**1 Introduction**

Auburn University’s 2010 college football team is remembered both for its glory and controversy. After a mediocre 8-5 season the previous year, the Tigers went 14-0 to claim the Southeastern Conference (SEC) title and BCS National Championship. In the final game of the regular season, the team was led back from a 24-point deficit by quarterback Cam Newton to beat in-state rival Alabama. It was the largest comeback in Auburn’s history. Newton, the star of the team, went on to win the 2010 Heisman Trophy in a landslide and was selected as the first overall pick in the 2011 NFL Draft.

As the 2010 season went on, the team’s successes were mirrored by growing controversy surrounding Newton’s eligibility to play. Amid intense media coverage, the National Collegiate Athletic Association (NCAA) investigated allegations that Newton’s father had solicited over $100,000 from university boosters during Newton’s recruitment process. A ‘pay-for-play’ scheme like this would have violated the NCAA’s amateurism rules and rendered Newton unable to compete.

The situation came to a climax when on November 30, only a few days before the SEC championship game, the NCAA declared Newton ineligible to compete, but reinstated him the very next day after an appeal by Auburn. This turn of events generated enormous controversy and restarted a debate around the ethics of the NCAA’s amateurism rules. Some argued that Newton should not have been reinstated so quickly, and only was reinstated because the NCAA, SEC, and Auburn University all stood to lose significant amounts of money if he did not compete. Others argued that, since Newton’s talents enabled the institutional powers to generate millions of dollars in revenue, the NCAA’s amateurism rules were exploitative and Newton should never have been suspended in the first place.

The debate around NCAA amateurism rules was reignited in 2014 when the University of Connecticut’s (UCONN) basketball star Shabazz Napier commented in the days leading up to the NCAA championship game that, due to NCAA regulations governing when he was allowed to access the school cafeteria, “there are hungry nights that I go to bed and I’m starving” (Gamin, 2015). This comment attracted massive public attention because of the stark contrast it painted: while the NCAA was generating roughly $700 million in revenue from the tournament’s television rights, some of the tournament’s participants were unable to feed themselves. Ironically, UCONN went on to win the national championship and Napier was named MVP of the championship game.

The central question in the debate around NCAA amateurism rules is the extent to which NCAA rules exploit the athletes they sponsor. With collegiate athletic revenue in the billions of dollars per year, and increasing every year, some argue that a college scholarship alone is not fair compensation for the athletes who generate that revenue.

One way that economists might contribute to this conversation is to estimate the marginal revenue product (MRP) of college athletes. While studies have generated estimates of premium college athletes’ MRP, few have generated estimates of non-premium athletes’ MRP, and none have estimated the MRP of non-premium college football players. In this study, I develop a new framework that uses a football player’s high school recruiting ranking as a proxy for their production in college. Using this framework, I generate MRP estimates for five-star players that are higher than previous studies. However, MRP estimates for lower-skilled players indicate that they may not contribute more to revenue generation than replacement-level players.

**2 Literature Review**

**2.1 The Market for College Football Players**

The market for college football players, which exists in the ecosystem of intercollegiate athletics, has not been the subject of much empirical research. However, intercollegiate athletics is a unique and burgeoning industry. A 2016 USA Today report estimated total Division I athletic department expenditures for the previous 11 years at $100 billion, with the football program often being the most expensive sport sponsored by a university (Brady et al., 2016; Fort, 2011, p.442). To achieve future success, college football programs compete for the services of talented amateur athletes. Langelett (2003) found that higher recruiting rankings were associated with better team performance, suggesting that programs maximize wins by competing for the best talent. However, the market for college football players is heavily regulated; due to NCAA rules, these athletes cannot be compensated beyond the cost of their college education, placing an effective wage ceiling on athletes. In an unrestricted labor market, athletes would have the opportunity earn a salary, rather than payment-in-kind. In order to study wages in this hypothetical market, researchers have set out to quantify the MRPs of college football players. Difficulties in developing a universally-accepted method of calculating MRP have generated incomplete and varied estimates of college football players’ MRPs. Most recently, the MRP of a premium college football player was estimated between $400,000 and $1,000,000 per year (Brown, 2011; Hunsberger and Gitter, 2015), which is an order of magnitude greater than the price tag of a full scholarship. Unfortunately, no studies to date have estimated MRPs for non-premium college football players.

