International Journal of Sport Finance, 2018, **13**, 18-33, © 2018 West Virginia University

Drafting a Successful Wide Receiver in the NFL—Hail Mary?

Aju J Fenn[1] and David Berri[2]

[1]*Colorado College*
[2]*Southern Utah University*

Aju J. Fenn, PhD, is a professor of economics. His research interests are in the areas of sports economics, applied econometrics and the pedagogy of economics.
David J. Berri, PhD, is a professor of economics. His current research focuses on the economics of sports, specifically the topics of managerial decision-making, women in sport, and worker productivity.

Abstract

This paper examines the efficacy of the NFL draft in selecting successful wide receivers that go on to be successful in the league. We identify variables that are significant determinants of draft day selection and investigate if those same variables explain productivity in the NFL.

Keywords: NFL, NFL draft efficacy, NFL draft criteria, wide receivers

JEL CODES: Z20, Z21

Introduction

The purpose of this paper is to examine the efficacy of the National Football League (NFL) draft in selecting wide receivers (WRs) that are successful players in the NFL. Are college statistics and combine performances significant determinants of draft order, and are those same measures good predictors of performance in the NFL? These questions are important because the game today relies heavily on a passing attack. The number of total passing yards has grown from 120,705 in 2010 to 128,898 in 2014.[1] An NFL team must have several important pieces in place to develop a passing attack. The foremost among these are a Quarterback, (QB) and multiple WRs. The QB position has been studied by Berri and Simmons (2011). This paper will modify their methods, and those of Mullholand and Jensen (2014), and apply them to the WR position. The paper contributes to the existing literature by using better measures of NFL productivity than the existing work in the field. We use receptions per target and yards per reception (given an average of at least 16 targets per year) as measures of NFL productivity at two, three, four, and five year intervals for wide receivers. In particular, these are WRs that, on average, are targeted at least once per game. We also look at the impact of *catch radius* and *hand size* on draft order. The impact of these variables on draft order or NFL productivity have not yet been studied. Finally, in keeping with Berri, Brook, and Fenn (2011) we use an integer count model that has not been applied to the NFL WR position before. The use of this model reveals that draft day determinants are also good long-term predictors of NFL productivity

[1] These figures were computed from the total passing yards per season from www.nfl.com

for WRs. The paper will provide a brief review of the literature, then discuss the data and methodology followed by a results section, and will conclude with results of the regression models and their implications for the research questions posed above.

Literature Review

The study of professional sports drafts is not new. There are several studies on the National Basketball Association (NBA), Major League Baseball (MLB) and the NFL. A search of the literature turns up about 20 peer reviewed articles in print that are related to the subject of the NFL draft. Among these there are only four that pertain to the WR position. For the purposes of this review. We will concentrate on the draft studies that pertain to the positions of WR and Tight End (TE). While our paper does not study tight ends, we review the relevant work because apart from blocking defenders, tight ends also catch passes.

One of the more recent studies by Treme and Allen (2011) examines the determinants of NFL draft order selection of WRs. They examined data over the 2001–2006 seasons. They modeled draft order as such; a function of media exposure (measured by the number of stories run in a major newspaper on a player), the class rank of the player (i.e., senior or not), the players ranking prior to the draft on draftscout.com, the player's Body Mass Index (BMI), the player's height, their 40-yard dash time at the combine, the number of offensive pro-bowlers on the team drafting the WR, the number of players that had over fifty catches on the team drafting the WR, the number of touchdowns the player had in their last year of collegiate play, and finally a dummy capturing whether the player attended a Bowl Championship Series (BCS) school or not. They found the number of media stories, the 40-yard dash time, the pre-draft ranking by draftscout.com, and the number of touchdowns caught in the last year of college to be significant determinants of the order in which players were selected in the draft. The authors also examine the impact of these players attributes on their performance in their first year in the NFL as captured by salary, games played, games started, and the number of receptions in the NFL during their rookie seasons. They find that newsworthy players start and play more games in their rookie seasons but that raw speed does not increase the number of rookie starts. Collegiate touchdown success does increase the number of NFL starts. They also find rookie receptions in the NFL are negatively impacted by the number of offensive pro-bowlers, being from a non BCS school, and the number of receivers on the team that had over 50 receptions the previous year. On the other hand, the number of rookie receptions is positively impacted by the number of touchdowns caught by the player in their last year of college. While Treme and Allen (2011) have a good starting point for the draft order of WR in the NFL, our paper improves upon theirs by using a larger dataset from 1999–2014. We also use measures of NFL productivity based on the number of times that a WR is targeted by the QB. These measures start in year two and extend to the player's fifth year in the NFL. Finally, our paper will use an integer count model, which is a more appropriate estimator for non-negative integers of the NFL draft order than OLS.

