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Estimating the Marginal Revenue Product of
College Football Quarterbacks**

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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

A recent National Labor Relations Board ruling declared Northwestern football players employees and gave them the right to unionize. This ruling is part of ongoing scrutiny of The National Collegiate Athletic Association (NCAA's) model which labels college athletes as amateurs and limits player compensation to grant-in-aid (scholarships). Our paper estimates the marginal revenue product (MRP) of an elite college quarterback using revenue and game level playing data from eight and nine seasons, respectively. Similar to previous studies we show that MRP for elite quarterbacks far exceeds the average value of a scholarship. Our paper also provides two contributions by using a new quarterback rating system and creating an estimate of the expected value of a blue chip college quarterback recruit. The new system is the Total Quarterback Rating (QBR), a metric developed by the Stats & Information Group of ESPN. The measure has a strong win predictive ability and makes important adjustments to identify the quarterback's contribution. We find a one standard deviation increase in QBR adds about 3 wins per season, and each additional win increases a school's football revenue roughly \$740,000 compared to the average quarterback, holding a variety of other determining factors constant, including school fixed effects. This suggests a superior quarterback to be worth millions of dollars a season. Teams recruit quarterbacks, however, *ex-ante* of the player revealing their college ability. Therefore, to estimate the value of a college recruit, we test for differences between quarterbacks rated as blue chip high school prospects and other QBs. We estimate that signing a blue chip quarterback is expected to produce roughly \$429,000 dollars in total additional revenue for a college team compared to signing a non-blue chip quarterback. The results show that *ex-post* estimates of college player value may differ from *ex-ante* estimates due to the difficulty of predicting which high school players will excel in college.

JEL Codes: L83, J30

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 recently ruled that because college football players receive compensation for performing a full week's worth of work, they should be considered employees of their university and have the right to unionize. This ruling will likely be the start of the negotiations for players to receive better compensation. That compensation may be determined by the marginal revenue product of the players. This paper could potentially aid in those negotiations by providing a measure of an upper bound estimate of player marginal revenue product.

It is generally agreed upon that the NCAA has historically operated as a cartel (Kahn, 2007), colluding between member institutions to exploit student-athletes in revenue producing sports (primarily men's basketball and football) by limiting compensation to a capped amount (in the form of grant-in-aid), as opposed to market wages, which for elite athletes are likely to be in excess of a given scholarship. By categorizing the student-athletes as amateurs (as opposed to professionals), the NCAA has been able to enforce rules severely limiting the rights of the student-athletes which are typically given to workers in a professional setting. For instance, only since 2012 has the NCAA begun to allow multi-year scholarships, and Wolverton and Newman (2013) found that schools so far have been slow to take advantage. The main risk with single-year scholarships from the players' perspective is that a scholarship can be pulled if a serious injury leaves them unable to perform at the same level, and because they are not classified as employees, they are not protected under workers' compensation. Further, the value of scholarship compensation is not tied to a player's ability or performance, but instead capped at the value of the education they receive at their institution. This capped compensation does not account for the wide variety of player ability and contribution. How all of this will change now that the NLRB has ruled that players should be considered employees is unclear.

Due to ongoing significant financial growth in college football over the past decade, most evident in the existing multi-year, multi-billion dollar contracts between television networks and the Bowl Championship Series (BCS) conferences, the monopsony rents collected by the NCAA and its member institutions continue to increase. In our sample of more than 60 schools from BCS conferences, the average annual inflation-adjusted football program revenues increased from about \$26 million in 2004-2005 to \$37 million in 2011-12, yet student athlete compensation remained capped at the value of grant-in-aid during that entire period.

This study attempts to estimate Marginal Revenue Product (MRP) for college football quarterbacks from BCS conferences. We choose to look specifically at quarterbacks for a few reasons. First, quarterbacks are directly involved in almost all offensive plays. Player statistical performance data is more readily available for quarterbacks as opposed to other positions, such as offensive linemen, and this allows us to measure their contribution to team success more precisely. Also, the value placed on the quarterback position in college football is significant. Since 2000, 11 of the 13 winners of the Heisman trophy have been quarterbacks. The importance of the quarterback position is also reflected in the professional salary distribution. Becht (2013) showed that in the NFL, quarterbacks are the highest paid position on

average. Elite quarterback wages can represent up to about 8% of total annual team revenues, or 17% of total player wages (note: there are 53 players on an NFL roster). Thus, our MRP estimate for quarterbacks can be considered an upper bound for college football athletes. Finally, we choose to limit the study to BCS conference quarterbacks to control for the heterogeneity of schools.

For our study, we use a quarterback's QBR as a proxy for contribution to team win probability. This is a relatively new statistic created by ESPN. As we detail below, we believe that the QBR statistic is superior because of its stronger link to winning than the passing rating efficiency statistic that uses only outcomes like yards, touchdowns and interceptions without adjusting for the contribution of other players. In order to obtain the marginal revenue product for an elite quarterback, we perform a two stage analysis estimating first their contribution to wins and then the value of a win.

We first examine the MRP of a player ex-post of their observed college outcomes. We find quarterbacks with ratings one standard deviation above the mean QBR were estimated to add roughly 3 additional wins per season. In the second stage we estimate the value of a win at \$740,000, including discounted revenues for the following season. Therefore, our main result is that elite quarterbacks, i.e. those whose QBR is at least one standard deviation above the mean, have the potential to add over 2 million dollars a season to team revenue.