**2.2 Estimating MRP in sports labor markets**

The literature on athletes’ MRP began with Scully (1974), in which Scully theorized that a player’s MRP could be estimated by breaking down MRP into its two components, marginal revenue and marginal product. Thus, by discovering how a player’s performance affects team performance (marginal product) and how team performance affects team revenue (marginal revenue), one could calculate that player’s MRP. However, because of the tools and data at his disposal, Scully crudely estimated the MRP of Major League Baseball players by finding the effect of team-level performance statistics on team revenue, then weighted team-level results by individual appearances to generate a MRP estimate for individual players. Crucially, Scully found that average players were compensated about 20% of their MRP over the course of their career.

This method for estimating MRP, known as the Scully method, has been criticized on multiple fronts. Krautmann (1999) argues that several methodological errors cause the Scully method to vastly overestimate player MRP. Namely, Krautmann posits that Scully’s failure to account for managerial performance and cross-player complementarities causes marginal product to be overstated. Moreover, he argues that because total team revenue is inclusive of revenues that are not linked to team performance, the use of total team revenue as a dependent variable (as opposed to ticket revenue) causes marginal revenue to be overstated. Although Scully’s study was done in the context of Major League Baseball’s labor market, which is fundamentally different than the market for college football players, any study using the Scully method should be mindful of his methodological errors.

**2.3 MRP of college athletes using Scully’s Method**

In the context of intercollegiate athletics, several studies have adopted and adjusted Sully’s method of measuring MRP. However, these studies have introduced methodological errors of their own, leaving us with a body of flawed or incomplete work.

In addition to the problems discussed in Krautmann (1999), one difficulty in applying the Scully method to college athletes is that there are many players who do not generate performance statistics, and will thus have a MRP of zero. However, despite the lack of playing time, these players still contribute to the development of the team by serving as practice opponents and reserves in the case of injury. Lane et. al (2014) navigated this problem by theorizing that one could use the distribution of player salaries in the National Basketball Association (NBA) as an approximation of the distribution of college basketball players’ MRPs. This assumption allowed the researchers to apply the distribution of professional players’ salaries to the average MRP of each school, as calculated by the Scully method, to generate a MRP estimate for all players at a school. However, since price signals in the NBA labor market are constrained by wage ceilings and wage floors, it is dubious to assume that the distribution of NBA salaries is representative of the true distribution of college basketball players’ MRPs. For similar reasons, it would be unwise to apply this approach to estimating college football player’s MRPs.

Another problem in applying the Scully method is the difficulty in allocating responsibility for team outcomes amongst individual players. While baseball is played such that players’ batting performances are relatively independent of each other, football is structured such that players’ performances are highly dependent on each other. For example, a pass completion in football could be the result of an accurate throw by the quarterback, an unlikely catch by the receiver, poor coverage by the defense, good blocking by the offensive line, an effective decoy by another offensive player, or some combination of these factors. For this reason, few metrics exist that isolate the performance of individual players, making it difficult to measure football players’ marginal product. Most recently, Hunsberger and Gitter (2015) used a metric called Total QBR to estimate the MRP of premium college football quarterbacks. While this approach allowed the researchers to generate the first Scully MRP estimates for college football players, it limited the pool of players to only high-productivity players in one position group. This flaw limits the study’s practical applicability in the discussion of NCAA amateurism rules.

**2.4 MRP of college athletes using alternative methods**

Because of difficulties in applying the Scully method to college athletics, researchers have developed alternative methods for measuring MRP, namely the method pioneered in Brown (1993). Instead of using performance statistics to estimate productivity, Brown theorized that one could estimate the value of a premium college athlete by using the number of players on a team that would eventually be drafted into a professional league as a proxy for total team productivity. This is the most popular method for estimating premium college athletes’ MRP, and has been applied to college football (Brown, 1993; Brown, 2011), men’s college basketball (Brown, 1994; Lane et al., 2014), women’s college basketball (Brown & Jewell, 2006), and men’s college hockey (Kahane, 2012). Unfortunately, this line of research does not provide intuition about the MRP of non-premium athletes, and may overestimate the value of premium athletes.

Similar to how the Scully method allocates MRP exclusively to athletes that generated performance statistics, Brown’s method allocates the MRP generated by a team exclusively to athletes from the team who were drafted. The implicit assumption of this method is that players who were not drafted into a professional league did not generate any MRP. This assumption may have some legitimacy: it is possible that adding low or average-skilled players to a team does nothing to increase team revenue. However, it stands to reason that many athletes who weren’t drafted still contributed to the successes of the team, and thus generated MRP. For this reason, Brown’s method could overestimate the value of a premium college athlete. Moreover, the overestimation of premium athletes’ MRPs would be exacerbated for teams that had fewer premium players. For example, if a team had only one future professional draftee on its roster, all of the team’s productivity would be assigned to that player. The shortcomings of Brown’s method necessitate the introduction of a framework that can estimate the MRPs of non-premium players.

