Data-Driven Drafting: Applying Econometrics to Employ Quarterbacks

By Jeremy Rosen and Alexandre Olbrecht[1]

Abstract: We show that firms can employ data-driven methods to improve their hiring decisions. Specifically, we use data available to National Football League (NFL) teams prior to the NFL draft to estimate econometric models that predict the future performance of drafted quarterbacks. Since our methods are replicable, stakeholders can use them to improve the draft's efficiency and help it accomplish its mission to promote competitive balance. Furthermore, data-driven methods such as ours can help firms avoid biases against employee characteristics that do not affect future job performance.

Keywords: Efficiency, Labor Market, NFL, Quarterback, Prediction Methods

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I. Introduction

In March 2019, the Bureau of Labor Statistics (BLS) reported that the United States added a net 196,000 new jobs (BLS 2019a). Yet this number fails to capture the magnitude of the labor market churn that produced it. That is because, per the Job Openings and Labor Market Turnover survey, 5.7 million people started new jobs, and 5.4 million people separated from their jobs (BLS 2019b). Furthermore, most of this churn was due to voluntary movements of workers (BLS 2019b). Therefore, from the viewpoint of firms, finding employees with the correct skill match and best future productivity is successful only some of the time. Furthermore, finding the next star employee is even more difficult.

However, per Groysberg, Nanda, and Nohria (2004), the battle for star talent may be fierce. For instance, when Wall Street firms "stumble across first-rate talent," they are willing to do almost anything to acquire that talent, including offering large salaries, signing bonuses, and stock options. Firms justify this business strategy by arguing that when their executives can "anticipate change, adapt quickly, and make decisions amid uncertainty," profits will soar. However, it is important to note that the term "stumble" acknowledges the hiring process is imperfect. In fact, Groysberg et al. (2004) conclude that pursuing stars often does not lead to long-term success.

Traditionally, firms make hiring decisions through an interview process. But this process requires the hiring manager to sort through his or her personal biases. In addition to biases that lead to race (Turner, Fix, and Struyk 1991), gender (Neumark, Bank, and Van Nort 1996), and sexual orientation (Weichselbaumer 2003) discrimination, there are more subtle ones as well. Baert and Decuypere (2014) find that perceived attractiveness and personality traits affect hiring decisions, and Cotton, O'Neil, and Griffin (2008) find that an applicant's first name does too. Moreover, Sameen and Cornelius (2015) find that the same may be true for social media profiles.

In response, some firms have attempted to revamp their hiring processes. Of these firms, some select for organizational fit rather than specific job skills (Barron, Bishop, and Dunkelberg 1985; Bowen, Ledford, and Nathan 1991). Others try to identify traits that will lead to success and then train hiring managers to look for those traits (Albrecht and van Ours 2006; Frijters 1999; Moy 2006; Schumacher, Grigsby, and Vesey 2015). Still others are using data-driven methods, such as job testing technologies (Hoffman, Kahn and Li 2017) and even credit scores (Kiviat 2017).

However, there are two issues with data-driven methods in particular. First, there may not be any available data correlated with an employee's future job performance, or any available in-job performance measures. In addition, an employee's performance should be linked at least partially to his or her human capital, some of which may be firm-specific. But in theory, if firms can identify useful data about prospective employees, then firms may be less susceptible to the previously-discussed biases.

In this paper, we investigate whether data-driven methods would help NFL teams looking to draft a quarterback. There are a few advantages to studying quarterbacks in the draft. First, unlike in many other industries, accurate performance data are readily available for both college and NFL quarterbacks. Second, the NFL is a multi-billion-dollar industry whose game outcomes are of great interest to society in general. Third, star quarterbacks greatly affect such outcomes, even more so than coaches, general managers, and owners (see Groysberg, Hecht, and Naik 2019). Fourth, general managers place a high level of importance on the quarterback position, knowing that a star, or franchise, quarterback is often integral to their job security. They may also feel the need to use a premium draft pick on a quarterback because of the challenge of convincing fans that a late-round quarterback is the future face of the team. Finally, unlike players of other positions or in other sports, quarterbacks undergo extensive pre-draft interviews.

Since the draft's inception, teams have allocated substantial resources to predict the future performance of drafted players. In a perfectly efficient reverse-order draft, the worst performing teams would select the best players, making the league more competitive. But the draft is currently not an efficient sorting mechanism. For example, Mulholland and Jensen (2014) show that the best predictors of where tight ends are drafted are not particularly good at predicting future NFL performance. As a result, teams overvalue physical traits such as body mass index, weight, and height (Mulholland and Jensen 2014).

In theory though, teams have more information about quarterbacks than other players, which should lead to better evaluations. But in practice, teams still struggle to evaluate quarterbacks. For instance, Wolfson, Addona, and Schmicker (2011) observe that teams have spent high picks on players who have failed in the NFL, such as Ryan Leaf (drafted in 1998) and JaMarcus Russell (2007). Teams have also let future stars, such as Tom Brady (2000) and Russell Wilson (2012), fall into later rounds.

However, since 2006, FootballOutsiders.com has posted statistical models for quarterback prospects, such as the Lewin Career Forecast (hereafter LCF).[2] The LCF uses two college statistics as predictors: Completion Percentage and College Games Started. Later models, like QBASE, incorporate additional information, such as Adjusted College Performance.[3] But Wolfson et al. (2011) find that the only reliable predictors of NFL success are Year Drafted and the log of Draft Position, and Berri and Simmons (2011) do not even find that much. Wolfson et al. (2011) conclude that models such as the LCF may not have predictive value, and NFL teams' draft mistakes may be largely due to unquantifiable factors.

Having said that, we build upon the empirical work of several authors and find that per Wolfson et al.'s (2011) criterion, predictive power under cross-validation, our models are more effective than draft position-only models. Therefore, we conclude that data-driven methods would in fact be helpful to NFL teams. More importantly, we show that when data are plentiful, data-driven methods can improve hiring processes. Section II explains the aforementioned previous empirical approaches, Section III describes our data, Section IV provides our methods and results, and Section V discusses those results. We conclude our paper in Section VI.

II. Literature Review

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[2] The LCF can be found in College Quarterbacks Through the Prism of Statistics. URL https://www.footballoutsiders.com/stat-analysis/2006/college-quarterbacks-through-prism-statistics.

[3] QBASE by Healy (2015) can be found in Introducing QBASE. URL http://www.footballoutsiders.com/stat-analysis/2015/introducing-qbase.

