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What is a Blue Chip Recruit Worth? Estimating the Marginal Revenue Product of College Football Quarterbacks

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Abstract

The National Collegiate Athletic Association has faced growing scrutiny due to the perceived disparity between the compensation athletes receive and their contribution to athletic revenue. Our novel use of college football game–level statistics shows a gap of millions of dollars between compensation and marginal revenue product (MRP) for elite quarterbacks, consistent with previous studies. Professional sports typically weight pay toward ex ante expected value of performance rather than incentives that pay ex post of performance. Using high school prospect rankings, we show ex ante estimates of elite quarterback expected MRP are substantially lower, roughly US$400,000, and have limited statistical significance with respect to winning or revenue. Our ex ante measurements suggest that expected player value may be closer to the value of scholarships than previous research suggests due to the difficulty in predicting which high school quarterbacks will excel in college.

Keywords

college football, college sports revenue, quarterback

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Introduction

College football players spend nearly twice the amount of time on practice and conditioning as they do in the classroom (Jenkins, 2014). They are compensated for this effort with a grant for education, housing, and food. The National Labor Relations Board (NLRB) recently ruled that college football players should be considered employees of their university and therefore be given the right to unionize. This ruling, along with a growing belief that athletes are not compensated commensurate with their contribution, has motivated a call to increase compensation. The data trends support the idea of a growing gap, as National Collegiate Athletic Association (NCAA) football revenue grew 42% during our sample period from 2004-2012, while student-athlete compensation remained relatively constant. The NLRB ruling may signal the start of negotiations for players to receive better compensation in order to shrink this gap. Measuring compensation is fairly straightforward; however, due to the team nature of football, estimating players' marginal revenue product (MRP) is challenging.

This study estimates MRP for college football quarterbacks from Bowl Championship Series (BCS) conferences.[1] We look specifically at quarterbacks because it is the most valuable position. From 2000-2014, of the 15 winners of the Heisman trophy,[2] 14 were quarterbacks. In the National Football League (NFL), quarterbacks are the highest paid position on average, and elite quarterbacks' salaries represent up to about 8% of a team's annual revenues, or 17% of the team's player payroll (Becht, 2013). Our estimate of MRP for quarterbacks can be considered an upper bound for college athletes, since other positions are likely to be less valuable, and football generates the most revenue. The second reason we limit the study to one position is that performance data are more readily available for quarterbacks than other positions, which allows us to measure their contribution to team success more precisely.

We estimate MRP for an elite quarterback using a two-stage analysis, estimating first their contribution to wins and then the value of a win. The first stage of the analysis is performed both before and after the player's college career. The ex post analysis uses a relatively new statistic called quarterback rating (QBR), which was created by Entertainment and Sports Programming Network (ESPN) and measures the quarterback's contribution to winning based on his play. The ex ante estimate uses a quarterback's ranking as a high school recruit to calculate expected contribution.

In the ex post analysis, we find that quarterbacks with average yearly ratings 2 *SD* above the mean season QBR were estimated to add roughly three additional wins per season over an average quarterback. In the second stage, we estimate the value of a win at US$740,000, including discounted revenues for the following season. Therefore, our main result is that an elite quarterback, one whose QBR is at least 2 *SDs* above the mean, has an estimated MRP of over US$2 million per season.

The ex ante analysis uses high school ability (as proxied by their ranking as a top 100 college recruit) to estimate future QBRs and winning percentage. Ex ante, we find that signing a quarterback with perceived high ability (based on high school recruiting ranking)—a "blue chip recruit"—adds roughly 0.3 wins per year in the third and fourth years after signing. Using the value of a marginal win (US$740,000), we estimate ex ante that signing a recruit identified as high ability is expected to add roughly US$429,000 over those 2 years. The substantially lower ex ante estimate reflects the fact that over a quarter of top quarterback recruits in our sample failed to record a qualifying game for the BCS schools that recruited them. These estimates provide a starting point for the expected value of blue chip high school quarterbacks. Furthermore, they show a gap between valuations that are performed ex post and ex ante, reflecting the inherent uncertainty in player evaluation.

Literature Review

Scully (1974) was one of the first to estimate MRP for athletes.[3] He first estimated the effect of team performance statistics in Major League Baseball on total revenues and then weighted the team results by individual appearances to arrive at predicted player MRP (often referred to as the Scully method). He found that players were generally exploited to a large degree due to baseball's reserve clause (in which player rights were retained by a team even after their contract had expired). Measuring the effect of individual players on team performance proved a difficult task without advanced metrics and statistics. Nevertheless, Scully's work was extremely important and led the way for much of the research that has since followed.

Previous work has estimated the MRP of NCAA football players using ex post observations of NFL draft status, but statistical performance has not been used due to the difficulty in measuring an individual's contribution in football. Brown (1993), Brown and Jewell (2004), and Brown (2010) used samples of NCAA Division 1 college football team revenue data to estimate a two-stage least squares model. The works first estimated premium-player rents by regressing the number of future professional league draftees (a proxy for premium players) on recruiting and market characteristics, then team program revenues on the number of players drafted, holding other factors constant. The MRPs were estimated at approximately US$500,000 for a premium player (a future NFL draft pick) in the early works and grew to US$1.1 million in later works, which added controls for team quality and additional data. These results far exceeded the estimated scholarship value of roughly US$25,000 (Huma & Staurowsky, 2012; Zimbalist, 2001). Other NCAA sports such as men's basketball, women's basketball, and men's hockey appear to have a gap between MRP and compensation when using the draft pick measure, as shown by Lane, Nagel, and Netz (2012), Brown and Jewell (2006), and Kahane (2012), respectively. Finally, Brown (2012) added to this work by comparing player MRPs with expected NFL compensation to determine whether lost wages in college were outweighed by increased future earnings. He found that, generally speaking, they do not.

Our work provides two contributions to the previous literature. First, we strengthen the link between performance and estimated MRP. Second, we create a method for estimating the expected MRP for future NCAA athletes. Our use of QBR creates a continuous estimate allowing for comparisons of all quarterbacks, while previous works have focused on the discrete difference between drafted and undrafted players. Additionally, the NFL values some skills and attributes that may not reflect a player's individual contribution to his team's win percentage, as evidenced by Heisman trophy winner Jason White's (Oklahoma, 2003) going undrafted and Troy Smith's (Ohio State, 2006) not being drafted until the fifth round. Our second contribution is to create ex ante estimates of player value, and to our knowledge this article is the first to do so. Moving from an ex post evaluation to an ex ante measure of expected value is important, as Krautmann (1999) points out that contact negotiations typically take place before performance has been revealed.

Data

Metrics for "wins above replacement" (WAR) have been developed and used for over 20 years (Miller, 2013) to estimate the number of additional wins a player would contribute compared to a replacement player in baseball. Previous studies of college athletes' MRPs have primarily focused on basketball and football, by far the biggest revenue producers in college athletics. Unfortunately, an adequate WAR-type statistic has not been historically available for these two sports. This makes MRP estimates difficult to obtain, though recent attempts have been made (Lane et al., 2012) in basketball. The main obstacle in developing a WAR-type statistic for football is that it is difficult to isolate an individual's contribution to winning in team-focused sports. To bridge this gap, we use a player metric recently developed by ESPN for college football quarterbacks, which may resolve the issue of linking player performance to team win probability.