Boulier, Stekler, Coburn, and Rankins (2010) examine whether draft order is successful in predicting long-term success in the NFL. They examine data on QBs and WRs from 1974–2005. WR are evaluated based on the number of years they played in the league specifically as a WR, and the total yards of receptions. Boulier et al. (2010) also look at the total number of years played by the player in the league. The authors conduct a year-by-year analysis in which WRs are ranked by the order they are drafted compared to other WRs. Negative and significant Spearman rank correlation coefficients between WR rankings and WR performance on a year-by-year basis suggest that NFL executives pick WR wisely, albeit not perfectly. In addition to computing survival tables that predict how long a WR drafted at a given spot is expected to play, the authors also regress performance measures on the actual draft rank at which a player was taken using a censored normal estimator. The authors performance measure of years played is censored, as high draft picks tend to play longer, and were still playing when the study was conducted—hence their average for years played would be an underestimate of the actual years played. The authors find negative and significant relationships between the performance of WRs and their rankings. They do not use combine statistics or college performance to explain a WR's performance in the NFL. We will use both groups of data to explain which types of WR are likely to be successful in the NFL.

Robbins (2011) analyzes data collected from all NFL players that attended the NFL combine from 2005–2009. He concludes that different positions require different skill sets, and that WRs and Cornerbacks have similar skills. He presents an excellent description of each of the combine drills.

Burnett and Van Scyoc (2013) examine the market for rookie WRs to test for racially based wage discrimination. Their dataset examines 436 rookie WRs over the 2000–2009 seasons. The authors regress the natural logarithm of real salary against draft number, race, and a dummy variable for undrafted players. Oxaca Blinder decomposition results from the quantile regressions suggest that players with similar attributes are paid accordingly. Black WRs tend to get drafted earlier and consequently paid more. The authors argue that this is because they possess a superior skillset and not because they are black. This study does not utilize any combine data, collegiate statistics of the WRs or NFL statistics such as receptions, yards, and touchdowns by the WRs. Our paper will incorporate all of these data.

Kuzmits and Adams (2008), use NFL Combine data from 1999–2004 to explain the NFL performance of 68 QBs, 152 WRs, and 86 running backs (RBs) drafted in those years. The NFL performance of WRs was captured by draft order, salary earned during years 1, 2, and 3, the average yards per reception in years 1, 2, and 3, and finally the games played in years 1, 2, and 3. The null hypothesis is that the correlation between each combine measure and each NFL performance measure is zero. Based on correlation coefficients that are below 0.5, the authors conclude that the Combine data have no bearing on performance of an NFL WR. The model used here takes a univariate approach in that it examines the correlation between a single combine statistic and a single NFL performance measure. Our paper will use a multivariate approach and will also examine the impact of a player's collegiate statistics on their NFL statistics.

Berri and Simmons (2011) study the order in which quarterbacks are drafted and the impact of their collegiate and combine statistics on their NFL production. We will adapt their methodology to the WR position. They find that many of the factors that enhance a QB's draft position are unrelated to future NFL performance. Koz, Fraser-Thomas, and Baker (2012) examine the relationship between games played and draft order in the NFL, along with other professional sports leagues such as the National Hockey League (NHL), the NBA, and the MLB from 1980–1989. They find that players drafted in higher rounds tend to play more games in the NFL.

Mulholland and Jensen (2014) use collegiate data, combine data, and physical measures to predict both the NFL draft order and NFL career success of tight ends (TEs) from 1999 2013. They find that size measures (BMI, weight, height) are over-emphasized in the NFL draft. Using OLS and a regression tree, they regress draft order against height, BMI, bench press, 40-yard dash time, a Bowl College Conference (BCS) dummy and college receiving yards. They find height, bench press, 40-yard dash time, and college receiving yards to be significantly correlated with draft order. The NFL performance measures that they employ are games started, NFL career score, and NFL career score per game. They regress each of these outcome variables against a variety of combine statistics, physical measurements, and collegiate statistics. The significant predictors of games started are BMI, broad jump, and career college receptions. The NFL career score is impacted by broad jump and college career yards. The final outcome measure of NFL career score per game is significantly impacted by the BCS dummy variable and by college career yards. The 40-yard dash and the BCS dummy variable are the only two significant variables in both the draft order and the NFL performance regressions. Since the variables in the draft order regression and the NFL performance regressions are different, other than the BCS dummy and the 40-yard dash time, the authors conclude that NFL teams can improve long run performance by focusing on statistics such as the broad jump. Our paper will improve upon their methodology by using a count model for the NFL draft order regression. We also employ NFL productivity measures after two, three, four, and five years. In the NFL games started regression, the authors have college yards per reception, college yards, and college receptions as explanatory variables. There is likely to be multi-collinearity between these variables as they are related by formula.

Most of the papers cited above, with the exception of Mullholand and Jensen, (2014) use either combine data or collegiate data to predict draft order and/or NFL performance. This paper will use combine data, physical measurements, and college data from the last year. In addition to using an integer count model for the NFL draft order variable, we will use NFL productivity measures that look at as far out as fifth year production averages. We turn next to the data used for this study.

Data and Methodology

Data is collected on 366 WRs that played in the NFL during 1999–2014 seasons. From this group 310 WRs attended the NFL combine and were drafted to play in the NFL. This time frame is chosen because NFL combine statistics are available for these years. Some WRs choose not to participate in certain combine drills such as the broad jump, the vertical leap, etc. When using these variables, we impute the relevant data using the Multiple Imputation (MI) method based on a Multivariate Normal distribution (Enders, 2010).[2] The assumption that the variables are distributed as a joint

[2] We are grateful to an anonymous referee for the data imputation suggestion. The MI method is chosen because it allows us to estimate binary and count models and only assumes that the data are missing at random.

