason is that college, rather than developmental leagues found in other sports (e.g., minor league baseball), is the primary developmental ground for future NFL players. This poses additional challenges as the level of competition varies dramatically across college football programs. Because of the disparity in competition level and the relative simplicity of college playbooks, college statistics do not always translate well into NFL performance (Berri & Simmons, 2009), though strides have been made recently in this regard (Mulholland & Jensen, 2014; 2016).

A second likely reason for draft busts is that football has a large number of specialized positions relative to other sports. Rather than playing both offense and defense like in many other sports, football players typically assume a single position. The responsibilities are drastically different across positions and rely on different players with unique skills. For example, a running back needs to navigate a path quickly through their blockers. By contrast, a tight end needs to be strong enough to block edge rushers *and* fast enough to outmaneuver defenders when aiming to catch a passed ball. Determining a player's potential for success in a given position may be difficult when general athletic skills do not necessarily "translate" to the position.

Finally, individual success depends heavily on team performance. It is therefore difficult to predict an individual player's potential success independent of other players. Game film, some may argue, is the best indicator of an individual's ability to play football. However, game film analysis is often subjective, and players might appear more or less talented depending on their teammates' talent and the level of competition. For example, a player may appear faster or stronger than he really is against slower, weaker, or smaller competitors. Additionally, different running surfaces are "faster" or "slower." Thus, it is difficult to know if a player who plays on a grass field is faster or slower than one playing more often on artificial surfaces, which tend to allow for faster performance and quicker changes of direction (Gains et al., 2010). To rectify this, scouts rely on measurements taken on the same surface on the same day for the majority of draft prospects: the annual NFL Scouting Combine. See Table 1 (next page) for a list of measures considered in the current study.

Does the Combine Matter?

Players' draft fortunes may rise or fall on a good or poor Combine performance (https://www.usatoday.com/story/sports/nfl/2017/02/27/nfl-scouting-Combine-draft-busts/98465506/). The Combine has been criticized for several reasons. One major criticism is that a players' speed on an artificial surface, in a straight line, wearing shorts and a T-shirt may not translate to running in pads on a grass field while making quick decisions in a game setting. Do these drills, which are performed in a controlled setting, translate to game performance?

Previous Research on the Combine

Over the past 20 years, a number of studies have examined Combine measures as predictors of success in the NFL in various positions (Asprey et al., 2020; Berii & Simmons, 2011; Cook et al., 2020; Kraeuter et al., 2017; LaPlaca & McCullick, 2020; Mulholland & Jensen, 2014; 2016; Pitts & Evans, 2018; Robbins, 2012; 2010; Vincent et al., 2019; Wolfson et al., 2011). First, we describe the major findings in the published literature thus far, on a position-by-position basis. This includes which variables predict draft status (i.e., what general managers and scouts seem to be using to make decisions) and on-field performance (i.e., what actually matters for success). See Table 2 (next page) for a glossary of NFL-specific performance terms. Next, we point out important limitations of this research. Finally, we make an argument for why discriminant function analysis (DFA) may be a better approach for investigating what combination of factors predicts NFL football player success at a given position.

Table 1. Combine measures, descriptions, and skillset associated with each measure (McShay, 2016)

Combine Measure	Skillset	Description
Height	Stature	Height in inches
Weight	Stature	Weight in pounds
40-yard dash	Speed and acceleration	The athlete sprints 40 yards. Time is measured in seconds to the nearest 100th of a second.
20-yard shuttle	Lateral movement and coordination	The athlete starts at the center cone of 3 cones, each 5 yards apart. The athlete then pushes off their dominant leg in the opposite direction for 5 yards and touches a line. They must then reverse direction and run 10 yards in the opposite direction and touch that line. Finally, they must reverse direction again, ending the drill at the starting point after traveling another 5 yards. 20-yard shuttle times are measured in seconds to the nearest 100th of a second.
Three-cone drill	Lateral speed, ability to change direction, and coordination	Three cones are placed five yards apart from each other forming a right angle. The athlete starts with one hand down on the ground and runs to the middle cone and touches it. They then reverse direction back to the starting cone and touch it. They then reverse direction again, but this time run around the outside of the middle cone on the way to the far cone, running around it in figure eight fashion on the way back around the outside of the middle cornering cone. Three-cone times are measured in seconds to the nearest 100th of a second.
Vertical jump	Explosiveness, jumping ability, and lower-body strength	Athletes stand flat-footed in front of a pole with many plastic tabs. The athlete extends their arm upwards touching the highest tab they can. They then jump from a crouching position and hit as many flags as they can with their outstretched arm. Vertical jump is measured in inches from the highest tab hit while standing to the highest tab hit when jumping. Thus, player height is not confounded with vertical jump height.
Broad jump	Horizontal explosiveness and lower-body strength	The athlete stands at a line marked on the ground with their feet slightly apart. They jump forward and land using both feet, swinging their arms and bending their knees to provide forward drive. Broad jump is measured in inches.
Bench Press/Work	Upper-body strength	The athlete presses 225lbs upwards while lying on a weight training bench. The player completes as many press repetitions as he can.

Note. The ability to score high on the bench press measure is influenced by the athlete's arm length: The longer the player's arms, the farther the player needs to move the weight to complete a single repetition. For our analyses, we created a Work variable to indicate strength independent of arm length. In physics, the term "work" is a measure of force applied to an object and is computed as force times distance (de Coriolis, 1829).

Table 2. Glossary of NFL-specific terms

Term	Definition
3-4 defense	Alignment of three defensive linemen and four linebackers
4-3 defense	Alignment of four linemen and three linebackers
All-pro team	Team compiled and voted on by the Pro Football Writers Association
Blitz	Defense tactic where multiple defensive players rush the quarterback
Block	Obstructing an opposing player's path or attempting to force opposing players into a new path with the body
Carry	A running play
Catch	A successful reception of the ball during a passing play
Cover	A defensive assignment to an opposing player or zone of the field
Down (played)	A single offensive play
Draft	A selection of incoming rookie players by the teams
Hand off	When the quarterback directly gives possession of the ball to an eligible receiver (usually the running back)
Interception	When a defensive player catches a pass meant for an offensive player
Line of scrimmage	The dividing line between the offense and defense where the ball is placed on the field at the beginning of each play
Make the roster	Selected onto the 52-person team at the start of the regular season
Pass	When the quarterback throws the ball downfield
Play	A plan of action used to move the ball down the field
Pressure	When the defensive line is able to shrink the protective space around the quarterback
Pro Bowl	Annual all-star game where players are chosen based on a combination of sports writers and fan voting
Rushing the passer	When defensive players attempt to tackle or sack the passer (usually the quarterback)
Sack	Tackling the passer (usually the quarterback) behind the line of scrimmage
Snap	The act of moving the ball that begins the play
Stopping the run	Preventing a ball carrier from moving far down the field
Tackle	When a defensive player physically forces a ball carrier to the ground
Touchdown	When the offense has possession of the ball inside their opponent's end zone

Positions

Quarterbacks

Quarterback is undeniably one of the most important positions in football (Berri & Simmons, 2011). The quarterback is the leader of the offensive team and handles the ball on almost all plays. Quarterback is also arguably the hardest position to evaluate (Wolfson et al., 2011). Because the position relies heavily on throwing strength and accuracy, along with the ability to process information on the field (Berri & Simmons, 2011), physical measurements such as speed, explosive power, and strength, may be less predictive of quarterback success than in other positions.

The most consistent finding across studies is that taller and faster quarterbacks tend to be drafted earlier than shorter and slower quarterbacks (Asprey et al., 2020; Berii & Simmons, 2011; Kraeuter et al., 2017; Pitts & Evans, 2018; Robbins, 2012). Quarterback height, body mass index (BMI), and 40-yard dash time are weakly correlated with passing performance and overall NFL success (Pitts & Evans, 2018). Likewise, 40-yard dash time is weakly associated rushing performance (Vincent et al., 2019).

Running Backs

Perhaps the most consistent association found between Combine and NFL performance is that faster 40-yard dash times predict greater rushing performance and longevity for running backs (Asprey et al., 2020; Robbins, 2010; Vincent et al., 2019). Taller running backs with higher BMI also tend to have better NFL performance (Pitts & Evans, 2019; but see LaPlaca & McCullick, 2020). Longer broad jumps also weakly correlate with better NFL performance (Robbins, 2010; Vincent et al., 2019).

Wide Receivers

Multiple studies show that faster wide receivers, as measured by the 40-yard dash, are more likely to be drafted early than are slower wide receivers (Fenn & Berri, 2018; Mulholland & Jensen, 2016; Pitts & Evans, 2019; Robbins, 2010). Additionally, both Mulholland and Jensen (2016) and Robbins (2010) found that wide receivers with longer broad jumps were drafted earlier.

Like the broad jump, higher vertical jumps have consistently predicted better NFL performance (Mulholland & Jensen, 2016; Pitts & Evans, 2019; Robbins, 2010; Vincent et al., 2019; but see Fenn & Berri, 2018 and LaPlaca & McCullick, 2020). This may be because the higher a wide receiver can jump, the greater the advantage he has when jumping up to make a contested catch (a catch when a defender is nearby and trying to intercept or knock away the pass).

Some studies have also found that faster 40-yard dash times are related to greater NFL career success (Cook et al., 2020; Muholland & Jenson, 2016; but see Pitts & Evans, 2019) and longevity (Asprey et al., 2016). Similar associations have been found for faster 3-cone times and longevity (Asprey et al., 2016; Cook et al., 2020). LaPlaca and McCullick (2020) also found that faster 20-yard shuttle times were associated with better route running. Interestingly, no study has found a relationship between NFL receiver performance and the broad jump—a test that both Mulholland and Jensen (2016) and Robbins (2010) found predicted draft status.