Total QBR

ESPN is a global sports and entertainment television network that reaches almost 100 million households in the United States alone (Sandomir, Miller, & Eder, 2013). In recent years, it has developed a specialized Stats and Information Group (ESPN Stats & Info). One of the first major analytic statistics it developed is total QBR. The historical NFL quarterback metric at the time, referred to as "passer rating," had been found to be lacking in many ways.[4] The metric measured only a few categories of quarterback performance, and, as the position evolved and included more multidimensional statistics, such as the ability to avoid sacks and run the football, passer rating became less and less relevant. QBR was introduced in 2011 for professional (NFL) quarterbacks, and the new metric had a stronger relationship to a team's success than passer rating.

Table 1. QBR, Strength of Opponent, and Home Field.

				QBR Distribution—# of Game Observations				
	Mean		*SD*	0–20	20–40	40–60	60–80	80–100
QBR[a]	52.64		27.20	1,059	1,409	1,502	1,501	1,413
	Win percentage			18%	36%	54%	75%	94%
	>25	21–25	16–20	11–15	6–10	1–5		
Opponent rank[a]	4,640	756	344	413	457	274		
Observations (%)	67	11	5	6	7	4		
	Mean							
Home	0.53							
Win	0.57							

Note. QBR = quarterback rating.
[a]N = 6,884.

There have been earlier attempts at the NFL level to improve upon the traditional passer rating method. Berri (2007), Berri, Schmidt, and Brook (2006), and Berri and Simmons (2011) used regression analysis to develop a new rating that assigned weights to different outcomes such as yardage and turnovers. These measures, however, do not control for the contribution of other players to the outcomes (such as sack prevention and yards after the catch), while the QBR measure we utilize does. Additionally, Burke (2007) showed a 95% correlation between ratings using regression analysis (cited earlier) and the traditional passer rating at the NFL level.

The methodology behind the QBR for NFL quarterbacks estimates the team's expected points added for each play and assigns a portion of credit to the quarterback, while also assigning a "clutch weight" based on the game situation (primarily used to de-weight plays that occur in a noncompetitive situation). After summing the plays of interest, they rescale the number to a range of 0–100 to arrive at the QBR. Over the course of 4 years and over 1,000 NFL games, ESPN found an 87% correlation with winning for games in which a team's quarterbacks had a higher QBR than the opposing quarterback. This exceeds the correlation with the previous passer rating of 79%.[5]

In 2013, ESPN introduced the total QBR for college football, and they applied the new QBR to individual game data from 2004 onward to provide historical rating comparisons. They were able to utilize an enormous quantity of game data that had been previously captured, some of it using video-tracking technology. As Table 1 shows, a fairly strong correlation between QBR and winning appears to exist in college football as it does in the NFL. In analyzing a subset of our data, for games in which both teams had just one quarterback with a qualifying QBR, we find that the team with a higher QBR won about 83% of the time.[6] The difference between the average QBR for a winning team (65.1) and a losing team (35.8) is statistically significant confirmed by means of a *t* test. The average QBR in our sample is 52.6 and the *SD* by game is 27.2. Of the 420 quarterback season observations (with at least 10 qualifying games), only 8 averaged above an 80 QBR over the course of the season.

Although we have QBR data for 94% of the potential games, the data we use for the game-level analysis are an unbalanced panel.[7] The data set is unbalanced because of missing game observations, which occur because a quarterback might not have enough "action plays" to have a qualifying QBR (which require at least 20 action plays). We do not include game observations in which multiple quarterbacks on the same team had qualifying QBRs in the same game, since we have no way to allocate the impact of each of the quarterbacks on the game-level win probability.

There is a clear linear relationship between QBR and winning, as shown in Table 1. Therefore, we use a linear functional form to estimate the relationship between the two. The distribution of QBR ratings is relatively uniform, with slightly fewer QBR scores under 20. This could be because multiple quarterbacks are likely to be used in games with extremely low QBRs and there may not be a qualifying quarterback. It is also unknown whether ESPN intended the distribution to be completely uniform.

There are three potentially valid criticisms of the QBR measure.[8] The biggest potential concern is that the QBR measure is biased by the quarterback's teammates. That is, if having better teammates increased both QBR and the likelihood of winning, the estimated impact of QBR on winning would suffer from omitted-variable bias and overstate the effect of QBR on winning. In Appendix C, we test the relationship between offensive teammate quality and QBR. The tests support the use of QBR as a measure of ex post MRP, as a proxy for the number of high-quality offensive teammates is found to be unrelated to QBR. When we break out teammates by offensive position, we find fairly weak statistical evidence for higher quality wide receivers' (WRs) improving a quarterback's QBR. However, the estimated bias from omitting WRs is small relative to the variation in QBR. Additionally, other offensive positions (e.g., running back, offensive line, and tight end [*TE*]) do not appear to impact QBR. Given these findings, using the QBR measure seems appropriate, with an acknowledgment that there might be a slight upward bias due to the quality of WRs.

The second concern is that the formula is proprietary. Ideally, we would like to inspect the internal workings of the measure. In this article, however, we are less concerned with how the measure is constructed than with how it is associated with such outcomes as wins and team revenue. Third, QBR is composed of several statistics. It might be useful to know if two quarterbacks with the same QBR had differences in running ability, as this might matter for revenue if fans prefer teams with running quarterbacks. In that sense, we cannot look at different aspects of a quarterback's ability that might impact revenue differently.

In addition to QBR, we use two variables to control for other factors that influence winning percentage: the strength of opponent and whether the game was played at the team's home stadium. For ease of interpretation, we place the teams ranked in the top 25 on average[9] during a season into five categories (top 5, top 6–10, top 11–15, top 16–20, and top 21–25), with teams not ranked all season omitted. It is also worth noting that 53% of the games were played at home, and this likely reflects the BCS schools' paying non-BCS conference schools in order to host more home games. Similarly, BCS teams are better than non-BCS teams on average, therefore the average winning percentage in the sample is 57%.

Revenue

According to a 2012 report, the median Division I Football Bowl Subdivision (FBS) football program generated nominal revenue increased at an average annual rate of about 15% from 2004-2012, while the BCS conference revenues grew at an average rate of about 9% (Fulks, 2013). This growth is quite remarkable, considering that this period included the economic recession stemming from the 2007 financial crisis. The BCS conferences, which make up just over half of the teams in the FBS (the remainder are affiliated with other conferences or play as independents), are in especially good shape, with lucrative television network rights contracts in place through 2030 and beyond.

The most comprehensive source of institutional financial information currently available is managed by the Office of Postsecondary Education of the U.S. Department of Education. As required by the Equity in Athletics Disclosure Act (EADA), all postsecondary institutions that participate in federal student aid programs and that have an intercollegiate athletics program must submit annual financial reports, which are then made public via the EADA website. We compare a few of the EADA figures to those reported by *USA Today* & *ESPN* (separately obtained through Freedom of Information Act requests) and the NCAA (since the NCAA did provide outliers such as max revenue in their annual report) for total athletic department revenues and they appear to be consistent.