If college teams were to sign players as professional franchises do, before their ability to perform at that level was revealed, then a measure of ex-ante expected college MRP would be more appropriate. To perform the ex-ante analysis, we use high school ability (as proxied by their ranking as a top-100 recruit) to estimate future quarterback ratings and winning percentage. Ex-ante, we find that signing a quarterback with perceived high ability (based on high school recruiting ranking), in other words a so-called blue chip recruit, adds roughly 0.3 wins per year in the third and fourth years after signing the player. Using the value of a marginal win (~\$740,000), we estimate ex-ante that signing a recruit identified as high ability is expected to add roughly \$429,000 over those two years. The substantially lower ex-ante estimate reflects that over a quarter of top 100 quarterback recruits in our sample failed to record a qualifying game. These estimates provide a starting point for the expected value of blue chip high school quarterbacks.

LITERATURE REVIEW

Scully (1974) was one of the first to estimate marginal revenue product for athletes³. He first estimated the effect of team performance statistics in Major League Baseball on total revenues, and then weighted the team results by individual to arrive at predicted player MRP (often referred to as the Scully Method). He found that in general, players were exploited to a large degree due to baseball's reserve clause. Krautmann (2011) pointed out that Scully's ex-post method of utilizing an individual's weighted contribution towards team performance measures grossly overstated MRP, as it ignored replacement player value. 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 attempted to estimate the MRP of college players using ex-post observations on draft status. Brown (1993) used a relatively small sample of NCAA Division 1 college football team revenue data to estimate a two-stage least squares model. He estimated premium player rents by first regressing the number of future professional league draftees (as a proxy for premium players) on recruiting and market characteristics, then team program revenues on the number of players drafted, holding other factors constant. He estimated MRPs equal to approximately \$500,000 for a premium player, which far exceeded the allowed \$20,000 in scholarship given per year at that time. Huma and Staurowsky (2012) estimate the average full athletic scholarship at a Division I Football Bowl Subdivision college or university is worth approximately \$23,000 per year, which is still within the range estimated by Zimbalist (2001) over a decade ago (he takes into account graduation rates). Brown and Jewell (2004) updated these MRP estimates with additional data and found a similar result.

Brown (2010) later was able to utilize a much more detailed set of revenue data, further improving the precision of his MRP estimates, again using future draft status as a proxy for elite players. The data were obtained by the *Indianapolis Star* newspaper through public records requests. The *Star* released 86 detailed financial reports from Division I schools, and the reports included a much more detailed accounting of revenue and expenses categories (as opposed to aggregate data previously made available), although only a single year of detailed data was released. Brown modified his previous model to account for team skill level. He showed that, holding other factors constant, an additional premium player adds over \$1.1 million of additional team revenue. This represented a 34% increase from Brown's 1993 estimates (adjusted for inflation). Finally, in 2012, he added to this work by comparing player MRPs with expected NFL compensation to determine if lost wages in college were outweighed by increased future earnings, and he found that generally speaking, they do not.

In college basketball, the other main revenue generating NCAA sport, Lane et al. (2012) also found that MRP for players far exceeded the value of a scholarship. Unlike the above mentioned football studies, they used college game-level performance data along with the draft pick measure. Similarly, Kahane

³ Bradbury (2013) claimed that Scully was actually the first to estimate marginal revenue products for workers in *any field*, not just professional athletes.

(2012) and Brown and Jewell (2006) found that elite college hockey and women's basketball players generated MRP in excess of the scholarships they receive.

Using actual results is preferred in this paper, as opposed to draft status, because there is some question as to whether future NFL draftee status is the best proxy for player contribution to a college team's success when estimating premium college football player MRPs. For instance, in 2003, Oklahoma quarterback Jason White won the Heisman trophy after leading the Sooners to a share of the national championship, but was not selected in the NFL draft. The NFL values some skills and attributes that may not be reflective of the player's individual contribution to college team win-percentage. Another example, Ohio State quarterback and 2006 Heisman trophy winner Troy Smith, was not drafted until the 5th round due to concerns over his height (Steele, 2007). Our model attempts to capture the true contribution of a college quarterback to his team's success by using actual college football game data, rather than NFL draft status.

Krautmann (1999) points out that contact negotiations typically take place ex-ante of the revealed performance. Scully (1974) takes this into account as expected MRP is estimated based on previous performance. This paper provides an additional contribution over previous college athlete MRP estimates in that we provide an estimate of the value based on ex-ante ability using the player's ranking as a high school prospect, as opposed to the previous literature which has focused on the ex-post observation of draft status or college game performance.

DATA

Metrics for "Wins Above Replacement" (WAR) have been developed and used for over twenty 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 athlete 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 creating MRP estimates difficult to obtain, though recent attempts have been made (Lane et al. 2012) in basketball. The main difficulty in developing a WAR-type statistic for football is that it is difficult to isolate an individual's contribution to winning in these team-focused sports. In an attempt to bridge this gap, we use a player metric recently developed by ESPN for college football quarterbacks that may provide a solution for this issue of linking player performance to team win probability.