**2.5 Recruiting Ranking as a Proxy for Player Productivity**

Several companies produce yearly ratings of high school seniors that are being recruited to play college football. These companies attempt to predict the future production of the athletes by assigning them a ‘star’ value. Star ratings range from one to five stars, with the five-star players being regarded as the most talented prospects. While it is not uncommon for a highly-rated player to underperform expectations or a lower-rated player to become a star, recruiting rankings are predictive of NFL draft status: higher-rated players are more likely to be selected in the NFL draft and are picked earlier than lower-rated players (Benes, 2015). Moreover, higher-rated players are more likely to play in the NFL after being drafted, and contribute more value when they do play (Beaton & Benes, 2016). The standard assumption in the MRP literature is that a player’s selection into a professional draft is indicative of high productivity in college; in fact, the entire line of literature following Brown (1993) is based on this assumption. Because players with a higher star rating are more likely to be drafted into the NFL and are more productive while in the NFL, we can safely assume that higher-rated players are more productive in college. College football players of varied skill can be likened to workers of varied productivity levels: all else equal, we should expect higher-skilled workers to generate more revenue than lower-skilled workers.

A crucial benefit of using recruiting rankings over other proxies for player production is that a player’s recruiting ranking is decided before he ever plays in a college game, and thus represents a pre-performance estimate of his production. This is an improvement over other methods because, in professional athletics, salary negotiations take place before services are rendered. Thus, we can interpret MRP estimates using recruiting ranking as a proxy for productivity as a rough indicator of the salaries players could have negotiated, regardless of their actual production. In an unrestricted market, highly-rated recruits would likely be paid a high salary, regardless of their production, because they had negotiated high-paying contracts prior to playing for a team.

Although there are several benefits to using recruiting ranking as a proxy for productivity, it is a noisy and imperfect measure. While a player’s recruiting rating does have predictive power regarding his future productivity, it is still a subjective rating that can differ across rating services. Even when rating services agree on a player’s star rating, there are numerous other factors that could affect a player’s ability to negotiate his salary. For example, teams may value a five-star quarterback over a five-star lineman.

All of the methods that have previously been used to estimate a football player’s productivity present empirical difficulties. In all known cases, the researchers produce MRPs only for a small subset of premium players. I propose high school recruiting rankings as a proxy of productivity that will allow me to produce MRP estimates for players of varied productivity levels.

**3 Economic Model**

I adopt the model of athletic department decision making developed by Hoffer et al. (2015). The model assumes a utility-maximizing athletic director whose utility depends on the quality and quantity of coaching staff (*S*), prestige (*G*), and total revenues generated by the athletic department (*R*). Athletic department prestige comes only from the coaching staff (*S*), and total revenue is a function of the quality and quantity of athletic programs offered (*Q*) and total investment in the coaching staff (*S*). Thus, athletic department decision-making can be modelled like so:

(1)

The model assumes diminishing marginal utility from athletic programs (U’Q > 0, U’’Q < 0), staff (U’S > 0, U’’S < 0), and prestige (U’G > 0, U’’G < 0). The model also assumes that, as the manager of a nonprofit organization, the athletic director is subject to a cost constraint where revenues must be greater than or equal to total cost. The cost function and cost constraint are modelled like so:

(2)

(3)

Maximizing the utility function subject to the cost constraint generates a Lagrangian, .

(4)

When we differentiate the Lagrangian function with respect to the choice variables, *Q* and *S*, we can arrive at a number of conclusions about athletic director behavior. When the break even constraint is not binding, the athletic director over invests in athletic programs (*Q*) and the coaching staff (*S*). Historically, we see that up to 65% of athletic departments in a single year failed to break even (Fort, 2011, pp.440). This suggests that the break even constraint is not binding in practice. Hoffer et al. (2015) show that in the case of a nonbinding break even constraint, there would be resources to compensate athletes closer to their free market value if athletic directors invested in programs and coaches only up to the efficient level.

I adjust the utility function above to model athletic program quality as a function of facility quantity and quality (*F*) and labor talent (*L*). In a world where athletes could be compensated beyond the cost of their scholarship, athletic directors would likely redirect resources from other aspects of program quality, such as stadium and facilities expenses, towards the payment of a more talented labor force. The new revenue function and utility function can be specified as such:

(5)

(6)

Later, I use this framework to build an econometric model that will allow me to empirically investigate the MRP of college football players.

