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Predicting the National Football League Potential of College Quarterbacks

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Abstract

We use college football data and, in some cases, ESPN scout grades to estimate (1) attributes that are likely to result in a college quarterback being selected by a National Football League (NFL) team, and (2) the performance of rookie quarterbacks in the NFL. We find that both college passing and rushing ability are significantly correlated with NFL selection, with strong passing ability the most important trait for making the NFL. Among quarterbacks selected for the NFL, college rushing ability is significantly correlated with NFL performance, but college passing ability is not. College rushing ability is also a significant determinant of NFL performance when scout grades are included as an explanatory variable. We conclude that rushing prowess is the key determinant of the NFL success of quarterbacks with sufficient passing skills to warrant NFL selection. Our findings also indicate that scouts systematically undervalue rushing ability when assessing the NFL potential of college quarterbacks.

Keywords: OR in sports; Selection; Multivariate regression analysis

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1. Introduction

Operations Research (OR) techniques have been widely used to evaluate outcomes and assist decision making in sports, with regression analysis one of the most common analytical approaches (Wright, 2014). For example, Müller et al. (2017) use multilevel regression analysis to estimate players' market values in association football. Lenten et al. (2018) propose an alternative method to allocate draft picks in the Australian Football League that reduces tanking (deliberately selecting losing teams to receive future benefits) relative to current rules. Kendall and Lenten (2017) examine sports rules from an OR perspective to explain situations where rules led to unforeseen and/or unwanted consequences. Scarf et al. (2019) examine the relationship between outcome uncertainty and scoring rates in international rugby union and conclude that increased scoring rates may reduce spectator interest. Arlegi and Dimitrov (2020) analyze the fairness of alternative elimination-type structures for sporting competitions. Also concerning tournament design issues, Winchester (2016) details how regression analysis inspires a change to rugby bonus points, and Winchester and Stefani (2013) and Winchester (2017) show that awarding rugby-style bonus points improves the accuracy of National Football League (NFL) competition tables in ranking teams from strongest to weakest.

A subset of the sports analytics literature focuses on drafting NFL players. Mulholland and Jensen (2014) use college data, NFL combined results, and physical measures to predict both NFL draft order and NFL career success of tight ends. Wolfson et al. (2011) use games played and net points to quantitate NFL success and conclude that college statistics have little value for predicting NFL quarterback performance. Berri and Simmons (2011) estimate what factors NFL teams consider when drafting quarterbacks and the relationship between draft position and NFL performance. They find many college metrics that improve a quarterback's draft position are unrelated to future NFL performance. Pitts and Evans (2018) show that quarterback Wonderlic scores – a test of cognitive ability – are positively correlated with NFL performance. Rosen and Olbrecht (2020) find that quarterbacks who demonstrated 'functional mobility' in college performed better than those who did not. The authors measure function mobility using rushing yards per attempt (positively correlated with NFL performance) and the log of the run-passing completion ratio (negatively correlated with NFL performance).[1]

As a quarterback is the highest-paid NFL position (DeSilva, 2017), we extend the literature that estimates the NFL success of quarterbacks using college statistics using a two-stage analysis. In the initial stage, we first estimate the relationship between NFL selection and college quarterback performance metrics, such as passing yards per attempt and rushing yards per attempt. In the second stage, we explore the relationship between the performances of quarterbacks in their first five years in the NFL using data from their college careers and, in some cases, scout grades.

Our analysis is novel in at least four ways. To our knowledge, we present the first study to use Total Quarter Back Rating (QBR) to measure NFL performance, which Stuart (2014) shows is more strongly correlated with quarterback win percentages than other performance measures, such as adjusted net yards per attempt used by Rosen and Olbrecht (2020).

Second, our NFL performance analysis adjusts quarterback college statistics for the strength of opposing defenses. Despite large differences in the quality of defenses across teams, as far as we can ascertain, no previous academic study has adjusted college statistics for the strength of defenses against which quarterbacks play.

Third, our study includes an NFL selection predictor that considers all quarterbacks who played Football Bowl Subdivision (FBS) college football during our sample period. In contrast, other studies that estimate a selection module only consider drafted quarterbacks and estimate the order in which these players will be drafted (e.g., Berri and Simmons, 2011). Consequently, our analysis considers a wider set of quarterbacks when assessing the aspects of college quarterback play that NFL teams value.

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[1] In addition to academic studies, many organization likely operate proprietary models to predict the NFL performance of college players. Internal models that we are aware of include a quarterback prediction model developed by ESPN Production Analytics (Katz and Bradshaw, 2015) and Football Outsiders' Quarterback-Adjusted-Stats-and-Experience (QBASE) projection system (Schatz, 2019).

Fourth, in some specifications, we include scout scores (in addition to college statistics) as a predictor of NFL performance, which allows us to evaluate whether scouts use college statistics efficiently. Several studies include the order in which a player was drafted as an independent variable to explain NFL success (e.g., Rosen and Olbrecht, 2020), but this 'expert opinion' metric is unable to capture absolute differences in ability and can be distorted by the quality of draftees for other positions (e.g., a quarterback drafted in a year with an outstanding crop of running backs may have a worse draft order than a similar quarterback drafted in another year).

This paper has three further sections. The next section outlines data and methods. Section 3 presents and discusses our results. The final sections offers concluding remarks.

2. Data and Methods

To determine which college quarterbacks will be successful in the NFL, we use data on college quarterbacks to estimate (1) the probability of quarterbacks being selected for the NFL, and (2) the expected performance of college quarterbacks in the NFL. Variables included in our analysis are summarized in Table 1. Our sample includes all quarterbacks that were drafted by the NFL and/or played an NFL game between 2006 and 2008 (inclusive).

2.1 Measuring NFL Selection and Performance

We consider two measures for the NFL selection of college quarterbacks. To be categorized as 'selected for the NFL', a quarterback must be drafted by an NFL team under the first measure, and in the second measure a quarterback must play (be on the field for at least one play) in an NFL game. Accordingly, we create two binary variables: *nfl_drafted*, is equal to one if the quarterback was drafted by an NFL team and zero otherwise, and *nfl_played*, is equal to one if the quarterback took the field for at least one play in the NFL and zero otherwise. The two measures differ in that a drafted quarterback may never take the field in an NFL game, and an undrafted quarterback added to a team's roster (e.g., as an undrafted free agent) may see playing time.