TOTAL QUARTERBACK RATING (QBR)

ESPN is a global sports and entertainment television network that reaches almost 100 million households in the U.S. alone (Sandomir et. al., 2013). ESPN has a very strong web presence, providing a reliable reference for sports statistics and information in real time. In recent years, they have developed a specialized Stats and Information Group (ESPN Stats & Info) in order to expand into more advanced analytics. One of the first major analytic statistics they developed in 2011 is called the Total Quarterback Rating (QBR). The historical NFL quarterback metric at the time, referred to as "Passer

Rating,” had been found to be lacking in many ways⁴. The metric measured only a few categories of quarterback performance, and as the position evolved and included more multi-dimensional statistics, such as the ability to avoid sacks and run the football, the passer rating became less and less relevant. The QBR was introduced in 2011 for professional (NFL) quarterbacks, and while the average viewer expressed confusion over how exactly it was calculated, the new metric had a stronger relationship to a team’s success.

At the NFL level there have been previous attempts before QBR to improve upon the traditional passer rating method. Berri (2006), Berri et al (2007) and Berri and Simmons (2011) used regression analysis to develop a new rating to assign weights to different outcomes such as yardage and turnovers (for ease of exposition, we will refer to this as the Berri QB Score). The Berri QB Score includes a quarterback’s rushing statistics. This measure, however, does 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 the Berri QB Score and QB rating at the NFL level.

Under the methodology behind the QBR for NFL quarterbacks for each play, they estimate the team expected points added and assign a portion of credit to the quarterback, while also assigning a “clutch weight” based on the game situation (such as time remaining, field position, down and distance, and closeness of game score). So, for example, a 10-yard gain on third-and-9 is worth more than a 10-yard gain on third-and-20. 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 their opponent’s quarterback compared to the previous passer rating which had a correlation of 79%⁵.

In 2013, ESPN introduced the Total Quarterback Rating for college football, and they applied the new QBR to individual game data from 2004 onwards 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 chart A below 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 time⁶. The average QBR in our sample is 52.6, and the difference

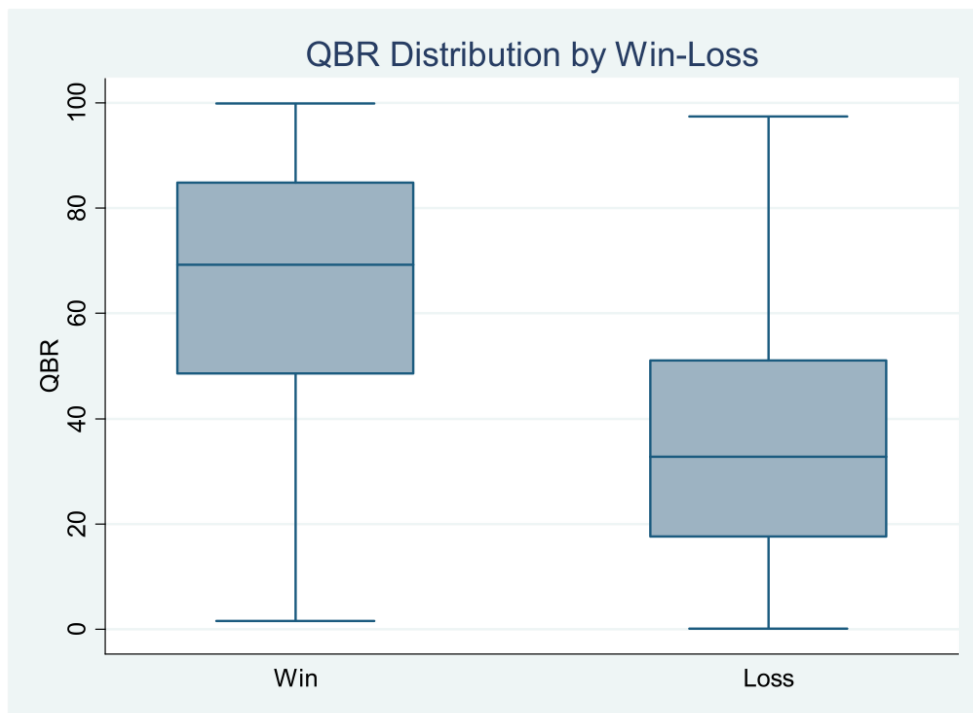
⁴ The NCAA version of the QB rating, known as “Passer Efficiency Rating”, uses the same components as the NFL passer rating, but does not impose limits on each of the components, and is scaled slightly differently.

⁵ The ESPN Stats & 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 game-level observations in our data set included team and opponent quarterbacks with qualifying QBR statistics.

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.

Chart A: QBR and Winning Percentage



The data we use for the game-level analysis is considered unbalanced panel data, although we have QBR data for 94% of the potential games.⁷ The data is unbalanced because of missing game observations which occur because a quarterback might not have enough “action plays” to have a qualified QBR (must have at least 20 action plays in a game to qualify). This could be because there are multiple quarterbacks rotating during the game, the team did not involve the quarterback in many plays (either intentionally or

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.

because of game situation), or the starting quarterback was injured or ineffective and replaced. Also, there was one team whose quarterback's entire season of game-level data (including QBR) were not available from ESPN for unknown reasons. Finally, we do not include game observations in which multiple quarterbacks on the same team had qualifying QBRs in the same game, since we would not have a way to allocate the impact of each of the quarterbacks on the game level win-probability.