The reports from EADA do not provide a categorical breakdown of revenue within each program, but they do provide total revenue figures by school for each year as well as total athletic department revenue. Due to the inclusion of a revenue category entitled "not allocated by sport," we construct a second version of revenue called "adjusted revenue." We do this because different schools likely have different methods of allocating other revenue (for donations, etc.), and this other revenue may be correlated with the independent variables. In order to calculate this adjusted revenue total, we first determine the percentage weight of football revenue in terms of net total athletic department revenue. Then, we apply this weight to the not allocated by sport amount and add the result to the total football revenue to arrive at the adjusted total football revenue. Our revenue regression results are included for total revenue and total adjusted revenue. We use total revenue for our MRP estimate because the total revenue figures are more reliable and comparable between schools. Nevertheless, it is worth noting that we might be underestimating MRP because of this unallocated revenue.

There are currently 124 full members of the NCAA Division I FBS. However, there is a large disparity between the highest and lowest revenue levels. For this reason, we limit the schools used for our study to members of the "Big 6" BCS conferences: the Atlantic Coast (ACC), Big East, Big Ten, Big 12, Pac-12 (formerly the Pac-10), and Southeastern Conference (SEC).[10] They are referred to as BCS Conferences because each of the conference champions receives an automatic bid to a BCS bowl game.[11] All of the conferences have at least 10 teams each year included in the data, except for the Big East (7–8 per year). The member schools of these conferences were fairly consistent over the period 2004-2012, with some notable changes in the last few years[12] but no major realignment. It is important to note that conference changes occurring in 2012 will not be reflected in the revenue regression results, as revenue data were available (at the time, this article was written) only for 2004-2011.

Like the game-level data, annual revenue is unbalanced panel data. First, because we account only for the BCS conferences, some teams are not included each year (i.e., if they joined or left a BCS conference between 2004 and 2011). Further, the EADA does not have data for the University of Maryland from 2005-2007.[13] While the omission might not be completely random, only seven teams fit into this category, and the reason for missing years is strictly due to conference membership. In fact, four of those seven were included in all but 1 year because they joined the Big East in 2005. Therefore, we do not believe there is any bias.

The average inflation-adjusted football program revenue for the sample over all years is approximately US$32 million, with a fairly large variance (*SD* of US$18 million). The SEC had the highest average revenues for the 2011 season at US$54 million, while the Big East conference averaged only US$21 million that year. The largest outlier for the 2011 season was the University of Texas (of the Big 12 conference), bringing in US$103 million (partly due to the aforementioned Longhorn Network). Overall, average inflation-adjusted annual growth rates were fairly consistent across all conferences over the sample period, ranging from 4.3% (Big East) to 7.6% (SEC).

Blue Chip Prospects

We utilize data from the *Rivals.com* annual lists of top 100 prospects (inclusive of all positions), often called "blue chip" prospects, for teams from Big 6 conferences that signed blue chip quarterbacks from 2002-2009.[14] Over the course of these 8 years, 64 quarterbacks were ranked on this list, but only 46 actually recorded a QBR for the team that signed them. In our sample, 16% of games were started by blue chip quarterbacks. As expected, blue chip–ranked quarterbacks who played outperformed others, with a QBR of 57 compared to 52 for those not ranked. This five-point gap is relatively small (around half a win in a 13-game season) as will later be shown in the results. This gap only applies to blue chip players who played and does not include the 18 players who did not contribute to their team.

One notable concern is that teams with blue chip quarterbacks may be historically better, thus be more likely to recruit a blue chip quarterback, so differences may reflect team quality. However, a comparison of average QBRs for a subset of schools that had at least one blue chip prospect during the sample period shows that QBRs for blue chip prospects are still 3 points higher than for non-blue chip quarterbacks (57 vs. 54) for the schools that had a blue chip quarterback during the period. Furthermore, as mentioned earlier, quality WRs may slightly bias the QBR measure. In Appendix C, we show that, on average, blue chip quarterbacks play with the same number of blue chip WRs, after controlling for team fixed effects. This supports our claim that the ex ante measure of quarterback quality is not biased by teammate quality, after we control for team fixed effects.

Econometric Framework

In this section, we present the four parts of our econometric analysis. The first three parts estimate a quarterback's value based on ex post results and the fourth uses high school ability to proxy estimated ex ante value. In the first part, we estimate the contribution of a team's quarterback to winning. In the second step, we estimate the value of a marginal win. In the third, we utilize the first two sets of results to estimate a quarterback's marginal product. Finally, in the fourth step, we estimate the value of a high-ability player using his ranking as a high school recruit.

Step 1: The Win Probability Model

To calculate a quarterback's MRP, we first need to estimate the relationship between quarterback performance and winning, while controlling for exogenous factors, such as the opponent and the game's location. In a given season, t, team j plays G games. The equation we use to estimate win probability across j, g, and t is as follows:

$$Pr(W_{gjt} = 1|X) = \beta\text{'}X + \omega_{gjt}, \tag{1}$$

where $\beta\text{'}kX$ is

$$\beta_0 + \beta_1 QBR_{gjt} + \beta_2 OPPRNK_{gjt} + \beta_3 HOME_{gjt} + \beta_4 TEAM_{gt}$$

The binary response variable W equals 1 if the jth team wins the gth game of season t. QBR represents the total QBR for the quarterback on the jth team in the gth game of season t.

For *OPPRNK*, we use five dummy variables for teams ranked on average 1–5, 6–10, 11–15, 16–20, and 21–25, using weekly BCS ranking data for the opponent in season t, with 1–5 representing the strongest opponent (an average BCS ranking in the top 5). A team ranked outside the BCS top 25 in each poll during that season has a 0 for all five dummies. *HOME* is a dummy variable equal to 1 for home games, excluding "home" games played at neutral sites. Finally, we run the model with and without *TEAM* fixed effects. The sample data for the win probability model consist of 6,884 game-level observations from 2004-2012 seasons.

To account for team fixed effects, we use dummy variables for all 68 teams. This can cause problems because of the potential for incidental parameters bias. However, we find similar results with and without team fixed effects.

Step 2: The Revenue Regression

The next step involves estimating the marginal revenue expected from an additional win. In a given season t, team j plays G games. The revenue of team j in season t is estimated as follows:

$$R_{jt} = \alpha\text{'}\mathbf{Z} + \varepsilon_{jt}, \tag{2}$$

where $\alpha\text{'}\mathbf{Z}$ is:

$$\alpha_0 + \alpha_1 WIN_{jt} + \alpha_2 WIN_{j(t-1)} + \alpha_3 CONF_{jt} + \alpha_4 7HOMEGAMES_{jt} + \alpha_5 YEAR_j + \alpha_6 STATEUNEMP_{jt} + \alpha_7 TEAM_t$$

The continuous variable R equals the total football program revenue for the jth team in season t. As explained in the previous section, we include two versions of revenue in our regression results—total revenue and adjusted total revenue. In addition to WIN_t, the number of wins in season t, we add the number of wins in season $t-1$, WIN_{t-1}. We include WIN_{t-1} because a successful season likely has a large impact on a team's revenues the following year, such as through increased season ticket sales. We assume that winning is linearly related to revenues, holding other factors constant. In order to ensure that marginal revenue for wins does not vary substantially between low- and high-revenue schools, we ran the regression separately for schools below and above the median revenue level and did not find statistically significant differences between the two groups.