Our goal is to identify pre-draft statistics that can predict NFL quarterback performance. However, many performance statistics that seem like they should be predictive, such as touchdown passes per game, are not. One major reason is that nearly every drafted quarterback threw a lot of touchdowns per game in college. As a result, there is not enough variance for touchdowns per game to predict NFL performance. A similar situation occurs when using GRE quantitative scores to predict graduation rates in top economics doctoral programs because all admitted students have perfect or near-perfect scores.

Despite the difficulty of predicting NFL performance with observable pre-draft characteristics or with proxy variables for unobservable ones, there have been limited successes. Treme and Allen (2009) show that data can help teams evaluate wide receivers, and Mulholland and Jensen (2014) show the same for tight ends. However, for the reasons stated in Section I, we focus on quarterbacks. As also stated in Section I, to do so, we build upon the work of other authors.

The LCF was the first quarterback-prediction model, and it aimed to predict the future Defense-adjusted Points Above Replacement (DPAR) of NFL quarterbacks drafted in the first two rounds Ultimately, Lewin finds that two college statistics, Completion Percentage and (College) Games Started, were statistically significant predictors of DPAR from 1997 to 2005. However, the LCF does not disclose how many statistical tests he performed before arriving at his final model, and there is a possibility that one or both predictors are Type I errors (Babyak 2004).

A few years later, a new version of the LCF, called the LCF 2.0, used NFL Defense-adjusted Yards Above Replacement (DYAR) as its dependent variable.[4] Its sample is quarterbacks drafted in the first three rounds from 1998 to 2008. The LCF 2.0 has an R-squared of 0.58, substantially greater than that of 0.24 for the original LCF (which, in order to compare R-squareds across models, Schatz modifies so that DYAR is the dependent variable).

In the same year as the LCF 2.0, Berri and Simmons (2011) studied quarterbacks drafted from 1970 to 2007. They conclude that NFL teams give highly-drafted quarterbacks more chances to play, but such quarterbacks do not perform significantly better than others. In addition, unlike Pitts and Evans (2018), they find that combine results, such as 40-yard dash times and Wonderlic test scores, strongly affect when a quarterback is drafted but are poor predictors of NFL success.

Also in that year, Wolfson et al. (2011) found that statistical models cannot predict quarterback prospects' NFL success better than NFL teams can. They define better as having less cross-validated error than a Draft Position-only model. Thus, they conclude that even though NFL teams regularly make mistakes drafting quarterbacks, teams use pre-draft information as efficiently as possible.

Finally, QBASE considers quarterbacks drafted in the top 100 picks (essentially the first three rounds). To limit overfitting, QBASE has only three variables: Adjusted College Performance (ACP), Adjusted Games Started (AGS), and NFL Draft Position (DP). QBASE projections correlate well with NFL success, but DP, a proxy for scouting data, helps. Therefore, we cannot

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[4] The LCF 2.0 by Schatz (2011) can be found in Introducing Lewin Career Forecast V2.0. URL http://www.footballoutsiders.com/stat-analysis/2011/introducing-lewin-career-forecast-v20.

know whether ACP or AGS have predictive power. If so, QBASE would perform worse than a DP-only model under cross-validation.

Having said that, we acknowledge that harder-to-observe factors, such as intelligence, may also predict NFL performance. For example, Mirabile (2005) tests whether a quarterback's intelligence level, as measured by his Wonderlic score, predicts NFL performance. Like Berri and Simmons (2011), he does not find an effect. However, more recently, Pitts and Evans (2018) find that Wonderlic scores are positively correlated with the NFL performance of quarterbacks drafted from 2002 to 2012. But Wonderlic scores are apparently not correlated with draft position, which implies that teams may be undervaluing the Wonderlic.

III. Data

We use data from 2000 to 2014, a 15-year period, to predict how well quarterbacks drafted from 2016 onward will perform in the NFL. We omit the class of 2015 because first-year performance data are often unreliable. For example, likely Hall of Famer Peyton Manning (1998) struggled in his first year, whereas Robert Griffin III (2012) won Offensive Rookie of the Year and has struggled ever since. Also, we are forced to omit Giovanni Carmazzi (2000) because his college statistics are unavailable and Jimmy Garoppolo (2014) because prior to 2017, he backed up another likely Hall of Famer in Tom Brady (2000). Therefore, he would not have gotten the opportunity to start regularly no matter how good he looked in practice.

To preview our results, we find that despite conventional wisdom, quarterbacks who played in a pro-style offense in college have not been more successful in the NFL than those who played in a spread offense. As a result, we decided to investigate the previous 15 years of data, namely quarterbacks drafted from 1985 to 1999. For this period, we omit Bubby Brister (1986) and Steve McNair (1995) because their college statistics are unavailable. The distinction of dividing our sample into two 15-year blocks is relatively inconsequential to our estimation results. Essentially, the effect of a pro-style dummy is strongest in the late 1980s and early 1990s and gradually fades during the late 1990s and early 2000s.

Furthermore, we primarily focus on quarterbacks drafted in the first three rounds because general managers usually target franchise-quality quarterbacks in those rounds. In turn, with a few notable exceptions, such as Brady, most quarterbacks drafted in later rounds do not see significant playing time. However, it is also worth building a model that incorporates quarterbacks drafted in all seven rounds because such a model can potentially help identify the next Brady, that is, a hidden gem found in later rounds. In addition, Berri and Simmons (2011) and Wolfson et al. (2011) study all drafted quarterbacks. Therefore, in Table 8 in Appendix II (available online), we expand our model to include all such quaterbacks.

For quarterbacks drafted in the first three rounds, our sample sizes are 74 for the period from 2000 to 2014 and 58 for the period from 1985 to 1999. Our data are from Sports-Reference.com and Pro-Football-Reference.com, except for Pro-Style Offense Dummy, which we collect from various sources. In Table 1, we provide summary statistics, for which we list the independent variables before the dependent variables. Also, for completeness, we include summary statistics for our model with all seven rounds in Table 7 in Appendix II (available online). There, our sample size is 176.