Tight Ends

The tight end position poses a unique challenge as blocking tight ends and receiving tight ends may have very different body types and athletic skill sets. Receiving tight ends (sometimes called F tight ends) and those who can both block and catch, tend to be drafted earlier than pure blocking tight ends (sometimes called Y tight ends; Hill, 2014). Interestingly, different studies find different predictors for draft status. Robbins (2010) identified vertical and broad jump as the only relevant abilities. By contrast, Pitts et al. (2019) and Mulholand and Jensen (2014), controlled for several other college performance and competition-level variables, and both studies identified height, BMI, and 40-yard dash time as the important predictors of draft status.

Regarding NFL performance, Muholland and Jensen (2014) found that only the longer broad jump and faster 40-yard dash times predicted greater career performance and longevity (see also, Pitts & Evans, 2019). Cook et al. (2020), on the other hand, found only faster 3-cone drill times predicted snaps played in the first five years.

Asprey et al. (2020) found that greater weight, higher vertical jump, and longer broad jump all predicted still being in the league five years later. Thus, jumping, speed, and size appear important for the tight end position, but results have been mixed across studies.

Offensive Linemen

Fewer studies have examined offensive linemen than other position groups, likely due to the lack of individual performance statistics for linemen. Offensive linemen include the left tackle, left guard, center, right guard, and right tackle. What little evidence there is concerning this position is mixed. Robbins (2010) found that faster 10- and 20-yard splits (the first 10 and 20 yards of the 40-yard dash) predict being drafted higher for centers and tackles, but not guards. Higher vertical jump also predicts being drafted earlier for offensive tackles and remaining in the league beyond four years for linemen in general (Asprey et al., 2020). Although an offensive lineman may not need to jump vertically during a game, jumping ability also relates to both explosiveness and lower body strength. Explosiveness and lower body strength may be especially important for offensive linemen who typically weigh 300 or more pounds and need to begin moving quickly from a standstill. That said, it is unclear why the vertical jump, rather than broad jump (horizontal explosiveness and strength) would be the better predictor of success for offensive linemen.

For NFL performance, LaPlaca and McCullick (2020) found that faster 40-yard dash times were related to better performance for tackles, but not guards or centers. They found consistent relationships between faster 20-yard shuttle performance and better pass blocking across offensive line positions. That is, linemen who can start and stop faster make for better pass blockers. This latter finding may reflect general footwork ability and short area quickness. The three-cone drill, a measure of agility, predicted better pass blocking grades only for tackles, who are more likely to have to move around in pass protection. Last, LaPlaca and McCullick (2020) found that better bench press for tackles, and guards to a lesser extent, predicted better pass blocking performance.

Defensive Tackles/Interior Defensive Linemen

Some defensive tackles are known for their athleticism and pass rush ability and others for their strength and run stopping ability. The latter do not always accumulate statistics, however, because their primary job on a play may be to hold their positions and keep the offensive linemen from blocking other players (who then record tackles or sacks). Thus, as with tight ends, the defensive tackle category contains two, sometimes very different, types of players.

Robbins (2010) found that longer broad jump and faster 3-cone drill predicted better draft status, but only after adjusting the latter for player size. Kraeuter et al. (2017) additionally found that defensive tackles drafted in the first round tend to be taller than those taken in the second round.

In terms of NFL performance, longer broad jump has been shown to be significantly correlated with sacks (Vincent et al., 2019) and other measures of pass rush ability (quarterback pressures, hits, hurries, etc.; LaPlaca & McCullick, 2020). By contrast, Cook et al. (2020) found that only faster 20-yard shuttle times predicted more snaps played in the first five years of a defensive tackle’s career, but this explained less than 5% of the variance.

Edge Rushers/Defensive Ends

As NFL offenses have shifted toward throwing the ball more and more, a premium has been placed on players who excel at rushing the passer, be it through size, speed, or both (Brooks, 2015). Kraeuter et al. (2017) found that first round defensive end draft picks tended to weigh more than second round defensive end draft picks. Robbins (2010) did not find any significant correlations between base Combine measures and draft status. However, after adjusting for player size, faster 40-yard dash (as well as 10- and 20-yard splits) and time in the 3-cone drill, all predicted better draft position. Thus, scouts and general managers appear to favor players who are big, fast, and agile.

In line with the data on draft position, Vincent et al. (2019) found that after adjusting for player size, faster 40-yard dash time and higher vertical jump related to more tackles recorded by a defensive end. They also found a correlation between better unadjusted broad jump and adjusted vertical jump and sacks recorded. By contrast, LaPlaca and McCullick (2020) found that heavier players were somewhat better at defending against running plays, whereas pass rush success was associated with lower weight, fast 40-yard dash, 3-cone, and 20-yard shuttle times, and better vertical and broad jump.

Linebackers

Robbins (2010) found generally positive relationships between draft status and faster 40-yard dash, 20-yard splits, and better vertical and broad jump—particularly when these measures were adjusted in some way for player weight. Thus, scouts and general managers appear to favor players at the linebacker position who are both big and athletic.

With respect to NFL performance, the data are less clear. Vincent et al. (2019) found a correlation between faster 40-yard dash times and recording more tackles and sacks. Sacks were also predicted by better vertical and broad jumps, but only after adjusting for player size (Vincent et al., 2019). Thus, similar to defensive ends, it is the combination of size, speed, and explosiveness that predicts pass rushing success for linebackers. By contrast, the base correlations between these measures and measures of success appeared sporadic in LaPlaca and McCullick (2020). That is, correlations were weak and inconsistent across measures of run defense (e.g., tackles, run defense grade, tackle grade, tackles missed) and pass rushing (e.g., sacks, hurries, QB hits).

LaPlaca and McCullick (2020) found multiple correlations suggesting that lighter players, when they rush the passer, are more likely to record sacks and pressures. Likewise, lighter players are giving up more catches and touchdowns when in coverage and are more likely to miss tackles on a given play. That said, they also *make* more tackles. However, these relationships were true only for outside linebackers (not inside linebackers). These seemingly backwards findings may reflect a general problem with the linebacker designation: that is, whether a 3-4 or a 4-3 defense is used. These two designations place different demands on the players, and the characteristics of the players differ depending on the designation.

Last, for inside linebackers, greater height and bench press appear to be related to better performance against the run, but worse performance against the pass (LaPlaca & McCullick, 2020). This likely reflects a difference in player builds and roles, where stronger players have an advantage against the run, and weaker players succeed only if they are particularly good against the pass.

It is important to note that although the effects for linebackers seem counterintuitive, they are often consistent across multiple related measures (consistent across measures of pass defense, run defense, or pass rushing). Thus, they do not appear to be spurious.

Defensive Backs

Among defensive backs there are two main types: cornerbacks and safeties. Cornerbacks (corners for short) are charged mainly with covering wide receivers. Safeties cover wide receivers, tight ends, and running backs, and are more heavily involved in defending against the run. Safeties can also be subdivided into free safeties and strong safeties with the former being somewhat more likely to cover the deeper portions of the field, and the latter more likely to play near the line of scrimmage with more responsibilities involving stopping the run. However, the roles and even use of the terms free and strong safety differ somewhat between defensive systems, and many players play both positions.

Robbins (2010) found that faster corners and free safeties were more likely to be drafted earlier than slower corners and free safeties, but these relationships were at times stronger when adjusting for player size. Robbins (2010) also found that higher bench press repetitions were related to being drafted earlier for free safeties.

In terms of performance, significant effects are few and potentially sporadic, as they appear for some measures of coverage or run defenses but not others. For example, faster corners (lower 40-yard dash time) played more games and broke up more passes, but paradoxically they gave up *more* catches per play and took more penalties per play.

Research Limitations and Challenges

Sample Size

The most striking limitation of many previous studies is the small sample sizes. Despite NFL Combine data being readily available as far back as 1999, many studies have focused on smaller data sets examining only a few years of Combine data. Studies are further limited because they look at only a limited number of performance years; few examine performance beyond the third year in the NFL. The argument for focusing only on the first three years is that the average NFL career length is 3.5 years (Lyons et al., 2011). However, this approach limits the conclusions that can be made only to predictions of early career success. If the goal for high draft picks is to acquire players who will eventually become "stars," it makes sense to look beyond the third year. Furthermore, many studies look at performance within each year separately. The problem with doing so is that injuries can drastically lower performance in a given year, not every player plays extensively their rookie season, and seasons last only 16 games (prior to 2021). This means that conclusions about each player, for each year, are drawn from a very small sample of both within- and between-subjects data. We argue that by expanding this timeframe, one can capture more stable performance estimates.

In the current study, we examine five years of performance data, as well as career data. We chose the first timeframe because, as of the NFL's 2011 collective bargaining agreement (NFL Players Association, 2011), newly drafted players sign four-year contracts with a fifth-year option. Thus, scouts and general managers should be most interested in determining which players can give the largest boost to their teams within five seasons. A player who reaches their potential only after the fifth year likely does so playing for a different team.

Combining and Splitting Position Groups

Another limitation of past research is inconsistency in how position groups are combined or divided. On the one hand, as we have described, positions within groups (e.g., defensive backs) might play different roles and therefore might have different predictors of performance. On the other hand, this further limits samples sizes, which limits statistical power.

Additionally, many positions are not exclusive. The same player may play one game at guard and another at center depending on injuries or performance. The NFL even has terms for such players: for example, "swing guard" (players who play guard or center) and "swing tackle" (players who play tackle or guard) are sometimes used to describe versatile backup linemen. The same issue applies to safeties. Depending on the defensive system, a strong and free safety may have very similar or very different jobs. Likewise, many safeties play both positions at different times. Thus, splitting position groups may not accurately capture a player's position.