**4 Data**

I collected data describing athletic department finances, football team performance, coach information, recruiting rankings, and state-level economic conditions for NCAA Division I Football Bowl Subdivision (FBS) schools[[1]](#footnote-1). Summary statistics can be viewed in Table 1.

Nearly all college football teams with a history of national success are members of a “Power” athletic conference. Until 2013, there were six power conferences: the Atlantic Coast Conference, the Southeastern Conference, the Big Ten Conference, the Big East Conference, the Big Twelve Conference, and the Pacific Ten Conference. Before the 2013 season, the Big East conference dissolved, and most of its prominent members found homes in one of the five remaining power conferences.

There is a stark contrast between “Power Five” schools and non Power Five schools. Members of power conferences have far greater political influence within the NCAA, partially because they generate the vast majority of all revenue in college football (Fort, 2011, pp.444-448). Because of this divide, it is worthwhile to split my sample into Power Five school and non Power Five school. Summary statistics for schools in power conferences can be found in Table 2, while summary statistics for schools in non power conferences can be found in Table 3.

**4.1 Revenue Data**

A central problem in MRP literature is the revenue specification problem discussed by Krautmann (1999). Krautmann points out that there are many parts of team revenue that are not responsive to team performance, and thus should be excluded from MRP calculations. College football teams generate revenue from many sources, including ticket sales, donations, sponsorships, payouts from bowl games, payouts from conference television contracts, and other media revenue. A team that outperforms expectations is likely to generate higher-than-expected ticket revenue, concessions revenue, and sponsorship revenue. However, most teams receive a predetermined payment from their athletic conference television contract every year that does not changed based on team performance. Since player performance has no influence on this revenue stream, it should be excluded when estimating player MRPs.

I gathered 2010-2014 athletic department revenue and expense data from Dr. Rodney Fort’s publicly available sports data repository. These data came from Member Financial Reporting System (MFRS) documents that are submitted to the NCAA by athletic departments. These data are not released to the public, but they have been gathered over time by the Chronicle of Higher Education through the Freedom of Information Act. Only public institutions are required to respond to requests through the Freedom of Information Act, so these data were not available for private universities. Table 4 lists private NCAA Division I FBS universities for which data are unavailable.

**Table 4.** Private universities and service academies not required to respond to data requests.

|  |
| --- |
| Air Force  Army  Baylor  Boston College  Brigham Young University  Duke  Miami (FL)  Navy  Northwestern  Notre Dame  Rice  Southern Methodist University  Stanford  Texas Christian University  Tulane  University of Southern California  Vanderbilt  Wake Forest |

Some schools have a state-related status that exempts them from reporting athletic department financial data. Additionally, some public schools simply failed to respond to requests for information. Table 5 lists public NCAA Division I FBS universities that failed to respond to requests for MFRS documents.

**Table 5.** Public universities that failed to respond to data requests.

|  |  |
| --- | --- |
| **School** | **Years Failed to Report** |
| Boise State | 2013 |
| Central Florida | 2010, 2011, 2012, 2013, 2014 |
| Cincinnati | 2010, 2011, 2012, 2013, 2014 |
| Kansas State | 2010, 2011, 2012, 2013, 2014 |
| Louisiana Monroe | 2010, 2011, 2012, 2013, 2014 |
| Michigan | 2013 |
| Penn State (state-related) | 2010, 2011, 2012, 2014 |
| Pittsburgh (state-related) | 2010, 2011, 2012, 2013, 2014 |
| San Diego State | 2010, 2011, 2012, 2013, 2014 |
| South Carolina | 2013 |
| Temple (state-related) | 2010, 2011, 2012, 2013, 2014 |
| Tennessee | 2010, 2011, 2012, 2013, 2014 |
| Texas San Antonio | 2012, 2013, 2014 |
| West Virginia | 2010, 2011, 2012, 2013, 2014 |

Importantly, MFRS documents list 15 different athletic department revenue streams, which makes it possible to exclude revenue that is not responsive to team performance. Table 6 defines all revenue streams listed on MFRS documents and whether they were counted as performance-responsive revenue.