Table 1: Summary Statistics, 1st 3 Rounds

Variable	1985-2014 (132 observations)				2000-2014 (74 observations)				1985-1999 (58 observations)			
	Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
Age When Drafted	22.6	0.9	21	28	22.7	1.1	21	28	22.6	0.7	21	24
Cleveland Browns Dummy	0.0	0.2	0	1	0.1	0.3	0	1	0.0	0.1	0	1
Completion Percentage	60.0	4.6	47.8	70.3	61.5	4.5	47.8	70.3	58.1	4.0	48.7	67.1
NFL Draft Position	36.2	30.3	1	97	35.5	30.8	1	97	37.1	29.7	1	91
log (NFL Draft Position)	2.9	1.5	0.0	4.6	2.9	1.5	0.0	4.6	2.9	1.5	0.0	4.5
Games Played	38.7	8.7	18	61	39.9	8.3	20	61	37.1	9.1	18	57
NFL Offensive Pro Bowlers	1.2	1.3	0	6	1.1	1.2	0	5	1.2	1.4	0	6
Pro-Style Offense Dummy	0.6	0.5	0	1	0.5	0.5	0	1	0.7	0.5	0	1
Run-Completion Ratio	0.4	0.2	0.1	1.5	0.4	0.3	0.1	1.5	0.4	0.2	0.1	0.8
log (Run-Completion Ratio)	-1.1	0.5	-3.0	0.4	-1.1	0.6	-3.0	0.4	-1.1	0.4	-2.0	-0.2
Run-Pass Ratio	0.2	0.1	0.0	1.0	0.3	0.2	0.0	1.0	0.2	0.1	0.1	0.5
log (Run-Pass Ratio)	-1.6	0.5	-3.3	0.0	-1.6	0.6	-3.3	0.0	-1.7	0.4	-2.5	-0.7
Rushing Yards per Attempt	0.8	2.5	-7.4	6.9	1.5	2.4	-3.8	6.9	-0.2	2.2	-7.4	4.4
Year Drafted	2000.6	8.6	1985	2014	2007.2	4.0	2000	2014	1992.2	4.5	1985	1999
NFL Adjusted Net Yards per Attempt	4.71	1.14	2.44	7.51	5.07	1.02	3.40	7.51	4.26	1.13	2.44	7.17
NFL Adjusted Yards per Attempt	5.7	1.1	3.6	8.6	6.0	1.0	4.3	8.6	5.3	1.0	3.6	7.6
NFL Approximate Value per Game Started	0.5	0.3	0.0	1.1	0.6	0.3	0.1	1.1	0.5	0.3	0.0	1.0
NFL Fantasy Points per Game Started	11.4	4.1	4.4	21.1	12.8	3.6	7.3	21.1	9.7	4.1	4.4	17.6
NFL Net Yards per Attempt	5.46	0.82	3.63	7.23	5.65	0.73	4.35	7.00	5.22	0.86	3.63	7.23
NFL Passer Rating	73.9	11.5	50.0	104.1	78.0	9.9	61.9	104.1	68.7	11.4	50.0	96.5
NFL Yards per Attempt	6.5	0.7	4.8	8.1	6.6	0.7	5.2	8.1	6.3	0.7	4.8	7.7

We start by describing our independent variables. As is relatively standard in many labor-type regressions, we log-transform some of them, namely NFL Draft Position, Run-Pass Ratio (defined as Rush Att / Pass Att), and Run-Completion Ratio (defined as Rush Att / Completions). In their paper, Wolfson et al. (2011) compare the predictive power of their models to that of a log (Draft Position) model. Therefore, we test Draft Position and log (Draft Position), so we can compare our models to the better NFL model. Also, Figures 1 and 2 contain histograms of Run-Pass Ratio and log (Run-Pass Ratio).

Fig 1. Histogram of Run-Pass Ratio, 1985-2014

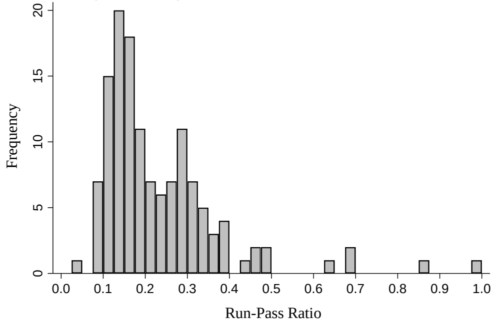
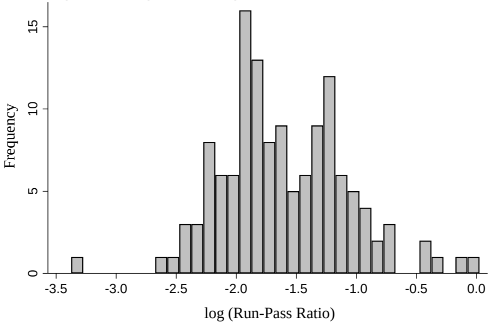


Fig 2. Histogram of log (Run-Pass Ratio), 1985-2014



For the most part, our log transformations are done for goodness-of-fit purposes, with the exception of Run-Pass Ratio, which should have a negative coefficient. If we did not transform Run-Pass Ratio, dual-threat quarterbacks, or those with a ratio greater than 0.5, would receive an overly harsh penalty, as the LCF 2.0 tries to avoid. A log transformation eliminates this problem. However, we only test log (Run-Pass Ratio), not Run-Pass ratio, so we do not use transformations to overfit the data. Our transformation of Run-Completion Ratio is analogous.

Having said that, our biggest challenge is selecting independent variables. Ideally, we would pre-specify our models (Wolfson et al. 2011), but many variables would be insignificant and have no predictive power. We could test these variables and keep only the significant ones, as the LCF did, but that may result in overfitting even if our final model is small (Babyak 2004). Moreover, cross-validation, which we use to measure predictive power, cannot detect this type of overfitting (Rao, Fung, and Rosales 2008). Worse still, a sample size of 74 does not give us much leeway for reserving a holdout set, which is considered best practice.

As such, we rely on Rao et al. (2008) for guidance. Aside from a holdout set if possible, they recommend limiting the number of candidate predictors and being selective with what we include in our final model. Thus, we limit our candidate predictors to five, all of which are available pre-draft and expected to be predictive: Age When Drafted, Completion Percentage, College Games Played, Pro-Style Offense Dummy, and Functional Mobility. Previous studies, such Berri and Simmons (2011) and Wolfson et al.'s (2011), done on overlapping but non-identical datasets, rule out many other variables. Finally, we use the Bonferroni Correction (see Section IV) to account for multiple hypothesis testing and further avoid overfitting.

