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Abstract

Over the past decade, the issue of player compensation in college sports has been the subject of several successful legal challenges. Athletes contend that the compensation they receive falls significantly short of the value they generate, attributing this gap to unlawful NCAA restrictions. Numerous tools exist in the sport economic literature that estimate the value of college athletes, with an emphasized focus towards premium college football players. In addition to providing updated estimate of player marginal revenue product (MRP), we review past and contemporary methodologies for estimating college player MRPs. We contend that, while presenting some evidence that restrictions on player compensation resulted in the extraction of the majority of the value generated by top college athletes, existing methods leave considerable uncertainty over the magnitude of exploitation.

On The Value of a Premium College Football Player: Evaluating the Literature

The National Collegiate Athletic Association (NCAA) restrictions of athlete compensation remain a centerpiece of the economic environment of college football. However, the past decade has witnessed a surge in litigation challenging the NCAA's compensation policies.[1] Central to these legal battles is the argument that a substantial disparity exists between the value generated by players and the compensation they receive, a gap attributed to the unlawful compensation restrictions imposed by the NCAA. The NCAA's defense has traditionally rested on the assertion that limitations on scholarships and grants-in-aid are an essential component to success in the market for college football (see, e.g., McCann, 2018), while simultaneously lobbying for federal antitrust exemption status.[1] Until recently, student athlete compensation was capped at basic education-related benefits.

In 2015, *O'Bannon v. NCAA* found the NCAA's compensation rules were an unlawful restraint of trade, barred the NCAA from using athletes' likeness in video games without compensation, and raised the cap on athletic scholarships to the full cost of attendance (Titus & Ashby, 2021). More recently, on June 21, 2021, the Supreme Court ruled in *Alston v. NCAA* that the NCAA could not restrict the amount of education-related benefits paid to student-athletes (Titus & Ashby, 2021).[2, 3] In a concurrent opinion, Supreme Court Justice Brett Kavanaugh laid the foundation for compensating athletes by stating: "Nowhere else in America can businesses get away with agreeing not to pay their workers a fair market wage on the theory that their product is defined by not paying their workers a fair market rate" (National Collegiate Athletic Association v. Alston Et Al., 2021). While athletes are now starting to receive compensation for their athletic prowess through the monetization of their name, image, and likeness (NIL), the issue of pay-for-play will likely continue to be a hot-button issue in collegiate athletics for the foreseeable future. The most recent major lawsuit, *House v. NCAA* (also called *In Re College Athlete NIL Litigation*), seeks damages for missed financial opportunities related to NIL restrictions and a share of the revenue earned by the NCAA and its member schools from the sale of the universities' telecast rights (Titus & Ashby, 2021).

With the future economic environment of college athletics in a state of flux, developing an understanding of the labor market for college athletes is especially important. In a highly original paper, Brown (1993) provided the first econometric estimate of the value of a premium college football player, defined as a player who is subsequently drafted by an NFL team. Building upon Scully's (1974) foundational framework linking stats to wins and wins to revenue, Brown amalgamated publicly available data on player and market characteristics with his own survey of college football revenues by school to model the marginal revenue product of premium players. Examining a sample from the 1988 season, during which football revenue averaged $5.4 million annually, Brown (1993) estimated that the average marginal revenue product of an additional premium player ranged from $500,000 to $600,000 per year. This figure starkly contrasted the value of the $20,000 annual scholarship limit in effect at that time, highlighting a significant disparity.

Brown's (1993) analysis, akin to Scully's findings in professional baseball, suggested that labor market constraints in college football resulted in the substantial extraction of value created by athletes in the sport.[4] In the case of college football, where student athletes lack the ability to unionize and partake in collective bargaining, these restrictions were unilaterally dictated by the supposedly competing academic institutions that comprise the NCAA. Brown's estimate of rent extraction is a powerful measure of a key market impact of the NCAA's cartelization of the college sports market (Fleisher et al., 1992). These restrictions on compensation might also have implications for economic and racial equality within college athletics. Rents generated from revenue-generating sports such as football and basketball, whose athletes are more likely to be black and come from poorer socioeconomic backgrounds, frequently subsidize non-revenue-generating sports, whose participants are more likely to be white and come from more affluent backgrounds (Garthwaite et al., 2020).

Since Brown's (1993) original research that estimated a player value of $500,000, revenues in college football have experienced a significant surge. This escalation is attributed to the substantial rise in media rights deals, the expansion of the college football playoff (CFP), and the introduction of conference-specific television networks. The growth served as a catalyst for scholars such as Brown (2011) and others (Brown & Jewell 2004, Borghesi 2017, among others) to re-estimate MRP using more recent data reflecting higher revenues. In his 2011 paper, utilizing 2004 data and an updated methodology, Brown (2011) found that the estimate for the marginal revenue product of a premium player had doubled in tandem with the growth in college football revenue, reaching approximately $1.2 million.

Brown's (1993, 2011) framework has long been a cornerstone in the literature for estimating the marginal revenue product (MRP) of elite college athletes, extending its application beyond football to sports such as men's basketball (Brown, 1994) and women's basketball (Brown & Jewell, 2006, 2013), among others. In recent years, however, the literature has quietly shifted to other methodologies. One such approach, the professional factor shares method, employs salary and revenue data from professional organizations as shadow prices, illuminating the relative importance of specific player types and positions (Goff et al., 2017; Lane et al., 2014). A second strategy emphasizes *ex ante* measures of player productivity, recruiting rankings, rather than *ex post* draft outcomes (Bergman & Logan 2020; Borghesi 2017;

Hunsberger & Gitter, 2015; Makofske, 2018). Another avenue arises from the expanding availability of data, enabling researchers to use panel data methodologies, most prominently school fixed effects (Lane et al., 2014; Makofske, 2018).

Despite the shift in methodologies, empirical evidence either supporting or refuting the Brown (1993, 2011) framework remains absent. This study contributes to the literature in three key ways. First and foremost, we replicate Brown's (1993, 2011) methodology using extensive recent data spanning multiple years. In doing so, we illustrate empirical and theoretical shortfalls that curtail the methodology's effectiveness. Specifically, we find that MRP estimates from Brown's (1993, 2011) approach lack stability over time, exhibit considerable noise, and likely suffer from endogeneity concerns. Second, we provide an overview of alternative empirical approaches prevalent in the literature for assessing the MRP of college athletes. While these methods might evade the pitfalls of Brown's approach, we acknowledge their own theoretical limitations. After an extensive review of the literature, we raise question about whether existing empirical tools and techniques produce MRP estimates that are viable for real-world application. Third, recognizing the necessity for enhanced tools, we frame the discussion for how future research should consider the MRP estimation question within the contemporary landscape of college sports. Our analysis indicates that prevailing tools in the literature are suited solely for estimating MRP for short-run, non-fixed revenue sources. As the NCAA undergoes transformative changes, and with pay-for-play potentially on the horizon, sport economists require improved empirical tools in order to better understand ongoing developments in the labor market for premium college football players.

The Brown Method and Replication

Brown (1993) Methodology

Brown's objective, in both his initial attempt in 1993 and more recent attempt in 2011, was to estimate the impact of an elite college football player on team revenues by using NFL draft selection as a proxy for elite player status. The resulting coefficient on number of draft picks would identify the marginal effect of adding one additional drafted player (interpreted as a premium player) to team revenues. However, the skill level of players acquired by a college team, and consequently, the number of drafted players on the school's roster, is likely to be endogenous to its recruiting efforts and resources, which could be referred to as recruiting ability. Teams with higher revenues possess more resources for recruiting, meaning revenues and draft picks are both correlated with a school's unobserved level of recruiting ability. Additionally, teams with better histories may have the highest recruiting ability and consequently receive the highest revenues.

In his initial paper, utilizing data from the 1988–89 college football season, Brown (1993) addressed this concern by employing a two-stage least squares approach. In the first stage, Brown (1993) estimated the following equation

$$\begin{aligned} DraftPicks_s = \alpha_0 + \alpha_1 Market_s + \alpha_2 OppMarket_s + \alpha_3 Pool_s + \alpha_4 OppPool_s + \\ \alpha_5 Retain_s + \alpha_6 Rank_s + \alpha_7 OppRank_s + \varepsilon_s, \end{aligned} \tag{1}$$

where $DraftPicks_s$ is the number of future draft picks on the roster of the football team at school s. $Market_s$ and $OppMarket_s$ capture the market potential, or ability to attract fans, for both the school and the average of all visiting schools. $Pool_s$ and $OppPool_s$ are exogenous variables measuring the size of a school's and its opponents' local recruiting pool.[5] $Retain_s$ quantifies the extent to which conference revenue sharing enables a school to retain its individually earned revenues. Finally, $Rank_s$ and $OppRank_s$ capture the recent success of a school and the average success of its opponents.