Multivariate Normal process are supported by Jarque-Berra tests which reveal that all the continuous explanatory variables follow a normal distribution (JB stat < 5.99). We ensure consistency between the corresponding regression models and their imputation counterparts by including all the variables in the imputation model that are used in the corresponding regressions themselves. In addition, Trace plots of the WLF and early EM algorithm convergence support the notion that the MCMC algorithm used to impute the data converge well within the range of iterations set for each imputation. These diagnostics suggest that the multiple imputation method accounts for the missing data reliably.

The data is organized by player and falls into two categories: Combine statistics on the various combine drills, such as the 40-yard dash time, the vertical jump etc., combine physical measurements such as height, BMI etc. and NFL performance statistics such as receiving yards, touchdowns etc. The sample statistics for the dataset are contained in Table 1.

Combine Statistics

Each year about three hundred of the best collegiate NFL prospects are invited to participate in the NFL combine, where they perform various drills under controlled circumstances.

The schedule for the combine according to the NFL is as follows:

- Day One: Registration, Hospital Pre-Exam & X-rays, Orientation, Interviews
- Day Two: Measurements, Medical Examinations, Media, Interviews
- Day Three: NFLPA Meeting, Psychological Testing, Bench Press, Interviews
- Day Four: On-Field Workout (timing, stations, skill drills), Departure from Indianapolis"[3]

The players performance times and outcomes are measured. Their physical dimensions such as height, weight, etc. are recorded. They undergo medical examinations and psychological testing. They are also interviewed by NFL teams that may be interested in drafting them.[4] The NFL Combine data is taken from http://nflcombineresults.com/nflcombinedata.php. For the purposes of this paper we gathered data on the WRs height, arm length, hand size and weight. We also gathered data on their 40-yard dash time, their vertical leap, broad jump, three cone drill, and shuttle drill. An excellent description of each of these drills is available at http://www.nfl.com/combine/workouts. Similar to Berri and Simmons (2011) we compute BMI using the height and weight for each player.[5]

Collegiate Statistics

We gathered statistics from the last year each player was in college, and also their college career statistics. There has hardly any impact on the significance of variables in our models with either version of college performance. In keeping with Mullholand

[3] http://www.nflcombine.net/players/schedule

[4] Further details of the NFL Combine may be found at http://www.nflcombine.net/?q=node/9

[5] BMI= [WEIGHT IN LBS ÷ (HEIGHT IN INCHES)2] x 703

and Jensen (2014), we use college career statistics. These statistics are taken from a number of websites.[6] The college career statistics collected during the player's college playing career are: Number of Games played, receptions, receiving yards, and receiving touchdowns. Since college receiving yards and college receiving touchdowns are highly correlated we combine them into a single variable called college score. Mullholand and Jensen (2014) use a similar measure for the NFL game. We adapt their measure to the college game. It is important to note that the significance of variables in the various regression models is unchanged whether we use College Score, College Receiving Yards or College Touchdowns.

$$\text{College Score} = \text{College Receiving Yards} + 19.3{*}\text{College Touchdowns} \quad (1)$$

NFL Statistics

Informed by Berri and Simmons (2011), we gathered data on the following NFL variables: receptions, receiving yards and touchdowns after two, three, four, and five years respectively. We compute NFL Score using the same method employed by Mullholand and Jensen (2014) but adjust the formula for the number of games played.[7]

$$\text{NFL Score per game} = (\text{NFL Receiving Yards} + 19.3{*}\text{NFL Touchdowns})/\text{Number of Games Played} \quad (2)$$

We also collected data on the number of times a wide receiver was targeted by the quarterback after two, three, four, and five years. We use the number of times a WR was targeted to calculate the number of receptions per target, and the number of yard per receptions for a WR. We then subset our data to those WRs that were targeted, on average, at least once per game. We then use Receptions per Target and Yards per Reception as outcome measures of production in the NFL. This is a non-trivial issue as NFL receptions depend on the number of targets or opportunities to catch the ball. Not all WRs play on all downs. The opportunities to catch the ball, in turn, depends on the offensive scheme being used (run vs pass), the score and time left in the game, (ahead or behind in the game) and the defensive coverage that is being played. Some teams will double cover the main WR of the opposing team making it more difficult for that WR to be targeted. If one does not control for the number of targets then these factors are incorrectly omitted in the analysis. We turn next to the model used.

Draft Status and Draft Position

The first two regression equations model the draft status (drafted or undrafted) and the overall draft position of a wide receiver as a function of their combine and college statistics. A list of the variables used is contained in Table 1. Table 2 contains sample statistics for the data employed in the Drafted and Overall Draft Pick regressions.

DRAFTED = f(CATCH RADIUS, HAND SIZE, BMI, FORTY YARD, JUMP, SHUTTLECONE, COLLEGESCORE, D_BCS, annual time dummies) (3)

OVERALL DRAFT PICK = f(CATCH RADIUS, HAND SIZE, BMI, FORTY YARD, JUMP, SHUTTLECONE, COLLEGESCORE, D_BCS, annual time dummies) (4)

---

[6] The college statistics are taken from http://www.sports-reference.com/cfb/players/, http://fs.ncaa.org/Docs/stats/football_records/2011/FCS.pdf, http://sports.yahoo.com/ncaa/football/players/153097 and http://www.totalfootballstats.com/PlayerWR.asp?id=2545

[7] We are grateful to an anonymous referee for this suggestion.