As seen in Table 1, the average QBR is 52.6 for players in our sample. The Table also shows winning percentage broken down by QBR, which suggests a clear linear relationship between the two; therefore we use a linear functional form to estimate the relationship between QBR and winning. The distribution of QBR ratings is relatively uniform with a slight under-representation of QBR scores under 20. This could be because in cases with extremely low QBRs multiple quarterbacks are likely to be used and there may not be a qualifying quarterback. It is also unknown if ESPN intended the distribution to be completely uniform or not.

There are two potentially valid criticisms of the QBR measure.⁸ First, the formula is proprietary. Ideally we would like to be able to inspect the internal workings of the measure. In this paper, however, we are less concerned with how the measure is constructed and more with how it is associated with outcomes such as winning and team revenue. Second, QBR is composed of several statistics. It might be useful to know if two quarterbacks with the same QBR had differences in clutch ability or running, as this might matter for revenue if fans prefer teams that pull off close games or 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 the QBR, we use two variables to control for other factors that influence winning percentage: the opponent's rank and whether or not the game was played at the team's home stadium. For ease of interpreting results, we place the teams ranked in the top 25 on average⁹ during a season into 5 categories (top 5, top 6-10, top 11-15, top 16-20, top 21-25), with teams not ranked all season omitted. It is also worth noting that 53% of the games were played at home; this likely reflects the BCS schools' choice to pay non-BCS conference schools in order to host more home games. Similarly, BCS teams are generally better than non-BCS teams on average, therefore the average winning percentage in the sample is 57%.

REVENUE

⁸ These concerns are raised in blog posts by David Berri (<http://wagesofwins.com/2011/08/20/commenting-on-espn-total-quarterback-rating-qbr/>) and Brian Burke (<http://www.advancednflstats.com/2011/08/espn-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 5 categories, we averaged a team's ranking across each of the 8 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.

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 to 2012, while the BCS conferences grew at about 9%. 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 affiliated with other conferences or playing as independents) are in especially good shape, with lucrative television network rights contracts in place through 2030 and beyond.

Table 1: Variables

	Mean	Std. Dev.	QBR Distribution - # of Game Observations				
			0-20	20-40	40-60	60-80	80-100
QBR	52.64	27.20	1,059	1,409	1,502	1,501	1,413
		<i>Win percentage:</i>	18%	36%	54%	75%	94%

	>25	21-25	16-20	11-15	6-10	1-5
Opponent Rank*	4,640	756	344	413	457	274
% of Observations	67%	11%	5%	6%	7%	4%

	Mean
Home	0.53
Win	0.57

*N= 6884

While the NCAA financial reports do not include details of specific athletic programs or a breakdown by school, there are some categorical summaries that provide insight. The breakdown of revenue in fiscal year 2012 for Division 1 FBS school athletic programs (of which football is the largest component), on average, consists primarily of: ticket sales (22%), donations (21%), distributions from the conferences and the NCAA (18%), and allocated institutional support (20%). The other 19% is primarily made up of royalties, sponsorship, concessions, and broadcasting rights. While this gives a general sense of the breakdown, the aggregated data makes it difficult to draw conclusions about individual sports, conferences, and schools. For instance, the University of Texas has its own “Longhorn Network” that was scheduled to pay the school \$12 million for the 2013 season (Smith, 2013).

Even where institution-level data is made available, the main challenge remains that there are inconsistent, non-standardized reporting measures. Categories such as ticket sales, NCAA and conference distributions, and merchandise can be interpreted and compared between institutions with a high level of confidence. However, contributions from alumni and institutional support can be accounted for in a variety of ways based on the interpretation and policy of the institution.

That being said, 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 have some correlation 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 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, but 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 top and bottom schools in terms of revenue. For this reason, we have limited the schools used for our study to only those 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 the winner of each of the conference champions receives an automatic bid to a BCS bowl game¹¹. 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 years¹² but no major

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 \$78 million.

¹¹ The Bowl Championship Series is a system of selection by which the top 10 ranked teams in the country play in 5 end-of-year bowl games. The system is set to expire in 2014, at which time a playoff system will be implemented.

¹² The ACC 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 4 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 SEC in 2012), adding TCU 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 shakeup. The conference lost Temple after the 2004 season (in addition to Boston College), and replaced these teams with Louisville, South

realignment. It is important to note that conference changes occurring in 2012 won't be reflected in the revenue regression results, as revenue data was only available (at the time this paper was written) for 2004-2011¹³.