Using the predicted values for number of draft picks from the first stage, $\widehat{DraftPicks}_s$, Brown (1993) estimates the following second-stage model

$$Revenue_s = \beta_0 + \beta_1 \widehat{DraftPicks}_s + \beta_2 Market_s + \beta_3 Rank_s + \beta_4 OppRank_s + \beta_5 Retain_s + \epsilon_s, \tag{2}$$

where $Revenue_s$ is a school's total revenue for that season, and β_1 provides Brown's estimate for the marginal revenue product of an elite college football player. Brown (1993) estimated that the marginal premium player generates over \$500,000 in annual revenues for his team.

Brown (2011) Methodology

In a follow-up paper to his original work, Brown (2011) updated his initial estimation technique to obtain new marginal revenue product estimates using 2004 data. Brown (2011) identified another potential problem: a team's rank and performance ($Rank_s$) is determined in part by the number of future draft picks on the roster, and both variables subsequently affect team revenues. To address this complexity, Brown (2011) employed traditional two-stage least squares to estimate a system of three equations, given by

$$DraftPicks_s = \alpha_0 + \alpha_1 Market_s + \alpha_2 Pool_s + \alpha_3 APR_s + \alpha_4 PastRank_s + \alpha_5 FootballEntertainment_s + \varepsilon_s, \tag{3}$$

$$Rank_s = \beta_0 + \beta_1 DraftPicks_s + \beta_2 CoachPay_s + \beta_3 OppRank_s + \epsilon_s, \tag{4}$$

and

$$Revenue_s = \gamma_0 + \gamma_1 \widehat{DraftPicks}_s + \gamma_2 \widehat{Rank}_s + \beta_3 OppRank_s + \beta_4 Market_s + \beta_5 FootballEntertainment_s + \varphi_s. \tag{5}$$

The first equation estimates the impact of recruiting and market characteristics on the number of NFL Draftees. Alongside the previously defined variables, APR_s is the school's academic progress report over the previous four years, serving as a proxy for academic resources provided to students. $PastRank_s$ is a measure of the team's recent success in the AP rankings over the previous six years. $FootballEntertainment_s$ is an index gauging the quality and quantity of teams within the team's market.[6]

The second equation estimates the team's rank performance using the number of NFL draftees, opponent 2004 top-25 rankings as a proxy for schedule difficulty, and a coaching productivity measure (proxied by coach salary).

The third equation produces estimates of marginal revenue product by regressing team revenues on the fitted number of NFL draftees from the first equation, the fitted team's 2004 top-25 rankings from the second equation, as well as the opponent's 2004 top-25 ranking, the market, and football entertainment variables. While Brown (2011) asserted this methodological approach resolves previously discussed endogeneity issues, we later identify concerns leading us to believe that endogeneity remains a pervasive challenge in this estimation procedure.

Brown (2011) determined that the marginal premium player in 2004 is worth nearly $1.2 million to total football revenues. Using detailed 2004–2005 revenue data obtained via *The Indianapolis Star* through public records requests in 2006, Brown (2011) further dissected the marginal revenue product by specific revenue categories. For instance, the marginal premium college football player is worth approximately $750,000 annually when only ticket sales were considered. When contributions, other game day sales, and ticket sales are combined, MRP was estimated at over $1.1 million. Other revenue sources, such as conference revenue sharing and student fees, may be less influenced by the presence of an additional premium athlete.

Replicating Brown's Methodology Reveals Structural Problems

Data Overview

To test Brown's (2011) methodology, we gather data on college football revenues from the Equity in Athletics Data Analysis (EADA) website and coaching salaries from USA Today. NFL draft pick data from the period 2006 to 2018 are sourced from Pro Football Reference and then matched with the EADA and USA Today data. To simplify the analysis, we assume that a player drafted in 2017 would have played on the school's roster for the 2013, 2014, 2015, and 2016 seasons.[7] Accounting for this and the need for four years' worth of draft picks for a single season's roster, our sample period encompasses 2006, 2007, and 2009–2015.[8]

Summary data on college football revenues by year are detailed in Table 1 for our specified period, along with the two years examined by Brown (1993, 2011). Revenue figures are adjusted for inflation, using 2015 as the base year. Notably, average football revenue per school surged from $10.8 million in 1988 to $20.8 million in the initial year of our sample and further escalated to $32.1 million in 2015. Even the lower echelons of the college football hierarchy experienced substantial growth—the minimum revenue increased by a factor of 2.4 from 2006 to 2015.

Table 2 provides summary statistics for the variables used to measure market and school characteristics—crucial inputs in Brown's estimation method—across the beginning, midpoint, and final years of our sample. The focal point of the analysis is the measure of the number of "premium players" on a team, captured in Brown's model by the number of future NFL draft picks on a team's roster. The typical Division I Football Bowl Subdivision (FBS) team in our sample boasts approximately seven future draft choices on its roster, as indicated by the sample means for the three representative years shown in the table. Our sample averages (ranging from

6.90 and 7.29 in the figures listed) fall below the mean number of draftees (8.0) in Brown's original sample, and the standard deviations are higher in our sample (ranging from 6.64 to 7.64 in the table, versus 5.2 in Brown). These discrepancies in mean and standard deviation may signify increased variability in team quality, measured by NFL draft picks, within our sample in comparison to Brown's, which was derived from a limited number of survey responses.

The remaining variables are defined as they were in Brown (2011). *This Year's Average AP Ranking* measures a team's average performance in the Associated Press Top-25 weekly rankings during the current season, with a number one ranking receiving 25 points, number two receiving 24 points, and so on. *Prior Average AP Ranking* measures a team's average performance in the Associated Press Top-25 weekly rankings over the preceding six seasons. *Opponent Average AP Ranking* is the average of a team's opponents' average Associated Press Top-25 weekly rankings during the current season. *Recruiting Pool* divides a school's state population by the number of other teams in the sample within that state, weighted by the quality of those programs using Top-25 weekly rankings. *Academic Progress Rate* (APR) is a team's four-year rolling average APR score for the football program, a composite score that considers the percentage of student-athletes that are academically eligible and remain enrolled. *Market Population* sums the total population of each metropolitan statistical area within 100 miles, weighted by the distance from the school. Since this weighted measure relies on zip code level data, which is difficult to obtain on an annual basis, we use a fixed measure of an MSA's population over the full sample period for simplicity. Finally, *Football Entertainment* considers other football-related entertainment options, both collegiate and professional. For each program within a school's 100-mile market area, the prior three years of Associated Press Top-25 rankings are summed, and school totals are converted to percentiles relative to the highest scoring program. *Football Entertainment* consists of the sum of scores for other schools in the market area, weighted by distance, plus one for each additional professional football team within the market area.

For certain schools, not all data are available. For example, we do not observe revenue data for Air Force, Army, or Navy. Additionally, there are gaps in revenue data for certain years for certain schools (such as Maryland in 2006 and 2007). Head coach salary data are also missing for particular schools in certain years.[9] Moreover, some schools underwent conference changes, especially during major conference realignment in the early 2010s, including transitions from the Football Championship Subdivision (FCS) or Division II to FBS. To better control for potential confounding factors, in certain model specifications we omit schools that changed conferences during the sample period.

Replication Results

Both Brown (1993) and Brown (2011) calculated MRP estimates of premier college football players using one-year samples (1988 and 2004, respectively). Both papers estimated marginal revenue products of over $1 million in 2015 dollars for the marginal drafted player. We adopt the methodology outlined in Brown (2011) and apply it across multiple seasons, estimating marginal revenue product for each year spanning from 2006 to 2015.[10] Given the yearly fluctuations in revenues, coupled with a notable positive trend, we conduct separate estimations for each year. This approach allows us to focus on the coefficient estimates for the marginal revenue product of future draft picks, facilitating an analysis of the stability in these estimates and enabling comparisons with Brown's original findings.

Additionally, our execution of two-stage least squares differs from Brown (2011). In his first stage estimation of what he has labeled as Equation 2 (our Equation 4), Brown (2011) incorporated the number of NFL draftees as an instrument. However, employing an endogenous regressor as an instrument for a different endogenous regressor raises methodological concerns. Further, Brown (2011) opted to include only a subset of the variables from the second stage in the first stage equations, contrary to the conventional two-stage least squares approach, which necessitates the inclusion of all regressors utilized in the second stage within the first stage equations. In our replication, we adhere to the same variables and employ a two-equation first-stage setup akin to Brown (2011), while modifying the estimation procedure to address these concerns.