**Table 6.** Revenue streams listed on MFRS documents.

|  |  |  |
| --- | --- | --- |
| **Revenue Stream** | **Description** | **Performance Responsive** |
| Ticket Sales | Revenue received for sales of admissions to athletic events, including sales to the public, faulty, and students. Does not include ticket sales for conference and national tournaments that are pass-through transactions. | Yes |
| Student Fees | Student fees assessed and restricted for support of intercollegiate athletics. | No |
| Guarantees | Revenue received from participation in away games. | No |
| Contributions | Amounts received directly from individuals, corporations, associations, foundations, clubs, or other organizations that are designated for the operation of the athletics program. | Yes |
| Compensation and Benefits Provided by a Third Party | Amounts provided by a third party and contractually guaranteed by the institution, but not included on the institution’s W-2 (e.g., car stipend, country club membership, entertainment allowance, etc) | No |
| Direct State and Other Government Support | State, municipal, federal, and other government appropriations made in support of the operations of intercollegiate athletics. | No |
| Direct Institutional Support | Value of institutional resources for the current operation of intercollegiate athletics, as well as unrestricted funds allocated to the athletics department by the university. | No |
| Indirect Facilities and Administrative Support | Value of facilities and services provided by the institution not charged to athletics. This support may include an allocation for institutional administrative cost, facilities and maintenance, etc. | No |
| NCAA/Conference Distributions, including all tournament revenues | Revenue received from participation in bowl games, tournaments, and all NCAA distributions. Includes shares of conference television agreements. | No |
| Broadcast, Television, Radio, and Internet Rights | Institutional revenue received directly for radio and television broadcasts, internet and ecommerce rights received through institution-negotiated contracts. | No |
| Program Sales, Concessions, Novelty Sales, and Parking | Revenue of game programs, novelties, food and other concessions, and parking revenues. | Yes |
| Royalties, Licensing, Advertisements, and Sponsorships | Revenue from corporate sponsorships, licensing, sales of advertisements, trademarks, and royalties. | Yes |
| Sports Camp Revenues | Amounts received by the athletics department for sports-camps and clinics. | Yes |
| Endowment and Investment Income | Endowment spending policy distribution and other investment income in support of the athletics department. | No |
| Other Operating Revenue | N/A | No |

To calculate performance-responsive team revenue, I summed ticket sales, contributions revenue, concessions and merchandise revenue, sponsorship revenue, and sports camp revenue. We should expect that interest in a team increases as team quality increases, leading to higher ticket revenue, contributions revenue, and sports camp revenue. Moreover, we should expect that higher attendance will lead to higher concessions and sponsorship revenue.

Most of the other revenue sources clearly cannot be classified as performance-responsive. However, there is an argument for some of them to be included. Notably, revenue from guarantees, NCAA and conference distributions, and broadcast rights seem on the surface to be responsive to performance. However, these revenue streams are generally the result of contracts signed years in advance, and thus could be attributed to the performances of past teams, but not current teams.

In my sample, performance responsive revenue had a mean value of $20.9 million, median value of $14.8 million, and a standard deviation of $21.1 million. Since a team cannot have negative revenue, we can conclude that a small number of teams are generating huge revenues, causing the distribution to skew right. If we look closer at the data, we can see that the University of Oregon had $40 million more in revenue in 2014 than any other team in the sample. This is due to a near $100 million donation from Nike founder Phil Knight (Kish, 2015). Aside from this outlier, the top revenue-generating seasons came from traditional powerhouses such as Texas, Michigan, LSU, and Ohio State.

When broken down by power conference membership, we can see that power conference members generate much more revenue than non power conference members. The average performance-responsive revenue was $30.2 million for Power Five schools and $3.8 million for non Power Five schools, meaning that we should expect players at Power Five schools to have higher MRPs than players at non Power Five schools.

**4.2 Star Rating Data**

My study is unique in this line of literature because I use star ratings as a proxy for player productivity. While Borghesi (2017) does include star rating variables in a regression on team revenue, he does not clearly explain what end this achieves, nor does he make a serious effort to control for all of the factors that impact a team’s revenue. In order to estimate player MRPs, I first gathered 2003-2017 recruiting data from *Rivals.com*. The data I collected include every recruit listed on the website that signed a letter of intent, the team they signed with, and the recruit’s star ranking. Unfortunately, *Rivals.com* does not track recruiting for every Division I FBS team. Table 7 lists teams for which no recruiting data is available.

**Table 7.** Universities where no recruiting data was available.

|  |
| --- |
| Air Force  Akron  Ball State  Bowling Green  Buffalo  Eastern Michigan  Georgia Southern  Hawaii  Idaho  Louisiana-Lafayette  Louisiana-Monroe  Massachusetts  Miami (OH)  Navy  Northern Illinois  Ohio  San Jose State  South Alabama  Utah State |

The teams for which recruiting data is not available are all non Power Five teams. After collecting the recruiting data, I summed the number of players of each star rating that committed to a school in the five years leading up a season. Since players generally have four or five years of athletic eligibility, I used the summed figure to estimate the number of players at each star level that were on a team in a given season. Because lowly-rated players are generally considered replacement-level players, each player with a rating of two stars or lower was counted as a two star player. This will allow me to calculate higher-rated players’ value in relation to a replacement-level player.