TABLE 1. Draft Order Regression Model Variables

Variable Name	Brief Description
Drafted	1 if drafted, 0 if undrafted
Overall Draft Pick	Overall draft pick number
Catch Radius	Player's height plus arm length in inches
Hand Size	Hand size in inches
BMI	Player's Body Mass Index
Forty Yard	40-yard dash time in seconds
Jump	Broad jump distance plus vertical leap in inches
Shuttlecone	Three cone drill time plus short 20 yard shuttle time in seconds
Collegescore	College receiving yards +19.3*College Touchdowns
D_BCS	1 if Player played for a BCS school, 0 otherwise

TABLE 2. Sample Statistics

	Mean	Median	Maximum	Minimum	Standard Deviation
Drafted	0.85	1.00	1.00	0.00	0.36
Overall Draft Pick	106.86	94.00	253.00	2.00	68.98
Catch Radius	104.90	105.25	112.50	93.38	3.45
Hand Size	9.34	9.25	10.75	7.50	0.56
BMI	26.58	26.69	29.83	22.03	1.37
Forty Yard	4.49	4.49	4.84	4.21	0.10
Jump	156.19	155.50	179.00	134.50	7.64
Shuttlecone	11.15	11.13	11.97	10.29	0.31
Collegescore	2,590.502	2,509.55	6,210.40	102.50	1,051.20
D_BCS	0.69	1.00	1.00	0.00	0.46

Dependent Variables

The first regression examines whether a player is drafted or not (*drafted* =1 if drafted, 0 if undrafted). Each year immediately after the NFL draft, teams rush to sign undrafted free agents. In addition teams add undrafted players through the season. Some of these undrafted players go on to make the practice squads and others actually end up on the teams' active rosters, playing on game day. The first set of regression results shed light on which combine and college performance measures are significant determinants of a player's draft status.[8] We use a Probit model, because the error terms are closer to a normal distribution than a log normal distribution.[9]

The second dependent variable in this study *overall draft pick,* is the actual spot at which the WR was picked by some NFL team. Earlier draft picks are used on players

[8] We are grateful to an anonymous referee for the suggestion to include equation (1) in addition to the overall draft pick regressions.

[9] We also ran a Logit model and the statistical significance of the variables remains unaltered.

that teams value more. Each team is awarded a draft pick in each of the seven rounds of the NFL draft in the reverse order in which they finished the preceding NFL season. Teams are also awarded compensatory picks if they have lost more or better compensatory free agents than they signed in the preceding year. Teams often trade draft picks during the draft or during the year. The earliest drafted player in the largest dataset we use is Calvin Johnson, who was picked at number 2 while the latest player drafted in the dataset is Tiquan Underwood, drafted at number 253. Independent variables are used in the draft pick regressions.

Independent Variables

The rationale for most of the independent variables is stated in terms of expected productivity in the NFL. We describe the exact measures of productivity before we present the NFL productivity regressions. For this section it suffices to think of the impact of these independent variables on receptions, yards, and touchdowns in the NFL. Unlike past studies such as Treme and Allen (2011), Mullholand and Jensen (2014); and Berri and Simmons (2011), we use *catch radius* as a determinant of NFL productivity. The catch radius is the distance around the player's position that a moving ball can be caught. Catch radius is the player's height plus arm length in inches (as measured at the combine). We posit that ceteris paribus, players with a larger catch radius may have an edge on getting to the balls thrown their way. Ceteris paribus, they may have relatively better NFL productivity than WRs with a smaller catch radius. Consequently we expect catch radius to be positively related to drafted and negatively related to *overall draft pick*.

We combine the broad jump and vertical leap distances to measure leaping ability in the variable *jump*. The broad jump measures the distance a player can leap horizontally from a standing position. Vertical leap measures the vertical distance a player's hand can reach over and above the raised arm from a standing position when a player leaps straight up. It is also a measure of explosiveness like the broad jump. These two variables are highly correlated so we combine them into a single variable—*jump*. The idea is that players that are able to out jump the competition are more likely to be open for receptions and accelerate past defenders. Similarly we posit that, ceteris paribus, players with a larger *hand size* may do a better job of catching the ball. As a result *jump* and *hand size* are hypothesized to be positively related with NFL productivity. Consequently we would expect them to be positively related to *drafted* and negatively related to *overall draft pick*.

In keeping with Mullholand and Jensen (2014) and Berri and Simmons (2011), we use Body mass index (BMI) and 40-yard time in seconds (*forty yard*) as explanatory variables. BMI is used as a proxy for muscle mass. Ceteris paribus, a more muscular WR will be able to make more catches, break more tackles, and presumably be a more durable player for the team. So BMI should be positively related to *drafted* and negatively related to *overall draft pick*.