The results of our Brown (2011) replication, conducted through two-stage least squares using data spanning from 2006 to 2015, are presented in Table 3. Panel A considers all schools in the sample for each year, while Panel B only includes schools that have complete data in all years of the sample, and Panel C includes only schools that have complete data for every year in the sample and did not change conferences. We segment results to address concerns that a lack of stability in annual estimates is caused by changing the schools in the sample. Brown (2011), using data from the 2004 college football season, identified positive and statistically significant effects for number of NFL draftees and opponent top-25-point ranking, and non-statistically significant results for the remaining coefficients. In Table 3, the findings are less definitive. Some years exhibit negative statistical significance for the *Market* variable, and some exhibit positive statistical significance for *Opponent AP Rank*. Given that college football interest is greatest in locales without professional sports teams (in much smaller markets), a negative coefficient on the market variable is not surprising. Generally, the remaining coefficients do not significantly differ from zero, with substantial standard errors observed for many coefficients following the 2007 season.

The coefficient estimates for the draft picks variable are positive and statistically significant for most years, except for 2009, with a point estimate of -$2.5 million and standard errors multiple magnitudes greater than for other years. Despite generating positive MRP estimates, the precision of these estimates remains a challenge. While the regressions from later years in the sample show the marginal effect of adding one additional elite player surpassing four million dollars, the standard errors are in the millions of dollars, severely limiting the precision of the MRP estimate. For instance, in the final year of the sample, 2015, the coefficient estimate for *Draft Picks* is $4.17 million in the unbalanced panel, with a 95% confidence interval between $2.32 million and $6.02 million. In Panel C, the coefficient estimate stands at $5.08 million, with a 95% confidence interval between $1.37 million and $8.79 million. The 95% confidence interval for 2014 is even more imprecise, with a point estimate of $4.65 million, and confidence interval between $1.19 million and $8.11 million (not statistically significant in Panel C).

Evaluating Brown's Methodology (1993, 2011)

The large coefficient values and wide standard errors in our replication attempt may be due to a lack of valid instruments. The Cragg-Donald Wald F statistics for the first stage regressions reveal that the endogenous regressors are under-identified using Brown's (2011) method.[11] Further, the instrumental variables may violate the exclusion restriction. For instance, the compensation of the head coach could be linked to the school's historical performance and correlated with the revenue the institute generates, even without the channel of draft picks. Similarly, the team's academic score might also be associated with the department's revenue without the influence of draft picks. For instance, schools with substantial football revenues may possess the resources to provide increased academic services for students. Lastly, the recruiting pool variable might also be correlated with the number of potential donors a school has, independent of drafted players.

Another factor contributing to the large standard errors is the relatively restricted sample size. In our replication, only 66 schools have data for each year in our sample, with no more than 120 teams in any given year. Brown's (1993, 2011) original samples consisted of 39 and 86 school observations, respectively. Given the inherent noise in 2SLS, dealing with a relatively small sample size could lead to especially large standard errors (see the discussion in Blomquist & Dahlberg, 1999).

In addition to the technical limitations of 2SLS in this context, there is a fundamental concern about the validity of using draft selections as a measure of premium college football players. First, the skills valued by NFL teams might differ from those contributing to a college football team's success. Second, only a fixed number of players are drafted annually, yet significantly more provide value for their schools. Third, professional salaries indicate that even subpar quarterbacks might be considered more valuable than the average defensive player. For instance, in 2019, the highest paid (measured by their salary cap number) NFL cornerback was Darius Slay at just under $16 million. There were 16 NFL quarterbacks in 2019 with a greater salary cap hit than Slay's. Fourth, using the number of draft picks as a measure for premium player treats the first overall selection and the last overall selection equivalently, although their expected productivity as NFL players significantly differs, as shown in Schuckers (2011).

To address the last concern, we replace the number of draft picks with a Schuckers-based measure of total draft value, a continuous measure reflecting higher average productivity for players drafted in earlier positions. Draft value aggregates the NFL draft value of all players drafted from a school. The first pick is credited with 1,000 draft-value points, while the 218th

pick, for example, is credited with 128 draft-value points. Table 4 provides our second-stage estimates using Brown's method with both our balanced and unbalanced panel. On one hand, using this approach allows for a more granular estimation of the worth of elite college football players. For example, Table 5 provides examples of the MRPs of players based on their draft selection, with the first selection being nearly eight times more valuable than the 218th. On the other hand, this methodology fails to resolve the imprecision problem in MRP estimates.

Given that Brown's methodology (2011) lacks valid instruments, produces imprecise estimates, and ultimately fails to generate the intended measure of interest, economists must continue to develop more robust methods for quantifying the marginal revenue product of a premium college football player. Although various techniques have been explored to enhance Brown's approach, as detailed in subsequent sections of this paper, it is evident that further research is needed.[12]

Addressing Other Empirical Solutions in the Literature

In the previous section, we highlighted significant limitations in Brown's (1993, 2011) methodology, raising doubts about its ability to yield reliable MRP estimates. However, since Scully (1974) and Brown (1993), other empirical approaches and solutions have arisen to estimate the marginal revenue product of elite college football players. In this section, we delve into these alternative empirical approaches, evaluating their suitability for generating meaningful MRP estimates.

Professional Factor Shares Approach

The first method we will explore is what we will refer to as the professional factor shares approach. This approach involves leveraging data from professional leagues to enrich the MRP estimation procedure at the college level. One might describe this as a revealed preference approach, with professional salaries allowing researchers to make somewhat educated empirical assumptions. Two notable papers, Lane et al. (2014) and Goff et al. (2017), have implemented this approach with slight variations. For instance, Lane et al. (2014) considered the distribution of NBA salaries to calculate MRP for college basketball players, particularly benchwarmers. They assumed that "if an NBA benchwarmer center receives a salary that is 5% of the average NBA player, the benchwarmer's MRP is 5% of the average NBA player's MRP." Lane and co-authors applied these pro basketball distributions to college players on individual teams, irrespective of whether these players had accrued any playing statistics.

Goff et al. (2017), in contrast, relied on professional factor shares to assess the value of starting and backup players across positions. Players at different positions are evaluated with vastly different metrics, making cross-positional comparisons difficult. Relying on salary shares across positions could provide insight on their relative worth. For example, in Goff et al.'s (2017) data, the average starting NFL quarterback and average starting right tackle earned salaries that constituted approximately 7.6% and 2.2%, respectively, of their team's total revenues. Continuing to use figures in Goff et al. (2017), if the average ACC school generates approximately $21,500,000 in annual revenue, and players are entitled to 50% of revenues, an average ACC starting quarterback would be valued at approximately $821,000, while an average ACC starting right tackle would be valued at approximately $242,000. This approach uses professional factor shares data to make assumptions about the percentage of revenues college players would earn, and a general way in which it would be distributed among players on the team.

The factor shares approach offers several evident advantages over the Brown (1993, 2011) methodology. First, by predefining the within-school athlete/revenue split *a priori*, endogeneity concerns are substantially mitigated. This is because these methodologies focus on the split of revenues rather than attempting to calculate the worth of individual athletes (especially using the Goff et al., 2017 methodology). Second, this approach allows for the calculation of MRP estimates for a broader range of players, extending beyond just those who are eventually drafted. Third, the specificity of MRP estimates is significantly enhanced, enabling the calculation of MRPs by position, school revenue, playing status, player quality, and more. The factor shares approach is valuable because, given the limitations in sample size, striving for greater granularity using the Brown (1993, 2011) approach becomes challenging and further exacerbates the noisiness problem. As illustrated in Table 6, where we use Brown (2011) to compute the MRP of elite college football players for both low and high revenue schools, MRP estimates suffer from the same unstable point estimates and large standard error problems observed in earlier analyses.

Despite the advantages over Brown (1993, 2011), there are critical assumptions and concerns that raise doubts about the usability of professional-factor-shares methods. Most notably, these approaches assume that professional salaries serve as accurate shadow prices for college player production. While the rules, game format, and positions are largely similar between college and professional levels, making relative player production comparable, there are uncertainties regarding whether talent distributions are the same and if the college game operates similarly to the professional game. Considering the vast number of players and skill levels, it is reasonable to suggest that the difference in abilities between the best and worst college football players is significantly greater than the difference in abilities between the best and worst NFL players. College football rosters are sometimes double the size of NFL rosters, and there are nearly five times as many teams at the FBS level compared to the NFL. If the shapes of the talent distributions differ, relying on average MRPs by teams and positions, as was done in Lane et al. (2014), might not be appropriate. Any analysis at the tails of the skill distribution (stars and benchwarmers) would be suspect if the relative abilities of stars (bench player) to the average player differ between the two levels.