Table 1. Variables Included in the Analysis.

Abbreviation	Description
NFL selection indicators	
nfl_drafted	Equal to one if the quarterback was drafted by an NFL team; zero otherwise
nfl_played	Equal to one if the quarterback played in the NFL; zero otherwise
NFL performance metrics, maximum qualifying season value in each quarterback's first five NFL years	
nfl_qbr	NFL Total QBR
College performance metrics, in each quarterback's showcase season adjusted for the quality of defenses faced	
qbr	ESPN Total QBR
epa_pass	Expected points added from passing per 100 plays
epa_run	Expected points added from running per 100 plays
epa_sack	Expected points added from sacks per 100 plays
epa_pen	Expected points added from penalties per 100 plays
epa_total	Total expected points added from all action plays
completions	Pass completion percentage
pass_yards	Passing yards per attempt
pass_td	Passing touchdowns per attempt
intercepts	Passes intercepted per attempt
rush_yards	Rushing yards per attempt
rush_td	Rushing touchdowns per attempt
Other variables	
scout_grade	ESPN scout grade of college quarterbacks
height	Quarterback height, in inches

The performance of quarterbacks in the NFL is measured using the 'Total Quarterback Rating' (Total QBR) metric developed by ESPN. We use Total QBR to measure quarterback performance since several studies show that this measure is more strongly correlated with team success that other measures. For example, with quarterbacks who played at least 14 games including 20 more action plays during the 2006 to 2013 season, Stuart (2014) examined the correlation between quarterback win percentages and several performance metrics. Total QBR had the highest correlation coefficient (0.68), followed by Adjusted Net Yards per Attempt (0.57), and Passer Rating (0.56).[2]

Total QBR is based on data from each action play (passes, rushes, sacks, scrambles, or penalties attributable to the quarterback) and attempts to measure each quarterback's contribution to his team's performance as accurately as possible (Burker 2016). It is built on Expected Points Added (EPA) in "nearly every aspect of quarterback play; from passing, to designed runs, to scrambles, to turnovers, and to penalties" (Burker 2016). In calculating Total QBR, EPA from different actions are adjusted by the quality of the defenses faced by each quarterback and combined and divided by the total number of plays to create a per-play measure of quarterback efficiency. Finally, the quarterback efficiency measures are transformed using a logistic regression so that they are on a 0-to-100 scale, with higher values indicating better performances. Total QBR data for this study are sourced from www.espn.com on July 9, 2019.[3]

To condense our NFL performance measure into a single number for each quarterback, we use the maximum season-aggregate QBR values recorded by each player in their first five 'qualifying' seasons in the NFL. To ensure that the performance values represent 'typical' results, for each quarterback, we define a qualifying season as a season with 100 or more passing attempts. We use the first five years of each players' NFL career in qualifying season calculations on the grounds that nearly all leading college quarterbacks enter the NFL via an annual draft for newly-eligible players, where first-round picks receive four-year contracts with a team option for a fifth year (Inabinett, 2019).

2.2 College Performance Metrics

To measure college performance, we start with game-level data from each player's games against designated Division I FBS teams. For our study, we define a 'designated FBS team' as any team that was classified as a Division I FBS team by the National Collegiate Athletic

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[2] Adjusted Net Yards per Attempt and Passer Rating attempt to quantify the performance of a quarterback's passing games using formulas that include passing yards, passing completions, passing touchdowns, and inceptions thrown.

[3] As Total QBR is a proprietary statistic, precise details on how it is constructed are not available. Overviews of the measure are provided by Burke (2016) and Katz and Burke (2016).

Association (NCAA) at any time since 2004. As non-FBS teams only occasionally play FBS teams, we do not measure the college performances of quarterbacks who played (exclusively) for non-FBS teams.[4]

For each game played by each quarterback against FBS opponents, we collect three sets of data: (1) Total QBR and EPA data, (2) 'traditional' quarterback statistics, and (3) scout grades and height. QBR-related data includes 'Raw QBR' (QBR values that are not adjusted for opposition quality), and EPA per 100 plays from passing plays, running plays, sacks and penalties, and EPA from all action plays. As described below, we adjust college metrics for the quality of opposing defenses. Once quality adjusted, we use *qbr* to denote quality-adjusted Raw QBR scores, and use *epa-pass*, *epa-run*, *epa-sack*, *epa-pen*, and *epa_total* to denote quality-adjusted EPA values. QBR and EPA data are sourced from www.espn.com on September 26, 2019.

Traditional quarterback statistics include the percentage of passes attempted that were completed (*completions*), passing yards per passing attempt (*pass_yards*), passing touchdowns per attempt (*pass_td*), passes intercepted per attempt (*intercepts*), rushing yards per rush attempt (*rush_yards*), and rushing touchdowns per attempt (*rush_td*). Data on these metrics are sourced from game logs at https://www.sports-reference.com/.

Quality Adjustments

There are currently 130 Division I FBS teams. These teams, with the exception of seven independent teams, are grouped into ten conferences. Each team usually plays 12-15 games per season, mainly against opponents in its conferences. As there are large differences in ability across teams,[5] there can be big differences in the average quality of defenses faced by quarterbacks, especially if they play in different conferences. Accordingly, for each game, college statistics are adjusted for the quality of defenses faced by each quarterback.

[4] NFL quarterbacks that played exclusively for the non-FBS teams during our sample include Joe Callahan, Ryan Fitzpatrick, Quinn Gray, Kyle Lauletta, Keith Null, J.T. O'Sullivan, Easton Stick, and Alex Tanney.
[5] For example, the Sagarin College Football Ratings, see https://www.usatoday.com/sports/ncaaf/sagarin/, typically estimate that top-ranked Division I teams will beat the bottom-ranked teams by margins that exceeds 50 points.

Our quality adjustments are built on a prediction model that, for each season, estimates the number of points each defense would concede against an average offense. Next, we divide these estimates by the number of points an average defense would concede against an average offense. Inverting this ratio results in a defense-quality scalar for each team, where a value less than one indicates a below average defense, and a value greater than one indicates an above average defense.[6] Quarterback metrics that are positively correlated with performance (*qbr, epa-pass, epa-run, epa-pen, completions, pass_yards, pass_td, rush_yards, rush_td*) are multiplied by defense-quality scalars so, for example, recording eight passing yards per attempt against a good defense is worth more than achieving the same value against a poor defense. Quarterback metrics that are negatively correlated with performance (*intercepts, epa_sack*) are divided by defense-quality scalars so, for example, conceding an interception to a good defense has a lower impact than giving up an interception to a poor defense.