Next, a series of *CONF* dummies are included to indicate conference affiliation.[15] Many of the lucrative television network contracts are conference specific, and the teams benefit through revenue sharing. In fact, much of the conference realignment in college basketball and football the past few years is likely due to the financial incentives available to schools' being offered membership in a richer conference. The 7*HOMEGAMES* variable is a dummy taking the value of 1 if the team had seven or more home games that season, 0 otherwise (since 89% of teams in the sample have six or seven home games). This is important because ticket sales represent a significant portion of annual generated revenues, and a difference in the number of home games impacts revenue. A *YEAR* dummy is included to account for the general growth in college football during the study period. *STATEUNEMP*, equal to the state's unemployment rate in year t, accounts for non-football-related economic conditions in a team's state. Finally, we run the model with and without *TEAM* fixed effects to control for any school-specific features that impact revenues and have not been accounted for elsewhere in the model.[16] The results are fairly similar between the two models.

Step 3: Estimating MRP

The final step in the process is to estimate the MRP of an elite quarterback. To do so, we first establish the link between a change in a quarterback's *QBR* and wins. The marginal effect of QBR on win probability changes based on the value of the other explanatory variables, so for our MRP calculation, we use the marginal effect of a change in QBR at the mean values of the other variables. The formula to estimate the marginal effect at a given level of QBR is:

$$Pr(W = 1|QBR_i) = \varphi(\beta' X) \tag{3}$$

Next, we calculate the marginal effect between two values of QBR. Assuming the change is positive, the difference between the two probabilities is the increased probability of winning from the change in QBR. Then, we multiply this difference by the average number of games for a full season, *G*, to predict total wins added for that year:

$$MP_t = \overline{G}_t * [Pr(W = 1|QBR_i = a) - Pr(W = 1|QBR_i = b)], \tag{4}$$

where $0 \leq a, b \leq 100$.

To account for the effect of lagged wins on current MRP, we estimate the increase in revenue in seasons $t(\alpha_1)$ and $t + 1(\delta\alpha_2)$, resulting from each additional win in season t by adding the coefficients from the revenue regression, discounting the lagged coefficient to account for this future revenue. Finally, we multiply the marginal revenue by the marginal product to arrive at MRP:

$$MR_t = \alpha_1 + \delta\alpha_2, \tag{5}$$

where $\delta =$ discount rate for $t + 1$.

$$MRP_t = MR_t * MP_t \tag{6}$$

The MRP for a quarterback in season t is equal to the additional predicted wins multiplied by the sum of current (t) and discounted future ($t + 1$) estimates of additional revenue per win.

As Kahane (2012) points out, an issue that can arise with this type of model is determining whether a fixed-effects or random-effects regression is appropriate. We utilized the Hausman test and concluded that the fixed-effects model is more appropriate.[17] We include revenue regression results with and without team fixed effects and show there is little difference.

Step 4: Ex Ante Estimation

In this fourth step, we move from ex post estimation of value to ex ante estimation of expected value. Equation 7 shows the econometric model we use to estimate the relationship between having signed a blue chip quarterback (one rated on the rivals.com top 100 between 2002 and 2009) and observed team QBR. We also use this model to estimate the relationship between having signed a blue chip quarterback and win probability. For ease of exposition, we denote both dependent variables (QBR and win probability) as Y since the same independent variables are used.

In both cases, we use the same predictive variables as Equation 1, except we replace QBR with a series of binary variables (*Top100QB*) that equal 1 if a team had signed a blue chip quarterback recruit $t - k$ years prior. In this case, $k = 1$ in the player's first year of eligibility and $k = 5$ represents the fifth season in the case of "redshirting."[18] We also provide a reduced form of Equation 7 that combines the third and fourth years of enrollment into a single dummy variable, as those are the years a positive impact is shown. This variable captures the total impact of a top 100 quarterback. This reflects the point at which blue chip quarterbacks have an expected QBR above the average quarterback's:

$$Y_t = \alpha_0 + \alpha_k \sum_{k=1}^{5} Top100QB_{gj(t-k)} + \alpha_6\ OPPRNK_{gjt} + \alpha_7 HOME_{gjt} + \alpha_8\ TEAM_{gt} \tag{7}$$

One can examine the outcomes for blue chip quarterbacks at the individual level or the team level. At the individual level, we can examine all quarterbacks who had played enough to obtain at least one qualified QBR score and see how blue chip quarterbacks differ. However, this excludes any blue chip quarterbacks who never play in a game. Therefore, we also run regressions on the team where the variable for blue chip is coded as 1 if the team had signed a blue chip quarterback. By signing a blue chip quarterback, other quality quarterbacks may have signed elsewhere, and the team signing a blue chip quarterback who does not play may have been left with an inferior backup. In this case, we expect the value of a blue chip quarterback to be lower at the team level because we include teams that signed a blue chip quarterback, who did not record a QBR.

Results

Win Probability

The win probability probit regression results are summarized in Table 2. The estimate of the effect of *QBR* on win probability is statistically significant, and the positive sign on the coefficient is as expected, as a higher QBR should result in a higher win probability. At the mean QBR (52.6), an additional QBR point raises winning percentage by 1 percentage point. The QBR statistic is statistically significant at the 1% level, with and without fixed effects. It also is consistent with the descriptive statistics that suggest a similar one-to-one relationship.

Overall, the model exhibits strong predictive ability in terms of wins and losses. In roughly 80% of the cases, the model correctly predicts a win, if $Pr(W) > 50\%$, with similar results for losses; the predictive accuracy is only marginally improved

Table 2. Win Probability Model—Panel Probit Regression Results.

Variables	With Team Fixed Effects	No Team Fixed Effects	
	$Pr(WIN)$	$Pr(WIN)$	Marginal Effects[a]
Total quarterback rating (QBR)	0.028 (0.001)***	0.028 (0.001)***	0.009 mean = 52.6
Home game dummy (HOME)	0.47 (0.04)***	0.46 (0.04)***	0.12 mean = 0.53
Average BCS OPPRNK = 1–5	−1.92 (0.13)***	−1.87 (0.13)***	−0.51 mean = 0.04
Average BCS OPPRNK = 6–10	−1.47 (0.08)***	−1.44 (0.08)***	−0.41 mean = 0.07
Average BCS OPPRNK = 11–15	−1.26 (0.08)***	−1.22 (0.08)***	−0.35 mean = 0.06
Average BCS OPPRNK = 16–20	−0.98 (0.09)***	−0.95 (0.09)***	−0.28 mean = 0.05
Average BCS OPPRNK = 21–25	−0.69 (0.06)***	−0.68 (0.06)***	−0.20 mean = 0.11
Intercept	Team dummy variables	−1.12 (0.07)***	

Note. $N = 6{,}884$ Games. BCS OPPRNK = Bowl Championship Series opponent rank. Standard error is given in parenthesis.
[a]Marginal effects are reported as averages.
***Significant at 1% level.

with team fixed effects. The other control factors have the hypothesized impact. The positive sign of the coefficient on *HOME* is to be expected. Home teams are typically favored to defeat visiting teams in most sports, due mostly to the support of the home fans and comfort of not having to travel. Our results suggest home field advantage increases winning percentage by 12% points. The sign of the coefficients on the *OPPRNK* factor variables are also as expected, and the effect decreases as the opponent strength weakens ($OPPRNK = 1 - 5 => OPPRNK = 21 - 25$). The best opponents ($OPPRNK =$ 1-5) have a large negative coefficient, with a larger drop from 1–5 to 6–10 than between the rest of the opponent rank categories, showing that the truly elite teams (average of a top 5 ranking in season t) have a more substantial negative marginal impact on win probability.