It is also unclear if the underlying MRP estimates are actually estimating anything that is meaningful. The Goff et al. (2017) method assumes that players would receive 50% of produced revenues, mirroring the split agreed upon at the professional level. However, it is unclear if college athletes unionized and collectively bargained, they would have the ability to negotiate such a split. Essentially, Goff et al. (2017) provided information on what players at different positions would be worth on average under a specific revenue split, without considering the feasibility of such a split in the college context.

Moreover, structural differences in revenue sharing schemes, labor market restrictions, and revenue generation priorities between college and professional football further complicate comparisons. Even differences in fan preferences between the two levels make comparison suspect. For example, college sports fans' consumption decisions might be less sensitive to team performance compared to professional sports fans' preferences. Professional player MRP might be comparatively greater than that of college player MRP, even after accounting for differences in total revenues.[13] Ultimately, if the objective is to gauge the degree of exploitation, predict athlete salaries under a pay-for-play scheme, or estimate what a college football player could earn without market restrictions, the factor shares approach falls short. It neither estimates the underlying value of player production, nor defines the parameters for a split in revenues. Additionally, Title IX regulations introduce ambiguity regarding whether a school could directly compensate football players using similar factor shares as a professional team.

While the approach provides a thought-provoking exploration of potential pay structures for college athletes based on existing professional models and provides relative comparisons of players, it ultimately falls short in its fundamental objective: identifying the MRP of college athletes.

Ex ante **Measures of Player Quality Approach**

Relying on *ex post* measures of player quality, such as number of drafted players used by Brown (1993, 2011), presents a significant limitation due to its failure to account for uncertainty in player outcomes. Utilizing number of drafted picks tells us *ex post* the value of adding an additional draft quality player. However, most sports labor markets compensate athletes based on their anticipated production, *ex ante*. An *ex post* measure makes sense for a labor market setup that compensates athletes for their production and output. However, if a future pay-for-play scheme involves compensating athletes based on some pre-determined salary, the *ex post* analysis would be inappropriate. In addition, estimates of college monopsony power and exploitation of college athletes would be overstated if *ex post* measures are used (Makofske, 2018).

Recent studies have shifted towards utilizing *ex ante* measures of athlete production, focusing on anticipated contributions rather than historical outcomes. These measures, primarily using recruiting rankings, offer valuable insights into the potential value of college athletes. Several researchers have adopted this approach, utilizing publicly available rankings and grades for high school athletes from national media outlets such as 247sports.com and Rivals.com. Borghesi (2017) estimated the MRP of five-, four-, three-, and low-star players using 247sports rankings. Bergman and Logan (2020), Hunsberger and Gitter (2015), and Makofske (2018) utilized recruiting data from Rivals to examine the value of different-starred recruits and, in specific cases, focusing on highly-ranked college football quarterbacks. Makofske (2018) incorporated *ex ante* and *ex post* information by placing players into various *ex post* quality tiers, calculating the MRP associated with having players in each tier, then using recruiting data to calculate conditional probabilities of players of different star ratings reaching different quality tiers. These studies produced *ex ante* expected MRP values, which align more closely with the value of the scholarship compared to estimates produced by Brown's (1993, 2011) methodology, although they generally still exceed scholarship values.

The *ex ante* measure of premium players offers strategic advantages over the *ex post* number of draft picks variable; however, it also presents certain limitations. First, archived recruiting data are not as historically available as draft-picks data, limiting the available time period of analysis. That said, substantial data covering most of the 21st century is still accessible. Second, while recruiting ranks effectively consider uncertainty before the player joins the school, they do not account for the additional information obtained with each subsequent year the player is on the roster. Uncertainty of a player's production should decline over time. Unless a pay-for-play system consists of fixed three-or-four-year contracts, the *ex ante* approach would likely underestimate the true MRP and degree of exploitation.

Fixed Effects and Panel Data Approaches

Another approach is born from the increasing availability of data, allowing researchers to use panel data methodologies, most prominently school fixed effects (Bergman & Logan, 2020; Lane et al., 2014; Makofske, 2018, for example). Endogeneity, a major concern in the Brown (1993, 2011) framework, especially given the lack of stability observed in the replication attempts, can potentially be mitigated using panel data tools, particularly school fixed effects.

School fixed effects capture several potential endogenous effects. Variables like school expenditures on academic services, coaching staff, and recruitment efforts are likely to remain stable year-over-year, with any deviations likely attributable to natural increases over time, which can be captured by season fixed effects. Moreover, schools with large alumni networks and substantial donation bases may have the ability to attract the best players and generate the most football revenue. In an estimation of the MRP for college basketball players, Lane et al. (2014) identified that the MRP estimates are reduced significantly when school fixed effects are included. A similar effect was found in Makofske (2018), which incorporated school fixed effects for college football.

Incorporating school fixed effects into our analysis, we test the impact of including school fixed effects with the following simple fixed effects model

$$Revenue_{st} = \beta_0 + \beta_1 Draft_{st} + SCHOOL + SEASON + \epsilon_{st}. \tag{6}$$

Results are presented in Table 7. Columns 1–3 use the number of draft picks, while Columns 4–6 replace draft picks with our draft value measure. We compare results obtained from pooled OLS with those from the model incorporating school fixed effects to emphasize the impact these fixed effects have on the model. We find that MRP estimates are reduced by 90–95% when school fixed effects are included. This suggests that schools with large numbers of premium players or draft value are also schools that already generate significant revenues. Moreover, this result implies that a school's revenue generation is less influenced by individual players or a season's collection of players. By controlling for the time-invariant elements of the school, including factors such as alumni base, brand value, historical success, market size, base student enrollment, and operational and recruiting budgets, and for natural growth in these categories with year fixed effects, the fixed-effect estimates better address endogeneity concerns compared to the two-stage least squares approach.

A criticism of school fixed effects is that there may not be enough within-school variability in the number of draft picks variable to accurately estimate a proper MRP. If schools maintain similar talent levels from year to year, which is often the case for many schools, school fixed effects may treat the number of draft picks as a time-invariant factor. For instance, if a school like LSU consistently has a high number of premium players every year in the sample, and LSU's revenues are consistently towards the top end of the distribution in the sample, the LSU fixed effect could absorb a large portion of the contribution of players from LSU. Said differently, we do not observe scenarios where LSU has few future draft picks on the roster, making it difficult to estimate the negative consequences of not having these players.

Another criticism of school fixed effects is that they may not handle individual school revenue shocks or regime changes effectively. The fixed effects approach relies on the relative stability of many school-specific factors over time. If a school decides to drastically increase or decrease spending and recruiting efforts, for example, a school fixed effect would not capture this change, which may re-introduce endogeneity concerns.

Short-run and Long-run Considerations When Estimating MRP

We have highlighted numerous methodologies that attempt to estimate the marginal revenue product of college athletes, especially premium college football players. Despite this extensive exploration, numerous unanswered questions persist. Which approaches are both appropriate and methodologically robust? Which method or methods yield MRP estimates that are not only reasonable but also accurate reflections of the athletes' actual worth? Table 8 compiles various MRP estimates from various studies in the literature. While Brown's (2011) estimate stands out as the highest for premium college football players, none of the panel estimation methods generate estimates exceeding one million dollars (with the exception of specific quarterback-focused analyses). Interestingly, *ex ante* measures of elite players result in lower MRPs compared to *ex post* measures (recruiting rankings versus draft picks). A comprehensive survey of these varying MRP estimates reveals a lack of consensus in the field.

Moreover, a significant limitation to all the methods discussed is their exclusive focus as short-run MRP estimates. Each analyzed paper confined its examination to revenues generated solely within the season under scrutiny (Hunsberger & Gitter, 2015, do include revenues from the most recent season as well). Yet, in college football, the adage `success breeds success' holds particular relevance. A team's current performance can profoundly influence its ability to recruit superior players in the future. Furthermore, it might catalyze heightened athletic fundraising efforts, which could aid in the construction of better facilities, bolstering recruiting and leading to more future success. The pivotal question remains: to what extent can we attribute future financial gains to the contributions of players today? The impact of player performance also extends well past athletic revenues. Athletic success has the potential to yield far-reaching benefits for the university, including increasing applications, increased enrollment, and other positive spillover benefits (see Pope & Pope, 2009, for example).

An additional imperfection of current approaches is in how current approaches credit resources from revenue sharing. Consider a scenario where a school consistently ranks low in their conference standings but continues to amass substantial revenues through their conference's media contracts. Adding an additional premium player would have no immediate impact on the dollars accrued from media contracts today. Consequently, conventional MRP techniques falter in attributing any portion of the media revenues to individual players. Media revenue serves as just one illustration of a revenue source that cannot be credited to individual players, instead being a collective outcome of all players (of course, schools still must participate in the games to earn media revenue). It is unclear if divvying this pie is a question for positive economics or an equity/fairness concern addressed with normative methods.