Showcase Year

Elite college quarterbacks typically play multiple seasons of FBS Division I football. For each quarterback, we identify a 'showcase' season and use (aggregate) data from that year to measure college ability. In determining a showcase season for a quarterback, we first drop all seasons in the athlete's college tenure that account for less than 15% of the player's career action plays. From the remaining seasons, we select the year in which that quarterback recorded his maximum play-weighted Total QBR value. Showcase season QBR and EPA values are calculated as action play-weighted averages of quality-adjusted games data, and showcase season traditional passing and rushing values are calculated as, respectively, pass attempt- and rush attempt-weighted averages of quality-adjusted game statistics.

Scout Grades and Height

Scouts evaluate many elements when assessing college quarterbacks, including physical attributes such as height, hand size, and speed; and less tangible qualities such as leadership,

[6] Defense-quality scalars for each team in each year, which are estimated using a propriety algorithm developed by Rugby Vision, are available from the authors upon request.

mental toughness, and competitiveness (Landry, 2014). Scouts base their assessments on many pieces of information, including college statistics, results from physical and mental tests, and expert opinions. We source scout grades, *scout_grade*, from ESPN Insider (http://insider.espn.com/). ESPN scout grades are on a 0 to 100 scale, with higher numbers assigned to superior NFL prospects. A scout grade between 90 and 100 indicates a 'Rare Prospect' typically rated as one of the top five in his position across all college teams. A 'Good Prospect', a player who gives good effort each week and is rated in the top half of college quarterbacks, is assigned a grade between 60 and 69.[7] Our final explanatory variable, quarterback height (in inches), *height*, is sourced from https://www.espn.com/.

2.3 Methods

Our analysis includes two sets of regressions. First, we estimate the probability of a college quarterback being selected by an NFL team using logit model with either *nfl_drafted* or *nfl_played* as the dependent variable, and quality-adjusted college QBR metrics (*qbr*, *epa_pass*, *epa_run*, *epa_sack*, *epa_pen*) as explanatory variables. Our sample includes all quarterbacks who played for a FBS Division I team and whose final college season was between 2005 and 2013 (inclusive). Summary statistics for variables used in the NFL selection analysis, which are based on data for 590 quarterbacks, are reported in Table 2. As college QBR values are multiplied by defense-quality scalars, and good college quarterbacks typically face above average defenses, some *qbr* values are greater than 100.

Table 2. Summary Statics for Variables Included in NFL Selection Analysis.

Variable	Medium	Mean	Standard Dev.	Minimum	Maximum
nfl_drafted	0	0.20	0.40	0	1
nfl_played	0	0.10	0.30	0	1
qbr	54.96	56.11	19.01	11.38	123.58
epa_pass	6.84	7.12	5.67	-8.27	28.43
epa_run	0.49	0.82	2.81	-12.99	13.08
epa_sack	-3.17	-3.44	1.50	-11.68	0.00
epa_total	5.45	5.35	6.61	-15.16	29.79

[7] For more details on ESPN scout grades, see http://insider.espn.com/nfl/draft/rankings?year=2009.

Second, we estimate the expected performance of college quarterbacks in the NFL by regressing the maximum season Total QBR value recorded by each quarterback in their first five years in the NFL on college performance metrics in the each quarterback's showcase year, scout grades and player height. Table 3 presents summary statistics for variables used in the NFL performance analysis, which are calculated using data for the 61 quarterbacks in our sample who played in the NFL.

Table 3. Summary Statics for Variables Included in NFL Performance Analysis.

Variable	Medium	Mean	Standard Dev.	Minimum	Maximum
nfl_qbr	52.10	49.71	15.93	9.20	72.70
qbr	79.50	79.49	17.96	48.97	123.58
epa_pass	13.54	14.01	5.18	1.64	28.43
epa_run	1.16	2.26	3.28	-2.22	13.08
epa_sack	-2.68	-2.81	1.06	-5.45	-1.24
epa_pen	0.42	0.44	0.59	-0.59	2.07
completions	0.77	0.79	0.12	0.57	1.08
pass_yards	9.72	10.05	2.01	7.16	14.94
pass_td	0.07	0.08	0.03	0.04	0.16
intercepts	0.02	0.02	0.01	0.00	0.05
rush_yards	2.12	2.47	3.35	-5.44	11.48
rush_td	0.05	0.06	0.04	0.00	0.16
scout_grade	85.00	75.95	21.40	30.00	99.00
height	75.00	75.03	1.81	71.00	79.00

3. Results

3.1 NFL Selection

As noted in the previous section, we first estimate the probability of quarterbacks being drafted and/or playing in the NFL based on college performance metrics. In our sample 19% of college quarterbacks were drafted into the NFL, and 10% were involved in at least one NFL action play. Table 4 presents marginal effects from logit regressions when the dependent variable is either *nfl_drafted* or *nfl_played* and all predictors are at their mean values.[8] Columns (S.1) and (S.4) report results when the only dependent variable is each quarterback's quality-adjusted QBR in their showcase college season. On average, a one-point increase in a player's *qa_qbr* increases that quarterback's probability of being drafted by an NFL team by about one percentage point, and the chances of playing in the NFL by about 0.6 percentage points. Since the average for *qbr* is 56.1 with a standard deviation of 19.0, increasing *qbr* by one standard deviation (from the average value) leads to a 18.1 (0.0095×19×100) percentage point increase in the probability of being drafted, and an 10.6 (0.00558×19×100) percentage point increase in the probability of playing. As 19% of quarterbacks in our sample were drafted and 10% played in the NFL, being one standard deviation above average effectively doubles a player's chances of both being drafted and playing in the NFL.

Table 4. Determinants of NFL Selection.