Likewise, splitting position groups is problematic when the position a player plays in college changes when entering the NFL. Many NFL guards are players deemed too short or unathletic to play offensive tackle (Butchko, 2018). Some of these players enter the Combine as tackles whereas others are listed as guards, in anticipation of a position change (Butchko, 2018). Thus, the separate designations listed at the Combine may not reflect the position these players play in the NFL.

NFL teams and databases also differ in how they list players on their rosters. Some choose to list more specific (e.g., left tackle, left guard, etc.) or more general (e.g., offensive lineman) positions. Thus, determining what position a player typically plays in the NFL can be difficult, especially for non-starters who back up multiple positions. Even more difficult is determining which position a player who did not make an NFL roster was playing (in training camp or preseason) before he was cut. Thus, any analysis of who does and does not make it in the NFL will have to use Combine rather than NFL position listings.

Combining position groups can create other problems as well. Some studies have combined defensive ends and defensive tackles into the same category despite defensive ends being much smaller and faster on average. Several studies even together Combine offensive and defensive position groups (McGee & Burkett, 2003; Sawyer et al., 2002). This can pose issues when comparing performance, as the skills needed to perform on offense and defense may differ substantially.

Another issue alluded to earlier is that terminology has changed over time. Players who excel at rushing the passer from the edges of the defense are now often referred to as “edge rushers.” These players may line up at defensive end in a 4-3 defense and outside linebacker in a 3-4. Likewise, the term interior defensive lineman is now applied to those who play defensive tackle in a 4-3, and nose tackle or defensive end in a 3-4 (ITP Editors, 2016).

Finding the right level of discrimination between positions is key for having ample sample sizes while still comparing players who ultimately perform similar roles.

Team Success Affects Player Success

Although studies vary in the outcome measures examined, many use individual statistics as outcome measures. This presents two main problems: 1) The success of any one individual is partially dependent on their teammates. 2) Some positions have few official statistics for use as outcome measures. For example, offensive linemen do not typically record catches, carries, or score touchdowns. The statistics they do log are often negative: allowed penalties or sacks. While these may seem useful, a player who is not on the field cannot log these, thus a good starter will still have more negative statistics than a backup who does not play. Similar problems exist for defensive backs. Although defensive backs do get credited for tackles, interceptions, and passes defensed, the best coverage players have fewer opportunities to log interceptions and passes defensed, because opposing teams avoid throwing their direction. As a result, most studies have focused on running backs, quarterbacks, and receivers, or have focused on limited and sometimes undiagnostic defensive statistics.

To address these issues, when testing which Combine measures predict elite performance, we focus on position-based accolades—pro bowls and all-pro recognitions. Although this cannot fully eliminate the effect of team success on player success, players from losing teams can and do often earn these accolades. Furthermore, accolades are given out to each position, not just players who log official statistics.

No Adjustment for Arm Length in the Bench Press

Many positions in the NFL rely heavily on size and strength. For this reason, it is surprising that so few studies have examined whether the 225lb bench press drill predicts NFL success. Studies that have examined bench press as a predictor often find weak, at best, relationships between strength and performance (e.g., Cook et al., 2020; LaPlaca & McCullick, 2020; McGee & Burkett, 2003). One reason bench press likely correlates poorly with performance is that studies examining this predictor have failed to account for player arm length. When lifting weights, the total force exerted is based not only on the weight moved, but the distance it is moved. In physics terms, work = force × distance. Two players completing 20 repetitions are not demonstrating equal strength if one of those players has considerably longer arms than the other. Although arm length is measured at the NFL Combine, these data are not readily available beyond the last few years. Arm length can be roughly estimated based on player height (see https://plot.ly/~16HGulick/11.embed). Adjusting for estimated arm length may reveal previously hidden relationships between the 225lb bench press and player success in the NFL.

Statistical Methodology

Many previous studies have relied on univariate methods. That is, they have looked at correlations between each measure and each performance outcome without controlling for other measures. Others have used stepwise regression to determine which variables best predict performance. Although stepwise regression “controls for” the variance in performance explained by other predictors, without the inclusion of interaction terms, the model assumes that each predictor is additive. This is in opposition to how scouts often describe the best prospects (Trapasso, 2020). Specifically, scouts often comment on players as being “big and fast,” suggesting that it is the combination of those traits, not either trait by itself, that makes some prospects so much better than others (Trapasso, 2020). Univariate correlations and simple regression models cannot answer the basic question being asked: "What combination of traits makes for an NFL player, starter, or star?" This is precisely the goal of DFA and the current study.

One notable exception is the analyses of wide receiver and tight end prospects conducted by Mulholland and Jensen (2014; 2016). These studies used a decision tree model that takes the statistically most predictive predictor and splits the sample according to this predictor before determining the next most important predictor for each of those two samples. This method creates a series of profiles that potentially describe different types of players at each position. One potential downside of this approach is that at each step in the decision tree, the sample size again gets split. This results in some very small samples and potentially non-representative findings at the lower levels of the decision tree.

Outliers and Missing Data

Finally, and critically, all studies of Combine data face issues with outliers and missing data. Not every player performs every drill, thus missing data is common. Often this results in players being dropped from the dataset if the analytic method cannot handle missing data. Unfortunately, this issue plagues both simple regression models, as well as the discriminant function models employed in the current study. Only players with data for all relevant skills can be included in the sample.

Outliers pose another issue. Univariate outliers in any correlational analysis can distort results (Tabachnick & Fiddell, 2013). Outliers in human performance data are particularly interesting as extremely poor values may be the result of missteps, injuries, or fatigue, which are not representative of the athlete's actual ability. By contrast, exceptional performance is unlikely to result from an error. However, both can influence the model in ways that misrepresent relationships between predictors and outcomes. Unfortunately, studies of the NFL Combine have not typically indicated any adjustments to curb the influence of outliers.

Multivariate outliers are another problem for multivariate analyses. Multivariate outliers occur when one or more scores are anomalously high or low given the other scores (which are loosely correlated among the rest of the dataset). When analyzing human performance data this could occur for one of two reasons: 1) An athlete may be a "one trick pony" who excels in one ability (e.g., sprinting) but is particularly weak in other, usually related abilities (e.g., change of direction); 2) One of the measures is not indicative of the athlete's ability; for example, if an athlete is injured during a drill, his performance on subsequent drills may be very poor whereas prior drill performance may be better. In this later case, the multivariate outlier indicates a potentially invalid measure of ability. No prior studies examining NFL performance have indicated how or if they dealt with multivariate outliers.

Methods

Experimental Approach to the Problem

The current study uses discriminant function analysis (DFA) to answer three questions for each position group:

1) What combination of NFL Combine measures do scouts and general managers use to select draft picks (drafted v. not drafted)?
2) What combination of NFL Combine measures predict who becomes a regular starter in the NFL (lower quartile v. upper quartile)?[2]
3) What combination of NFL Combine measures predict who becomes a star in the NFL (selected for all-pro team and/or pro bowl vs. not selected for either honor)?

Subjects

Subjects for this study included Combine participants from the years 2000 and 2018. Subjects were analyzed by their position groups listed in pro-football-reference.com/draft; however, some groups were combined for reasons described below. Final sample sizes for each position group are shown in Table 3.

Institutional Review Board approval was not required for this study, as this study was a secondary analysis of data available through web-based public access domains which disclose no individual health information.

Table 3. Sample size by position

Position	Combine participants	Missing data	Multivariate outliers	Number Winsorized		Final *n*
				High Performers	Low Performers	
Quarterbacks	170	53	0	0	1	117
Running backs	408	137	0	1	0	271
Wide Receiver	608	145	1	1	3	462
Tight Ends	260	93	0	3	2	167
Offensive Linemen	692	257	1	4	5	434
Defensive Linemen	371	141	0	1	3	230
Edge rushers	390	130	0	1	0	260
Linebackers	567	197	0	3	2	370
Cornerbacks	503	162	0	1	1	341
Safeties	358	116	0	2	0	242
Fullbacks	79	N/A	N/A	N/A	N/A	N/A
Kickers	35	N/A	N/A	N/A	N/A	N/A
Punters	46	N/A	N/A	N/A	N/A	N/A
Long snappers	7	N/A	N/A	N/A	N/A	N/A

Note. Number Winsorized = number of subjects with at least one predictor that was Winsorized at 2.99 standard deviations above or below the mean. Fullbacks, safeties, kickers, punters, and long snappers were not included in any analyses.

Quarterbacks. We coded any player labeled as quarterback (QB) in pro-football-reference.com/draft as quarterback in our dataset.

Running backs. We coded any player labeled as running back (RB) in pro-football-reference.com/draft as running back in our dataset. We did not include fullbacks (FB) in our analyses as too few players were listed at this position and not every team employs these players in their offenses (Freeman, 2017).

Wide receivers. We coded any player labeled as wide receiver (WR) in pro-football-reference.com/draft, as wide receiver in our dataset. We did not differentiate between outside “X” receivers who typically line up on the edge of the offense and “slot” or “Z” receivers who typically line up closer to the offensive line and a step or two behind the line of scrimmage (Kelly, 2012). This is because these designations are not available in our databases and some players will line up at as an X receiver on one play and a Z on another.
Tight ends. We coded any player labeled as tight end (TE) in pro-football-reference.com/draft as tight end in our dataset. As with wide receivers, we did not differentiate between differ “types” of tight ends (“F” receiving tight ends versus “Y” blocking tight ends) as these designations are not available in our database (Hill, 2014).

Offensive linemen. We coded any player listed as an offensive lineman (OL), offensive guard (OG), offensive tackle (OT), or center (C) in pro-football-reference.com/draft as an offensive lineman. Although we suspect that height and athleticism are more important for an NFL tackle than an NFL guard, many college tackles lacking in these areas are moved to guard or center in the NFL and many players in the NFL ultimately end up playing more than one offensive line position (Butchko, 2018).