Like the game-level data, the annual revenue is considered unbalanced panel data. First, because we are only accounting 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 2005-2007¹⁴. While the Maryland omission appears to be by chance the incoming/outgoing conference team issue does give us some pause. While the omission might not be classified as completely random, there were only 7 teams that fit into this category and the reason for missing years is strictly due to conference membership. In fact, 4 of those 7 were included in all but one 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 \$32 million, with a fairly large variance (standard deviation of \$18 million). The SEC had the highest average revenues for the 2011 season at \$54 million, while the Big East conference averaged only \$21 million that year. The largest outlier for the 2011 season was the University of Texas (of the Big 12 conference), bringing in \$103 million (partially 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

Since 2001, *Rivals.com* has released an annual list of the top 100 high school football recruits in the nation. Previous top rated high school recruits from the list include such college and NFL stars as Vince Young and Adrian Peterson. *Rivals* is a website devoted to college recruiting and was acquired by Yahoo! in 2007. The website *Alexa Internet*¹⁵ estimates that *Rivals.com* is in the top 600 of all (not just sports) websites in terms of traffic in the United States. We utilize data from the *Rivals.com* annual lists of top 100 prospects, often called "blue chip" prospects, for teams from Big 6 conferences that signed blue chip quarterbacks from 2002 to 2009.

Florida, and Cincinnati the following year. After a relatively quiet period, West Virginia left for the Big 12 and Temple returned in 2012.

¹³ Most institutions have fiscal year-ends based on the academic calendar (June, August, etc.). For all revenue data, we are referencing financial data by years in terms of the football season in question. For instance, the last set of revenue data available from the EADA website is FY 2011-2012, which would include the 2011 college football season, so we refer to that year's data in this paper as 2011.

¹⁴ We contacted the EADA 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".

¹⁵ As for March 24th 2014 <http://www.alex.com/siteinfo/rivals.com>

If being a blue chip ranked prospect is a sign of higher ability, then on average we would expect for blue chip quarterbacks to have higher QBR ratings than non-blue chip quarterbacks, and this turns out to be the case, though by a lower amount than one might expect. In our sample, 16% of games were started by blue chip quarterbacks and they averaged QBR of 57, compared to 52 for non-blue chip quarterbacks. A break down by the players' experience shows that blue chip prospects do not outperform the average non-blue chip prospect until their second year of eligibility, and the difference is largest in the fourth year of eligibility. We explore the relationship between experience and QBR for blue chip quarterbacks in the econometric section. One concern is that teams with blue chip quarterbacks may be historically better and differences may only 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 QBR for blue chip prospects are still 3 points higher compared with non-blue chip quarterbacks (57 vs. 54), although this difference represents only 0.1 standard deviation difference.

ECONOMETRIC FRAMEWORK

In this section we present the four parts of our econometric analysis. The first three parts estimate 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 create an estimate of a quarterback's marginal product. Finally, the fourth step we estimate the value of a high ability player using their ranking as a high school recruit.

Step 1: The Win Probability Model

In order to calculate a quarterback's marginal revenue product, 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 will use to estimate win probability across j , g , and t is as follows:

$$Pr(W_{gjt} = 1 \mid \mathbf{X}) = \beta\mathbf{X} + \omega_{gjt} \quad (1)$$

where \mathbf{X} is

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

The binary response variable W is equal to 1 if the j^{th} team wins the g^{th} game of season t . The QBR variable represents the Total Quarterback Rating for the quarterback on the j^{th} team in the g^{th} game of season t .

For $OPPRANK$, 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), and a team ranked outside the BCS top 25 in each poll during that season would have a 0 for all five dummies. The *HOME* dummy variable is 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 consists of 6,884 game-level observations from 2004-2012 seasons.

In order to account for team fixed effects, we use dummy variables for all 68 teams. This can create an issue, because of the potential for incidental parameters bias. However, we find similar results with and without team fixed effects so this does not appear to be an issue.

Step 2: The Revenue Regression

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

$$R_{jt} = \alpha Z + \epsilon_{jt} \quad (2)$$

where 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 is equal to the total football program revenue for the j^{th} 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 the *WIN* variable, equal to the number of wins in season t , we have also added a lagged *WIN* variable, equal to the number of wins in season $t-1$. This lag variable is included because a successful season likely has a large impact on a team’s revenues the following year through season ticket sales. We are assuming that winning is linearly related to revenues, holding many other factors constant. In order to ensure that marginal revenue for wins doesn’t 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.

Next, a series of *CONF* dummies are included to indicate conference affiliation¹⁶. Many of the lucrative television network contracts are agreed to by the conference, 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 *7HOMEGAMES* variable is a dummy taking the value of 1 if the team had 7 or more home games that season, 0 otherwise (since 89% of teams in the sample have 6 or 7 home games). This is important because ticket sales represent a significant portion of annual generated revenues, and a difference in number of home games can impact revenue. A *YEAR* dummy is included to account for the

¹⁶ 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.

general growth in college football during the study period. The *STATEUNEMP* variable is equal to the state's unemployment rate in year t , in order to account 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. The results are fairly similar between the two models.

Step 3: Estimating Marginal Revenue Product

The final step in the process is to estimate the marginal revenue product (MRP) of an elite quarterback. In order to do so, we first need to establish the link function used to estimate the marginal effect of a change in a quarterback's QBR. The marginal effect of QBR on win probability changes based on the value of the other explanatory variables, so for our MRP calculation, we will 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 as follows:

$$Pr(W = 1 | QBR_i) = \varphi(\beta X) \quad (3)$$

Next, we need to 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 resulting from the change in QBR. Then, we multiply this difference by the average number of games G for a full season to estimate total wins-added predicted for that year:

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

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

In order to account for the effect of the lagged win variable on current year marginal revenue product, we estimate the increase in revenue in seasons t (α_1) and $t + 1$ ($d\alpha_2$) resulting from each additional win in season t by adding the coefficients from the revenue regression, discounting the lagged coefficient to accurately account for this future revenue. Finally, we multiply the marginal revenue by the marginal product to arrive at MRP:

$$MR_t = \alpha_1 + d\alpha_2 \quad (5)$$

$$where d = discount rate for t + 1$$

$$MRP_t = MR_t * MP_t \quad (6)$$

The marginal revenue product for a quarterback in season t is equal to the additional predicted wins-

added (MP), multiplied by the sum of current (t) and discounted future ($t + 1$) year estimates of additional revenue per win (MR).