We turn next to the attribute of speed. A player's speed is measured by the 40-yard dash at the combine (*forty yard time*).[10] Starting from a sprinter's stance WRs sprint down a straight path for 40 yards. They are timed at 10, 20, and 40 yard intervals. We

[10] Descriptions of each combine drill and their use to scouts may be found at http://www.nfl.com/combine/workouts

will use the 40-yard time as a proxy for their speed. A faster WR should be able to get open for catches and gain more yards and score more touchdowns than a slower WR. We expect this variable to be negatively related to *overall draft pick,* as speedier players will be chosen earlier in the draft. However, 40 yard time should be positively related to *drafted.*

WRs that get open are those that are able to make defenders miss by making sharp cuts and sudden changes in direction in tight spaces. The Three Cone Drill and Short Shuttle drills at the combine measures acceleration with changes in direction in tight areas. It is no surprise that these two drill times are highly correlated. We combine the three cone drill and short shuttle drill time in seconds into a single variable called Shuttle Cone Time. We posit that Shuttle Cone Time should be positively related to receiving yards. Consequently it should be negatively related to *drafted* and positively related to *overall draft pick.*

Having discussed the Combine metrics we turn next to the measures of collegiate statistics that may foreshadow their NFL career statistics and subsequently impact their draft status and overall draft pick. We gathered data on both college career statistics and statistics during the player's last year in college. Given that there is little difference in significance of the variables between the two sets, we choose the college careers statistics in accordance with Mullholand and Jensen (2014).[11] Since collegiate receiving yards and college touchdowns are highly correlated we adapt Mullholland and Jensen's NFL formula to combine these variables into a single measure called College Career Score. College Career Score is given by the number of college receiving yards plus 19.3 times the number of college touchdowns. We posit that College Career Score should be positively related to NFL performance and *drafted*. It should be negatively related to *overall draft*.

In keeping with Treme and Allen (2011) and Mullholand and Jensen (2014), we employ a dummy variable D_BCS that takes a value of 1 if a player played in one of the following collegiate conferences: ACC, Big 12, Big East, Big 10, Pac 10, SEC or if they played for Notre Dame. D_BCS takes on a value of zero otherwise. These collegiate conferences have the highest level of talent in the country. Do teams pay attention to pedigree when drafting WRs? If so, we posit that this variable will be negatively related to *overall draft pick* and positively related to *drafted*. Does pedigree matter in NFL production? The results to the NFL productivity regressions will provide that answer.

In addition to these variables we also create season specific dummy variables that take on a value of one for each NFL season a player played in the NFL and zero otherwise. The reason for this is to control for season-specific effects. The rules of the game change from year to year. For example, in 2014 the manner in which the officials called pass interference changed. Almost any contact outside ten yards beyond the line of scrimmage was sure to draw a flag for pass interference unless the defender was looking back at the ball. We are not aware of past studies that have done this.

We use a Probit regression to model draft status because the error terms approximate a normal distribution better than a Log-Normal Distribution. The Negative Binomial Count model is used because a Poisson Count model for these data reveal Overdispersion. Specifically, a count model is an improvement over OLS because

[11] We thank an anonymous referee for the suggestion to use college career statistics in lieu of statistics from the player's last year in college.

unlike OLS with a continuous dependent variable the probability mass of the dependent variable is concentrated at specific integer values.

Table 3 reveals that *speed* (40-yard time), jumping and leaping ability (*jump*) and past production on the job (*college career score*) matter for both whether a player is drafted or not and for the specific position in the draft (*overall draft pick*). A faster 40-yard time is related negatively to the player's exact draft spot, as faster players will be drafted earlier. Among all WRs that play in the NFL a faster 40 time increases a player's probability of getting drafted. Better college career yards and touchdowns improve the probability of being drafted and move a player up in the draft.

TABLE 3. Draft Status and Overall Draft Pick Regressions

	Probit Model	**Negative Binomial Count Model**
Explanatory Variable	**Drafted or Not**	**Overall Draft Pick**
Catch Radius	0.0133	0.0082
	(0.33)	(0.49)
Hand size	**0.6846**	-0.1432
	(2.38)	(-1.52)
BMI	0.0248	-0.0285
	(0.34)	(-1.11)
Forty Yard Time	**-3.9612**	**2.0316**
	(-4.15)	(5.05)
Jump	**0.0367**	**-0.0086**
	(2.38)	(-1.71)
Shuttle Cone time	0.3476	-0.0748
	(1.06)	(-0.54)
College Career Score	**0.0003**	**-0.0002**
	(2.97)	(-3.65)
BCS Dummy	0.1286	-0.4034
	(0.62)	(-5.41)
N	366	310

*Standard errors are Robust, T-stats are in parentheses, all significant variables are in bold face. Significance is usually at the 5% level unless otherwise noted. Jump is significant at the 10% level in the Overall Draft Pick Regression

A WRs hand size only helps at the margin to get drafted but does not improve a player's draft position. A player that attended a BCS school gets drafted earlier than one that has not attended a BCS school, so pedigree does seem to matter in relative positioning. However, attending a BCS school alone will not get you drafted. Finally it is interesting to note that front offices do not pay attention to catch radius, shuttle cone time and BMI when it comes to drafting a player, and the position at which they draft that player as is evidenced by the insignificance of catch radius, shuttle cone time and BMI in both regressions. We turn next to the results of the NFL productivity regressions to see which variables actually impact the NFL production of a WR.