Starting with Age When Drafted, we observe that with few exceptions, quarterbacks are drafted between 21 and 24 years old. Theoretically, younger ones are better because they have more potential and can play more years in the NFL. Stuart acknowledges this possibility and investigates whether NFL teams, who draft younger quarterbacks higher, properly value age.[5] He compares the actual performance of the 392 quarterbacks who played in the NFL from 1970 to 2008 to their expected performance based on draft position. Because age is not correlated with the difference between actual and expected performance, he concludes that unlike some mock drafters, NFL teams value age correctly.

Next, Completion Percentage is one of two variables in the LCF because quarterbacks accurate in college are likely to be accurate in the NFL. One may think Passing Yards per Attempt also translates to the NFL, but the opposite is true. Paradoxically, drafted quarterbacks who threw for more yards per attempt in college are less likely to succeed in the NFL (Wolfson et al. 2011).

Games Started is the other variable in the LCF. That is because college quarterbacks who started a lot of games should have been good, more games started equals more experience, and NFL teams can more accurately scout those quarterbacks. However, we can also argue that quarterbacks who started a lot of games in college were not good enough to get drafted sooner. Furthermore, as the LCF 2.0 points out, the LCF systematically overvalues quarterbacks with a high number of starts who were drafted after 2006. Without publicly available data for Games Started, we substitute Games Played. Ultimately, we expect a significantly positive coefficient from 1985 to 1999 only.

As for Pro-Style Offense Dummy, a challenge for quarterback prospects is that NFL offenses are different from college ones. Recently, colleges have adopted fast-paced but simplified spread offenses designed to wear down opposing defenses. Unfortunately, quarterbacks from such

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[5] See Stuart, C. (2013). Do NFL teams properly value age when drafting quarterbacks? URL http://www.footballperspective.com/do-nfl-teams-properly-value-age-when-drafting-quarterbacks/.

schools may be unprepared for the NFL. There, quarterbacks must know a wide variety of plays, change plays at the line of scrimmage, and scan the field repeatedly to find an open receiver.

While most colleges do not ask quarterbacks to do those things, some run pro-style offenses. We expect quarterbacks with experience in these offenses, who are assigned a value of 1, to perform better in the NFL, all else constant. Despite that, no published study has tested this hypothesis, as there is no database, aside from ours, identifying which quarterbacks played in pro-style offenses. We use online sources, such as scouting reports and newspaper articles, to determine whether a quarterback played in a pro-style offense. For example, Ron Musselman of the *Toledo Blade* reported in 2001, "Marshall, Western Michigan, Buffalo, Bowling Green, and Toledo" run "some version of the spread offense." Chad Pennington (2000) quarterbacked Marshall, so we assign him a value of 0. A link for each quarterback is in Appendix I (available online).

Our last candidate predictor is Functional Mobility. Per Farrar, unlike a dual-threat quarterback, a functionally mobile quarterback does not run often.[6] However, when he runs, he is an effective runner. Farrar claims that Functional Mobility "takes a great quarterback and makes him nearly unbeatable." Therefore, similarly to the LCF 2.0, we use the variables log (Run-Pass Ratio) and Rushing Yards per Attempt to identify functionally mobile quarterbacks. We expect log (Run-Pass Ratio) to have a negative coefficient and Rushing Yards per Attempt to have a positive coefficient. In addition, we prefer Rushing Yards per Attempt over 40-yard dash time because quaterbacks rarely rely on straight-line speed, even when scrambling.

Moreover, in college football, sacks count as rushing attempts and negative rushing yards. Therefore, college quarterbacks with a low log (Run-Pass Ratio) and high Rushing Yards per Attempt are sacked less on average. Sacks are a problem as quarterbacks sacked often may have difficulty making defensive reads and/or may have a slow release. In addition, we establish that no multiple model includes one variable without the other; for inclusion, both must be significant. In addition, if log (Run-Pass Ratio), Rushing Yards per Attempt, and Completion Percentage are significant, we omit Completion Percentage and change log (Run-Pass Ratio) to log (Run-Completion Ratio). This substitution works because Completions = Pass Attempts × Completion Percentage.

As well as our five candidate predictors, we test whether quarterbacks drafted by NFL teams with better players are more likely to succeed. To do so, we consider the number of non-quarterbacks who made the Pro Bowl on each prospect's NFL team's offense the year before he was drafted. While NFL rosters frequently turn over from year to year, our measure proxies the offensive environment he will face once drafted. Due to Draft Day trades, we look at a quarterback's eventual team to assess the number of Pro Bowlers for the upcoming season.

Thus, we make data adjustments. We consider Eli Manning (2004) a Giant and Philip Rivers (2004) a Charger because they were swapped on Draft Day. In addition, Brett Favre (1992) was drafted by the Falcons but traded to the Packers immediately after a first season in which he barely played. Thus, we set Favre's value for NFL Offensive Pro Bowlers to be the number of

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[6] See Farrar, D. (2015). The NFL's Hidden Talents: Best functionally mobile quarterbacks. URL http://www.si.com/nfl/2015/05/14/functionally-mobile-quarterbacks-aaron-rodgers-tom-brady-drew-brees.

Pro Bowlers who played on the 1992 Packers. However, because a quarterback's NFL team is not known before the draft, we do not include NFL Offensive Pro Bowlers in our models regardless of its significance.

Finally, two variables we do not test are Wonderlic scores and the strength of a quarterback's college team. While Pitts and Evans (2018) find Wonderlic scores are predictive, Berri and Simmons (2011) find the opposite is true. Therefore, we err on the side of not testing too many candidate predictors and do not test Wonderlic scores. In addition, a few of the quarterbacks in our dataset, such as Joe Flacco (2008), did not play in the premier Football Bowl Subdivision (FBS), formerly Division 1-A. Rather, they played in the smaller Football Championship Subdivision (FCS), formerly Division 1-AA. But despite the skill gap between the FBS and FCS, a dummy variable for non-Division 1-A quarterbacks is not a significant predictor of Wins Produced per 100 Plays (Berri and Simmons 2011), which is analogous to ANY/A.