Similarly, a parallel limitation lies in the fixed nature of many athletic revenue sources in the short run. Sales from season tickets, sponsorships, television and radio deals, among others, remain unaltered by team performance in the immediate context. Frequently, there exists a time lag between success and the realization of long-term revenue streams. For instance, current season success likely influences subsequent season ticket sales or sponsorship agreements. Conversely, a school's poor performance can lead to diminished viewership or listenership, potentially impairing future negotiations for media rights contracts. None of these dynamics are captured in short-run MRP estimates, except in instances where research specifically targets game-day sales, such as Brown (2011) and Wilson and Papagapitos (2021). The interplay between short-term gains and their long-term repercussions almost certainly results in underestimated evaluations of player MRP.

Attempts have been made to estimate the salary determination process in professional leagues in the presence of fixed revenues. Berri et al. (2015) demonstrated that player salaries significantly surpass what one might anticipate if they were solely remunerated for their contributions to team victories.[14] The difference between player MRPs and their actual salaries comes from bargaining power, in which there is a negotiation for a split of fixed revenues. Consequently, these estimations, devoid of the influence of bargaining, undervalue what athletes could potentially earn in a less constrained labor market. This undervaluation, in turn, understates the degree of exploitation.

An alternative perspective is taken by Bradbury (2019). MRP estimates, derived from returns to winning, capture the value of performance relative to other players, but fail to encompass the intrinsic quality of the players themselves. Consumer willingness to pay arises not merely from supporting a winning team, but also from witnessing exceptional talent. To put Bradbury's argument into perspective, the willingness to pay for a poorly performing college team surely surpasses that of a highly accomplished high school team. Emphasizing relative quality over absolute quality likely results in an underestimation of a player's total value, consequently downplaying the degree of exploitation. In essence, current economic tools and empirical techniques lack the capability to fully resolve this aspect of the college athlete pay-for-play dispute.

Moving Forward and Future Research

Amidst the ongoing legal and public discourse surrounding contentious issues like pay-for-play and the exploitation of student-athletes, there exists a pressing need to comprehensively grasp and quantify the value that players contribute to their respective institutions. This urgency is particularly pronounced for highly skilled athletes, who face a heightened risk of exploitation due to the constraints imposed by the NCAA on their compensation. Building upon prior literature—notably the seminal work of Brown (1993, 2011), which estimated the value of top players to exceed $1 million in present-day terms—our paper undertakes a critical re-examination of the methodologies employed in the existing literature to assess the marginal revenue product of elite college football players.

Employing more recent data and a refined econometric methodology, our study finds that while the marginal revenue product of an elite college football player remains positive and substantial, determining its precise magnitude proves more challenging than previous research implies. When attempting to replicate Brown's (2011) methodology over multiple seasons, sizable standard errors render calculating accurate marginal revenue product estimates or trends for premium college football players exceedingly problematic. Concerns regarding endogeneity prompted our exploration of alternative econometric approaches. Although Brown (2011) did address some endogeneity concerns in his work, his approach likely fails to adequately control for other time-invariant school factors that correlate with variables, such as the number of future draft picks, recruiting efforts, team success, and generated revenues. Our first principal finding is that the Brown methodology is likely unsuitable for estimating premium player MRP. While the estimates generally appear substantial, they suffer from considerable noise and lack stability from one year to the next.

Subsequently, we examine recent alternative methodologies in the literature, such as the professional factor shares approach, *ex ante* measures of player quality, and the incorporation of school fixed effects. Despite their emergency as alternatives, each of these methods comes with inherent shortcomings, necessitates strong assumptions, or can only be applied in specific situations. Our second principal finding underscores that, although recent literature has proposed alternatives to the Brown methodology, the existing tools continue to grapple with the challenge of accurately estimating MRP.

Lastly, we delve into conceptual concerns regarding the prevailing methods employed in estimating the MRP of college athletes, whether they are elite or not. Our third principal finding is that existing techniques are applicable solely to MRP estimates derived from non-fixed short-term revenue sources. These estimates overlook the contributions athletes make to long-term revenue streams, as well as the athletes' share of short-run fixed revenues such as media revenues.

Numerous challenges in estimating the MRP for premium college football players mirror those tackled in the professional sports literature (see Simmons, 2022 for an overview). Krautmann (1999) highlighted the complexities associated with linking production to salaries, particularly in the context of multi-year contracts. Generally speaking, past production should only inform expected salaries to the extent that it predicts future performance during the contract's duration. Such a concern provides support for *ex ante* measures of expected production. In another line of research, star players may be compensated above and beyond the market value of their on-field production (see Garcia-del-Barrio & Pujol, 2007; Humphreys & Johnson, 2020; Kuethe & Motamed, 2010, among others). Additionally, challenges arise when disentangling individual player contributions in contexts where performances are intertwined, a prevalent concern, especially in the NFL, as illuminated by Berri and Burke (2012).

The evidence presented in our paper, along with the existing literature, despite limitations, strongly suggests that premium college football players contribute significantly more value to their universities than the compensation they receive for cost of attendance. This conclusion holds even when considering the conservative fixed effect coefficients outlined in Table 7. It is abundantly clear that premium college football players are worth considerably more to their schools than the cost of attendance. Although quantification of a satisfactory and precise measure of the value generated by premium players for their schools remains elusive, and thus the degree to which exploitation exists under current NCAA rules, the question remains important. Achieving a deeper understanding of the impact of potential future changes in pay-for-play rules would greatly benefit from a more definitive understanding of the true value generated by these premium players.

A crucial insight derived from this study is the need for ongoing development of theoretical and empirical tools to effectively grapple with the intricate issues surrounding college athlete compensation. As the landscape of college athletics remains in a state of uncertainty, these tools must possess the flexibility to adapt to evolving market dynamics influenced by legal challenges and potential legislative interventions. Perhaps, exploring a potential avenue forward involves examining a parallel market with significantly fewer market constraints: the coaching market. Intriguingly, coaches and administrators have reaped substantial benefits from the existing systems devoid of athlete compensation. Schools remunerate coaches for their roles in both short-term and long-term revenue production, among other contributions to the institution. Delving deeper into the coaching market could offer valuable insights into what an unrestricted market for student athletes might resemble.[15]

A significant area warranting exploration in the literature pertains to how revenue sharing arrangements, both at the conference and NCAA levels, impact MRP estimates. Revenue sharing agreements, designed to distribute revenues irrespective of team performance, inherently diminish player MRPs. Athletes in leagues like the National Football League, National Hockey League, and National Basketball Association address revenue sharing concerns through collective bargaining, securing negotiated shares of overall revenues. Moving away from traditional methods like Scully's (1974) approach, which links production to winning and winning to revenues, future methodologies must delve into the realm of labor inputs' entitlement to various revenue streams. This includes revenue sources such as television contracts, sponsorships, merchandise, and more, which often evade capture in conventional MRP estimation techniques. Understanding the intricate interplay between revenue sharing schemes and athlete compensation necessitates innovative approaches attuned to the contemporary complexities of the sports industry.

Another critical question for the literature centers around the evolving landscape of NIL, where athletes receive compensation from third parties.[16] Athletes might select schools based on relationships and affiliations that enhance their NIL earnings, turning NIL opportunities into indirect monetary benefits constituting athlete "compensation." The rise of NIL could potentially alter the MRP equation, leading to changes in donor-giving patterns, transitioning toward supporting athlete collectives, and a shift in sponsorships toward direct-to-athlete endorsements. Comprehensive research is essential to reassess the degree of exploitation within the framework of NIL, as this transformative era brings forth complex dynamics that necessitate a reevaluation of existing paradigms.

Similarly, the evolution of the transfer portal raises intriguing questions about athlete compensation. Labor mobility, previously an uncommon privilege for college athletes, now emerges as a potential non-monetary benefit. The newfound freedom of players to move between schools could also be viewed as a factor influencing compensation, given that a player's peak performance often occurs in their final seasons. Schools may have a lower willingness to pay for incoming first-year players as that is when they are least productive and there is no guarantee they will stay when their peak performance emerges. This may also impact their willingness to invest significantly in player development. For instance, a school may "invest" in a player by paying him to stay at the school, even during the low-production freshman and sophomore seasons. The dynamic investment concerns are similar to those addressed in the movie industry by Hanssen and Raskovich (2020) after the end of long-term, studio-specific contracts for actors and actresses. The intricate interplay between labor mobility and compensation in collegiate sports demands thorough examination.