Defensive tackles. We coded only players listed as defensive linemen (DL) or defensive tackles (DT) in pro-football-reference.com/draft as defensive linemen. We did not differentiate between defensive linemen who specialize in rushing the passer and those who specialize in stopping the run for the same reasons we do not differentiate between different types of wide receivers or tight ends. We did not include players listed as defensive ends (DE) or as edge rushers (EDGE) in this category, as these players fill a fundamentally different role and with it, often possess different body types (see Table 4) and skill sets (Dockett, 2018).

Table 4. Means and standard deviations for Combine measures by position

	Offensive Positions									
	Quarterbacks		Running Backs		Wide Receivers		Tight Ends		Offensive Line	
Combine measure	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Height	**75.0**	**1.55**	**70.6**	**1.92**	**72.7**	**2.23**	**76.2**	**1.41**	**76.6**	**1.49**
Weight	**223**	**10.9**	**215**	**13.0**	**201**	**14.6**	**254**	**11.5**	**313**	**12.5**
40-yard dash	**4.82**	**0.19**	**4.54**	**0.10**	**4.50**	**0.10**	**4.75**	**0.15**	**5.24**	**0.17**
20-yard shuttle	**4.31**	**0.18**	4.26	0.16	4.20	0.15	4.34	0.16	**4.71**	**0.19**
3-cone drill	**7.14**	**0.24**	7.05	0.22	6.94	0.21	7.15	0.23	**7.80**	**0.29**
Vertical jump	**31.7**	**3.01**	**34.8**	**3.00**	**35.5**	**3.19**	**33.5**	**3.32**	**28.1**	**2.97**
Broad jump	**110.1**	**6.89**	**119.2**	**5.47**	**120.8**	**5.66**	**115.5**	**5.96**	**102.4**	**6.23**
Bench press (work)	865	217	**940**	**216**	711	197	**1,049**	**211**	**1,305**	**252**
	Defensive Positions									
	Defensive Tackles		Edge Rushers		Linebackers		Cornerbacks		Safeties	
Combine measure	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Height	**74.9**	**1.42**	**76.0**	**1.42**	**73.8**	**1.22**	**71.4**	**1.70**	**72.6**	**1.54**
Weight	**307**	**14.34**	**268**	**13.61**	**241**	**8.54**	**194**	**8.86**	**208**	**8.48**
40-yard dash	**5.08**	**0.15**	**4.81**	**0.14**	**4.69**	**0.12**	**4.48**	**0.09**	**4.54**	**0.09**
20-yard shuttle	4.62	0.18	4.41	0.17	4.28	0.15	4.15	0.15	4.18	0.14
3-cone drill	7.67	0.27	7.30	0.24	7.12	0.22	6.93	0.21	6.97	0.21
Vertical jump	**29.4**	**2.94**	**33.3**	**3.19**	**34.3**	**3.28**	**36.1**	**2.81**	**35.9**	**2.91**
Broad jump	**105**	**5.53**	**115**	**6.10**	**117**	**5.82**	**122**	**5.40**	**121**	**5.81**
Work (in foot pounds)	**1,405**	**271**	**1,229**	**245**	**1,124**	**222**	**699**	**199**	**823**	**202**

Note. Numbers in bold type indicate measures retained for analysis.

Edge rushers. The classification of players on the defensive side of the ball has changed somewhat over the past two decades (Holler, 2017). Because the same player may play what were traditionally different positions (e.g., defensive end and outside linebacker) in different formations, the use of the term defensive end as a position category has fallen out of favor. More recently, the term “edge rusher” has supplanted defensive end to indicate a player whose primary job is to rush the passer and stop the run while playing at the “edge” of the defensive line (a defensive end in a four-man defensive front and an outside linebacker in a three-man defensive front; ITP Editors, 2016). Thus, we coded both defensive ends (DE) and edge rushers (EDGE) in Pro Football Reference (pro-football-reference.com/draft) as edge rushers in our data set.[3]

Linebackers. Similar to edge rushers, changes to the NFL defensive strategies have led to a change in the terminology used to categorize linebackers. The distinction between outside linebackers and middle linebackers has blurred to the point where both have been replaced by the singular "linebacker" designation for draft purposes. As with offensive linemen, this is further complicated by the fact that many players will play multiple "linebacker positions" throughout their careers. Thus, we coded any player listed as a linebacker (LB), outside linebacker (OLB), inside linebacker (ILB), or middle linebacker (MLB) in pro-football-reference.com/draft as a linebacker.

Cornerbacks. We coded any player labeled as a cornerback (CB) in pro-football-reference.com/draft as cornerback in our dataset.

Safeties. Similar to edge rushers and linebackers, the traditional designations of free safety (FS) and strong safety (SS) do not apply to each defensive system. Thus, we coded any player listed as safety (S), strong safety (SS), or free safety (FS) in pro-football-reference.com/draft as a safety in our dataset.

Procedures

Data Collection

The data of the NFL Combine and success measures were obtained from pro-football-reference.com. Combine data and physical measurements (height and weight) were first collected for each year included in the analyses (2000-2018). Specific Combine drills included in the analyses are described below. Then, success measures on each participating subject, whether drafted or undrafted, were collected for the subject's first five years playing in the NFL, and for the subject's career. The success data collected is described below.

NFL Combine Predictors

We include 40-yard dash, three-cone drill, and 20-yard shuttle times. We also include height, weight, vertical and broad jumps (each in inches), and a measure of physical strength as a function of player height.

To estimate physical strength, we first estimated player arm length by multiplying the player's height by 0.43). We then multiplied estimated arm length by 225 pounds and the number of repetitions a player performed in the 225lb bench press event. This yields a measure of inch pounds, which is then converted to the more common "foot pounds" by dividing by 12. Thus, unlike previous analyses using bench press repetitions (Teramoto et al., 2016), we control for (approximate) player arm length. This measure approximates "total work done" in the physics sense (work = force × distance).

Measures of Success

Drafted

Our first analysis addresses what information scouts and general managers are (apparently) using when drafting players by looking at which measures best predict who gets drafted at each position. These analyses can be compared to the analyses of performance-related outcomes to see where scouts and general managers are perhaps over- or under-valuing certain measures from the Combine. For these analyses, players were categorized as being selected or not being selected in the NFL draft.

Games Started in First 5 Years

Whereas the previous analyses determined who was drafted, the next set of analyses looks at who is most likely to become starters at their respective positions. Here, our outcome variable is whether a player falls in the upper or lower quartile for their position for games started in their first five years. This metric was adjusted for players fewer than five seasons removed from the draft (at the time of analysis). The lower quartile contains mostly players who failed to make the roster, whereas the upper quartile typically contains players who started roughly half of their games.

Multiple Honors in a Career

Last, we look at what predicts who will become one of the better players at their respective position. We use two awards for our analysis here: the All-Pro team and the Pro Bowl rosters.

The All-Pro team is compiled and voted on by the Pro Football Writer Association (a set of sports writers and thus, presumed football experts). Although the exact makeup of the All-Pro team differs from year-to-year, the team typically consisted of two to four players per position group.

The Pro Bowl is the NFL's annual all-star game. Players are chosen based on a combination of sports writers and fan voting. Although the format has changed over the years in question, there are typically 1-3 players per starting position and from each conference who are named to the two respective Pro Bowl teams, plus alternates who play (and receive honors) if a player ahead of them opts out. In all, two to three times as many players are named to the Pro Bowl each year as the All-Pro Team. In our dataset we treat these measures as equivalent as most All-Pro selections typically also make the Pro Bowl. Thus, being awarded both honors in a single season is treated the same as being awarded Pro Bowl honors in two seasons. Here the outcome variable is whether players earn two or more such honors during their career vs. those who earn fewer than two such honors in their careers.

Statistical Analyses

Predictors

Discriminant function analyses (DFA) are statistical models designed to predict group membership from a set of predictors. The model creates a discriminant function, which is a latent variable representing a linear combination of the predictor variables and reveals the best linear *combination* of predictors that differentiate groups. DFA is similar to binary logistic regression (when differentiating two groups) but is more powerful (Tabachnick & Fidell, 2007) and provides more accurate classifications than binary logistic regression when assumptions are held (Grimm & Yarnold, 1995).

DFA also has advantages over univariate analyses such as ANOVAs that test for differences between groups along a single dimension. When complex datasets are analyzed in this way, effects from predictors that work with other predictors will be parceled out and can therefore give an inaccurate picture of predictors working in tandem. DFA also provides information on the sensitivity and specificity of the model—in our case, how well the model correctly classifies more successful players as more successful and less successful players as less successful.

DFA requires full data and thus removes cases using list-wise deletion. We set a criterion of 74%, where only measures that 74% of the participants completed would be included for each position group. This cutoff was chosen post-hoc but before running our primary analyses. To raise this criterion to 75% would have eliminated the three-cone drill as a predictor for quarterbacks and offensive linemen. Lowering this criterion below 74% would have added 20-yard shuttle time as a predictor to the edge rushers, but at the cost of 10% of that sample (an additional 10% of the players would be lost because they did not complete this drill). Table 3 shows the measures retained for each position and their means and standard deviations.

Next, we eliminated all players with missing data on the retained predictor variables. We then *z*-transformed all predictors separately by position group. Because DFA is sensitive to outliers, we Winsorized outliers that were greater than three standard deviations above their position mean by setting those values to 2.99. Table 3 shows the number of individuals Winsorized in each position group, separately for high performing outliers (likely valid data points) and low performance outliers (likely a combination of valid and invalid data points, i.e., a player falls or gets injured during a drill resulting in a poor performance measure).