	Dependent variable *nfl_drafted*			Dependent variable *nfl_played*		
	(S.1)	(S.2)	(S.3)	(S.4)	(S.5)	(S.6)
qbr	0.0095***			0.00558***		
	[0.00064]			[0.0006]		
epa_total		0.0314***			0.01794***	
		[0.0020]			[0.0020]	
epa_pass			0.03163***			0.01832***
			[0.002305]			[0.002]
epa_run			0.02111***			0.0123***
			[0.0048]			[0.0037]
epa_sack			0.0226**			0.0132
			[0.01109]			[0.0098]
epa_pen			0.02288			0.0097
			[0.02189]			[0.0188]
Constant	-6.873***	-3.824***	-4.002***	-7.344***	-4.413***	-4.618***
	[0.588]	[0.310]	[0.549]	[0.700]	[0.379]	[0.682]
Observations	590	590	590	590	590	590
log likelihood	-209.0	-197.5	-189.3	-145.2	-143.1	-136.6

Notes: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.1 level; Standard errors in parenthesis. Marginal effects for logit regression when predictors are at their sample means.

Regressions (S.2) and (S.5) investigate the effect of total expected points added per 100 plays on the probability of being drafted by an NFL team. Regression (S.2) indicates that, on average, an

[8] For robustness, results from probit estimation of the NFL selection equations are included in Appendix Table A1.

additional expected point added per 100 plays increases the probability of a quarterback being drafted into the NFL by 3.14 percentage points, and the probability of playing in the NFL by 1.79 percentage points. As the *total epa_total* sample average is 5.3 and the standard deviation is 6.6, being a standard deviation better than average leads to a 20 percentage point increase in the probability of being drafted, and a 12 percentage point increase in the probability of playing in the NFL. Like specifications (S.1) and (S.4), these results indicate that being a standard deviation better than average essentially doubles the probability of a quarterback being drafted by an NFL team or playing in the NFL.

Specifications (S.3) and (S.6) investigate the components of a quarterback's skill set that are important for NFL selection. Passing ability has the largest impact on the NFL selection of college quarterbacks. The coefficient on *epa_pass* is statistically significant at a one percent significance level in both the *nfl_drafted* and *nfl_played* equations. The estimates indicate that an *epa_pass* value one standard deviation above average increases the chances of a quarterback being drafted by the NFL by 17.9 (0.03163×5.67×100) percentage points, and increases the probability of playing by 10.4 (0.01832×5.67×100) percentage points.

Running ability, as measured by *epa_run*, is the next most import attribute for NFL selection and like passing ability has a p-value less than 0.01. A quarterback with an *epa_run* value one standard deviation above average increases that player's chance of playing in the NFL by 5.9 (0.02111×2.81×100) percentage points, and increases the probability of playing by about 3.5 (0.0123×2.81×100) percentage points. Comparing the estimates for *epa_pass* and *epa_run* indicates that a player with a passing ability one standard deviation above average is twice as likely to make the NFL, and a quarterback with rushing ability one standard deviation above average, one-third more likely.

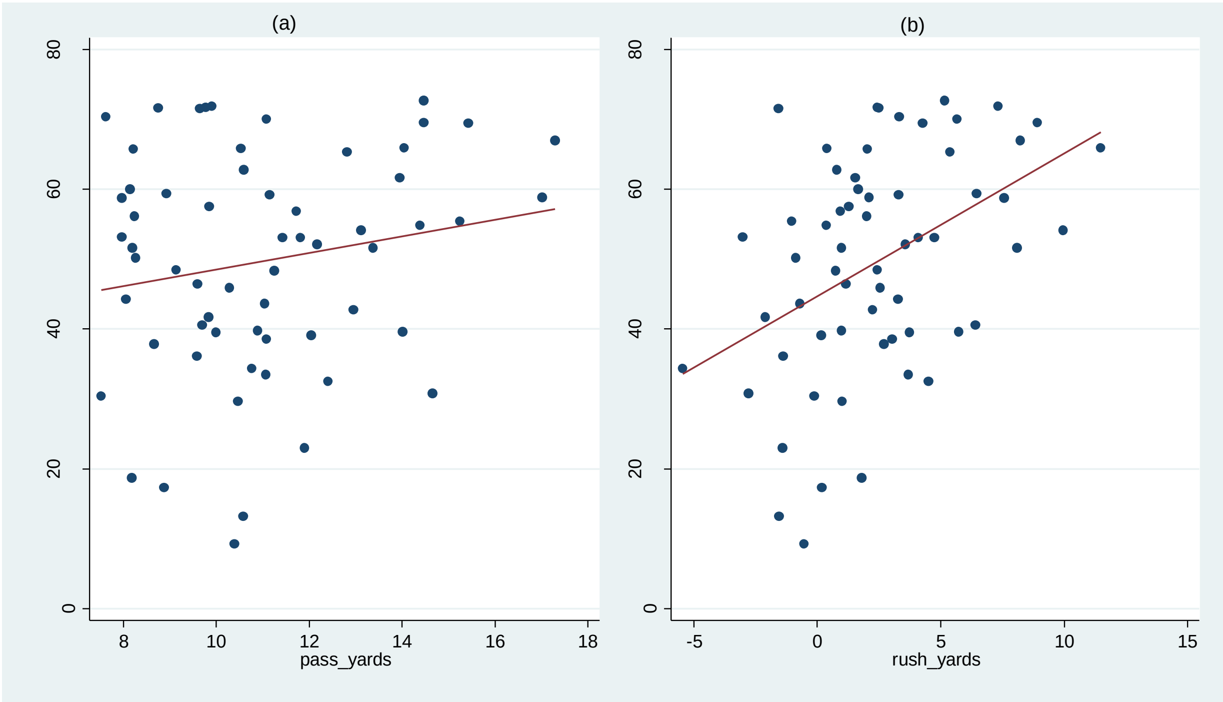
The ability to avoid sacks, as measured by *epa_sack*, is a statistically significant determinant for being drafted by an NFL team but the impact is relatively small: a quarterback that is a standard deviation better at avoiding sacks than average increases the probability of that player being drafted by about 3.4 (0.0226×1.5×100) percentage points. The ability to avoid sacks is not a statistically significant determinant of playing in the NFL. Expected points added from penalties (*epa_pen*) is not statistically significant in either the *nfl_drafted* or *nfl_played* equations.

To summarize our NFL selection results, both quality adjusted QBR and total expected points added are strong predictors of a college quarterback being selected for the NFL. When considering the different components of college performance measures, passing ability is the most important determinant of NFL selection followed by running ability. Evidence on the ability to avoid sacks being an influence on NFL selection is mixed and at best indicates that this is a moderately important attribute for progressing from college football to the NFL. Expected points added from penalties is not a statistically significant predictor of NFL selection.