We conclude this section by addressing our dependent variables, which represent common measures of NFL quarterback performance. We use each of these variables for completeness and get similar results with each one. However, our preferred dependent variable is NFL Adjusted Net Yards per Attempt (ANY/A) because it has the highest correlation with wins.[7] Adjusted Net Yards per Attempt is defined as:

$$[1]\ \text{ANY/A} = \frac{\text{pass yards} + 20 \times \text{pass TD} - 45 \times \text{INT thrown} - \text{sack yards}}{\text{pass attempts} + \text{sacks}}.$$

Passing touchdowns are multiplied by 20 because Stuart finds that statistically, a touchdown is worth about 20 yards.[8] While many quality passes do not go for touchdowns, throwing touchdowns, especially in the red zone, is an important skill. Also, interceptions are multiplied by -45 because Stuart agrees with Carroll, Palmer, and Thorn (1988) that an interception is worth -45 yards.[9] It is important to note that like Berri and Simmons (2011), Stuart does not arbitrarily choose the weights in his statistic. Rather, he assigns them based on empirical analyses so that the statistic accurately measures quarterback performance.[8]

Unfortunately, from 1985 to 2014, 19 quarterbacks played just a handful of NFL snaps. For example, Pat White (2009) only threw five passes in his career and has an ANY/A of -1.50. Because such a small sample most likely does not reflect his true ability, we may have a problem estimating our models. Thus, our approach is to set a minimum value for ANY/A equal to the lowest ANY/A of any quarterback who started at least 10 career games.

From 2000 to 2014, that quarterback was Jimmy Clausen (2010, ANY/A = 3.40), and from 1985 to 1999, he was Kelly Stouffer (1987, ANY/A = 2.44). Because the aforementioned 19 quarterbacks would have likely had low, but not abnormally low, ANY/A's if given the chance to

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[7] See Stuart, C. (2012). Correlating passing stats with wins. URL http://www.footballperspective.com/correlating-passing-stats-with-wins/.

[8] See Stuart, C. (2008). The final value of a passing touchdown. URL https://www.pro-football-reference.com/blog/index4db6.html?p=633.

[9] See Stuart, C. (2014). Thoughts on the value of a fumble vs. an interception. URL https://www.footballperspective.com/thoughts-on-the-value-of-a-fumble-vs-an-interception/.

play, we believe a minimum ANY/A is best. In Figures 3 and 4, we provide histograms of the distributions of ANY/A from 2000 to 2014 and from 1985 to 1999 respectively.

Fig 3. Histogram of ANY/A, 2000-2014

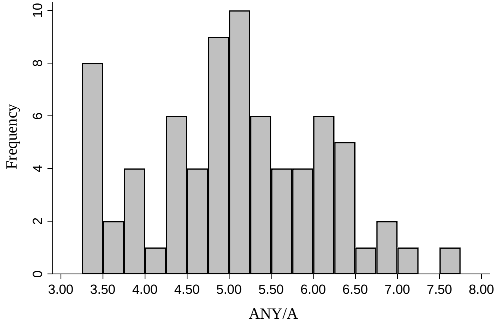
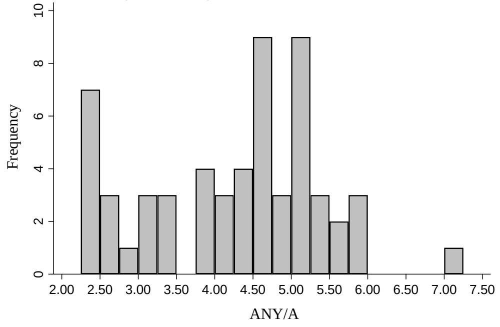


Fig 4. Histogram of ANY/A, 1985-1999



We could also omit quarterbacks with little or no NFL playing time. For example, Berri and Simmons (2011) do not consider quarterbacks with fewer than 100 career plays. But Wolfson et al. (2011) suggest that doing so is a form of selection bias because such quarterbacks are not representative of those drafted in the first three rounds. Furthermore, we could use a quarterback's actual value, or for one who did not play, set his value at zero. But because the quarterbacks' sample sizes are small or nonexistent, such values are not likely to be accurate.

The literature is not in agreement with what the best strategy is, but fortunately, changing our approach does not seem to influence our results in any significant way. Omitting quarterbacks with fewer than 10 starts, which is our threshold for using a minimum ANY/A, does not change the signs or significance of the coefficient estimates. Using actual values also does not change the signs or significance, but it does reduce the goodness-of-fit of the regressions, mostly due to the occasional non-positive ANY/A.

IV. Empirical Methods and Results

We wish to build a model that can predict the success of quarterback prospects better than NFL teams do. Consistent with Wolfson et al. (2011), we define such a model as one with a higher Cross-Validated (hereafter CV) R-squared than an NFL Draft Position-only model, where Draft Position proxies NFL scouting. For CV R-squared to be high, the independent variables should be significant in the sample. But CV R-squared will be biased upward if a variable is significant in the sample but not the population (Rao et al. 2008), that is, the variable is a Type I error.

Thus, we select only variables that we are confident, by theory and statistical analysis, are not Type I errors. While such parsimony may bias coefficients, we seek only an unbiased CV R-squared because our models are for prediction, not explanation (Ganesan 2012). One exception is Functional Mobility. Including only one of log (Run-Pass Ratio) or Rushing Yards per Attempt would severely bias that coefficient because dual-threat quarterbacks and efficient runners are highly correlated ($\rho = 0.762$). Therefore, we include both or neither. With that in mind, we build a univariate linear model for each variable and test the coefficient for significance. If it is significant, we include the variable in our final multiple linear model. We prefer this method over dropping insignificant predictors from a larger multiple model because we want to know which variables, even on their own, can predict NFL success.

First, we test Year Drafted, which accounts for positive changes in ANY/A over time, that is, improvements in NFL offenses. If it is significant at the 5% level, we include it in the NFL model and ours. Next, we test NFL Draft Position and log (NFL Draft Position). Whichever has the lower p-value makes up the NFL model, along with Year Drafted if appropriate. After that, we test at the 5% level Offensive Pro Bowlers, which does not appear in any model.

The remaining tests are for the college statistics. To avoid Type I errors, we implement the Bonferroni Correction, which divides the typical 5% significance level by the number of tests performed. Because we test five predictors, we lower their significance level to 1%. The Bonferroni Correction tests the universal null hypothesis, which states that all variables are insignificant, and it is used when "it is imperative to avoid a Type I error" (Armstrong 2014). The Bonferroni Correction may cause underfitting, but we are not concerned because the worst outcome is a CV R-squared that is not as high as it could be. Ultimately, we do not need the true model, just one with a trustworthy CV R-squared higher than the NFL model. We provide the results of our hypothesis tests from 2000 to 2014 and 1985 to 1999 in Table 2.