Future research in this field should adopt a forward-looking perspective, considering how potential shifts in the college-sports landscape might influence athlete compensation. If legal actions lead to the reclassification of players as employees rather than student athletes, it could empower athletes significantly through employee protections and potential unionization efforts, reshaping the bargaining dynamics in compensation negotiations. Additionally, as pay-for-play discussions progress, Title IX implications are bound to take center stage. Does athlete unionization or a classification change from students to employees impact equality protections afforded under the law? Such a question will surely impact any future pay-for-play framework. Moreover, who exactly is the “employer” in the college-athlete market? Is it the school, the conference, or the NCAA? Is there a future pay-for-play scheme that involves payments not just from the schools but also from conferences? These inquiries profoundly influence the compensation structures, not just for college football players, but for athletes across all sports, both men’s and women’s.

The focus of this paper on men’s college football players stems from football’s status as the primary revenue generator for major athletic departments. However, it’s crucial to acknowledge the substantial revenue disparities across various sports, necessitating tailored MRP estimation tools and potentially diverse payment frameworks. For example, Beaudin (2023) showed that improved softball success could positively increase attendance for both baseball and softball games. Such a dynamic should be captured in the MRP for women softball players. Furthermore, while existing research predominantly centers on football and basketball, there is a pressing need for more comprehensive studies estimating the value of elite male and female athletes in other NCAA-sponsored sports. Exploring these diverse athletic domains is vital for developing nuanced, sport-specific compensation models that accurately reflect the unique contributions and value brought by athletes in each sport.

The findings and analysis presented in this study cater primarily to economists and academics engaged in the analysis of the marginal revenue product (MRP) and the broader labor market for student-athletes. Nevertheless, our discussions hold relevance for a wide array of stakeholders, including college sport administrators, politicians, legal experts, athlete representatives, and the athletes themselves. While current economic techniques can gauge the marginal impact of adding a player of specific ability (as indicated by recruiting rankings, draft picks, etc.) on short-term non-fixed revenue sources (such as single-game ticket sales, concessions, parking, and merchandise), they fall short in addressing revenues fixed at the school and conference level, as well as the revenues realized by the university or conference in the long run.

Given the critical importance of accurately estimating the marginal revenue product of college football players to the academic community, athletes, and institutions, future research must address the shortcomings we have identified in the existing literature. Only through these endeavors can we develop a robust estimate of the degree of exploitation prevalent in the market for premium college football players. As the dialogue around athlete compensation continues to evolve, addressing these gaps in understanding becomes increasingly imperative, ensuring that future policies and practices are informed by comprehensive and nuanced research in this domain.

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Notes

[1] The NCAA argues that pay-for-play restrictions are needed to maintain a necessary level of competitive balance. Mills and Winfree (2018) did not find evidence supporting that claim, suggesting that player pay is unlikely to hurt competitive balance. Instead, an increase in direct payments would likely crowd out indirect compensation, such as more school spending on facilities and coaches.

[2] A full timeline of NCAA pay-for-play related litigation can be found here: https://www.wuft.org/news/2021/11/02/uf-was-subpoenaed-for-student-athlete-records-in-an-antitrust-lawsuit-against-the-ncaa/

[3] Sports Economists (2021) submitted an amicus brief in support of Alston (Nos. 20-512 & 20-520), in which co-author Raymond Sauer is a signatory.

[4] The extraction argument excludes any additional benefits of playing collegiate sports beyond the value of the scholarship, which overestimates the exploitation of student athletes by undercounting the value of the additional benefits. For instance, Heckman and Loughlin (2021) found that college athletes may be more likely to graduate with a bachelor's degree and may earn higher wages, compared to non-athletes.

[5] Brown (1993) used measures from Rooney Jr (1987) to identify the relative sizes of the recruiting pools. Rooney Jr (1987) calculated the number of major college players produced in each state relative to the number of Division I-A teams it supports. Brown (2011) proxied for a team's recruiting pool by dividing a school's state population by the number of teams in its market area, weighted by the quality of programs using cumulative top 25 average point rankings.

[6] See Brown (1993, 2011) for a more detailed explanation of the variables and models used in the original studies.

[7] The transfer portal was not nearly as prominent during our sample period as it is today. While our simple accounting approach overcounts the number of premium players on a given team, it should still give a relatively strong approximation to the true value. The alternative, collecting and cleaning roster and playing time data by school each year, would have been especially time intensive with very minimal expected gain.

[8] We do not have data on coaching salaries for 2008. As this is a key variable in Brown's model, we exclude 2008 from our initial analysis.

[9] A full list of schools missing data is available upon request. There is a mixture of Power 5 and non-Power 5 schools included.

[10] A more appropriate approach would be to compare growth in revenues for just the schools used in Brown's (2011) original sample. The exact schools included in his sample were not reported.

[11] The average F-value is 1.08 and the maximum is 3.29, which occurs in 2015. For brevity we have excluded first stage results from the paper. They are, however, available upon request.

[12] Two approaches to improve Brown (2011) were also attempted in Wilson and Papagapitos (2021). The first standardized the dependent variable, dividing revenue by the stadium's capacity times the number of games, to get an MRP measure that is school stadium-size dependent. The second introduced a quadratic term for elite players to capture diminishing returns of elite players. While Wilson and Papagapitos (2021) evaluated these approaches using the same Brown (2011) data, they went away from using two stage least squares in their

empirical strategy. Based on their results from just 2004 data, MRP estimates were significantly lower when factoring in stadium capacity. There was also evidence of diminishing returns. We believe that standardizing revenue is indirectly controlling for time-invariant factors. We do not address diminishing returns to elite players in our empirical techniques, but recognize its potential influence on reasonable MRP estimates.

[13] We thank an anonymous referee for suggesting this as another reason the comparison between college and professional MRP is difficult.

[14] We thank an anonymous referee for pointing us to this line of literature. While more is needed to consider the issue of fixed revenues in collegiate sports when estimating MRPs, the Berri et al. (2015) paper provided insight on ways to proceed with the analysis.

[15] Relevant recent studies that consider compensation of college football head coaches include Brook (2021), Leeds et al. (2018), and Leeds and Pham (2020), among others.

[16] See Ehrlich et al. (2023) for a discussion of issues in college athletics related to NIL that go beyond direct athlete compensation.

Tables

Table 1

Average Total Football Revenues by Season

Season	Observations	Mean	Std. Dev.	Min	Max
1988	39	\$10.821	\$8.026	-	-
2004	86	\$18.563	\$16.932	\$0.995	\$66.762
2006	115	\$20.759	\$18.793	\$1.316	\$75.057
2007	115	\$22.592	\$19.702	\$2.151	\$83.374
2008	117	\$22.710	\$19.845	\$1.737	\$96.458
2009	117	\$24.295	\$21.558	\$2.520	\$103.804
2010	117	\$25.162	\$22.077	\$3.210	\$104.076
2011	117	\$26.458	\$22.379	\$3.782	\$109.393
2012	121	\$27.062	\$22.866	\$3.383	\$112.901
2013	122	\$28.281	\$23.806	\$4.178	\$114.454
2014	125	\$29.908	\$25.730	\$4.076	\$121.504
2015	125	\$32.137	\$27.675	\$3.215	\$127.465

Note. All figures are in U.S. dollars (millions) rounded to three decimal places and adjusted for inflation with 2015 as the base year. 1988 and 2004 are figures reported by Brown (1993, 2011), but adjusted for inflation.

Table 2

Key Variable Summary Statistics (Mean and Standard Deviation)

	2006	2011	2015
Drafted Players (NFL Draft Picks)	7.27	7.12	6.90
	(6.64)	(7.15)	(7.64)
Real Head Coach Salary (Millions)	$1.091	$1.564	$2.029
	($0.802)	($1.151)	($1.591)
This Year's Average AP Ranking	2.81	2.78	2.58
	(5.87)	(5.78)	(5.43)
Prior Average AP Ranking	2.79	2.74	2.59
	(4.76)	(4.49)	(4.39)
Opponent Average AP Ranking	2.61	2.45	2.42
	(1.64)	(1.50)	(1.68)
Recruiting Pool (Millions)	3.618	3.701	3.714
	(6.087)	(6.325)	(6.392)
Academic Progress Rate	935.30	953.37	965.86
	(22.63)	(17.66)	(14.74)
Market Population (Millions)	1.561	1.602	1.585
	(3.108)	(3.138)	(3.054)
Football Entertainment	1.62	1.65	1.65
	(1.65)	(1.61)	(1.57)

Note. Summary statistics for the first, middle, and last year in the sample are rounded to the nearest shown digit. Head coach salary values are adjusted for inflation with 2015 as the base year. Average AP Rankings are actually AP Points, such that being ranked 25th is worth one point and being ranked first is worth 25 points. Standard deviations are included in parentheses.