3.2 NFL Performance

We now focus on predicting the performance of college quarterbacks selected for the NFL who recorded at least one season with 100 or more passing attempts in their first five years of NFL eligibility. To eyeball the data, Figure 1 presents scatter diagrams for (a) NFL performance (*nfl_qbr*) and college passing performance (*pass_yards*), and (b) NFL performance and college rushing performance (*rush_yards*), and a linear line of best fit between for each pair of variables. The diagrams indicate that college rushing ability is more strongly correlated with NFL performance than college passing performance. This view is substantiated by the linear lines of best fit for the two scatter diagrams. These equations are: (a) $nfl\_qbr = 36.68 + 1.18 \times pass\_yards$, slope coefficient p-value = 0.167 and $R^2 = 0.032$; and (b) $nfl\_qbr = 44.67 + 2.04 \times rush\_yards$, slope coefficient p-value = 0.001 and $R^2 = 0.185$. Notably, *rush_yards* is a statically significant determinant of NFL performance, but *pass_yards* is not. Combined, the NFL selection results and our preliminary NFL performance analysis indicate that quarterbacks selected for the NFL are good (or better) passers, and that rushing ability is a better predictor of NFL performance than differences in passing ability among good passers.

Figure 1. The relationship between NFL QBR values (a) passing yards per attempt, and (b) rushing yards per attempt.



To further investigate what college performance metrics are associated with NFL success, the results from regressing *nfl_qbr* on multiple college metrics are reported in Table 5. Regression (P.1) includes *qbr* and *height* as dependent variables. The estimate for *qbr* is a statistically significant determinant of NFL performance at a 5% significance level (p-value 0.014) and indicates that, a one point increase in a quarterback's college (quality-adjusted) QBR increases that player's expected NFL QBR by 0.28 points. At the 10% significance level, the equation also suggests that, *ceteris paribus*, taller quarterbacks perform better in the NFL, with an extra inch in height increasing a player's expected *nfl_qbr* by 1.8 points.

Regression (P.2) replaces QBR with the EPA components that feed into this metric. This allows us to assess what attributes of college quarterback play are most important for NFL success. Consistent with our preliminary NFL performance analysis, the coefficient on *epa_pass* (p-value = 0.938) is not a statistically significant determinant of NFL performance but *epa_run* (p-value = 0.009) is. The point estimate for *epa_run* suggests that an additional one point from rushing per 100 plays increases a player's *nfl_qbr* by 1.9 points. The standard deviation for *epa_run* is 3.28, so a player with an *epa_run* of one standard deviation above the average is expected to record a *nfl_qbr* value of 6.2 (1.89×3.28) points higher than an quarterback with average rushing ability.

Section 3.1 revealed that good passing ability is effectively a prerequisite for NFL selection, so this outcome confirms the results in our preliminary analysis that a key indicator of the NFL performance of good college passers is their rushing ability. The finding that passing ability is not a significant determinant of the NFL performance of selected quarterbacks is consistent with the conclusions of Wolfson et al. (2011) and Pitts and Evans (2018), and the result that college rushing ability is positively correlated with NFL success concurs with Rosen and Olbrecht (2020). Katz and Bradshaw (2015) postulate that good college rushers succeed in the NFL because good runners have the ability to extend drives.

The estimate for *epa_pen* indicates that the ability of college quarterbacks to draw penalties is also positively correlated with NFL success, but the association is not as strong as for rushing ability. A one standard deviation improvement in *epa_pen* increases a player's expected *nfl_qbr* by 3.89 (6.59×0.59) points, and the p-value for this variable (0.128) is higher than that for *epa_rush*. The higher $\bar{R}^2$ value in regression (P.2) relative to (P.1) value – it increases from 0.100 to 0.176 – suggests that the weights on the EPA variables in QBR calculations are not optimal for estimating the NFL performance of college quarterbacks.

Regression (P.3) replaces EPA values with traditional college quarterback performance metrics. The rushing ability measure (*rush_yards*, p-value = 0.003) is the only statistically significant determinant of NFL performance. The estimate for this variable indicates that a one standard deviation increase in *rush_yards* increases a player's expected *nfl_qbr* by 6.33 (1.89×3.35) points. This result is further evidence that rushing ability is, on average, a key determinant of the NFL success of college quarterbacks. The increase in the $\bar{R}^2$ (from 0.176 to 0.184) when traditional college performance metrics are used in place of EPA values, suggests that (quality-adjusted) traditional metrics are better at capturing the ability of college quarterbacks relative to QBR components.

Regression (P. 4) uses scout grades to predict NFL performance. The coefficient on *scout_grade* is statistically significant at all conventional levels (p-value = 0.001), indicating that scouts do a reasonable job (or better) assessing the NFL potential of college quarterbacks. Height is not statistically significant in regression (P.4), implying that scouts factor in height when assigning grades to quarterbacks. The R^2 in regression (P.4) is lower than those in (P.2) and (P.3), indicating that some aspects of a quarterback's play may not be correctly assessed by scouts. This possibility is evaluated in the next two specifications.

Table 5. Determinants of NFL Performance.

	P.1	P.2	P.3	P.4	P.5	P.6	P.7	P.8
qbr	0.277**							
	[0.109]							
scout_grade				0.332***	0.259**	0.256**	0.285***	0.259***
				[0.0936]	[0.103]	[0.109]	[0.0851]	[0.0874]
height	1.823*	1.794*	1.629	0.169	0.568	0.202		
	[1.082]	[1.051]	[1.131]	[1.108]	[1.114]	[1.243]		
epa_pass		0.179			-0.0285			
		[0.370]			[0.362]			
epa_run		1.890***			1.595***		1.421**	
		[0.600]			[0.585]		[0.555]	
epa_sack		-0.408			-1.675			
		[1.903]			[1.884]			
epa_run		6.593**			4.940			
		[3.274]			[3.193]			
pass_yards			0.724			1.817		
			[2.356]			[2.309]		
pass_td			1.264			-28.75		
			[118.0]			[114.0]		
intercepts			-312.4			-189.9		
			[267.4]			[261.8]		
completions			-17.76			-42.46		
			[32.59]			[32.99]		
rush_yards			1.891***			1.467**		1.483**
			[0.601]			[0.605]		[0.557]
rush_td			70.52			67.06		
			[47.31]			[45.42]		
Constant	-109.1	-95.69	-69.05	11.81	-22.68	28.50	24.89***	26.37***
	[82.35]	[80.57]	[85.45]	[80.84]	[82.15]	[91.88]	[6.517]	[6.541]
Observations	61	61	61	61	61	61	61	61
R-squared	0.1306	0.2443	0.2795	0.2062	0.3242	0.3489	0.2866	0.2922
Adjusted R-squared	0.1006	0.1756	0.1844	0.1788	0.2491	0.2488	0.262	0.2678
P-value of F-Stat Test of Regression	0.0173	0.0074	0.0113	0.0012	0.0013	0.0027	0.0001	0.0000

Notes: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.1 level; Standard errors in parenthesis. Marginal effects for logit regression when predictors are at their sample means.