NFL Performance Regressions

In order to measure performance in the NFL, following Berri and Simmons (2011), we look at some alternate measures of NFL performance for WRs that are, on average, targeted at least once per game. We collect data on the number of receptions (*receptions*), the number of receiving yards (*receiving yard totals*) and the number of touchdowns (*touchdowns*) as cumulative totals after two, three, four, and five years in the NFL. If a player has only played two years in the league then his two year total will be the same as his three, four, and five year totals. For players that are still playing in the league and have not played a full five years, their latest totals are also used as their cumulative totals beyond their playing time frame. We adapt this convention from Berri and Simmons (2011). We combine receiving yard totals and receiving touchdowns into an NFL career score per game as specified in equation (2). The NFL Score per game for each time period is the number of receiving yards plus 19.3 times the number of receiving touchdowns. Receiving yards and receiving touchdowns are highly correlated. The same results hold with either receiving yards or receiving touchdowns in place of NFL score. Since both receiving yards and receiving touchdowns are important we combine the two following Mullhoand and Jensen (2014).[13] The results for these regressions are contained in Table 4. Bold text indicates coefficients that are significant at the 5% level, unless noted otherwise. These results are based on all 366 WRs that played in the NFL.

Table 4 reveals that NFL Score per game is impacted significantly by the 40-yard time, college career score, and the BCS Dummy. The slower the 40-yard dash time, the smaller the NFL score per game. As the 40-yard dash time increases, the NFL score per game decreases. A player that is a tenth of a second slower will score 1.7 to 3.1 less than otherwise. Past success in college matters. A player that scores a hundred points more on the college scoring index will score 0.5 to 4.7 more on the NFL score per game index in the pros. Finally, a player that came from a BCS school will score 5.4 to 6.9 more points per game on the NFL score per game index. Hand size is only significant at the 10% level in the 2 year NFL Score per game regression. Catch radius, shuttle cone time, BMI and jump do not impact the NFL score per game significantly. Interestingly, when the set of WRs is restricted to those with at least an average of 16 catches per season, the same variables turn out to be significant as discussed above.

Table 5 presents the results of the receptions per target for the set of WRs that were targeted (on average) at least 16 times per season. The receptions per target are recorded after two, three, four, and five years in the NFL. Catch radius, 40-yard time, and jump tend to be significant in most of the regressions.

Catch radius is significant but negative. This would suggest that taller players with longer arms catch the ball fewer times per target than shorter players with shorter arms. A reason for this could be that players with a larger catch radius, such as Calvin

---

[12] Computing marginal effects for MI are complicated at best and the existing procedure mimreg in STATA by Daniel Klein still has some issues so we choose not to report marginal effects for the Probit and Negtaive Binomial models. We choose to focus on which variables statistically impact the respective dependent variables.

[13] We are grateful to an anonymous referee for this suggestion.

TABLE 4. NFL Score Per Game Regression Results

NFL score per game	after 2 years	after 3 years	after 4 years	after 5 years
Explanatory Variable				
Catch Radius	0.2516	0.5802	0.6217	0.6323
	(0.73)	(1.15)	(1.26)	(1.27)
Hand size	3.1250	3.3716	2.8652	2.7642
	(1.63)	(1.34)	(1.15)	(1.09)
BMI	-0.0939	0.1120	0.3007	0.3405
	(-0.14)	(0.14)	(0.38)	(0.42)
Forty Yard Time	-17.6763	-28.4266	-30.0746	-31.4804
	-(2.24)	-(2.73)	-(3.00)	-(3.13)
Jump	0.0139	0.0057	-0.0154	-0.0041
	(0.11)	(0.04)	(0.10)	(-0.03)
Shuttle Cone time	2.2260	2.0952	2.5469	2.7176
	(0.64)	(0.5)	(0.63)	(0.67)
College Career Score	0.0032	0.0045	0.0047	0.0051
	(3.78)	(4.01)	(4.25)	(4.56)
BCS Dummy	5.4113	6.9670	6.7411	6.1834
	(3.08)	(3.04)	(3.00)	(2.74)
N	366	366	366	366

* T-stats are in parentheses
All standard errors are robust
Hand size is significant at the 10% level in the first model

Johnson, are double covered and/or jammed at the line of scrimmage. Such players may also be targeted often because the QB hopes that even if the pass is not completed, the WR is long enough to prevent an interception. In fact, separate regressions of receptions against the same independent variables suggests a negative relationship between receptions and catch radius. On the other hand, separate regressions of targets against the same independent variable suggest a positive relationship between targets and Catch Radius. Thus, the driver of the negative sign of catch radius with receptions per target is the receptions part of the variable. Players with a larger catch radius have fewer receptions. BMI is only significant in the receptions per target after 2 years regression. This suggests that, while NFL WRs are fresh out of college, the more muscular WRs tend to do better. This effect fades, presumably because other WRs tend to bulk up as they continue to train in years 3, 4, and 5. Slower 40-yard times correspond with more receptions per target. This is actually due to the fact that each part of the dependent variable is negatively related to the 40-yard time in three of the four models. Separate regressions of the number of receptions against the same set of independent variables yield a negative coefficient for 40-yard time. This is also the case in separate regressions of the number of targets against the same independent variables. Once again, 40-yard dash times are negatively related to the number