Importantly, it is possible that my method of calculating these variables generates a nonrepresentative sample. In order to estimate the talent of a team in year *t*, I simply summed up the recruits of each star level that committed to each team in the five years leading up to year *t*. However, most recruits that commit to a team are not with the team five years later. Some recruits that commit to a team never actually enroll in school, some finish their careers in four years, some have career-ending injuries, some transfer to other schools, and some leave the team for other reasons. Unfortunately, there is no accurate historical data that I can feasibly collect that tracks recruits through the end of their college career. However, it is likely that lower-rated players finish their eligibility at a lower rate than higher-rated players. If this is true, then low-rated players necessarily make up a higher proportion of players in my sample than they do in the population. This would certainly affect coefficient estimates.

Unsurprisingly, players of all talent levels are not distributed equally across the teams in my sample. The average Power Five team had about 17 two-star players, 53 three-star players, 21 four-star players, and two five-star players. In comparison, non Power Five teams had an average of 62 two-star players, 28 three-star players, and one four-star player. There are three seasons in which a single five-star player played for a non Power Five team. All of this would indicate that Power Five schools are, on average, attracting more talented players. However, the data also show that even when we consider only Power Five schools, the distribution of five-star players is still skewed. While the average Power Five team has about two five star players, there is a standard deviation of about 3 players. We can interpret this to mean that a small number of Power Five schools are getting the majority of the five-star players.

Unfortunately, the availability of revenue and recruiting data dramatically reduced the sample size of my study. There are only 378 team seasons for which I can match a team’s performance responsive revenue to its recruiting data.

**4.3 Independent Variable Data**

Next, I collected data for many other variables that I could match to my revenue and recruiting data. First, I collected data on a team’s past performance. Because a team that had a successful previous season is likely to attract more sponsorships and sell more tickets, it is important to include a variable to account for past performance. I use lagged Simple Rating System (SRS), a metric that is produced by *Sports-Reference.com*. SRS is calculated by defining a system of *n* equations which can be solved with a collection of *n* values, each of which correspond to a single team’s SRS rating. Each equation defines a team *i*’s SRS rating, which is the sum of the team *i*’s average point margin and the average of their opponents’ ratings.

To limit the impact of blowout wins and increase the impact of close wins in SRS calculation, *Sports-Reference.com* sets a minimum point margin of seven points and a maximum point margin of 24 points in a single game. Average SRS is zero, and the rating indicates the number of points better than average team *i* was. For example, a team with a SRS of six was six points better than the average team that season.

The primary benefit of using SRS to proxy team performance is that it gives much more insight into a team’s performance than the team’s winning percentage. Due to differences in schedule difficulty, it is common for highly productive teams to have worse winning percentages than less productive teams. We should expect that better teams would generate more revenue than worse teams, regardless of record, all else equal. This makes SRS a clear choice over more traditional metrics, such as winning percentage, for proxying performance.

As with previously discussed variables, there is a clear difference in lagged SRS between Power Five teams and non Power Five teams. While the average lagged SRS across the entire sample was 1.8, the average was 6.2 among Power Five teams, compared to -6.2 among non Power Five teams. The distribution of lagged SRS within and across both groups is near-normal, which is what we would expect given how SRS is calculated.

I gathered yearly unemployment rates by US state from the St. Louis Federal Reserve database. I use this variable to account for the general economic conditions in the state that each team is located in. One would expect that teams in states with higher unemployment rates would earn less revenue than teams in states with lower unemployment rates, all else equal. The average state unemployment rate in my sample was 7.9%, and there is not a large difference in the average unemployment rate between Power Five teams and non Power Five teams.

I gathered stadium data from a combination of Dr. Rodney Fort’s sports data repository and internet searches. First, I found the home stadium capacity of every team and year in my sample. One should expect that teams with bigger stadiums have less restriction on the amount of ticket revenue they can generate. Unsurprisingly, Power Five teams have much larger stadiums than non Power Five teams; on average they have nearly twice the capacity. Next, I found how long the home stadium of each team had been open for, and how many years it had been since it had gone through a renovation or expansion. These variables will help me account for stadium quality. Stadium renovations are generally considered to improve stadium quality, and older stadiums might have a special positive quality related to tradition or history. The data show that Power Five teams, on average, have older stadiums that have been renovated more recently than non Power Five teams. While the average home stadium of a Power Five team was 70 years old and had been renovated 6.4 years previously, the average home stadium of non Power Five team was about 45 years old and was last renovated 8.2 years previously.