Before conducting the models, we checked for multivariate outliers by computing Mahalanobis distance and removing any observations significant at the .001 level. This resulted in the removal of one wide receiver and one offensive lineman. Q-Q plots were visually inspected and showed no marked deviations from normality.

We used stepwise discriminant function analyses. The stepwise method is best when there are many predictors and the analyses are data-driven; this method automatically selects the predictors with the greatest discriminatory ability for the model. Only models significant at the $p < .05$ level (two-tailed) were deemed significant.

Outcome Variables

Draft status was scored 0 (not drafted) or 1 (drafted). For games started, we coded the lower quartile as 0 and the upper quartile as 1, removing the intermediate observations. Receiving multiple honors in a career was scored a 0 if a player made fewer than 2 all-pro and/or pro bowl teams, and a 1 if they made two or more such teams.

Importantly, each outcome variable is analyzed separately. Although they are correlated somewhat, these correlations are relatively low (*r*s = .08—.53), making the analyses largely, but not entirely independent.

Results

Prior to *z*-transforming the predictors, correlations between Combine measures for the sample were high (many *r*s > .70, Appendix A), particularly among timed measures (40-yard dash, 20-yard shuttle, 3-cone drill) as well as measures of explosiveness (vertical jump and broad jump). Thus, at the sample level, the correlations pick up differences in player types (skill position players with great speed versus linemen with greater strength and lesser speed). However, correlations between measures within a position group were much smaller (most *r*s < .50, Appendix B). Thus, each measure is dissociable at the position level. This is critical for DFA and more generally the utility of having multiple measures of athletic ability.

Position-by-Position Results

For each position group we explore three questions and discuss the results relative to each other. A successful DFA is one in which more than one predictor emerges. However, we report the results when a single predictor differentiates groups as well (in this case, the DFA becomes a univariate analysis). Our discriminant function analyses produce two different effect sizes: a percentage of the variance in the dependent variable explained by the combined predictors (a canonical *R*-squared value × 100) and a percentage of how many players are correctly classified by the predictor variables. When one group is substantially smaller than the other, as is the case for players who are drafted vs undrafted, and players who earn honors during their careers vs those who do not, most players will fall within a single group, making the aforementioned percentage correctly classified appear deceptively high. Thus, we only present this outcome for those who starts on a regular basis where the groups are relatively even. Descriptive statistics for each position can be found in Appendix C.

Quarterbacks

Who gets drafted? Quarterbacks with the best combination of height and change-in-direction speed performance were significantly more likely to be drafted, Wilks' Lambda = 0.85, $\chi^2 = 18.42$, $p < .001$. The combination of height and time on the 20-yard shuttle accounted for 15% of the between group variance.

Who becomes a regular starter? Quarterbacks with faster shuttle times were most likely to be regular starters, Wilks' Lambda = 0.91, $\chi^2 = 5.77$, $p = .016$. Shuttle time accounted for 9% of the between group variance.

Who becomes a star? No statistical model successfully discriminated between the quarterbacks meeting our elite All-Pro/Pro Bowl roster criteria for their first five years and those not meeting our criteria for any Combine measure or combination of measures. Likewise, no statistical model successfully discriminated between the quarterbacks meeting our elite All-Pro/Pro Bowl roster criteria for their entire career and those not meeting our criteria for any Combine measure or combination of measures.

Quarterback Discussion. Our findings largely suggest that while focus on 20-yard shuttle times is appropriate, the focus on quarterback height during the draft may be misguided. Of all the positions, the quarterback might be most likely to be drafted and succeed based on non-physical skills such as quickly processing information, reading the defense, and recognizing blitzes—skills not captured by NFL Combine measures.

Running Backs

Who gets drafted? The fastest running backs were most likely to be drafted, Wilks' Lambda = 0.87, χ^2 = 39.07, p < .001. Forty-yard dash times accounted for 14% of the between-group variance.

Who becomes a regular starter? Running backs with the best combination of body mass and speed were most likely to be regular starters, Wilks' Lambda = 0.91, χ^2 = 13.41, p = .001. Weight and 40-yard dash times accounted for 9% of the between-group variance. Overall, the statistical model with weight and 40-yard dash times as predictors correctly classified 63% of the running backs.

Who becomes a star? The fastest running backs were most likely to join elite rosters in their career, Wilks' Lambda = 0.97, χ^2 = 8.80, p = .003. Forty-yard dash times accounted for 3% of the between-group variance.

Running Back Discussion. The finding that running back height was related to games started was unexpected. However, the general finding that 40-yard dash times translate into running back success are consistent with previous research (Kumitz & Adams, 2008; Vincent et al., 2019). The use of the 40-yard dash in drafting running backs appears to be wholly appropriate. Unfortunately, too few running backs complete the 20-yard shuttle or 3-cone drills. Thus, we were not able to assess how agility relates to draft status or success at the position.

Wide Receivers

Who gets drafted? Wide receivers with the best combination of speed and vertical jumping ability were most likely to be drafted, Wilks' Lambda = 0.91, χ^2 = 43.79, p < .001. The combination of 40-yard dash times and vertical inches accounted for 9% of the between-group variance.

Who becomes a regular starter? Wide receivers with the highest vertical jump were most likely to be regular starters, Wilks' Lambda = 0.95, χ^2 = 12.86, p < .001. Vertical inches accounted for 5% of the between group variance.

Who becomes a star? No Combine measures successfully discriminated between the wide receivers meeting our elite All-Pro/Pro Bowl roster criteria.

Wide Receiver Discussion. These results suggest that teams may be placing too much value on speed at the wide receiver position. By contrast, the emphasis on the ability to jump high (critical for catching high passes) is appropriate and in line with previous research (Mulholland & Jensen, 2016; Pitts & Evans, 2019; Robbins, 2010; Vincent et al., 2019). As with running backs, too few draft prospects completed the agility drills for us to evaluate their contribution to draft status or success at the wide receiver position.

Tight Ends

Who gets drafted? Tight ends with the best combination of speed and strength were most likely to be drafted, Wilks' Lambda = 0.88, χ^2 = 20.35, p < .001. Forty-yard dash and bench press (work) combined accounted for 12% of the between-group variance.

Who becomes a regular starter? Tight ends with the greatest strength were most likely to be regular starters, Wilks' Lambda = 0.86, χ^2 = 11.74, p = .001. Bench press (work) accounted for 14% of the between group variance.

Who becomes a star? No statistical model successfully discriminated between the tight ends meeting our elite All-Pro/Pro Bowl roster criteria.

Tight End Discussion. As indicated previously, tight end success is particularly difficult as tight ends often fall into different "categories" as primarily receiving tight ends, primarily blocking tight ends, or in rare cases, those who excel at both aspects of the position. Indeed, some general managers and coaches describe tight ends as being either "F" (mobile receiving) tight ends or "Y" (blocking) tight ends (Hill, 2014). However, without an objective way of knowing how teams would classify each player in our dataset, we cannot test whether certain measures are tied more closely to success at one or the other type of tight end.

Offensive Linemen

Who gets drafted? Offensive linemen with the best combination of speed and vertical jumping ability were most likely to be drafted, Wilks' Lambda = 0.96, $\chi^2 = 17.54$, $p < .001$. Forty-yard dash times and vertical inches combined accounted for 4% of the between-group variance.

Who becomes a regular starter? Offensive linemen with the best vertical jumping ability were most likely to be regular starters, Wilks' Lambda = 0.97, $\chi^2 = 7.30$, $p = .007$. Vertical inches accounted for 3% of the between-group variance.

Who becomes a star? The strongest offensive linemen were more likely to meet our elite All-Pro/Pro Bowl roster criteria for their entire career than those not meeting these, Wilks' Lambda = 0.98, $\chi^2 = 7.38$, $p = .007$. Bench press (work) accounted for 2% of the between-group variance.

Offensive Linemen Discussion. The finding that vertical jump (an indicator of lower body strength for linemen) predicts games started is consistent with past research showing vertical jump to be a significant predictor of an offensive lineman's longevity (Asprey et al., 2020), though a different predictor emerged for honors. Greater upper-body strength (225lb bench press) was associated with elite performance among offensive linemen.

Defensive Tackles

Who gets drafted? Defensive tackles with the best combination of body mass and horizontal jumping ability were most likely to be drafted, Wilks' Lambda = 0.95, $\chi^2 = 12.65$, $p = .002$. Weight and broad jump inches combined accounted for 5% of the between-group variance.

Who becomes a regular starter? Defensive tackles with the best combination of body mass and speed were most likely to be regular starters, Wilks' Lambda = 0.90, $\chi^2 = 12.68$, $p = .002$. Weight and 40-yard dash times combined accounted for 10% of the between-group variance. Overall, the statistical model with weight and 40-yard dash as predictors correctly classified 66% of the players to their respective group.

Who becomes a star? The fastest defensive tackles were more likely to meet our elite All-Pro/Pro Bowl roster criteria for their career than those not meeting these criteria, Wilks' Lambda = 0.98, $\chi^2 = 5.80$, $p = .016$. Forty-yard dash times accounted for 3% of the between-group variance.

Defensive Tackle Discussion. Especially strong defensive tackles (sometimes called 2-gap tackles) are often charged with occupying blockers to "free up" other players to make tackles or get sacks. In contrast, especially fast defensive tackles (sometimes called 1-gap tackles) are often asked to disengage from blockers to make tackles and directly apply pressure on the quarterback. As a result, it is these faster players who often compile better stats and get more attention from fans. Thus, they play a different role on the team, but are more likely to end up with honors than their bigger, stronger peers.

Edge Rushers

Who gets drafted? Edge rushers with the best combination of speed, vertical jumping ability, and body mass were most likely to be drafted, Wilks' Lambda = 0.82, $\chi^2 = 51.73$, $p < .001$. Forty-yard dash times, vertical inches, and weight combined accounted for 18% of the between-group variance.