TABLE 5. Receptions Per Target Regression Results

	Receptions Per Target After 2 Years	Receptions Per Target After 3 Years	Receptions Per Target After 4 Years	Receptions Per Target After 5 Years
Explanatory Variable				
Catch Radius	-0.0051	-0.0750	-0.0656	-0.0630
	(-2.21)	(-3.89)	(-3.88)	(-4.34)
Hand size	0.0141	0.2449	0.2609	0.1494
	(1.05)	(1.72)	(2.87)	(1.73)
BMI	0.0117	0.0113	0.0100	0.0058
	(2.84)	(0.68)	(0.75)	(0.55)
Forty Yard Time	0.1928	0.5974	0.5206	0.6406
	(3.44)	(1.85)	(1.75)	(3.06)
Jump	0.0001	0.0151	0.0120	0.0123
	(0.14)	(3.00)	(2.99)	(3.18)
Shuttle Cone time	-0.0248	0.0762	0.0503	0.0716
	(-1.12)	(0.99)	(0.58)	(0.95)
College Career Score	0.0000	-0.00001	-0.00001	0.00001
	(1.08)	(-0.65)	(-0.5)	(0.33)
BCS Dummy	0.0151	0.0105	-0.0024	-0.0033
	(1.18)	(0.24)	(-0.06)	(-0.08)
N	227	223	220	204

* T-stats are in parentheses
** Dataset contains only receivers with at least an average of 16 targets per year
All standard errors are robust
Forty yard time in years 3 and 4 is significant at the 10% level

of targets. Combining receptions per target yields the positive sign on the 40-yard dash time. Another reason could be that faster WRs face double coverage. The Jump variable is significant in most of the regressions suggesting that players with leaping ability are able to make more catches per target than those with lesser leaping ability. Shuttle Cone time, College Career Score and the BCS dummy are insignificant.

Table 6 shows the results of the regressions that examine the determinants of the yards per reception for all WRs that had an average of at least 16 targets per season. WRs with a larger catch radius are able to generate more yards per reception. This may be because taller WRs have longer strides and are able to gain more yards once they catch the ball. Hand size is insignificant, except in the last model where it is negative and significant at the 10% level. This is a counterintuitive result, as it suggests that WRs with smaller hands gain more yards per reception than those with larger hands. Body Mass Index (BMI) is negative and significant in all the regressions. This suggests that heavier WRs gain fewer than lighter WRs. In all the models, the 40-yard dash time is significant and negative. This suggests that pure speed matters when it comes to gaining yards per reception. Speedier WRs gain more yards than slower WRs. This

TABLE 6. Yards Per Reception Regression Results

Yards Per Reception After:	After 2 Years	After 3 Years	After 4 Years	After 5 Years
Explanatory Variable				
Catch Radius	0.2530	0.2598	0.2520	0.3362
	(3.20)	(3.01)	(2.74)	(4.21)
Hand size	-0.1349	-0.1409	-0.2069	-0.6437
	(-0.34)	(-0.35)	(-0.46)	(-1.75)
BMI	-0.2349	-0.4518	-0.3443	-0.2901
	-(1.71)	-(3.49)	-(2.69)	-(2.32)
Forty Yard Time	-6.3080	-4.3288	-4.1803	-4.7979
	-(3.77)	-(2.54)	-(2.94)	-(3.41)
Jump	0.0057	0.0037	-0.0217	-0.0330
	(0.21)	(0.13)	(-0.71)	(-1.29)
Shuttle Cone time	1.8217	1.4833	1.6321	1.5149
	(2.59)	(2.46)	(2.98)	(2.48)
College Career Score	0.0002	0.0003	0.0004	0.0004
	(1.31)	(1.84)	(2.45)	(2.87)
BCS Dummy	-0.1044	0.0384	0.1747	0.1080
	(-0.27)	(0.11)	(0.52)	(0.33)
N	227	223	220	204

* T-stats are in parentheses
** Dataset contains only receivers with at least an average of 16 targets per year
All standard errors are robust
Hand size is significant at the 10% level in the last model

variable happens to have the largest coefficient in the various models suggesting that if a WR can catch the ball then speed is the single most important determinant of the yards per reception.

Shuttle cone time is positive and significant, suggesting that WRs that can change directions more quickly and accelerate rapidly, gain fewer yards per reception than those that cannot change directions and accelerate as quickly. This apparently counterintuitive result is most likely due to the larger number of yards that are gained on a single typical deep reception versus the yards gained on a single typical short completion. Short routes are often run by shifty smaller WRs with deeper routes being run by taller WRs who have slower acceleration in change of direction drills (i.e. longer Shuttle Cone times). These vertical route runners may not be as quick in change of direction drills as the smaller shiftier slot WRs like Danny Woodhead, Danny Amendola, etc. Finally, College Career Score is statistically significant but not really practically significant. Being a good WR in college does impact one's yards per reception in the NFL but by a very small amount as evidenced by the tiny coefficients for the College Career Score Variable. Finally, when looking at the WRs that average at least 16 targets per season, the BCS dummy variable is insignificant. This suggests that the level of competition in college does not matter as much as the other variables in the model.