Home games are significant opportunities for teams to collect ticket and concession revenue. Because game days have such high revenue potential, we should expect that teams that play more home games to collect more revenue, all else equal. I gathered data on the number of home games each team played in each year from *Sports-Reference.com*. Power Five teams played an average of 6.7 home games, while non Power Five teams played an average of 5.9 games. This is likely because many Power Five teams play a home game against non Power Five teams in the beginning of the season.

Finally, I gathered coach-level data from *Sports-Reference.com* with the intention of controlling for coaching staff quality. Although there are many aspects to coaching staff quality, data was only readily available for head coaches. In order to account for head coach experience, I use one variable for the total number of years a coach has been the head coach of a Division I FBS team, and one variable to account for how long a coach has been the head coach of his current team. Teams with more experienced coaches may perform better and generate more revenue than teams with less experienced coaches, all else equal. When comparing the head coaches of Power Five teams to head coaches of non Power Five teams, we see that Power Five coaches have 3.5 more years of head coaching experience on average, and have been the head coach of their current school for 1.8 years longer. Notably, the standard deviation number of years a Power Five coach has been at his current school is 4.9 years, while the average is 4.3 years. This indicates that there are a few outlier Power Five coaches who have been at their current university for many years.

Two other variables I use to account for coach quality are dichotomous variables that represent whether the team’s head coach has ever won a conference coach of the year award or a national coach of the year award. I would expect that a coach who had won these awards would be a higher quality coach than one who had not, and would therefore help the team generate more revenue. Here, we see another distinction between Power Five schools and non Power Five schools. Sixty-two percent and 24% of Power Five coaches in the sample had won a conference and national coach of the year award, respectively, compared to only 36% and 6% for non Power Five coaches.

**4.4**  **Instrument Data**

The data I have explain so far contain observations of multiple variables collected over multiple years for the same football teams. There are several types of regressions built for this type of data, known as panel data. Two-stage least squares regressions utilize instrumental variables to yield consistent estimators when independent variables are correlated with the error terms of the regression model.

Independent variables may be correlated to the error term when variables that affect both the dependent and independent variables are omitted, when changes in the dependent variable cause changes in one or more of the independent variables, or when there is non-random measurement error in the covariates. A valid instrument allows us to isolate the changes in the dependent variable that are caused solely by changes in the independent variables, and ignore the changes in the dependent variable that are caused by the model error through the correlation between the error and the independent variable.

There are two main requirements for properly implementing instrumental variables. The first requirement is that the instruments are correlated to the explanatory variables that are endogenous to the dependent variable. If the correlation between the instruments and the endogenous variables is weak, the instrument is considered a “weak instrument”. Weak instruments somewhat defeat the purpose of implementing an instrumental variable model in the first place, as they can lead to large inconsistencies in parameter estimates. Indeed, Bound, Jaeger, and Baker (1993) commented that, in terms of weak instruments, “the cure can be worse than the disease”. The second requirement is that the instruments must not be correlated with the error term. If an instrument meets this requirement, it passes the “exclusion restriction”. If an instrument does not pass the exclusion restriction, then it suffers from the same problem that the endogenous dependent variables suffer from.

It is possible that higher performance-responsive revenues give teams an increased ability to attract highly-rated players. This is a classic reverse causation problem, and a good opportunity to implement a two-stage least squares model. I collected data on five instruments that would allow me to implement a two stage least squares model. As described above, the instruments I choose must be correlated to the exogenous dependent variable, but be uncorrelated to the model error. So, my instruments should be correlated with the number of players at each star level on a team, but be uncorrelated with the team’s performance-responsive revenue.

The first instrument I gathered data for was the state population of the state team *j* is located in, divided by the number of Division I FBS football teams in that state. One could reasonably expect that teams from states with a high state-population-to-teams ratio would be able to successfully recruit a higher proportion of the local talent pool. However, the state-population-to-teams ratio is probably not correlated to performance-responsive revenue, and thus would meet the exclusion restriction.

To calculate this variable, I collected state population data from the US Census and linked it to team-per-state data I collected from *NCAA.org*. There is a substantial amount of variation between states, however there is very little variation within states. This is because the population of a US state is unlikely to change much from one year to the next, and the number of Division I FBS teams in a state will rarely change. If the instrument does not explain variance in star rating variables within a team between years, it may produce inconsistent parameter estimates.