Revenue Regression

The final piece of the ex post MRP equation is the marginal revenue estimate. The revenue regression results are summarized in Table 3. The coefficients on $WINS_t$ and $WINS_{t-1}$ are statistically significant and the signs are as expected, as additional wins should result in additional revenue. An additional win is estimated to be worth approximately US$420,000, controlling for team fixed effects in the current year. Lagged wins have a slightly smaller effect ($\sim$US$340,000) on current season revenues than current season wins, which holds with and without team fixed effects.

As outlined previously, the MRP is calculated by multiplying marginal revenue by marginal product. Marginal revenue is a combination of the coefficients on wins and lagged wins from the revenue model, while marginal product is the difference in win probability between two values of QBR over a full season. For our sample, we find the increase in win probability between an average quarterback (QBR = 52.6) and an elite quarterback (QBR = 79.8), that lies 1 *SD* above the mean QBR over the course of a season. Using the estimated increased win probability of .25 over a mean number of games (12.5), we arrive at a marginal product estimate of 3.1 additional wins. The marginal revenue equals the coefficient on wins from the revenue regression plus a discounted lagged win coefficient. We use the total revenue version of the revenue regression model with team fixed effects. Applying a discount rate of 5% to the lagged win component, we find that the marginal revenue from an additional win is approximately US$740,000. Multiplying marginal revenue by marginal product gives us a MRP estimate of US$2.3 million for a 1 *SD* increase in quarterback quality. In Appendix C, we show weak statistical evidence that having elite receivers may bias this estimate upward, although the amount of bias is small relative to the variation in QBR. It is important to note that we have not estimated replacement player value. That is, this US$2.3 million estimate represents the marginal revenue produced by an elite quarterback over an average quarterback.

For the *CONF* dummies, we use the version with no fixed effects, since coefficient estimates for some conferences are not included in the fixed effects version due to static conference membership over the sample period. The results reveal a stark

Table 3. Revenue Model—Panel Regression Results.

	With Team Fixed Effects		No Team Fixed Effects	
Variables (in US$ millions)	Total Revenue	Adj. Total Revenue	Total Revenue	Adj. Total Revenue
Total season wins	0.42 (0.11)***	0.44 (0.13)***	0.50 (0.11)***	0.58 (0.14)***
Total season wins (lag)	0.34 (0.11)***	0.31 (0.13)**	0.41 (0.11)***	0.44 (0.14)***
Conference—Big 12	*8.44 (5.36)*	*−0.93 (6.54)*	12.22 (3.95)***	16.94 (4.54)***
Conference—Big Ten	*11.91 (7.55)*	*−10.26 (9.21)*	18.14 (4.15)***	19.95 (4.75)***
Conference—SEC	*(omitted)*[a]	*(omitted)*[a]	25.27 (4.35)***	27.81 (4.93)***
Conference—Pac-12	*(omitted)*[a]	*(omitted)*[a]	4.94 (4.17)	11.64 (4.78)**
Conference—Big East	*2.87 (5.36)*	*2.35 (6.54)*	−0.91 (3.71)	−3.29 (4.37)
Seven Home games dummy	1.07 (0.57)*	0.66 (0.69)	1.22 (0.58)**	0.94 (0.73)
Year = 2005	1.43 (0.90)	2.95 (1.10)***	1.42 (0.93)	2.95 (1.16)**
Year = 2006	2.55 (0.99)***	5.04 (1.20)***	2.41 (1.01)**	4.83 (1.27)***
Year = 2007	4.89 (0.97)***	6.87 (1.19)***	4.72 (1.00)***	6.60 (1.25)***
Year = 2008	6.07 (0.95)***	8.61 (1.15)***	5.84 (0.97)***	8.22 (1.22)***
Year = 2009	10.75 (1.47)***	13.76 (1.80)***	10.40 (1.49)***	13.12 (1.86)***
Year = 2010	12.00 (1.54)***	16.49 (1.88)***	11.65 (1.55)***	15.84 (1.94)***
Year = 2011	13.41 (1.39)***	16.16 (1.70)***	12.98 (1.40)***	15.40 (1.75)***
State unemployment rate	−75.36 (30.61)**	−100.16 (37.34)***	−71.65 (30.58)**	−92.20 (38.12)**
Intercept	20.50 (3.09)***	38.92 (3.77)***	12.30 (3.56)***	21.67 (4.20)***

Note. $n = 515$. SEC = Southeastern Conference. Conference dummy Atlantic Coast included in constant. Standard error is given in parenthesis.
[a]SEC and PAC-12 conference dummies omitted because of fixed effects (no changes over t).
***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

contrast across conferences, with large gaps between the SEC and Big Ten (over US$18 million) and the Pac-12 and Big East (less than US$5 million but with large variances)—these figures are in comparison with the ACC, which is the omitted category. Another interesting result of note is the adjusted revenue coefficient for the Pac-12. This indicates that they have large amounts of unallocated revenue, and thus football program revenue could be particularly underestimated.

The *YEAR* dummies show a general growth in revenues since 2004, and all but 2005 are statistically significant. The *7HOMEGAMES* dummy, representing seven or more home games in a given season (vs. six or less), is consistent with the expectation that teams with an additional home game have higher revenue. Finally, the STATEUNEMP coefficient indicates some correlation between local economic conditions and program revenue, as an increase in the unemployment rate reduces expected revenue, with a 1percentage point increase in state unemployment, causing a decrease of roughly US$750,000 in revenue.

In this case, as opposed to the win probability model, team fixed effects do have some slight effect on the estimates. Because there is very little change in the conference structure during this period, the conference dummy effect mostly disappears when fixed effects are included. The year and unemployment variable coefficients are slightly larger with fixed effects, while the effect of wins (and lagged wins), and along with the home dummy, is smaller. For our final MRP calculation, we use the total revenue regression results with team fixed effects included.