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 found that the fixed-effects model is more appropriate¹⁷. We include revenue regression results with and without team fixed-effects and show there is little difference.

Step 4: Estimating Ability

One concern with the measure of QBR is that it may be endogenous to winning. That is, like other QB ratings, QBR may overestimate the quarterback's contribution if his ability to complete a pass was based on an uncounted contribution of, say, a left tackle or a coaching staff's play call. In this case, we need a measure of a player's ability independent of his team's performance. We replace QBR with a lag measure of a team signing a blue chip quarterback.

To determine the lag, we present two regressions on the relationship between blue chip prospects years' of enrollment and QBR. We choose to use two different approaches. First we use a binary dummy for each year after signing to test the relationship between experience (years of enrollment) and outcomes. Next we combine the third and fourth years of enrollment into a single dummy variable, as those are the years a positive impact is shown. This reflects the point at which blue chip quarterbacks have an expected QBR above the average quarterback. The variable replaces QBR in equation #1 and winning in equation #2. The number of lagged years was chosen based on the fact that many college quarterbacks do not play until their third or fourth year after enrolling (most are redshirted their first year, and are backups for at least their second year). Of the sample, 16% of games involved a team that had signed a blue chip quarterback 3 or 4 seasons prior.

There are two ways to examine the outcomes for blue chip quarterbacks: the individual level and 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 would exclude any blue chip quarterbacks who never play in a game. As 16 of the 62 blue chip quarterbacks from our sample did not register a single game with a qualified QBR for the team that signed them, we would be overestimating the value of the blue chip quarterbacks by just using the individual data. Therefore, we also run regressions on the team where the variable for blue chip is coded as one 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 would expect the value of a blue chip quarterback to be lower at the team level because we would also include those who never started.

¹⁷ The Hausman test showed a Chi-squared of 44.56, with a p-value of 0.0001.

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 to be 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* stat 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.

The other control factors are consistent with the hypothesized direction. The positive sign of the coefficient on *HOME* is to be expected. Home teams are typically favored to win over 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 percentage 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 most difficult 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.

Table 2. Win Probability Model - Panel Probit Regression Results (n=6,884 Games)

Variables	<i>With Team Fixed Effects</i>	<i>No Team Fixed Effects</i>	Marginal Effects†
	Pr(WIN)	Pr(WIN)	
Total Quarterback Rating (QBR)	0.028 (0.001)***	0.028 (0.001)***	0.01 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	<i>Team Dummy Variables</i>	-1.12 (0.07)***	

Standard error is given in parenthesis.

***Significant at 1% level

† Marginal effects are reported as averages

Next we utilize the regression framework to create probabilities vs. actual outcomes of each game from the sample. In Table 3, we find that our model correctly predicts roughly 80% of games. There were no instances of predicted values of exactly 0.5, so we use $Pr(W) > 0.5$ to indicate a predicted win, and $Pr(W) < 0.5$ to indicate a predicted loss, then compare these predictions to actual results.

Table 3. Win Probability Model - Predicted vs. Actual Game Results

Predicted vs. Actual Result	Predicted Win	Predicted Win w/F.E.	Predicted Loss	Predicted Loss w/F.E.	Total	Total w/F.E.
% of Correct Predictions	79%	82%	76%	78%	78%	80%
n	4,144	4,103	2,740	2,781	6,884	6,884

Both win probability models, with and without team fixed effects, reflect strong predictive ability, though the model that controls for team fixed effects shows results that are slightly more predictive. Interestingly, the model is slightly better at predicting a win than a loss. This could be due to the fact that teams play early season games against non-conference opponents, many of whom are much lower ranked teams. A below average QBR in a game against a non-conference team with inferior ability could still produce a win even though the model would predict a loss based on the QBR. This is partially due to the difficulty in assessing opponent ranking for teams outside of the top-25 BCS ranking. Our opponent ranking factor variable only accounts for teams with a very high ranking, as the BCS system only ranks the top 25 teams, so we are left with a large number of teams with large variance in strength. Overall, however, the model exhibits strong predictive ability in terms of wins and losses.

Marginal Effects on Win Probability

This paper is most interested in the marginal effect of a change in *QBR* on win probability. As a quarterback's *QBR* increases, we find that a team's win probability increases. The average marginal effect of a one unit *QBR* increase is equal to about a 0.01, or approximately 0.9%, increase in probability of winning. As we outline later in this paper, a one standard deviation increase from the mean *QBR* (so, an increase in *QBR* of about 27 points) results in an increased probability of winning of approximately 25%. We also find that blue chip prospects add about 5 points to a team's future *QBR*, or a 5% increase in win probability.