Table 3

Brown (2011) Replication

Panel A (Unbalanced Panel): 2SLS Regressions (By Season); Dependent Variable = Real Revenue (In Millions)									
Variables	**2006**	**2007**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Draft Picks	2.606**	1.803*	-2.539	6.183**	3.452*	4.920**	4.313***	4.652***	4.171***
	(1.327)	(0.968)	(6.879)	(2.744)	(1.903)	(2.180)	(1.457)	(1.764)	(0.945)
AP Rank	-0.187	1.091	5.908	-2.482	0.089	-2.061	-1.548	-2.837	-1.666
	(1.593)	(1.129)	(7.266)	(2.868)	(2.263)	(2.652)	(2.011)	(3.134)	(1.266)
Opponent AP Rank	1.917	3.287**	11.380	-6.385	0.054	0.281	1.539	3.314*	3.785**
	(1.190)	(1.341)	(13.260)	(5.558)	(2.897)	(2.136)	(1.614)	(1.795)	(1.502)
Market (Million)	-1.079***	-1.118**	0.232	-0.556	-0.127	-1.419	-1.240	-1.379	-1.109
	(0.361)	(0.480)	(1.699)	(1.048)	(0.838)	(0.949)	(0.774)	(1.086)	(0.714)
Football	-0.152	0.853	-0.802	-2.153	-0.421	0.852	1.297	0.713	-0.211
Entertainment	(0.719)	(0.907)	(1.855)	(2.274)	(1.140)	(1.303)	(1.259)	(1.540)	(1.258)
Constant	1.719	-1.927	-0.612	9.874	2.869	-0.632	-0.988	-1.293	0.629
	(3.762)	(3.264)	(7.215)	(7.993)	(3.781)	(5.057)	(3.920)	(6.401)	(4.062)
Observations	104	104	108	107	107	113	114	117	118

Panel B (Balanced Panel): 2SLS Regressions (By Season); Dependent Variable = Real Revenue (In Millions)									
Variables	**2006**	**2007**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Draft Picks	2.937**	2.092***	-0.540	6.022**	4.282*	5.166*	4.402***	4.599*	5.393***
	(1.228)	(0.968)	(6.244)	(2.357)	(2.422)	(2.684)	(1.441)	(2.582)	(1.651)
AP Rank	-0.229	1.168	4.028	-2.390	-0.883	-2.315	-1.406	-1.998	-2.866
	(1.238)	(0.866)	(6.569)	(2.464)	(2.889)	(3.273)	(1.819)	(3.951)	(2.082)
Opponent AP Rank	1.611	2.316*	7.692	-6.146	-1.126	0.037	0.952	1.676	1.580**
	(1.564)	(1.282)	(12.512)	(4.868)	(3.544)	(2.564)	(1.877)	(1.725)	(2.375)
Market (Million)	-0.367	0.012	0.852	-0.594	-0.517	-1.729	-0.935	-0.815	-1.091
	(0.395)	(0.460)	(2.040)	(1.086)	(1.111)	(1.489)	(0.788)	(1.049)	(0.964)
Football	-0.257	-0.183	-2.160	-1.862	-0.274	1.259	0.779	0.088	-0.009
Entertainment	(0.724)	(0.872)	(3.173)	(2.377)	(1.489)	(1.780)	(1.389)	(1.480)	(1.781)
Constant	-3.210	-1.763	-0.014	9.219	2.567	-1.595	-0.334	1.116	0.997
	(3.166)	(2.966)	(5.115)	(7.793)	(4.554)	(6.064)	(4.183)	(6.497)	(5.341)
Observations	95	95	95	95	95	95	95	95	95

Panel C (No Conference Changes, Balanced): 2SLS Regressions (By Season); Dependent Variable = Real Revenue (In Millions)

Variables	**2006**	**2007**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Draft Picks	4.055**	2.842***	-8.861	1.539	0.763	6.650	4.836***	1.853	5.080***
	(1.604)	(0.840)	(21.012)	(1.646)	(1.567)	(10.383)	(1.396)	(2.596)	(1.894)
AP Rank	-1.121	0.465	13.824	2.829	3.672*	-4.222	-2.132	1.794	-2.797
	(1.514)	(0.854)	(23.949)	(2.098)	(2.006)	(12.334)	(1.673)	(4.296)	(2.431)
Opponent AP Rank	-0.463	0.535*	19.878	0.430	2.497	-0.776	1.087	3.022	2.387
	(2.300)	(1.497)	(35.838)	(3.026)	(3.019)	(8.352)	(2.125)	(1.910)	(2.766)
Market (Million)	0.158	0.250	0.968	-0.785	1.301	-3.346	-2.504**	-0.512	-2.250
	(0.726)	(0.677)	(4.081)	(1.212)	(1.415)	(7.575)	(1.258)	(1.656)	(1.595)
Football	0.570	0.283	-0.446	0.707	-0.503	1.515	0.768	0.205	-0.266
Entertainment	(1.149)	(1.144)	(6.264)	(2.129)	(2.100)	(3.426)	(1.851)	(1.799)	(2.304)
Constant	-4.567	0.246	2.553	5.180	4.318	-1.454	1.018	6.126	3.066
	(5.218)	(4.046)	(21.080)	(6.523)	(6.686)	(13.525)	(5.825)	(7.552)	(6.736)
Observations	66	66	66	66	66	66	66	66	66

Note. Standard Errors in parentheses. *p < 0.1; **p < 0.05; ***p < 0.01

Results are broken into three panels. Panel A includes all schools in the sample. Panel B only includes schools that are present in each season of the sample. Panel C only includes schools that are present in each season of the sample and never change conferences. Only final stage results are shown for brevity. Figures are rounded to three decimal places.

Table 4

Brown (2011) with Draft Value

Panel A (Unbalanced Panel): 2SLS Regressions (By Season); Dependent Variable = Real Revenue (In Millions)									
Variables	**2006**	**2007**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Draft Value (x1,000)	8.867	3.761*	-9.753	14.038**	9.887*	10.196**	14.640**	10.426**	11.958***
	(6.176)	(2.110)	(19.619)	(5.995)	(5.503)	(4.159)	(6.379)	(4.652)	(3.207)
AP Rank	-1.487	1.414	7.154	-1.500	-0.069	-1.062	-4.312	-2.840	-3.168*
	(3.073)	(1.004)	(7.924)	(2.360)	(2.389)	(2.050)	(3.771)	(3.647)	(1.877)
Opponent AP Rank	1.986	3.795***	13.795	-5.110	-0.481	1.578	2.278	5.037**	5.118***
	(1.587)	(1.178)	(14.788)	(4.849)	(3.283)	(1.625)	(1.860)	(2.148)	(1.640)
Market (Million)	-1.381**	-1.147**	0.368	0.004	0.254	-0.586	-1.495	-1.060	-0.954
	(0.556)	(0.492)	(1.719)	(0.961)	(0.808)	(0.658)	(1.086)	(1.064)	(0.844)
Football	0.853	1.052	-0.953	-2.023	-0.720	0.390	1.584	0.522	-0.347
Entertainment	(1.182)	(0.922)	(2.169)	(2.173)	(1.372)	(1.190)	(1.697)	(1.512)	(1.563)
Constant	-1.955	-0.611	-4.115	12.060	5.085	2.420	-0.704	2.046	1.214
	(5.268)	(3.062)	(12.160)	(8.423)	(4.756)	(4.095)	(5.047)	(5.861)	(4.799)
Observations	104	104	108	107	107	113	114	117	118

Panel B (Balanced Panel): 2SLS Regressions (By Season); Dependent Variable = Real Revenue (In Millions)									
Variables	**2006**	**2007**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**
Draft Value (x1,000)	9.097*	4.619***	-17.307	14.245**	10.993*	9.851**	13.053***	8.114	13.998***
	(4.886)	(1.651)	(38.497)	(5.580)	(6.666)	(4.684)	(4.939)	(5.266)	(5.091)
AP Rank	-1.098	1.435*	10.445	-1.690	-0.544	-0.830	-3.118	-0.698	-4.217
	(2.045)	(0.739)	(15.596)	(2.209)	(2.899)	(2.306)	(2.729)	(3.699)	(2.948)
Opponent AP Rank	1.800	2.879***	20.276	-5.569	-1.185	1.688	2.142	3.645**	4.155*
	(1.906)	(1.108)	(30.628)	(4.678)	(3.846)	(1.782)	(1.849)	(1.626)	(2.258)
Market (Million)	-0.374	-0.044	2.577	-0.020	-0.027	-0.509	-0.917	-0.415	-0.978
	(0.493)	(0.459)	(4.628)	(1.045)	(1.015)	(0.930)	(0.914)	(0.874)	(1.146)
Football	0.212	0.112	-5.195	-1.911	-0.576	0.409	0.962	0.175	0.828
Entertainment	(0.947)	(0.867)	(8.098)	(2.412)	(1.671)	(1.474)	(1.631)	(1.317)	(2.270)
Constant	-2.896	-0.634	-7.487	12.363	4.871	1.705	0.523	4.602	1.312
	(3.890)	(2.851)	(20.791)	(8.642)	(5.374)	(4.706)	(4.785)	(5.031)	(6.399)
Observations	95	95	95	95	95	95	95	95	95

Note. Standard Errors in parentheses. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. Figures are rounded to three decimal places.