Who becomes a regular starter? Edge rushers with the best combination of body mass and horizontal jumping ability (broad jump) were most likely to be regular starters, Wilks' Lambda = 0.84, $\chi^2 = 22.12$, $p < .001$. Weight and broad jump inches combined accounted for 16% of the between-group variance. Overall, the statistical model with weight and broad jump as predictors correctly classified 70% of the players to their respective group.

Who becomes a star? Edge rushers with the best combination of speed and body mass were more likely to meet our elite All-Pro/Pro Bowl roster criteria for their career than those not meeting these criteria, Wilks' Lambda = 0.95, $\chi^2 = 13.13$, $p = .001$. Forty-yard dash times and weight combined accounted for 5% of the between-group variance.

Edge Rusher Discussion. Our discriminant function analyses were more successful for predicting edge rusher performance than any other position. Our results suggest that scouts and general managers generally use the same variables that predict success, with one exception: Scouts and general managers more often draft big, fast players who excel at the vertical jump. However, it is actually big, fast players who excel at the broad jump that typically go on to be the most productive players.

Linebackers

Who gets drafted? The fastest linebackers were most likely to be drafted, Wilks' Lambda = 0.93, χ^2 =26.12, $p < .001$. Forty-yard dash times accounted for 7% of the between-group variance.

Who becomes a regular starter? Linebackers with the best combination of speed and body mass were most likely to be regular starters, Wilks' Lambda = 0.90, χ^2 = 20.96, $p < .001$. Forty-yard dash time and weight combined accounted for 10% of the between-group variance. Overall, the statistical model with 40-yard dash and weight as predictors correctly classified 61% of the players to their respective group.

Who becomes a star? Linebackers with the best combination of vertical jumping ability and body mass were more likely to meet our elite All-Pro/Pro Bowl roster criteria for their career than those not meeting these criteria, Wilks' Lambda = 0.93, χ^2 = 28.41, $p < .001$. Vertical inches and weight combined accounted for 7% of the between-group variance.

***Linebacker Discussion*.** Teams appear to value speed at the linebacker position, and faster linebackers are more likely to contribute as starters. However, it was the bigger linebackers with better jumping ability—an indicator of lower body strength and explosive movement—that typically won honors at the position. This position, like offensive linemen, is another where vertical, rather than horizontal jumping ability predicted success. Size also appears important for linebackers.

Cornerbacks

Who gets drafted? Cornerbacks with the best combination of speed and strength were most likely to be drafted, Wilks' Lambda = 0.91, χ^2 = 30.40, $p < .001$. Forty-yard dash times and bench press (work) combined accounted for 9% of the between-group variance.

Who becomes a regular starter? Cornerbacks with the best combination of speed and body mass were most likely to be regular starters, Wilks' Lambda = 0.85, χ^2 = 29.68, $p < .001$. Forty-yard dash time and weight combined accounted for 15% of the between-group variance. Overall, the statistical model with 40-yard dash times and weight as predictors correctly classified 68% of the players to their respective group.

Who becomes a star? Cornerbacks with better horizontal jumping ability were more likely to meet our elite All-Pro/Pro Bowl roster criteria for their career than those not meeting these criteria, Wilks' Lambda = 0.98, χ^2 = 5.61, $p = .018$. Broad jump inches accounted for 2% of the between-group variance.

Cornerback Discussion. While the emphasis on speed in the draft appears appropriate for evaluating cornerbacks, the inconsistency between predictors for elite performance (honors) and lower-level measures of success (games started) are reasons to be cautious about overinterpreting the data with respect to elite performance.

Safeties

Who gets drafted? Safeties with the best combination of speed and height were most likely to be drafted, Wilks' Lambda = 0.94, χ^2 =14.56, $p < .001$. Forty-yard dash times and height combined accounted for 6% of the between-group variance.

Who becomes a regular starter? No Combine measure successfully differentiated safeties who were frequent starters from safeties who infrequently started.

Who becomes a star? The fastest safeties were more likely to meet our elite All-Pro/Pro Bowl roster criteria for their career than those not meeting these criteria, Wilks' Lambda = 0.95, χ^2 = 13.18, $p < .001$. Forty-yard dash time accounted for 5% of the between-group variance.

Safety Discussion. While speed is perhaps rightly emphasized when trying to find an elite safety, no measure predicted who would become a regular starter at the position. We found no evidence that height contributes to success at the position, despite its apparent emphasis in the draft process. Indeed, we did not expect that height would be a factor at all for safeties, thus we interpret its appearance in the model for draft status cautiously.

General Discussion

The current study is the largest examination of NFL Combine scores as predictors of football player success metrics to date, utilizing more years of data and more participants in total than any other study on the topic. The current study also represents the first to use discriminant function analysis to examine the *combination* of traits that best predicts who will be drafted, who will be a regular starter, and who will be a star at multiple positions. Although Mulholland and Jensen's (2014; 2016) recursive partitioning trees also identify a combination of traits related to success, their analyses were restricted to wide receivers and tight ends and produce rapidly diminishing sample sizes at each step, limiting power.

The discriminant function analysis results point to a number of interesting findings, some novel, and some reflective of the existing literature. In each case, we argue that these findings are important for determining whether previous studies, often using univariate statistics, represent reliable or spurious findings, and whether certain variables "hide" in multivariate space, because they are primarily useful when combined with other necessary abilities.

Discriminant Function Analyses Predict Draft Status

Overall, the results for draft status were stronger than those for player success. Eight of the ten discriminant function analyses were successful in determining a combination of traits that predicted who was drafted. Even so, these analyses varied in their ability to explain variance across participants, from over 18% in edge rushers down to less than 5.5% for defensive tackles.

The Combine is more Predictive of Defensive Success than Offensive Success

Our discriminant function analyses were generally more successful for finding a combination of abilities predicting defensive, rather than offensive success, with 6 of 10 discriminant function analyses revealing more than one predictor for defensive player success but only 1 of 10 for offensive player success. These results suggest that having the right combination of raw athletic abilities may be more important for defensive players and, statistically speaking, provide a much better predictor of defensive performance.

Scouts and GMs Have it Mostly Right

In many cases, the same predictors emerged for both draft status and player performance, but in other cases scouts and general managers appear to be weighing potentially undiagnostic variables or failing to consider others. Notably, fast wide receivers, tight ends, and offensive linemen are more likely to be drafted, but not necessarily more likely to be successful. Likewise, cornerback strength, edge rusher vertical jump, safety height, and defensive tackle broad jump were all predictive of draft status, but not performance. By contrast, defensive tackle speed, and linebacker weight were both significant predictors of multiple performance measures, but presumably overlooked by scouts and general managers.

Past Research Generally Replicates, but New Patterns Emerge

Our findings are generally consistent with those of past research. Running back speed and wide receiver and offensive lineman vertical jump remain solid predictors of performance. However, our data demonstrate the importance of cornerback speed and weight; edge rusher speed, weight, and horizontal jumping ability (broad jump); and defensive tackle and linebacker speed and weight. It is perhaps not surprising that the "failed" discriminant function analyses, where only a single predictor was significant, mirror previous univariate findings for those positions: our analyses reduce to theirs. By contrast, it is among defensive players where we find new, multivariate relationships that remained hidden in previous univariate analyses. For example, LaPlaca and McCullick (2020) found a relationship between edge rusher success and the broad jump but found a negative correlation between size and pass rushing ability. Our analyses reveal the opposite pattern, where larger edge rushers are actually more successful, provided that they possess the necessary horizontal explosiveness (what the broad jump presumably measures) despite their size. Thus, the univariate data might mislead a scout or general manager to disregard the benefits of a player's size—or worse, lower an evaluation because of a presumed disadvantage related to size (though the latter seems unlikely given the way "big and fast" is often used to describe elite prospects).

Limitations

Despite the interesting findings, there are a number of limitations to the current analyses with respect to both the predictors and outcomes used.

Predictors

Relying solely on NFL Draft Combine performance data, we were able to predict 5-18% of the variance for most of our significant discriminant function analyses. Perhaps the most obvious missing predictors are college performance and competition level, both of which have been shown to be significant predictors in other studies (most notably, Mulholland & Jensen, 2014; 2016). We omitted these data so that we could run similar analyses for each position group. Additionally, like NFL performance statistics, using college statistics as a predictor is problematic as they are confounded with team success. To eliminate this issue, advanced statistics that evaluate a player's performance on a situational basis could be useful, but such statistics have only recently (2014) been made available, and not for every player at every university.

Another limitation is that of missing data. Due to missing data, we had to drop some predictors and some participants from each position group. Most notably, few players complete the 3-cone and 20-yard shuttle drills at the Combine. Thus, it is impossible to know whether these measures, in combination with others, might be important for NFL success at various positions. Although this study is the largest to date in this area, it could not include all relevant data points for this reason. Further, these data points are unlikely to be missing at random and thus could be skewing our effects.

The issue of player classification is another limitation. As mentioned earlier, some pre-draft player positions may not reflect the position players play in the NFL. Without statistics for each player's performance at a given position, it is difficult to discern how certain abilities may differentially predict performance at different positions or tasks. For example, a different combination of skills may be needed for playing offensive guard than for offensive tackle (Butchko, 2018). The same may be true when comparing the coverage and run defense abilities of a linebacker. Although other studies (e.g., LaPlaca & McCullick, 2020) have attempted to do this using advanced statistics as outcomes, these studies were limited to univariate statistics that do not consider the combination of skills (e.g., speed, size, *and* explosiveness) that may be needed for high-level performance.