Case Study: You Got Lucky

In 2009, Stanford redshirt freshman quarterback, Andrew Luck took over the starting reigns from incumbent Tavita Pritchard, who in the previous year won only five games with an average QBR[19] of 47, slightly below our sample average of 53. Luck played 12 games in 2009 with an average QBR[20] of 71.2. Overall, he led his team to an 8-4 regular season record (they would lose their bowl game, but without Luck, as he was injured), just 1 year after they were 5-7 with Pritchard under center. Luck followed up his solid freshman season with an even more impressive sophomore year. He led the Cardinal to a 12-1 record, while averaging a remarkable 88.7 QBR over the course of the season. Luck played his final season at Stanford in 2011, finishing 11-2 and being drafted first overall in the following year's NFL draft. During his three seasons playing for Stanford, the school's inflation-adjusted football revenues increased at an average annual rate of 24%, much higher than the average annual growth rate from our sample over this time period (which is about 5%, inflation adjusted).

While Andrew Luck performed at an elite level over his final two seasons at Stanford, his story should be considered the exception and not the rule. Few quarterbacks in our sample had such remarkable seasons. As such, the ex post MRP estimate for an elite quarterback can be considered an upper bound for the position, as only eight quarterbacks in our sample averaged QBRs more than a single deviation above the mean (our proxy for "elite") over the course of an entire season; Luck was the only one to have more than one such elite season. The chance of a team in our sample having one of these elite quarterbacks is less than 2%.

Estimating Quarterback Value Ex Ante

We present the results of both the individual estimates (a comparison between blue chip quarterbacks and all others) and the team estimates, which measure the effect on QBR and win probability for teams that signed a blue chip quarterback, regardless of whether he played. In our sample, 28% of the 64 blue chip quarterbacks in our sample never recorded a single QBR score for a team in a Big 6 conference.[21]

We first identify the level of experience at which blue chip quarterbacks have an above average QBR. In Part A of Table 4, we present a QBR regression at the individual level with dummies for blue chip quarterbacks in their first through fifth season after being recruited (which would include redshirt seasons, transfers, etc., as players have only 4 years of eligibility). The result is clear: blue chip quarterbacks peak in their fourth year of enrollment, which is typically their junior (if they redshirt as a freshman) or senior year. The increase in average QBR over a quarterback's first 4 years indicates a positive relationship between experience and outcomes. The QBR increase of 6.34 points is meaningful, as it results in a 0.06 increase in winning percentage (0.79 wins per season) or US$555,000 based on the value of each additional win (calculated above). The third year of eligibility also shows a positive although not statistically significant impact on QBR. In the fifth year, the best players are likely already in the NFL, while quarterbacks starting in their first 2 years may lack experience. Moving on to the team-level analysis, because over one quarter of the top 100 quarterback recruits in our sample failed to register a single QBR, the impact of a blue chip prospect is smaller if we include both teams that signed and played a blue chip quarterback and those that signed but did not play the blue chip recruit.

In part B of Table 4, we estimate the impact on the team's QBR of signing a blue chip quarterback who would be in his third or fourth year of eligibility. We find a statistically significant increase in the team's average QBR of 2.3. This causes an increase of about 0.023 in winning percentage, or roughly 0.29 wins over the course of a normal season, for a total of 0.58 wins over the third and fourth years (combined) from recruiting the blue chip quarterback. At a value of US$740,000 per win, 0.58 wins represent roughly US$429,000 in expected additional revenue. This 2-year total is lower than the individual results (US$555,000 in the fourth year alone), which reflects the fact that some blue chip quarterback signings do not pan out.

As a final check, we estimate the effect of signing a blue chip quarterback on team wins in the player's third and fourth year of eligibility. The probit estimate shows the marginal effect of an added blue chip player 3 or 4 years after he signs is an increase in winning percentage of 0.027, which is not substantially different

Table 4. Blue Chip Regression Results.

	By Player			By Team		
Key Variables	QBR	*Pr*(*WIN*)	Marginal Effects[a]	QBR	*Pr*(*WIN*)	Marginal Effects[a]
Part A: Blue chip effect on QBR and win probability by season (by QB and team)						
First season	−10.46 (3.04)***	−0.250 (.17)	−0.075 (.050)	−1.29 (1.34)	−0.018 (0.074)	−0.005 (0.022)
Second season	−0.42 (1.77)	−0.070 (0.097)	−0.020 (.028)	−0.26 (1.24)	−0.189 (0.067)***	−0.056 (0.020)***
Third season	1.75 (1.56)	0.209 (0.089)**	0.062 (.026)**	0.87 (1.23)	0.095 (0.069)	0.028 (0.020)
Fourth season	6.34 (1.56)***	0.318 (0.090)***	0.094 (.027)***	2.89 (1.24)**	0.048 (0.069)	0.014 (0.021)
Fifth season	−3.01 (2.75)	−0.203 (0.144)	−0.060 (.043)	−1.84 (1.27)	−0.109 (0.070)	−0.032 (0.021)
Part B: Blue chip effect on QBR and win probability in third/fourth seasons (by QB and team)						
Third/Fourth season	4.78 (1.20)***	0.305 (0.068)***	0.090 (.020)***	2.34 (1.02)**	0.090 (0.056)	0.027 (0.017)

Note. $N = 6{,}884$. QBR = quarterback rating. *QBR:* Included team dummies to account for team fixed effects (results not reported). *Pr*(*WIN*): Included opponent rank, home game, and team dummies (results not reported). Sixth season not included in results, as only one player from our sample had a sixth season (took 2 years off). Standard error is given in parenthesis.

[a]Marginal effects are reported as averages.

***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

than the estimated impact above of 0.023. One difference is that the statistical significance disappears, which may stem from factors other than team fixed effects, the quarterback, the opponent, and game's location.

Conclusions

To be sure, many factors influence both the outcome of a college football game and a quarterback's performance. Nevertheless, the QBR developed by ESPN captures a quarterback's performance and the impact it has on the team's win probability with only weak evidence of bias. It also allows us to estimate a quarterback's MRP by providing a statistical link between player performance and winning. Marginal product has historically been the most difficult part of the MRP equation to estimate accurately, and with QBR, we can have more confidence in our estimates because of the strong correlation between a quarterback's QBR and the team's win probability. We estimate that elite quarterbacks have a MRP of roughly US$2.3 million, although this may represent an upper bound based on the aforementioned weak omitted variable bias. We also find that quarterbacks ranked as top 100 prospects coming out of high school are expected to increase college football program revenues by around US$400,000 dollars over their careers compared to the average quarterback.

We might understate the MRP because other institutional benefits may not be captured by football program revenue. For instance, after a college has a successful season, it may have an increase in applications, potentially improving the quality of the student body. This was well documented after George Mason University made a surprise run to the Final Four of college basketball in 2006, with university officials reporting a 24% increase in freshman applicants (Carroll, 2008). Also, there may be an increase in alumni support stemming from athletic success. In September 2013, Texas A&M University reported that donations had reached a school record of US$740 million for the year, exceeding the previous high by 70% (Troop, 2013). While there were likely a variety of reasons for this, the fact that it came the year after Johnny Manziel won the Heisman Trophy should not be ignored.