Table 5

MRP Estimates In Millions by Draft Position (Balanced Panel)

NFL Pick	NFL Draft Value	2006	2011	2015
1	1000	$9.097	$10.993	$13.998
33	670	$6.095	$7.365	$9.378
65	449	$4.084	$4.936	$6.285
100	289	$2.629	$3.177	$4.045
137	191	$1.737	$2.100	$2.674
177	138	$1.255	$1.517	$1.932
218	128	$1.164	$1.407	$1.792

Note. MRP estimates are in millions of dollars, rounded to three decimal places.

Table 6

Brown (2011) Replication MRP Low Revenue Versus High Revenue Schools

	Unbalanced Panel		Balanced Panel	
Season	Low-Revenue School MRP	High-Revenue School MRP	Low-Revenue School MRP	High-Revenue School MRP
2006	1.217***	2.467	1.065***	2.606
	(0.313)	(2.404)	(0.249)	(2.678)
2007	2.139*	1.888	2.291*	2.175
	(1.155)	(1.774)	(1.318)	(1.421)
2009	1.071**	7.008	0.824*	2.778
	(0.504)	(9.452)	(0.434)	(3.994)
2010	1.566**	4.982**	1.675**	4.399**
	(0.746)	(2.304)	(0.668)	(2.180)
2011	1.532***	2.613**	1.119***	1.713
	(0.363)	(1.290)	(0.295)	(1.301)
2012	2.152***	-1.799	1.793***	-2.487
	(0.569)	(4.108)	(0.410)	(3.370)
2013	3.162***	5.679*	2.838***	5.194**
	(1.033)	(3.339)	(1.068)	(2.634)
2014	1.836	1.714	-0.617	1.883
	(1.786)	(1.460)	(4.765)	(1.842)
2015	1.788	3.785***	3.733**	4.343***
	(1.108)	(1.395)	(1.783)	(1.579)

Note. Standard Errors in parentheses *p < 0.1; **p < 0.05; ***p < 0.01

Each cell includes the MRP coefficient estimate and standard error (in millions of dollars) from the regression that corresponds with that row's season and that column's revenue group. The dependent variable is number of draft picks (number of premium players). Sample sizes for each regression are approximately half of the sample size listed in the corresponding columns on Table 3. Coefficients for other covariates are available upon request. All figures are rounded to three decimal places.

Table 7

MRP with School and Year Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
Draft Picks	2.428***	0.308**	0.307**			
	(0.173)	(0.126)	(0.126)			
Draft Value (x1,000)				5.777***	0.563*	0.560*
				(0.470)	(0.324)	(0.324)
2007	1.791***	1.827***	1.854***	1.754***	1.825***	1.852**
	(0.597)	(0.395)	(0.398)	(0.632)	(0.399)	(0.402)
2008	1.982**	2.177***	2.176***	1.982**	2.183***	2.181***
	(0.803)	(0.515)	(0.518)	(0.931)	(0.523)	(0.526)
2009	3.672***	3.776***	3.817***	3.683***	3.780***	3.821***
	(1.033)	(0.631)	(0.635)	(1.178)	(0.638)	(0.642)
2010	4.891***	4.687***	4.739***	4.723***	4.663***	4.717***
	(1.204)	(0.679)	(0.684)	(1.422)	(0.693)	(0.698)
2011	6.063***	5.968***	5.995***	5.958***	5.953***	5.982***
	(1.235)	(0.728)	(0.735)	(1.400)	(0.739)	(0.746)
2012	7.178***	7.339***	7.382***	6.948***	7.321***	7.358***
	(1.262)	(0.755)	(0.753)	(1.402)	(0.762)	(0.761)
2013	8.375***	8.737***	8.744***	8.213***	8.733***	8.739***
	(1.390)	(0.974)	(0.988)	(1.538)	(0.977)	(0.990)
2014	10.211***	10.932***	11.012***	10.149***	10.946***	11.031***
	(1.374)	(1.065)	(1.079)	(1.529)	(1.074)	(1.087)
2015	12.265***	13.201***	13.376***	12.320***	13.230***	13.407***
	(1.588)	(1.219)	(1.245)	(1.760)	(1.228)	(1.253)
Constant	3.110**	17.870***	18.624***	6.368***	18.690***	19.468***
	(1.117)	(0.999)	(1.023)	(1.316)	(0.898)	(0.917)
Obs	1,191	1,191	1,140	1,191	1,191	1,140
R-squared	0.592	0.388	0.390	0.547	0.383	0.384
Balanced?	No	No	Yes	No	No	Yes
School FE?	No	Yes	Yes	No	Yes	Yes
Schools	126	126	114	126	126	114

Note. Clustered (school) robust standard errors in parentheses. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$ All season coefficients are compared to the excluded 2006 season. Real revenue is in 2015 dollars (in millions). Columns 1–3 use number of draft picks and Columns 4–6 use draft value. Columns 1 and 3 use pooled sample OLS, Columns 2 and 4 include school fixed effects, and Columns 3 and 6 include school fixed effects and exclude schools that do not appear in each year in the sample. All figures are rounded to three decimal places.

Table 8

College Football Marginal Revenue Product Estimates in the Literature

Paper	Years Covered	Technique Used	Marginal Unit of Observation	Nominal MRP Estimates
Bergman & Logan (2020)	2002-2012	Scully method. Panel data. Team dummy variables. Include effect on wins and probability of bowl appearance.	Five Star Recruits (without/with school fixed effects) Four Star Recruits Three Star Recruits	$660,136/$193,893 $346,435/$89,866 $153,626/$33,282.69
Borghesi (2017)	2003-2014	2SLS. Panel data. Team dummy variables. Players receive 47% revenue split and freshmen receive 25% of that. Assumptions regarding costs factored in as well.	Five Star Recruits Four Star Recruits Three Star Recruits Low Star Recruits	$799,000 $361,000 $29,000 $21,000
Brown (1993)	1988	2SLS. Cross-section data. Survey data for revenues.	Drafted Player	$500,000
Brown (2011)	2004	2SLS. Cross-section data. Estimates by revenue category (shown is MRP when including just tickets, contributions, and game day sales)	Drafted Player (MRP) Drafted Player ("Average" MRP)	$1,176,826 $1.1 million
Goff et al. (2017)	2011-2013	Professional factor shares approach. Assumes 50% of revenues would go to players.	MRP of starting players by position and conference; Examples include: Quarterback (ACC) Safety (ACC) Center (Sun Belt)	 $821,000 $221,000 $48,000
Hunsberger & Gitter (2015)	2004-2012	Scully method. Panel data. Team dummy variables. "Big 6" BCS Conferences only.	Elite (Top 100 Overall Ranked) High School Quarterbacks *Ex ante* Measure	$429,000

		Includes wins and lagged wins and discounts lagged wins by 5%.	Elite Quarterbacks Over Average Quarterbacks (one SD above mean QBR over the course of a season) *Ex post* Measure	$2.3 million
Makofske (2018)	2004-2011	Scully method. Panel data. Team dummy variables. Also accounts for *ex ante* probability of finishing as a draft eligible player given recruit ranking (results not shown here).	Drafted Players (All FBS) Drafted Players (BCS AQ only)	$576,000 (career MRP) $868,000 (career MRP)
Wilson & Papagapitos (2021)	2004	Similar data to Brown (2011). Controls for diminishing marginal revenue product of elite players. Controls for stadium capacity. Uses game revenues only.	Drafted Player (Game-day revenues)	$303,741.46

Note. Selected MRP estimates from papers in the literature are included here. Some MRP estimates are approximations as reported by the respective authors. These are all nominal estimates, so adjustments for inflation are necessary for direct comparison.