Last, the current analyses do not include any cognitive or personality measures. The ability to process information quickly and focus attention are potentially relevant to football, as is the ability to learn the playbook. Despite this, the only cognitive measure included at the Combine is the Wonderlic test—a measure of non-football crystalized intelligence. Previous data find only weak relationships between this measure and on-field performance (e.g., Lyons et al., 2009). Additionally, these data are not publicly available, and the values reported on websites are not official. Both these issues could be remediated by using a series of cognitive ability measures and position-specific tests of football knowledge. For cognitive abilities, it would be highly interesting to know if fluid intelligence, working memory, or processing speed measures, which should reflect players' ability to reason and process multiple pieces of information, can predict future NFL success.

Outcomes

The other major limitation comes in the form of the outcome variables used. As with our predictors, we chose outcome variables that are ubiquitous across position groups and less dependent on team success than individual player statistics. However, these measures, particularly when artificially categorized, as is necessary for discriminant function analysis, lose a great deal of nuance. Additionally, variables such as games started do not fully capture a player's contributions. Statistics such as downs played may be better but were not readily available for the time period analyzed (snap counts are available only going back to 2012).

Our measures of elite performance were also limited. Pro Bowl and All-Pro honors are rare and miss important variability among starters. These are also contingent upon who else is in the league. For example, only two quarterbacks will make the All-Pro list, but there are more than two super-star quarterbacks in the league.

Last, although individual statistics are highly sensitive to team success, more advanced statistics could remedy this problem, as sites like pro-football-focus code data based on whether a given player effectively executed their (presumed) assignment, or how well opposing players do when targeting a player in coverage. These stats allow for a more isolated and precise measure of player performance in specific game situations but are available only after 2006 at the earliest and vary in their availability depending on the measure. Thus, when analyzing such data, one invariably runs into issues of power with limited sample sizes.

Practical Applications

As the most comprehensive study of the NFL Draft Combine success metrics to date and the first to employ discriminant function analysis, the current study makes an important contribution to our understanding of how the Combine does and does not predict future player success. These data, in combination with game film and other scouting information, can help scouts and general managers determine which sets of physical traits and skills to prioritize when drafting players. We do not suggest that our results should supplant scouts' observations of on-field player performance, but our results could reasonably serve as important supplemental data. In the event of two players being ranked similarly on other measures, we think that it would be more than reasonable to use NFL Combine data as a tiebreaker—provided that the right *combination* of traits are considered.

Our results also suggest that some measures are erroneously factored into a scout's judgments despite the evidence. Namely, information such as a defensive ends' vertical jump or a cornerback's strength appear to be given consideration that is not warranted. Ultimately, we hope that these results will be useful—for scouts and general managers in the immediate future as well as providing a path for current and future researchers to generate further research using discriminant function analyses for predicting future player performance and success in the NFL.

Endnotes

1. American football is a game akin to rugby and commonly referred to simply as "football" in the United States of America. By contrast, the game known as "football" in most countries is called "soccer" in the United States.
2. We initially intended to examine games played and games started. However, the two measures were so highly correlated for most positions (rs = .65—1.00) as to render the analyses redundant.
3. Admittedly there are some players who might be described differently today than they are coded based on their draft day descriptions from over a decade ago. However, these players do not make up the majority of the data, and similar instances occur with all position groups when a player gets moved to a new position after being drafted. The same was true when evaluating players who earned one or more honors during the first five years of their careers and those earning multiple honors within their entire careers. Thus, we chose to retain the latter, larger sample analysis.

Authors' Declarations

The authors declare that there are no personal or financial conflicts of interest regarding the research in this article.

The authors declare that the research reported in this article was conducted in accordance with the Ethical Principles of the *Journal of Expertise.*

The authors declare that the datasets are publicly available at the following website: https://osf.io/9ntjv/

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Appendix A

Correlations between Combine measures (all positions)

	1	2	3	4	5	6	7
1. Height							
2. Weight	.71						
3. 40-yard dash	.61	.87					
4. 20-yard shuttle	.52	.77	.78				
5. 3-cone drill	.50	.80	.81	.83			
6. Vertical jump	.41	.64	-.73	-.68	-.65		
7. Broad jump	.42	.72	-.82	-.71	-.73	.81	
8. Bench press (work)	.46	.70	.54	.46	.50	-.36	-.44

Note. All correlations are significant at the $p < .001$ level.

Appendix B

Correlations between Combine measures (Quarterbacks)

	1	2	3	4	5	6	7
1. Height							
2. Weight	.62						
3. 40-yard dash	.26	.21					
4. 20-yard shuttle	.21	.12	.47				
5. 3-cone drill	.14	.19	.46	.66			
6. Vertical jump	-.21	-.08	-.65	-.49	-.41		
7. Broad jump	-.08	-.03	-.66	-.49	-.54	.75	
8. Bench press (work)	-.02	.11	.00	.13	.06	-.03	-.03

Note. Correlations of .19 or larger are significant at the $p < .05$ level.

Correlations between Combine measures (Running backs)

	1	2	3	4	5	6	7
1. Height							
2. Weight	.61						
3. 40-yard dash	.08	.26					
4. 20-yard shuttle	.22	.28	.08				
5. 3-cone drill	.13	.24	.03	.74			
6. Vertical jump	.15	.03	-.29	.03	.07		
7. Broad jump	.13	-.04	-.36	-.10	-.06	.64	
8. Bench press (work)	.08	.35	-.07	.05	.09	.12	.04

Note. Correlations of .12 or larger are significant at the $p < .05$ level.

Correlations between Combine measures (Wide receivers)

	1	2	3	4	5	6	7
1. Height							
2. Weight	.71						
3. 40-yard dash	.14	.21					
4. 20-yard shuttle	.02	.01	.08				
5. 3-cone drill	.02	.03	.13	.92			
6. Vertical jump	.03	.01	-.30	-.14	-.10		
7. Broad jump	.22	.12	-.34	-.06	-.08	.57	
8. Bench press (work)	.08	.20	-.09	.10	-.09	.02	.06

Note. Correlations of .10 or larger are significant at the $p < .05$ level.

Correlations between Combine measures (Tight ends)

	1	2	3	4	5	6	7
1. Height							
2. Weight	.37						
3. 40-yard dash	.10	.50					
4. 20-yard shuttle	.19	.11	.20				
5. 3-cone drill	.08	.25	.40	.65			
6. Vertical jump	-.18	-.29	-.52	-.18	-.23		
7. Broad jump	-.03	-.28	-.61	-.18	-.34	.67	
8. Bench press (work)	.08	.23	-.19	-.06	-.05	.19	.18

Note. Correlations of .16 or larger are significant at the $p < .05$ level.

Correlations between Combine measures (Offensive linemen)

	1	2	3	4	5	6	7
1. Height							
2. Weight	.33						
3. 40-yard dash	-.01	.35					
4. 20-yard shuttle	.15	.46	.43				
5. 3-cone drill	.01	.43	.49	.64			
6. Vertical jump	-.02	-.28	-.46	-.43	-.30		
7. Broad jump	.09	-.31	-.58	-.45	-.40	.55	
8. Bench press (work)	-.12	.04	-.27	-.10	-.14	.16	.21

Note. Correlations of .10 or larger are significant at the $p < .05$ level.

Correlations between Combine measures (Defensive linemen)

	1	2	3	4	5	6	7
1. Height							
2. Weight	.17						
3. 40-yard dash	-.03	.41					
4. 20-yard shuttle	-.03	.33	.26				
5. 3-cone drill	.00	.37	.33	.71			
6. Vertical jump	-.06	-.23	-.45	-.21	-.14		
7. Broad jump	.05	-.40	-.58	-.21	-.18	.57	
8. Bench press (work)	-.01	.19	-.10	-.10	-.09	.21	.07

Note. Correlations of .13 or larger are significant at the $p < .05$ level.

Correlations between Combine measures (Edge rushers)

	1	2	3	4	5	6	7
1. Height							
2. Weight	.34						
3. 40-yard dash	.14	.43					
4. 20-yard shuttle	.10	.24	.22				
5. 3-cone drill	.01	.26	.24	.62			
6. Vertical jump	-.08	-.33	-.41	-.33	-.22		
7. Broad jump	.01	-.37	-.50	-.31	-.30	.60	
8. Bench press (work)	.00	.27	-.11	-.02	.00	.11	.03

Note. Correlations of .13 or larger are significant at the $p < .05$ level.

Correlations between Combine measures (Linebackers)

	1	2	3	4	5	6	7
1. Height							
2. Weight	.36						
3. 40-yard dash	-.08	.21					
4. 20-yard shuttle	-.01	.18	.10				
5. 3-cone drill	-.02	.11	.09	.62			
6. Vertical jump	.10	-.08	-.46	-.14	-.03		
7. Broad jump	.17	-.11	-.51	-.19	-.16	.66	
8. Bench press (work)	-.07	.20	-.11	.03	.03	.15	.10

Note. Correlations of .11 or larger are significant at the $p < .05$ level.

Correlations between Combine measures (Cornerbacks)

	1	2	3	4	5	6	7
1. Height							
2. Weight	.54						
3. 40-yard dash	.11	.08					
4. 20-yard shuttle	.00	.00	.05				
5. 3-cone drill	-.08	-.04	.07	.65			
6. Vertical jump	-.02	-.02	-.18	-.16	-.11		
7. Broad jump	.21	.12	-.26	-.13	-.16	.55	
8. Bench press (work)	.04	.20	-.20	.00	-.02	-.05	.05

Note. Correlations of .11 or larger are significant at the $p < .05$ level.

Correlations between Combine measures (Safeties)

	1	2	3	4	5	6	7
1. Height							
2. Weight	.33						
3. 40-yard dash	.04	.04					
4. 20-yard shuttle	.00	-.09	.20				
5. 3-cone drill	.01	.01	.19	.62			
6. Vertical jump	.03	.02	-.30	-.09	-.17		
7. Broad jump	.24	.07	-.38	-.19	-.30	.66	
8. Bench press (work)	-.03	.32	-.15	-.10	-.11	.14	.11

Note. Correlations of .13 or larger are significant at the $p < .05$ level.