Table 2: Hypothesis Tests, 1st 3 Rounds

Dependent Variable: NFL ANY/A

Note: P-values are one-sided. For NFL predictors, α = 0.05. For college predictors, α = 0.01.

Predictor	2000-2014			1985-1999		
	Exp	Est	P-val	Exp	Est	P-val
Year Drafted	+	+	0.145	+	+	0.375
NFL Draft Position	-	-	**0.001**	-	-	0.211
log (NFL Draft Position)	-	-	**0.002**	-	-	0.053
NFL Offensive Pro Bowlers	+	-	0.879	+	+	**0.024**
NFL Offensive Pro Bowlers (no Culpepper)	NA	NA	NA	+	+	0.070
Age When Drafted	-	-	0.079	-	-	**0.002**
Completion Percentage	+	+	**0.008**	+	+	0.036
Games Played	+	-	0.683	+	+	0.196
Pro-Style Offense Dummy	+	-	0.724	+	+	**0.001**
log (Run-Pass Ratio)	-	-	**0.001**	-	-	0.495
Rushing Yards per Attempt	+	+	**0.000**	+	+	0.345

From 2000 to 2014, NFL Draft Position and log (NFL Draft Position) are significant, an outcome consistent with previous research. The log transformation increases the p-value slightly, so we choose the untransformed version for the NFL model. The other significant variables are Completion Percentage and Functional Mobility. Surprisingly, NFL Offensive Pro Bowlers, Games Played, and Pro-Style Offense Dummy have the wrong signs. We focus on the signs of the estimates for simplicity because their values are of less relevance.

Berri and Schmidt (2010) provide ancillary evidence that Completion Percentage and Functional Mobility can predict NFL success. They ask, "How much of the variation in current season performance [of NFL quarterbacks] is explained by performance last season?" Of the eight statistics they test, Completion Percentage, Sacks per Pass Attempt, and Rushing Yards per Attempt are the best, explaining 24, 25, and 26% of the variation respectively. Completion

Percentage is our measure of accuracy, and Sacks per Pass Attempt and Rushing Yards per Attempt are almost identical to our measures of Functional Mobility.

In addition, from 1985 to 1999, neither NFL Draft Position nor its log are significant. But the transformed version has a lower p-value, so we use it for the NFL model. NFL Offensive Pro Bowlers is significant at the 5% level, but that is because Daunte Culpepper (1999) was drafted by a Minnesota Vikings team with six offensive Pro Bowlers and had an ANY/A of 5.91. If we omit the Culpepper observation, we no longer find this variable to be significant. Ultimately, the significant college predictors are Age When Drafted and Pro-Style Offense Dummy. Although Completion Percentage is significant at the 5% level, we do not include it in our model because it is not significant at the 1% level. Surprisingly, Games Played is not significant.

Having established which variables to use in our models, we estimate multiple regressions. Our 2000-2014 model contains log (Run-Completion Ratio) and Rushing Yards per Attempt and rewards quarterbacks who are accurate, pocket passers, and good runners when necessary. On the other hand, our 1985-1999 model contains Age When Drafted and Pro-Style Offense Dummy and rewards those who are younger and played in a pro-style offense.

We use only the 2000-2014 model to make predictions; the 1985-1999 model shows that the quarterback position has changed over time. Table 3 contains the regression results for our 2000-2014 model, the NFL 2000-2014 model, our 1985-1999 model, and the NFL 1985-1999 model. In this table, all p-values are one-sided. As stated in Section III, we also estimate our 2000-2014 model on quarterbacks drafted in all seven rounds. Per Table 8 in Appendix II (available online), including all seven rounds does not materially impact our results.

Table 3: Models, 1st 3 Rounds

Dependent Variable: NFL ANY/A

Model	R2	Adj R2	CV R2	Regressor	Coef	P-val
Our, 2000-2014	0.178	0.155	0.114	Constant	3.541	0.000
				log (Run-Completion Ratio)	-1.033	0.000
				Rushing Yards per Attempt	0.281	0.000
NFL, 2000-2014	0.126	0.114	0.074	Constant	5.487	0.000
				NFL Draft Position	-0.012	0.001
Our, 1985-1999	0.318	0.293	0.244	Constant	17.483	0.000
				Age When Drafted	-0.618	0.001
				Pro-Style Offense Dummy	1.044	0.000
NFL, 1985-1999	0.046	0.029	0.000	Constant	4.733	0.000
				log (NFL Draft Position)	-0.161	0.053

While we do care about the coefficients, we are mainly interested in the CV R-squareds, which are found with Leave-One-Out Cross-Validation (LOOCV). LOOCV successively leaves each observation out of the sample and uses the left-out point for validation (Arlot 2010). As we hoped, in both time periods, our model's CV R-squared, despite being less than 0.25, is greater than the NFL's. From 2000 to 2014, the more important period, it is over 1.5 times greater. While we cannot show that our 2000-2014 model will beat NFL teams in the future, we are confident due to the Bonferroni Correction that log (Run-Completion Ratio) and Rushing Yards per

Attempt are not Type I errors. Thus, the Bonferroni Correction makes CV R-squared a more reasonable estimate for our model's predictive power (Rao et al. 2008).

Furthermore, we choose LOOCV over 5-fold CV (Wolfson et al. 2011) because our samples are smaller than Wolfson et al.'s (2011) sample of 160. Therefore, for our models and the NFL's, 5-fold CV R-squareds would be pessimistically biased (Breiman and Spector 1992). While unbiased, LOOCV estimates have high variance due to the similarity of the training sets (Raidl and Cagnoni 2003). Thus, we find whether our models also have greater predictive power than the NFL's for related dependent variables. These variables are Passing Yards per Attempt (Y/A), Adjusted Yards per Attempt (AY/A), Net Yards per Attempt (NY/A), Passer Rating (Rate), Approximate Value per Game Started (AV/GS), and Fantasy Points per Game Started (FP/GS). Y/A, AY/A, and NY/A are similar to ANY/A; their formulas are as follows:

$$[2]\ \text{Y/A} = \frac{\text{pass yards}}{\text{pass attempts}}$$

$$[3]\ \text{AY/A} = \frac{\text{pass yards} + 20 \times \text{pass TD} - 45 \times \text{INT thrown}}{\text{pass attempts}}$$

$$[4]\ \text{NY/A} = \frac{\text{pass yards} - \text{sack yards}}{\text{pass attempts} + \text{sacks}}$$

Rate is the most popular metric, but it contains the same information as AY/A. Unlike the other statistics, AV/GS and FP/GS credit quarterbacks for rushing yards; FP/GS also penalizes quarterbacks for fumbles lost. In addition, from 2000 to 2014, Jimmy Clausen's (2010) values are the lower bounds (see Section III) for all variables but Y/A and AV/GS. For Y/A, Brodie Croyle's value (2006) is the lower bound, and for AV/GS, Brady Quinn's value (2007) is the lower bound. From 1985 to 1999, Kelly Stouffer's (1987) ANY/A and FP/GS are the lower bounds for all ANY/As and FP/GSs. But for Y/A and NY/A, Akili Smith's (1999) values are the lower bounds, and for AY/A, Rate, and AV/GS, Ryan Leaf's (1998) values are the lower bounds.