The EPA components are included with scout grades in regressions (P.5). The statically significant estimate for *epa_run* (p-value = 0.009) indicate that scouts underestimate rushing ability when assessing the NFL potential of college quarterbacks. Moreover, the point estimate for *epa_run* is similar to that when *scout_grade* is excluded (the p-value for *epa_run* being the same in both regressions = 0.176), implying that scouts pay too little attention to rushing ability. As the p-value for *epa_pen* is 0.13 there is also weak evidence that scouts underestimate the ability of college quarterbacks to draw penalties on NFL performance. At the same time, the greater explanatory power in regression (P.5) relative to (P.2) (the $\bar{R}^2$ increases from 0.176 to 0.249), reveals that scout grades include relevant information that is not captured by EPA variables. The results from regression (P.6), which include traditional college performance metrics and scout grades, yield similar conclusions: rushing ability is not appropriately evaluated by scouts, but scouts include pertinent information that is not captured in traditional college metrics.

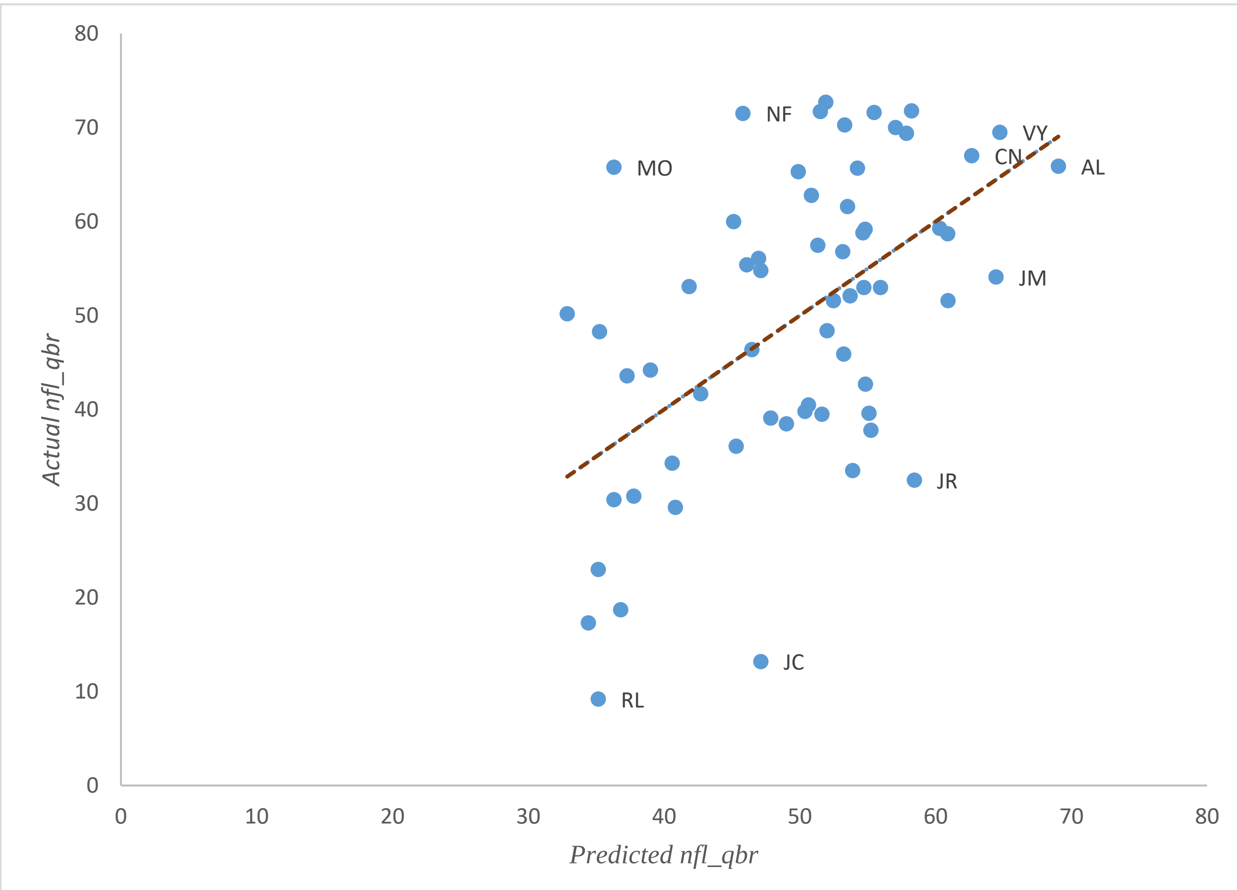
Regression (P.7) and (P.8) examine the robustness of our findings by omitting college performance metrics that are not statistically significant in, respectively, (P.5) and (P.6). College rushing ability – whether measured using EPA or rushing yards per attempt – continues to be a statistically significant determinant of NFL performance when scout grades are included.

In summary, our results reveal that passing ability is important for being selected by an NFL team; however, among good passers selected for the league, rushing ability is the key attribute that, on average, determines the performance of quarterbacks in the NFL. Scouts do reasonably well at predicting the NFL performance of college quarterbacks, but appear to consistently underweight players' rushing ability. In measuring rushing ability, it appears that rushing yards per attempt (adjusted for opposition quality), are a better metric than ESPN's EPA from running plays.

3.3 Predicted vs. Actual NFL Performance

To assess the accuracy of the mode to predict NFL performance, predicted *nfl_qbr* ($\widehat{nfl\_qbr}$) values from regression (P.8) – which includes only *rush_yards* and *scout_grades* as explanatory variables – are plotted against observed *nfl_qbr* values in Figure 2. Quarterbacks in our sample are identified by their initials. An initials-to-full concordance and predicted and actual *nfl_qbr* values are reported in Appendix Table A2. By design, the average observed value equals the average predicted value, which is 49.7.