Appendix C

Table 1. Combine measure descriptive statistics that differentiated less-successful from more-successful quarterbacks.

Combine Measure	**Success Metric**			
	Draft Status			
	Undrafted (*n* = 23)		Drafted (*n* = 94)	
	M	*SD*	*M*	*SD*
Height	74.1	1.08	75.2	1.58
20-yard shuttle	4.38	0.18	4.29	0.18
	Frequency of Games Started			
	Lower Quartile (*n* = 36)		Upper Quartile (*n* = 27)	
	M	*SD*	*M*	*SD*
20-yard shuttle	4.38	0.18	4.27	0.15
	Elite Roster Selection: Career			
	Unselected (*n* = 107)		Selected (*n* = 10)	
	M	*SD*	*M*	*SD*
N/A	---	---	---	---

Note. N/A = no measure significantly differentiated the groups in this model. Success metrics with multiple Combine measures indicate that the combination of these measures significantly differentiated the groups. The measures are listed in descending order of weight (importance) in the model.

Table 2. Combine measure descriptive statistics that differentiated less-successful from more-successful running backs.

Combine Measure	**Success Metric**			
	Draft Status			
	Undrafted (*n* = 71)		Drafted (*n* = 200)	
	M	*SD*	*M*	*SD*
40-yard dash	4.61	0.11	4.52	0.09
	Frequency of Games Started			
	Lower Quartile (*n* = 83)		Upper Quartile (*n* = 66)	
	M	*SD*	*M*	*SD*
Weight	214	13.4	219	13.0
40-yard dash	4.56	0.11	4.53	0.09
	Elite Roster Selection: Career			
	Unselected (*n* = 250)		Selected (*n* = 21)	
	M	*SD*	*M*	*SD*
40-yard dash	4.55	0.10	4.48	0.08

Note. Success metrics with multiple Combine measures indicate that the combination of these measures significantly differentiated the groups. The measures are listed in descending order of weight (importance) in the model.

Table 3. Combine measure descriptive statistics that differentiated less-successful from more successful wide receivers.

Combine Measure	**Success Metric**			
	Draft Status			
	Undrafted (*n* = 107)		Drafted (*n* = 356)	
	M	*SD*	*M*	*SD*
40-yard dash	4.54	0.08	4.48	0.09
Vertical inches	34.4	3.27	35.8	3.09
	Frequency of Games Started			
	Lower Quartile (*n* = 141)		Upper Quartile (*n* = 105)	
	M	*SD*	*M*	*SD*
Vertical inches	34.7	3.10	36.1	3.13
	Elite Roster Selection: Career			
	Unselected (*n* = 438)		Selected (*n* = 25)	
	M	*SD*	*M*	*SD*
N/A	---	---	---	---

Note. N/A = no measure significantly differentiated the groups in this model. When a combination of measures differentiates groups for a success metric, the measures are listed in descending order of weight (importance) in the model.

Table 4. Combine measure descriptive statistics that differentiated less-successful from more-successful tight ends.

Combine Measure	**Success Metric**			
	Draft Status			
	Undrafted (*n* = 33)		Drafted (*n* = 134)	
	M	*SD*	*M*	*SD*
40-yard dash	4.84	0.14	4.72	0.14
Bench press (work)	964	238	1070	199
	Frequency of Games Started			
	Lower Quartile (*n* = 40)		Upper Quartile (*n* = 43)	
	M	*SD*	*M*	*SD*
Bench press (work)	1009	215	1168	196
	Elite Roster Selection: Career			
	Unselected (*n* = 159)		Selected (*n* = 8)	
	M	*SD*	*M*	*SD*
N/A	---	---	---	---

Note. N/A = no measure significantly differentiated the groups in this model. When a combination of measures differentiates groups for a success metric, the measures are listed in descending order of weight (importance) in the model.

Table 5. Combine measure descriptive statistics that differentiated less-successful from more-successful offensive linemen.

Combine Measure	**Success Metric**			
	Draft Status			
	Undrafted (n = 60)		Drafted (n = 373)	
	M	*SD*	*M*	*SD*
40-yard dash	5.31	0.17	5.23	0.17
Vertical inches	26.9	2.51	28.3	2.99
	Frequency of Games Started			
	Lower Quartile (n = 110)		Upper Quartile (n = 112)	
	M	*SD*	*M*	*SD*
Vertical inches	27.67	3.19	28.80	2.80
	Elite Roster Selection: Career			
	Unselected (n = 403)		Selected (n = 30)	
	M	*SD*	*M*	*SD*
Bench press (work)	1296	250	1425	253

Note. When a combination of measures differentiates groups for a success metric, the measures are listed in descending order of weight (importance) in the model.

Table 6. Combine measure descriptive statistics that differentiated less-successful from more-successful defensive tackles.

Combine Measure	**Success Metric**			
	Draft Status			
	Undrafted (n = 41)		Drafted (n = 188)	
	M	*SD*	*M*	*SD*
Weight	303	16.1	308	13.8
Broad jump	103.8	5.45	105.4	5.52
	Frequency of Games Started			
	Lower Quartile (n = 67)		Upper Quartile (n = 61)	
	M	*SD*	*M*	*SD*
Weight	312	10.8	313	12.7
40-yard dash	5.26	0.18	5.20	0.16
	Elite Roster Selection: Career			
	Unselected (n = 215)		Selected (n = 14)	
	M	*SD*	*M*	*SD*
40-yard dash	5.08	0.15	4.98	0.16

Note. Success metrics with multiple Combine measures indicate that the combination of these measures significantly differentiated the groups. The measures are listed in descending order of weight (importance) in the model.

Table 7. Combine measure descriptive statistics that differentiated less-successful from more-successful edge rushers.

Combine Measure	Success Metric			
	Draft Status			
	Undrafted (*n* = 44)		Drafted (*n* = 216)	
	M	*SD*	*M*	*SD*
40-yard dash	4.91	0.13	4.80	0.13
Vertical inches	31.2	3.51	33.7	2.96
Weight	268	15.7	268	13.2
	Frequency of Games Started			
	Lower Quartile (*n* = 67)		Upper Quartile (*n* = 61)	
	M	*SD*	*M*	*SD*
Weight	263	14.5	272	12.9
Broad jump	115	5.96	117	6.16
	Elite Roster Selection: Career			
	Unselected (*n* = 243)		Selected (*n* = 17)	
	M	*SD*	*M*	*SD*
40-yard dash	4.81	0.14	4.75	0.12
Weight	268	13.5	274	14.3

Note. Success metrics with multiple Combine measures indicate that the combination of these measures significantly differentiated the groups. The measures are listed in descending order of weight (importance) in the model.

Table 8. Combine measure descriptive statistics that differentiated less-successful from more-successful linebackers.

Combine Measure	Success Metric			
	Draft Status			
	Undrafted (*n* = 64)		Drafted (*n* = 306)	
	M	*SD*	*M*	*SD*
40-yard dash	4.75	0.11	4.67	0.11
	Frequency of Games Started			
	Lower Quartile (*n* = 100)		Upper Quartile (*n* = 93)	
	M	*SD*	*M*	*SD*
40-yard dash	4.72	0.13	4.65	0.10
Weight	241	7.6	243	9.3
	Elite Roster Selection: Career			
	Unselected (*n* = 349)		Selected (*n* = 21)	
	M	*SD*	*M*	*SD*
Vertical inches	34.1	3.20	37.4	3.18
Weight	241	8.4	246	9.8

Note. Success metrics with multiple Combine measures indicate that the combination of these measures significantly differentiated the groups. The measures are listed in descending order of weight (importance) in the model.

Table 9. Combine measure descriptive statistics that differentiated less-successful from more-successful cornerbacks.

Combine Measure	Success Metric			
	Draft Status			
	Undrafted (*n* = 55)		Drafted (*n* = 286)	
	M	*SD*	*M*	*SD*
40-yard dash	4.53	0.10	4.47	0.08
Bench press (work)	625	204	713	194
	Frequency of Games Started			
	Lower Quartile (*n* = 91)		Upper Quartile (*n* = 94)	
	M	*SD*	*M*	*SD*
40-yard dash	4.51	0.09	4.45	0.09
Weight	192	8.7	196	9.3
	Elite Roster Selection: Career			
	Unselected (*n* = 311)		Selected (*n* = 30)	
	M	*SD*	*M*	*SD*
Broad jump	122	5.19	124	5.33

Note. N/A = no measure significantly differentiated the groups in this model. Success metrics with multiple Combine measures indicate that the combination of these measures significantly differentiated the groups. The measures are listed in descending order of weight (importance) in the model.

Table 10. Combine measure descriptive statistics that differentiated less-successful from more-successful safeties.

Combine Measure	Success Metric			
	Draft Status			
	Undrafted (*n* = 46)		Drafted (*n* = 196)	
	M	*SD*	*M*	*SD*
40-yard dash	4.58	0.08	4.53	0.09
Height	72.2	1.55	72.7	1.53
	Frequency of Games Started			
	Lower Quartile (*n* = 70)		Upper Quartile (*n* = 58)	
	M	*SD*	*M*	*SD*
N/A	---	---	---	---
	Elite Roster Selection: Career			
	Unselected (*n* = 225)		Selected (*n* = 17)	
	M	*SD*	*M*	*SD*
40-yard dash	4.55	0.09	4.47	0.08

Note. N/A = no measure significantly differentiated the groups in this model. Success metrics with multiple Combine measures indicate that the combination of these measures significantly differentiated the groups. The measures are listed in descending order of weight (importance) in the model.