Finally, because quarterbacks with fewer than 10 starts may have unrealistically low or high AV/GSs and FP/GSs, we assign all such quarterbacks the lower bound for these variables. Also for these variables, we omit Charlie Whitehurst (2006), Ryan Mallett (2011), Brock Osweiler (2012), and Johnny Manziel (2014) because in 2016, they had fewer than 10 starts but were still active. Finally, we omit Tom Tupa (1988) for AV/GS because AV/GS credits him for being a punter as well as a quarterback. Ultimately, from 2000 to 2014, our model's CV R-squareds are higher than the NFL's for all dependent variables but Y/A and AV/GS. Also, from 1985 to 1999, ours are higher for all variables. We show these results in Table 4. Therefore, LOOCV's high variance is probably not responsible for our models appearing more predictive than the NFL's.

Table 4: CV R2, 1st 3 Rounds

Dependent Variable	2000-2014		1985-1999	
	Our Model	NFL Model	Our Model	NFL Model
Adjusted Net Yards per Attempt	0.114	0.074	0.244	0.000
Adjusted Yards per Attempt	0.079	0.064	0.205	0.000
Approximate Value per Game Started	0.071	0.098	0.136	0.000
Fantasy Points per Game Started	0.137	0.080	0.142	0.000
Net Yards per Attempt	0.115	0.095	0.263	0.000
Passer Rating	0.069	0.028	0.193	0.000
Yards per Attempt	0.056	0.080	0.211	0.000
Average	0.092	0.074	0.199	0.000

V. Discussion

To provide insight as to how our models may be used, we use our 2000-2014 model to make predictions for the 2015 and 2016 draft classes, along with Jimmy Garoppolo (2014). We present these predictions in Table 5, in which we derive the "Our Pick" column by calculating the value for Draft Position that, per the NFL model, results in each quarterback's ANY/A. We also notice that there is a strong correlation ($\rho = 0.735$) between our grades and the NFL's. This correlation was not always so strong, so NFL teams may have recently considered models such as ours.

Table 5: 2014-2016 Predictions

Quarterback	Our ANY/A	95% PI	Our Pick	NFL Pick
Marcus Mariota	6.27	(4.28, 8.26)	1	2
Carson Wentz	5.49	(3.59, 7.40)	1	2
Jameis Winston	5.49	(3.60, 7.38)	1	1
Paxton Lynch	5.21	(3.33, 7.09)	24	26
Jared Goff	5.16	(3.26, 7.06)	28	1
Garrett Grayson	5.13	(3.25, 7.01)	30	75
Jacoby Brissett	5.02	(3.13, 6.91)	40	91
Jimmy Garoppolo	4.91	(3.02, 6.80)	49	62
Cody Kessler	4.52	(2.60, 6.45)	82	93
Christian Hackenberg	4.46	(2.55, 6.37)	87	51
Sean Mannion	4.10	(2.08, 6.11)	97	89

Furthermore, per the NFL model, the expected ANY/A for the first pick is 5.46. However, our model projects Mariota (2015), Winston (2015), and Wentz's (2016) ANY/As to exceed 5.46. Also, the expected ANY/A for the 97th pick, which is the latest pick in our dataset (Chris Simms 2003), is 4.42. But our model projects Mannion (2015)'s ANY/A to be less than 4.42. Despite that, Mariota, Winston, and Wentz's projected Draft Positions are each 1 and Mannion's is 97. Finally, our model's coefficients are large enough that the difference between Mariota and Mannion's projections is the same as that between a good starter and a career backup.

Due to the Bonferroni Correction, we are confident that our CV R-squared value is trustworthy. Thus, if the quarterback position does not change in the next two years, and NFL teams do not improve at drafting quarterbacks, our model may beat the NFL. That said, our 1985-1999 model shows that the significant predictors of NFL success change over time. Therefore, we should not use our 2000-2014 model on draft classes after 2016 without considering how additional data may affect the model's specification.

Finally, we estimate three additional models: one with only the Functional Mobility variables, one combining our 2000-2014 model with the NFL's, and one that adds a dummy variable indicating if a quarterback was drafted by the Cleveland Browns. The results are in Table 6.

Table 6: Additional Models, 1st 3 Rounds, 2000-2014

Dependent Variable: NFL ANY/A

Model	R2	Adj R2	CV R2	Regressor	Coef	P-val
Functional Mobility	0.162	0.138	0.096	Constant	2.973	0.000
				log (Run-Pass Ratio)	-1.064	0.001
				Rushing Yards per Attempt	0.290	0.000
Combined	0.225	0.192	0.134	Constant	4.101	0.000
				NFL Draft Position	-0.008	0.022
				log (Run-Completion Ratio)	-0.854	0.003
				Rushing Yards per Attempt	0.219	0.003
Cleveland Browns	0.270	0.228	0.171	Constant	3.922	0.000
				NFL Draft Position	-0.007	0.039
				log (Run-Completion Ratio)	-0.995	0.001
				Rushing Yards per Attempt	0.251	0.001
				Cleveland Browns Dummy	-0.884	0.021

Starting with the Functional Mobility Model, we find that Functional Mobility is the best predictor of NFL success. In fact, its CV R-squared is higher than Draft Position's, which means that for quarterbacks drafted in the first three rounds from 2000 to 2014, Functional Mobility has outperformed NFL scouts. Also, because there was not always a strong correlation between Functional Mobility and Draft Position, teams may have undervalued Functional Mobility. A similar phenomenon happened in Major League Baseball; until the Oakland Athletics pioneered the use of analytics, teams undervalued on-base percentage (Lewis 2003).