Figure 2. Actual and Predicted Values for *nfl_qbr* from Regression (P.8).



Note: Dashes represent the line where actual values equal predicted values.

The scatter plot indicates that regression (P.8) does, on average, a good job predicting successful NFL quarterbacks, but there is some variability in prediction accuracy. The regression equation has mixed success when predicting quarterbacks that record very low *nfl_qbr* values. Specifically, even though the model correctly predicted that Ryan Lindley (RL) was one of the weakest quarterbacks selected for the NFL in the sample, his observed *nfl_qbr* (9.2) is much lower than his predicted value (35.2). Similarly, Jimmy Clausen (JC) recorded the second lowest *nfl_qbr* value (13.2) in our sample but his predicted value was 47.1 (slightly below the average predicted value). JaMarcus Russel (JR) also performed worse than expected. His predicted *nfl_qbr* was 58.44 but he only achieved 32.5. Considering that the Raiders used their first pick of the draft JaMarcus Russel and paid him one of the highest rookie quarterback salaries in the history of the NFL (Gay, 2007), other predictors also overestimated JaMarcus Russel's NFL potential. The model also expected Johnny Manziel (JM) to perform better than he did, although his predicted *nfl_qbr* valued (64.5) is in the same neighborhood as his observed value (54.1) and, as expected, he performed better than the average rookie NFL quarterback in our sample.[9]

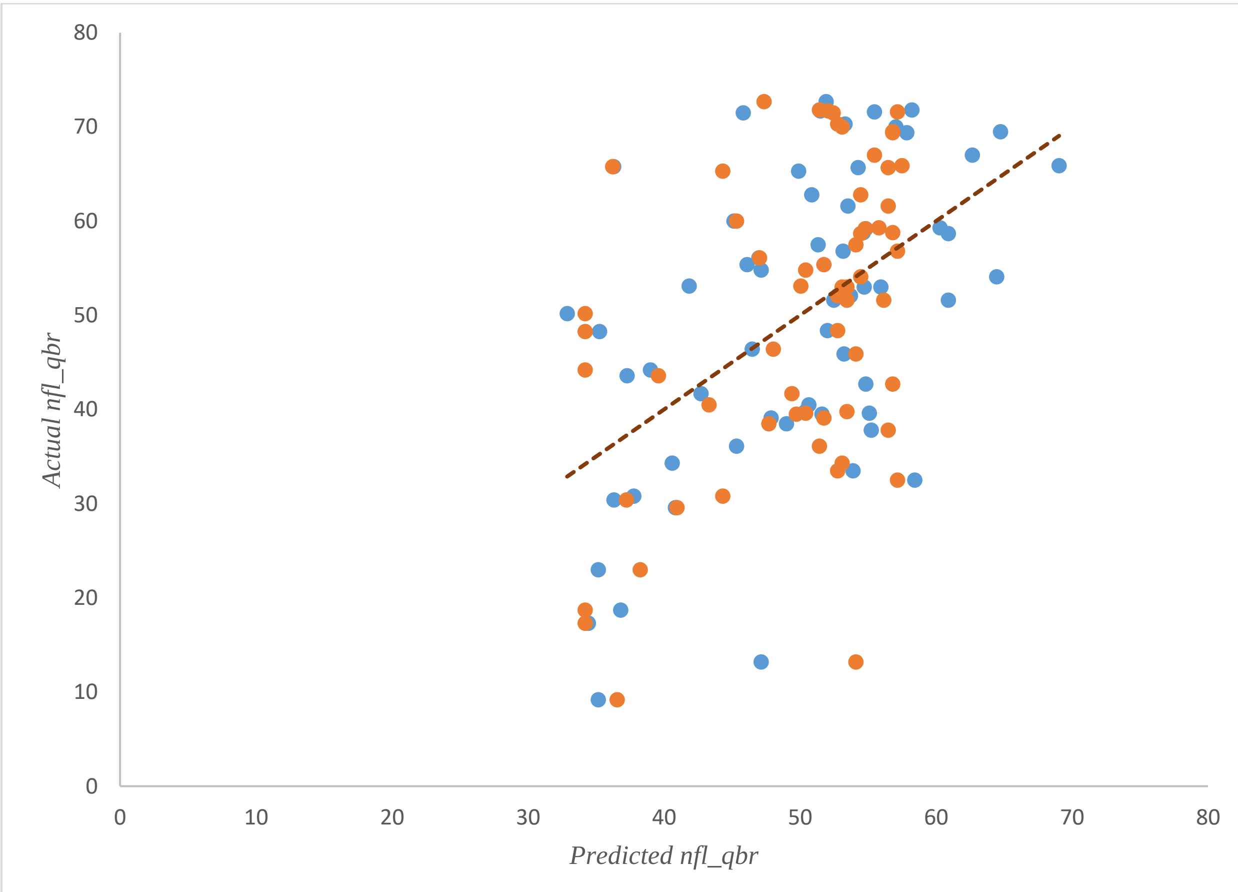
Turning to quarterbacks who performed better than predicted by the model, Matt Moore (MMO) was predicted to record the lowest *nfl_qbr* in the sample (36.3) but his actual value (65.8) was 17.1 points above the average. Nick Foles (NF) also recorded a higher *nfl_qbr* (71.5) than predicted by the model (45.8).

Nevertheless, as noted above, the model does a reasonable job predicting the NFL performance of college quarterbacks overall. Players who the model correctly predicted would be good NFL quarterbacks include Cam Newton (CN, predicted *nfl_qbr* 62.7 and actual *nfl_qbr* 67.0), Vince Young (VY, 64.7 and 69.5) and Andrew Luck (AL, 69.0 and 65.9).

To further illustrate the importance of rushing ability for successful NFL quarterbacks, Figure 3 plots predicted and actual values for regression (P.8), which includes *scout_grade* and *rush_yards* as explanatory variables, and an equation regression that only includes *scout_grade*. The comparison reveals that there is a marked improvement in predictions when rushing ability is explicitly included, especially for elite quarterbacks. That is, by not appropriately accounting for rushing ability when measuring the NFL potential of college quarterbacks, scouts have difficultly differentiating elite quarterbacks from those who are very good. For example, Andrew Luck was expected to register a *nfl_qbr* value of 57.5 based on scout grades, but this increases to 69.1 when *rush_yards* are included (and is close to his observed value of 65.9).