The marginal effects of the other explanatory variables are also shown in the last column of Table 2. The average marginal effect of facing a very strong opponent is negative and substantial, decreasing the win probability by more than 50% (for opponents with average BCS rankings in the top 5). The effect slowly decreases as the opponent strength weakens, but is still at -20% for teams averaging just inside the top 25. The marginal effect of playing at home is positive as expected, but the effect on win probability is smaller than we had anticipated at less than a 12% increase in win probability.

Revenue Regression

The final piece of the MRP equation is the marginal revenue estimate. The revenue regression results are summarized in Table 4. The coefficients on *WINS* and lagged *WINS* are statistically significant and the signs are to be expected, as additional wins should result in additional revenue. An additional win is

estimated to be worth approximately \$420,000 controlling for team fixed effects in the current year. Lagged wins have a slightly less substantial effect (~\$340,000) on current season revenues than current season wins, and this is consistent with and without team fixed effects.

As outlined previously, the marginal revenue product is calculated by multiplying the marginal revenue by the marginal product. The marginal revenue is a combination of the coefficients on wins and lagged wins from the revenue model, while the marginal product is the difference in win probability between two values of QBR taken over a full season. For our sample, we find that the increase in win probability between an average quarterback (QBR = 52.6) and an elite quarterback (QBR = 79.8), i.e. one standard deviation above the mean QBR. Using this estimated increased win probability of 0.25 over a mean number of season games (12.5), we arrive at a marginal product estimate of 3.1 additional wins. The marginal revenue is equal to the coefficient on wins from the revenue regression, plus a discounted version 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 equal to approximately \$740,000. Multiplying the marginal revenue by the marginal product gives us a marginal revenue product estimate of \$2.3 million for a one standard deviation increase in quarterback quality. It is important to note that we have not estimated replacement player value. That is, this \$2.3 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 a few are not included in the fixed effects version due to static conference membership over the sample period. The results reveal a stark contrast across conferences, with large gaps between the SEC & Big Ten (\$18m+) and the Pac-12 & Big East (less than \$5m, although they have large variances) – these figures are in comparison with the ACC which is the omitted category) –. Another interesting thing to note is the adjusted revenue coefficient for the Pac-12; this indicates that they have large amounts of unallocated revenue and football program revenue could be underestimated.

The *YEAR* dummies show a general growth in revenues over time and all but 2005 are statistically significant. The *7HOMEGAMES* dummy, representing 7 or more home games in a given season (versus 6 or less) is consistent with the expectation that teams with an additional home game should have higher revenue. Finally, the *STATEUNEMP* coefficient indicates some correlation between local economic conditions and program revenue, as an increase in the unemployment rate decreases expected revenue with a one percentage point increase in state unemployment leading to a decrease of roughly \$750,000 in revenue.

In this case, as opposed to the win probability model, team fixed effects do appear to 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), along with the home dummy, are smaller. For our final MRP calculation, we will use the total revenue regression results with team fixed effects included.

Table 4. Revenue Model - Panel Regression Results (n=515)

Variables (in \$millions)	With Team Fixed Effects		No Team Fixed Effects	
	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 - BIG12	8.44 (5.36)	-0.93 (6.54)	12.22 (3.95)***	16.94 (4.54)***
Conference - BIG10	11.91 (7.55)	-10.26 (9.21)	18.14 (4.15)***	19.95 (4.75)***
Conference - SEC	(omitted)†	(omitted)†	25.27 (4.35)***	27.81 (4.93)***
Conference - PAC12	(omitted)†	(omitted)†	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)
7 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)***

Conference dummy ACC included in constant. Standard error is given in parenthesis.

***Significant at 1% level

**Significant at 5% level

*Significant at 10% level

† SEC and PAC12 conference dummies omitted because of fixed effects (no changes over t)

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 5 games with an average QBR¹⁸ of 47, slightly below our sample average of 53. Luck played 12 games in 2009 with an average QBR¹⁹ 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 one 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 3 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).

ESTIMATING QB VALUE EX-ANTE

In 2008 Andrew Luck was ranked the 68th best high school football prospect by Rivals.com, behind five other quarterbacks: Terrelle Pryor (#1), Blaine Gabbert (#14), Dayne Crist (#25), EJ Manuel (#43), Mike Glennon (#59) [no other QBs made the top 100]. All of the teams performed well under the helm of their blue chip QBs, with the exception of Dayne Crist who suffered injuries after signing with Notre Dame, before a disappointing 1-11 season with Kansas after transferring. 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 or not they played for them. In the latter case, quarterbacks such as Tommy Grady's effect on Oklahoma would be estimated, even though he never registered a QBR for them²⁰. This reflects that 28% of the 64 blue chip quarterbacks in our sample never recorded a single QBR score for a team in a Big 6 conference²¹.

We first attempt to indentify the level of experience at which blue chip quarterbacks have a positive average QBR. In Part B of Table 5, we present a QBR regression at the individual level with dummies for blue chip quarterbacks in their first through sixth season after being recruited (which would include redshirt seasons, transfers, etc., as players only have four years of eligibility). The result is clear, that

¹⁸ Pritchard had a qualified QBR in 10 of the 12 games in which he played in 2008

¹⁹ Luck didn't have a qualified QBR against San Jose State, a blowout win for Stanford

²⁰ Grady was recruited by Oklahoma in 2003, transferring to Utah (not a member of a Big 6 conference at the time) after playing sparingly in his first two seasons.