On the other hand, we might overstate MRP on an ex post basis for a variety of reasons. First, we are looking only at the quarterback position and a quarterback's success depends upon his teammates, as noted in Appendix C. If a quarterback has a highly skilled WR or running back playing alongside him, his job becomes much easier. While QBR does attempt to divide credit on each play to account for this, it might not fully account for teammates' skill level. However, we find little evidence of this. Other team factors outside of the offense—defense, special teams, and coaching—might also have an impact on the quarterback's MRP or on winning but not be accounted for sufficiently in the model. On the other hand, our ex ante estimates may be more precise if variation in outside factors is unrelated to quarterback quality.

Finally, more detailed financial data from NCAA member institutions would likely allow for a more precise estimate of marginal revenue. While this has been done before, most notably by the *Indianapolis Star* newspaper in 2006, it would be beneficial to have such highly detailed data covering many years and many schools. Hopefully, future work will address some of these issues.

Appendix A

Data Sources

Win–Loss and Home-Away data: James Howell's college football historical schedule and result database (http://www.jhowell.net/cf/scores/ScoresIndex.htm).*

Total QBR: Game-level QBR data obtained via database of weekly qualified QBRs on ESPN.com (http://espn.go.com/ncf/qbr).

Opponent Ranking: Historical BCS rankings obtained via unaffiliated database (http://bcscentral.info/h/history.html).

Revenue: The Equity in Athletics Data Cutting Tool, an online database maintained by the Office of Postsecondary Education of the U.S. Department of Education (http://ope.ed.gov/athletics/).

State Unemployment Rate: Historical data obtained through the United States Department of Labor Bureau of Labor Statistics website (http://www.bls.gov/lau/).

Conference Affiliation: James Howell's college football historical schedule and result database (http://www.jhowell.net/cf/scores/ScoresIndex.htm).*

**Note.* Data were verified via ESPN.com in addition to Howell's database.

Appendix B

Table B1. Total Football Program Revenues.

	Inflation Adj. Revenues (in millions)		By Conference					
	Mean	*SD*	ACC	BIGEAST	BIG10	BIG12	PAC12	SEC
2004	25.8	14.2	18.1	16.0	33.2	26.6	21.9	35.3
2005	27.3	15.4	19.0	16.8	35.8	26.8	23.3	38.0
2006	29.7	16.5	22.9	17.0	37.6	27.6	25.6	42.6
2007	32.2	17.6	23.1	17.8	40.5	32.7	27.3	46.1
2008	32.4	18.0	22.5	18.9	39.8	34.7	26.7	46.8
2009	34.3	20.1	21.9	19.7	42.5	37.1	25.8	53.0
2010	35.3	20.7	24.0	19.7	43.7	37.1	26.1	55.1
2011	37.0	20.2	27.5	20.7	45.7	38.9	29.9	54.0

Note. ACC = Atlantic Coast; SEC = Southeastern Conference. Program revenue data obtained via the Office of Postsecondary Education of the U.S. Department of Education (http://ope.ed.gov/athletics/).

Appendix C

Testing for Bias in QBR

ESPN claims that its QBR corrects for potential bias from the quality of a quarterback's teammates. We test for potential bias using the number of a team's non-quarterback offensive top 100 blue chip recruits (as identified by rivals.com), as a proxy for teammate quality. Our first test supports ESPN's claim that QBR corrects for bias of teammates, as it does not reject the null hypothesis that the number of blue chip recruits at other offensive positions has no effect on QBR. Breaking the offensive recruits out by position, we find that additional blue chip WRs are associated with higher QBR; however, this bias is small when compared to the variation found in QBR scores and statistically weak given the number of tests. The results suggest that the QBR's bias makes the estimates of ex post MRP an upper bound. A final bias test shows that blue chip quarterback recruits are not more likely than other quarterbacks to have blue chip WR teammates after controlling for team fixed effects; this reduces the concern of teammate bias influencing the ex ante estimates of quarterback MRP based on the quarterback's high school rating.

In order to measure the quality of a quarterback's offensive teammates, we added the number of top 100 recruits from rivals.com (see footnote 14 for more information). Using the ex ante quality of teammates reduces the potential for reverse causality when using ex post measures of teammates, as better quarterbacks may improve the likelihood another offensive player is drafted in the NFL or named All-Conference or All-American. We included the standard offensive positions of running back, offensive line, TE, and WR. We further limited a team's count in a given year to offensive recruits that would be in their third or fourth season of play. This is consistent with our QB ex ante approach; players are most likely to have their biggest impact in their junior and senior seasons.

The mean number of blue chip offensive recruits (excluding quarterback) that would have been in their third or fourth season on a given team was 1.17, with a *SD* of 1.72. The mean number of blue chip recruits at each position ranges from 0.08 for TEs to 0.40 for offensive line. For WRs, the position most likely to have an impact on QBR based on our tests, the sample mean was 0.37 with a *SD* of 0.71.

We run two regressions using QBR as the outcome variable of interest, for game g in year t for team j. In both regressions, we control for quarterback quality by including a dummy for whether a blue chip quarterback in his third or fourth season played in the game. In Equation C1, we use only the sum of a team's top 100 offensive recruits in their third or fourth season after signing (*Top100OffRecr*), excluding the quarterback position. Because average QBR changed over the years slightly, we include a series of time dummies (*YEAR*), where YEAR $= 1$, if Year $= t$. A change in the average sample QBR from year to year may represent a change in the measure or a change in rules or coaching tendencies that favor throwing. We include team fixed effects to control for

Table C1. Bias Testing—Panel Regression Results.

Variables	QBR_{gjt}	QBR_{gjt}	Top 100 Recr WR
Top 100 quarterback recruit$_{gjt}$	5.290 (2.126)**	5.189 (2.141)**	0.167 (0.121)
Top 100 offensive recruits	0.458 (0.547)	NA	
Top 100 running back recruits		0.026 (1.051)	
Top 100 offensive lineman recruits		−0.566 (1.051)	
Top 100 tight end recruits		0.530 (2.001)	
Top 100 WR recruits		1.938 (0.896)**	
Year dummy (2006)	0.207 (1.772)	0.173 (1.762)	0.054 (0.073)
Year dummy (2007)	2.505 (1.921)	2.567 (1.957)	0.035 (0.104)
Year dummy (2008)	0.541 (2.279)	0.500 (2.258)	0.028 (0.106)
Year dummy (2009)	1.366 (2.140)	1.266 (2.157)	0.077 (0.099)
Year dummy (2010)	4.612 (2.140)**	4.471 (2.169)**	0.111 (0.105)
Year dummy (2011)	5.436 (1.862)***	5.268 (1.872)***	0.143 (0.100)
Year dummy (2012)	5.341 (2.228)**	5.268 (2.240)**	0.069 (0.088)
Constant	49.084 (1.739)***	49.148 (1.732)***	0.265 (0.071)***
Team fixed effects included	✓	✓	✓

Note. $n = 6{,}237$ Games. WR = wide receiver. *Top 100 Quarterback Recruit* represents third/fourth season blue chip QBs that actually played in game *g*. Year dummy (2005) included in constant. Robust standard errors given in parentheses.
***Significant at 1% level. **Significant at 5% level.

the overall program quality, where Team = 1 if Team = *j*. Recall, these are also controlled for in the estimate of quarterback MRP. In Equation C2, we break out the effects by position: offensive line, running back, *TE*, and *WR*. Finally, errors are clustered at the team level.