[9] One reason the regression may have overestimated Manziel's NFL performance is that it does not account for his off-field issues – see, for example, Kaplan (2016).

Figure 3. Actual and predicted values for *nfl_qbr* for regressions (P.8) (blue) and when *scout_grades* is the only explanatory variable (orange).



Note: Dashes represent the line where actual values equal predicted values.

4. Conclusions

Drafting quarterbacks who are likely to have successful professional careers is crucial to the success of NFL teams. In this paper, we identified traits of college quarterbacks who are linked to success in the NFL. Our investigation employed a two-stage analysis. In the first stage, we estimated the relationship between NFL selection and college quarterback performance metrics adjusted for the quality of opposing offenses. This analysis revealed that passing ability is the most important aspect of quarterback play for NFL selection. Our numbers indicate that a college quarterback with passing ability one standard deviation above average is twice as likely to make an NFL team than an average quarterback. Rushing ability is also positively correlated with NFL selection. Our estimates suggest that a quarterback with rushing ability one standard deviation above the average is one-third more likely to be selected by an NFL team than an average quarterback.

In the second stage, we explored the relationship between the performances of rookie quarterbacks in their first five years in the NFL, as measured by ESPN's Total QBR, using data from their college careers adjusted for the quality of opposing defenses and, in some cases, scout grades. We found that quarterbacks who recorded higher college QBR values performed better in the NFL than players with lower QBR values. Deconstructing the aspects of college quarterback play important for NFL success, players with better college rushing statistics performed better in the NFL than players with worse rushing statistics. The same was not true for players with better college passing statistics. That is, among quarterbacks selected for the NFL, college passing ability was not significantly correlated with NFL performance. These results were present both when the EPA components used for QBR calculations (EPA from passing and EPA from rushing) were utilized to measure college performance, and when traditional college metrics (passing yards per attempt and rushing yards per attempt) were applied. Combining results from the two stages suggest that college quarterbacks have to be high-quality passers to make the NFL but, on average, quarterbacks also have to be good rushers to succeed in the NFL.

The finding that college rushing performance is a key determinant of NFL success also persisted when we controlled for ESPN scout grades. This indicates that scouts systematically undervalue rushing ability when assessing the NFL potential of college quarterbacks. A practical implication is that NFL teams should pay more attention to rushing ability when assessing college quarterbacks. Determining why good college rushers perform better in the NFL than inferior rushers is a fruitful avenue for further research.

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Appendix

Table A1. Determinants of NFL Selection Estimated Using a Probit Model.

	Dependent variable *nfl_drafted*			Dependent variable *nfl_played*		
	S.1	S.2	S.3	S.4	S.5	S.6
epa_total	0.0096***			0.00572***		
	[0.00063]			[0.0006]		
epa_pass		0.0314***			0.0182***	
		[0.0020]			[0.0020]	
epa_run			0.0318***			0.0187***
			[0.0023]			[0.0021]
epa_sack			0.0223***			0.0126***
			[0.0048]			[0.0038]
epa_pen			0.0199*			0.0123
			[0.0109]			[0.0094]
epa_total			0.0259			0.0104
			[0.022]			[0.0184]
Constant	-3.969***	-2.177***	-2.358***	-4.080***	-2.440***	-2.604***
	[0.309]	[0.158]	[0.304]	[0.357]	[0.185]	[0.353]
Observations	590	590	590	590	590	590
log likelihood	-207.3	-196.7	-188.0	-144.0	-142.4	-135.5

Notes: *** significant at the 0.01 level; ** significant at the 0.05 level; * significant at the 0.1 level; Standard errors in parenthesis. Marginal effects for probit regression when predictors are at their sample means.

Table A2. Actual and Predicted *nfl_qbr* Values.

Name	*Actual nfl_qbr*	*Predicted nfl_qbr*	Name	*Actual nfl_qbr*	*Predicted nfl_qbr*
Matt Barkley	39.8	50.4	EJ Manuel	39.5	51.6
John Beck	39.1	47.9	Johnny Manziel	54.1	64.5
Blake Bortles	59.2	54.8	AJ McCarron	54.8	47.1
Sam Bradford	58.8	54.6	Colt McCoy	53	54.7
Teddy Bridgewater	57.5	51.3	Matt McGloin	50.2	32.9
Derek Carr	56.1	47.0	Zach Mettenberger	30.8	37.8
Jimmy Clausen	13.2	47.1	Kellen Moore	23	35.2
Kellen Clemens	33.5	53.9	Matt Moore	65.8	36.3
Kirk Cousins	71.7	51.5	Cam Newton	67	62.7
Brodie Croyle	36.1	45.3	Brock Osweiler	53	55.9
Jay Cutler	65.7	54.3	Curtis Painter	30.4	36.3
Andy Dalton	70	57.0	Tyler Palko	29.6	40.8
Austin Davis	44.2	39.0	Christian Ponder	52.1	53.7
Trent Edwards	48.4	52.0	Terrelle Pryor	40.5	50.6
Nick Foles	71.5	45.8	Brady Quinn	42.7	54.8
Josh Freeman	70.3	53.3	JaMarcus Russell	32.5	58.4
Blaine Gabbert	37.8	55.2	Matt Ryan	71.6	55.5
Mike Glennon	53.1	41.9	Mark Sanchez	51.6	52.5
Bruce Gradkowski	60	45.1	Tom Savage	41.7	42.7
Robert Griffin III	69.4	57.8	Geno Smith	45.9	53.2
Caleb Hanie	17.3	34.4	Troy Smith	38.5	49.0
Chad Henne	62.8	50.9	Matthew Stafford	61.6	53.5
Colin Kaepernick	71.8	58.2	Drew Stanton	51.6	60.9
Case Keenum	48.3	35.3	Ryan Tannehill	59.3	60.3
Kevin Kolb	46.4	46.5	Tyrod Taylor	65.3	49.9
Matt Leinart	56.8	53.2	Tim Tebow	39.6	55.1
Thaddeus Lewis	18.7	36.8	Brandon Weeden	34.3	40.6
Ryan Lindley	9.2	35.2	Russell Wilson	72.7	51.9
Jake Locker	58.7	60.9	TJ Yates	43.6	37.3
Andrew Luck	65.9	69.0	Vince Young	69.5	64.7
Ryan Mallett	55.4	46.1			