²¹ Of the 64 quarterbacks ranked in the *Rivals.com* top 100 list from 2002 to 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.

blue chip quarterbacks peak in their fourth year of enrollment, which is typically their Junior year (assuming they redshirt as a freshman). The increase in average QBR over a quarterback's first four years indicates a positive relationship between experience and outcomes. The QBR increase of 6.34 points is meaningful, as it is essentially a .06 increase in winning percentage or .79 wins per season or \$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 two years may lack experience.

Table 5. Blue Chip Regression Results (n=6,884)

Key Variables	By Player			By Team		
	QBR	Pr(WIN)	Marginal Effects†	QBR	Pr(WIN)	Marginal Effects†
Part A: Blue Chip Effect on QBR and Win Probability in 3rd/4th Seasons (by QB & Team)						
3rd/4th Season	4.78 (1.20)***	0.305 (0.068)***	0.090 (.020)***	2.34 (1.02)**	0.090 (0.056)	0.027 (.017)
Part B: Blue Chip Effect on QBR and Win Probability by Season (by QB & Team)						
1st Season	-10.46 (3.04)***	-0.250 (.17)	-0.075 (.050)	-1.29 (1.34)	-0.018 (.074)	-0.005 (.022)
2nd Season	-0.42 (1.77)	-0.070 (.097)	-0.020 (.028)	-0.26 (1.24)	-0.189 (.067)***	-0.056 (.020)***
3rd Season	1.75 (1.56)	0.209 (.089)**	0.062 (.026)**	0.87 (1.23)	0.095 (.069)	0.028 (.020)
4th Season	6.34 (1.56)***	0.318 (.090)***	0.094 (.027)***	2.89 (1.24)**	0.048 (.069)	0.014 (.021)
5th Season	-3.01 (2.75)	-0.203 (.144)	-0.060 (.043)	-1.84 (1.27)	-0.109 (.070)	-0.032 (.021)

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)

6th Season not included in results, as only 1 player from our sample had a 6th season (took 2 years off)

Standard error is given in parenthesis.

***Significant at 1% level

**Significant at 5% level

*Significant at 10% level

† Marginal effects are reported as averages

Next we move to the team level analysis. In Part A of Table 5, we estimate the impact on the teams QBR by signing a blue chip quarterback who would be in their third or fourth year of eligibility. We find a statistically significant increase in the team's average QBR of 2.3. In other words this would be an increase of 0.023 in winning percentage, or roughly 0.29 wins over the course of a normal season, for a

total of 0.58 over their third and fourth years of eligibility. At a value of \$740,000 a win, the 0.58 wins represent roughly a \$429,000 in expected additional revenue. This two year total is lower than the individual results (\$555,000 in the fourth year alone), which reflects that some blue chip quarterbacks 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 show the marginal effect of adding a blue chip player 3 or 4 years after they sign to increase winning percentage .027, which is not substantially different than the estimated impact above of .023. One difference is that the statistical significance disappears, which may be related to factors other than team fixed effects, the quarterback, the opponent and game's location.

CONCLUSIONS

To be sure, there are many factors that influence the outcome of a college football game, as well as a quarterback's performance, for that matter. Nevertheless, the QBR developed by ESPN has managed to capture the importance of a quarterback's performance and the impact it has on the team's win probability. It has also allowed us to estimate a quarterback's marginal revenue product by providing a statistical link between player performance and winning; the marginal product has historically been the most difficult part of the MRP equation to accurately estimate, 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 an increase in a quarterback's average season QBR of one standard deviation equates to a \$2.3 million increase in program revenues. We also find that quarterbacks ranked as a top 100 prospect coming out of high school are expected to increase college football program revenues by around \$400,000 dollars over their career compared to the average quarterback.

It is important to note that we might be underestimating the MRP, because there may be other institutional benefits not captured by the football program revenue figure. For instance, after a team has a successful season, they may have an increase in new student applicants, 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 \$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 this came the year after Johnny Manziel won the Heisman Trophy should not be ignored.

On the other hand, we might be overestimating MRP for a variety of reasons. First, we are only looking at the quarterback position, and a quarterback's success is still dependent upon his teammates. If a quarterback has a highly skilled wide receiver or running back playing alongside him, his job becomes much easier. While the QBR statistic does attempt to divide credit on each play to account for this,

there is likely still some effect of teammates' skill level not controlled for. There could be other team factors outside of the offense – defense, special teams, coaching – that might also have an impact on the quarterback's MRP or on winning that are not controlled for sufficiently in the model. In this paper we do not establish a replacement value, instead estimating the difference in value between an average and an elite quarterback.

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 & Home-Away data: James Howell’s college football historical schedule and result database (<http://www.jhowell.net/cf/scores/ScoresIndex.htm>)*

Total Quarterback Rating (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 was verified via ESPN.com in addition to Howell’s database

Appendix B: Total Football Program Revenues

	Inflation Adj Revenues (in millions)		by Conference					
	Mean	Std. Dev.	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

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