$$QBR_{gjt} = \alpha_0 + \alpha_1 Top100RecrQB_{gjt} + \alpha_2 Top100OffRecr_{jt} + \sum_{t=2006}^{2012} \gamma_t YEAR_t + \sum_{j=1}^{67} TEAM_j \tag{C1}$$

$$QBR_{gjt} = \alpha_0 + \alpha_1 Top100RecrQB_{gjt} + \alpha_2 Top100RecrOL_{jt} + \alpha_3 Top100RecrRB_{jt} + \alpha_4 Top100RecrTE_{jt} + \alpha_5 Top100RecrWR_{jt} + \sum_{t=2006}^{2012} \gamma_t YEAR_t + \sum_{j=1}^{67} TEAM_j \tag{C2}$$

The estimates for the two regressions of offensive recruits on QBR are shown in Table C1. In column 1, we see that the coefficient on the number of offensive blue chip recruits (*Top*100*OffRecr*) is about 0.46, but with a p value >.40. In other words, teams that have more offensive blue chip recruits do not see their QBR improve by a statistically significant amount. This result supports ESPN's claim that QBR is generally unbiased. However, when we break out the blue chips by position, we find that recruiting an additional blue chip WR adds about 1.9 points to QBR, and this is statistically significant at the .05 level. As pointed out above, a 1 *SD* increase in WR recruits (0.71) adds only 1.4 points to QBR, given the total variation in QBR (*SD* of about 27), this represents a small proportion. Additionally, we are now testing four positions, so there is roughly a 19% chance of rejecting the null hypothesis for at least one position by random chance (i.e., $1 - 0.95^4$). A standard Bonferroni correction that divides the significance level (p value < .05) by the four tests would suggest a threshold of 0.0125, which the WR variable does not meet. The other positions show mixed effects on QBR and are not statistically significantly different from zero.

One concern is that blue chip receivers and quarterbacks might be more likely to play on the same team. If this is the case, the ex ante estimate is biased upward. We test the relationship between the two and do not find evidence of bias. In Equation C3 below, we estimate the number of expected WR recruits for teams with a blue chip quarterback. We also control for year fixed effects, and this accounts for the fact that the number of WRs that each recruiting class produces may vary from year to year. Finally, we add in team fixed effects to control for time invariant team quality.

$$Top100RecrWR_{jt} = \alpha_0 + \alpha_1 Top100RecrQB_{gjt} + \sum_{t=2006}^{2012} \gamma_t YEAR_t + \sum_{j=1}^{67} TEAM_j \tag{C3}$$

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Notes

1. We limit the sample to Bowl Championship Series (BCS) conference teams to limit heterogeneity of players and school revenue.
2. The Heisman trophy is an annual award given to the best college football player.
3. Bradbury (2011) claimed that Scully was actually the first to estimate marginal revenue products for workers in any field, not just professional athletes.
4. The National Collegiate Athletic Association version of the quarterback rating (QBR), known as "Passer Efficiency Rating," uses the same components as the NFL passer rating but does not impose limits on each of the components, and is scaled slightly differently.
5. The ESPN Stats and Information Analytics Team explained the total QBR in great detail in their presentation entitled "QBR: What ESPN Analytics Learned" presented at the MIT Sloan Sports Analytics Conference in 2012. http://www.sloansportsconference.com/wp-content/uploads/2012/03/QBR_Lessons.pdf
6. About 77% of the games in our data set included team and opponent quarterbacks with qualifying QBR statistics; those that did not were mostly due to non-BCS conference opponents whose quarterbacks weren't rated.
7. Of the 6% of game observations that are not included, most are due to multiple observations in the same game. The remaining missing observations (about 1% of total potential game-level observations) are minimal and there is no evidence to suggest that their omission would bias the win probability estimates.
8. The second and third concerns are raised in blog posts by David Berri (http://wagesofwins.com/2011/08/20/commenting-on-espns-total-quarterback-rating-qbr/) and Brian Burke (http://www.advancednflstats.com/2011/08/espns-new-qb-stat.html).
9. The BCS ranking is a hybrid of polls and computer rankings and is first released about 8 weeks into the season, then each week until the final poll after the conference championship games. For the five categories, we averaged a team's ranking across each of the eight polls that are released in a single season. Because rankings are only provided for the top 25 teams, we included teams in the 21–25 category even if they were ranked in some weeks and unranked in other weeks, since an average is no longer possible in that situation.
10. Notre Dame, which does not belong to a conference, was not included in this sample. Their football program revenues in for 2012-2013 were around US$78 million.
11. The BCS is a system of selection by which the top 10 ranked teams in the country play in five end-of-year bowl games. The system is set to expire in 2014 at which time a play-off system will be implemented.
12. The Atlantic Coast has only gained one team since 2004, with Boston College moving from the Big East that year. The Big Ten added Nebraska (from the Big 12) in 2011 but were otherwise unchanged. The Big 12 lost four teams in 2011 and 2012 (Colorado to the Pac-12 and Nebraska to the Big Ten, followed by Missouri and Texas A&M heading to the Southeastern Conference [SEC] in 2012), adding Texas Christian University and West Virginia (from the Big East) in 2011. Missouri and Texas A&M were the only changes the SEC has seen during this time period. In addition to Colorado, the Pac-12 added Utah in 2011 (they were previously in a non-BCS conference). Finally, the Big

East has seen quite a bit of shake-up. The conference lost Temple after the 2004 season (in addition to Boston College) and replaced these teams with Louisville, South Florida, and Cincinnati the following year. After a relatively quiet period, West Virginia left for the Big 12 and Temple returned in 2012.

13. We contacted the Equity in Athletics Disclosure Act administrator about the missing Maryland revenue, and they informed us that there was a "technical discrepancy on data that was to be included in the report."
14. Rivals is a website devoted to college recruiting and was acquired by Yahoo! in 2007. The website Alexa Internet estimates that Rivals.com is in the top 600 of all (not just sports) websites in terms of traffic in the United States, as of March 24, 2014: http://www.alexa.com/siteinfo/rivals.com.
15. *Note.* When the revenue regression is run to include team fixed effects, the SEC and Pac-12 conference dummies are omitted, since there were no changes to the teams in these conferences from 2004-2011.
16. Of note, we found no significant variation in stadium capacity over the sample period.
17. The Hausman test showed a χ^2 of 44.56, with a p value of .0001.
18. In NCAA football, players are eligible to play for 4 years; however, players may be redshirted for one season in order to extend eligibility to a fifth year. For instance, freshmen are sometimes redshirted if it is determined that they are not ready for game competition and could benefit from a year of practice. Redshirted players cannot participate in games.
19. Pritchard had a qualified QBR in 10 of the 12 games in which he played in 2008.
20. Luck did not have a qualified QBR against San Jose State, a blowout win for Stanford.
21. Of the 64 quarterbacks ranked in the *Rivals.com* top 100 list from 2002-2009, two of them were recruited by Notre Dame (not in a Big 6 conference) and not included at all in our results. There was one additional Notre Dame recruit (Dayne Crist) who transferred to a Big 6 conference and is included in the player results.

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