Conclusion

In this paper we examine the factors that impact the selection of a WR in the NFL draft based on available college and combine statistics and the ability of those same factors to predict the WRs subsequent success in the NFL. In both cases we find that using collegiate statistics from the player's entire college career yields mainly the same results as using their statistics from their last year in college.

We improve upon the literature by using multiple imputation multivariate normal methods for missing data, added explanatory variables, an appropriate integer count model and examining WRs that are targeted, on average, at least 16 times or more per season. We find that the likelihood of a player being drafted is impacted positively, by the size of their hands, their speed as measured by their 40-yard dash time, their jumping ability, their ability in college to gain yards and score touchdowns. We also examine the impact of these explanatory variables on a WRs position in the draft.

We find that speed, jumping ability, college performance, and attending a BCS school help a WR to move up in the draft. When it comes to performing in the NFL, a WRs NFL *score per game,* which is a combination of yards plus touchdowns multiplied by 19.3, is explained only by their 40-yard dash time, their college career score and whether they attended a BCS school. Alternatively, NFL yards per reception are impacted positively by Catch Radius (height plus arm length) their speed (40-yard time) and their college career score. The NFL yards per reception are impacted negatively by faster times in the sum of the short shuttle and the three cone drill (Shuttle Cone time). This counterintuitive result is most likely due to the larger number of yards that are gained on a single deep reception versus the yards gained on an average short route.

In conclusion, it appears that while drafting WRs NFL teams pay attention to speed, past college performance and whether the WR comes from a BCS school. While signing undrafted free agents NFL teams consider hand size, speed and past college performance. The actual performance of WRs in the NFL as measured by NFL Score per game and yards per reception suggest that speed and past collegiate performance are significant determinants although the impact of speed is far and away the largest on NFL performance. In addition NFL teams may wish to consider a WRs catch radius (height plus arm length) if they are interested in WRs that can gain more yards per reception.

The implication of this paper go beyond what it says about wide receivers in the NFL. Studies of decision-making in baseball (see Bradbury, 2007 and Holmes, Simmons, & Berri, 2014) have found that evaluations of hitters and pitchers are generally efficient. However, studies of decision-making in basketball have found that player evaluation with respect to player salaries (see Berri, Brook, & Schmidt, 2007 and Berri et al., 2011) are less efficient. Our study of wide receivers suggests that this market is more like baseball. This may be because the evaluation of these athletes—like the evaluation of baseball players—is easier since the better players (i.e. those who are faster) are easier to identify. All of this literature suggests markets are more efficient when the problem decision-makers consider is easier. As that problem become more complex, though, inefficiencies can appear. We suggest future research into decision-making in sports should focus on whether or not the market is more like baseball (or wide receivers) or more like basketball.

References

Berri, D., Brook, S., & Fenn, A. (2011). From college to the pros: Predicting the NBA amateur player draft. *Journal of Productivity Analysis, 35*(1), 3525–3535.

Berri, D., Brook, S., & Schmidt, M. (2007). Does one simply need to score to score? *International Journal of Sport Finance, 2*(4), 190–205.

Berri, D., & Simmons, R. (2011). Catching a draft: On the process of selecting quarterbacks in the National Football League amateur draft. *Journal of Productivity Analysis, 35,* 37–49.

Boulier, B., Stekler, H., Coburn, J., & Rankins, T. (2010). Evaluating National Football League draft choices: The passing game. *International Journal of Forecasting, 26,* 589–605.

Bradbury, J. C. (2007) Does the baseball player labor market properly value of pitchers? *Journal of Sports Economics, 8*(6), 616–632.

Burnett, N. J., & Van Scyoc, L. J. (2013). Compensation discrimination for wide receivers: Applying quantile regression to the National Football League. *Journal of Reviews on Global Economics, 2,* 433–441.

Enders, C. K. (2010). *Applied missing data analysis.* New York: Guilford Press.

Holmes, P., Simmons, R., & Berri, D. (2014). Moneyball and the baseball players' labour market, paper presented at Western Economic Association meetings, Denver, CO.

Koz, D., Fraser-Thomas, J., & Baker, J. (2012). Accuracy of professional sports drafts in predicting career potential. *Scandinavian Journal of Medicine & Science in Sports, 22*(4), e64–e69.

Kuzmits, F. E., & Adams, A. J. (2008). The NFL combine: does it predict performance in the National Football League? *The Journal of Strength & Conditioning Research, 22*(6), 1721–1727.

Long, J. S. (1997). Regression models for categorical and limited dependent variables. *Advanced Quantitative Techniques in the Social Sciences Series,* vol. 7.

Mulholland, J., & Jensen, S. T. (2014). Predicting the draft and career success of tight ends in the National Football League. *Journal of Quantitative Analysis in Sports, 10*(4), 381–396.

Robbins, D. W. (2011). Positional physical characteristics of players drafted into the National Football League. *The Journal of Strength & Conditioning Research,* 25(10), 2661–2667.

Treme, J., & Allen, S. (2011). Press pass: payoffs to media exposure among National Football League (NFL) Wide Receivers. *Journal of Sports Economics, 12*(3), 370–390.