On the other hand, MLB scouts often overrated prospects who looked the part of major leaguers (Lewis 2003). Similarly, conventional NFL wisdom holds that quarterbacks without pro-style experience are deficient. For example, in an interview with *The Wall Street Journal*, executive Doug Whaley said the prevalence of spread quarterbacks makes him "a little nervous about the long-term future of this game."[10] But we find that since 2000, pro-style quarterbacks are no more likely to succeed in the NFL than spread ones.

Moving to the Combined Model, we show that our models are a complement for scouting reports and not a substitute. One of our limitations is that before we can apply our models, we depend on scouts to identify which quarterbacks are worthy of being drafted in the first three rounds. Even when we expand our dataset to include quarterbacks drafted in all seven rounds, we still depend

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[10] For the full quote, see Clark, K. (2015). Why the NFL Has a Quarterback Crisis. URL http://www.wsj.com/articles/why-the-nfl-has-a-quarterback-crisis-1441819454.

on scouts to identify the draftable quarterbacks. Also, although our model's CV R-squared is higher than the NFL's, the Combined Model's is even higher. While Draft Position is not available until after the draft, scouting grades can suffice as an approximation for this model. Thus, combining statistical analysis with scouting yields optimal results.

As for the Cleveland Browns Model, we find that for the most part, teams have been equally adept at drafting quarterbacks. For this reason, we do not generally include team-specific effects in our models. However, the Browns are an exception. Prior to drafting Baker Mayfield with the first overall pick in 2018, they started over 20 different quarterbacks. Their futility inspired an infamous jersey with nearly all the quaterbacks' names on it. Browns quarterbacks in our dataset include Charlie Frye (2005), Brady Quinn (2007), Colt McCoy (2010), Brandon Weeden (2012), and Johnny Manziel (2014). Quinn, Weeden, and Manziel were drafted in the first round and Frye and McCoy in the third. As of the start of 2016 season, none are with the Browns, and only McCoy and Weeden are still in the NFL.

When we add a Browns dummy to the Combined Model, we find the coefficient is negative and significant. Thus, quarterbacks taken by the Browns did worse than our statistical model would otherwise suggest. The interpretation of the dummy's coefficient is that such quarterbacks have a career ANY/A nearly one yard less than otherwise. This effect is large, considering the ANY/As in the sample range from 3.40 (multiple quarterbacks) to 7.51 (Aaron Rodgers 2005). Therefore, Browns quarterbacks have underperformed considerably relative to the rest of the NFL.

VI. Conclusion

We study the efficiency of NFL teams in the draft through the lens of firms making hiring decisions. We focus specifically on quarterbacks because they are especially important in the NFL, and teams rely on pre-draft interviews to evaluate them. In addition, we emphasize quarterbacks drafted in the first three rounds because general managers typically search for their next franchise quarterback during those rounds. However, since our model can also be used to help identify a sleeper pick in subsequent rounds, we estimate it with a larger sample as well. We find no significant difference in the results when we include quarterbacks from later rounds.

For our models, we consider college statistics, such as Completion Percentage, and demographic predictors, such as whether a quarterback played in a pro-style offense. When tested with cross-validation, our models predict quarterbacks' NFL success more accurately than Draft Position-only models. Therefore, our models may be able to make accurate predictions, not just explain which traits have made past quarterbacks successful.

In contrast to the most recent literature, we conclude that teams may be able to do a better job drafting quarterbacks. If so, there is a labor market inefficiency that teams can correct with our methodology and models. The NFL's stated goal for the draft is to improve competitive balance; data-driven methods such as ours, combined with traditional scouting, may help accomplish this goal and improve the draft's efficiency.

For example, teams have undervalued African-American (Berri and Simmons 2011) and short quarterbacks (Berri and Simmons 2011), and many scouts look for pro-style quarterbacks.

However, there is no evidence that African-American, short, and/or spread quarterbacks perform worse in the NFL than Caucasian, tall, and/or pro-style quarterbacks. Yet views in the NFL may be changing. In 2019, the first pick in the draft was Kyler Murray, who is African-American and short (5'10") and played in a spread offense at Oklahoma.

Having said that, while pre-draft statistics can help predict NFL performance, they are not a comprehensive way to do so. Drafting quarterbacks is an immensely difficult task despite the incentives for teams to improve their decision-making and the steps they have taken to do so. Unfortunately, some problems, such as this one, do not have any simple solutions. However, if the NFL, which is known for resisting change, can reform its hiring processes, then perhaps other industries can as well. Therefore, by identifying measurable data correlated with future productivity, firms in general can limit the negative effects of biases against such characteristics as race and other attributes irrelevant to future performance. In turn, firms can improve their hiring decisions and become more efficient. Most importantly, our work with data-driven methods suggests that other firms may be successful with such methods.

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Supplementary Online Material

Appendix I: Links for Pro-Style Offense Dummy (1 = Pro-Style, 0 = Not Pro-Style)

1. Randall Cunningham 1 http://articles.latimes.com/1987-08-23/sports/sp-3245_1_black-quarterbacks
2. Frank Reich 1 http://articles.baltimoresun.com/1993-01-09/sports/1993009074_1_frank-reich-odonnell-scott-zolak
3. Jim Everett 1 http://onlineathens.com/stories/123099/dog_gam8.shtml#.V75WxJgrI2w
4. Chuck Long 1 https://www.landof10.com/big-ten/five-big-ten-schools-that-could-join-ohio-state-michigan-on-reddits-celebrated-most-hated-list
5. Jack Trudeau 1 http://www.nytimes.com/1985/12/31/sports/peach-bowl-army-and-illinois-an-offensive-match.html
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Appendix II: Summary Statistics and Empirical Results for All Seven Rounds

Table 7: Summary Statistics, All 7 Rounds, 2000-2014 (176 Obs)

Variable	Mean	SD	Min	Max
log (Run-Completion Ratio)	-1.1	0.6	-3.0	0.4
Rushing Yards per Attempt	1.3	2.5	-3.8	6.9
NFL Adjusted Net Yards per Attempt	4.10	1.06	3.40	7.51

Table 8: Our Model, All 7 Rounds, 2000-2014

Dependent Variable: NFL ANY/A

R2: 0.069, Adj R2: 0.059, CV R2: 0.038

Regressor	Coef	P-val
Constant	3.185	0.000
log (Run-Completion Ratio)	-0.644	0.001
Rushing Yards per Attempt	0.178	0.000