For my next instrument, I obtained data on the percentage adults aged 25-64 in a state that have a high school diploma. It is possible that states with a lower percentage of adults that obtain high school diplomas prioritize athletic achievement over academic achievement, and thus teams in those states have access to better in-state talent, leading to more talented teams, all else equal. However, performance-responsive revenue is probably exogenous to the high school graduation rate. I obtained high school graduation rates for US states from the American Community Survey. The distribution of these rates is centered on 88.2% and has a near-normal distribution. However, similar to the last instrument, I fear that this variable will vary little within states, thus generating inconsistent parameter estimates.

The high school football season usually begins in the late summer and continues through the late autumn. However, some state high school athletic associations allow high school teams to hold a spring practice period. This period gives high school players in those states opportunities to receive extra coaching and refine their skills during the offseason. All else held equal, states that allow a spring practice period will probably have more talented high school football players than states that do not allow a spring practice period. As a result, college teams that are located in states where high school football teams have spring practice periods have a better pool to recruit from, leading to more talented teams. Because the existence of high school football spring practice is likely correlated to a team’s talent level, but exogenous to performance-responsive revenue, I include a dichotomous instrument that indicates whether high schools in the team’s state are allowed to hold a spring practice period.

I gathered this data from web searches of state high school athletic association webpages. If the site did not make mention of a spring practice period, I counted the state as not allowing them. In my sample, about 58% of the teams were in states that allowed high school spring practice. I have the same concern with this instrument that I had with previous instruments: it does not vary across time within states, so it may generate inconsistent parameter estimates.

For my fourth instrument, I use the ratio of professional sports teams in a state per million people in the state. I used the same census data that was used to calculate other variables, and I gathered the number of professional sports teams in each state from the league web pages[[2]](#footnote-2). I only counted professional teams from the National Football League, Major League Baseball, and National Basketball Association, and National Hockey League. Since professional sports teams tend to gravitate to densely-populated areas, there are many states in my sample that have zero professional teams. As a result, the distribution is skewed, with a mean of 0.29 professional teams per million people and a standard deviation of 0.25 professional teams per million people.

States that have a high ratio of professional teams per million people may have a greater cultural investment in athletics. If this is true, then we might expect that football teams in those states will have access to more talented players. However, the ratio of professional teams per million people in a state is probably exogenous to performance-responsive revenue. Additionally, since state populations change very little from year to year and it is uncommon for professional sports teams to move between states, there is very little variance in the ratio of professional sports teams per million people within states over time. As noted earlier, this has the potential to generate inconsistent parameter estimates.

Finally, I gathered data for the number of junior college football teams in a state from *NJCAA.org*. Junior college teams are populated by players that did not qualify for NCAA Division I out of high school. Many of these players are very talented and have multiple years of post high school playing experience, making them highly valuable recruits. It stands to reason that teams with more junior colleges in their state would have a higher ability to recruit junior college players, thus leading to more talented rosters. However, the number of junior colleges in a state is likely exogenous to a team’s performance-responsive revenue.

With an average of 1.8 teams and a standard deviation of 3.4 teams, the distribution of junior college football teams across states is highly skewed in my sample. Moreover, the median state has zero junior college teams. As with other instruments, there is no variation in the number of junior college teams across time.

Although my instruments likely pass the exclusion restriction, there is serious danger that they are weak instruments because they vary so little across time within teams. If this is the case, then the estimates generated by a two-stage least squares regression will not yield consistent estimators.

**5 Econometric Models**

In this section, I will describe the econometric models I use to estimate player MRP. Since I collected data on multiple parallel time series related to the schools in the sample, I have panel data. Consequently, I employ fixed-effects regressions and two-stage least squares regressions. Fixed effects regressions are commonly used for panel data when each entity has time-invariant characteristics that impact either the dependent or independent variables. The use of a fixed effects model allows us to ignore the effect of time-invariant characteristics and isolate the effect of the independent variables on the dependent variable. In my case, I assume that teams have time-invariant qualities that affect both their ability to generate performance-responsive revenue and recruit talented players. I run fixed effects models for my entire panel, and for Power Five teams and non Power Five teams separately.

Earlier, I explained how two-stage least squares models yield consistent estimators when independent variables are correlated with the error terms of the regression model. It is possible that higher performance-responsive revenue leads to larger recruiting budgets, increasing a team’s ability to attract high quality recruits. If this is true, then the star-rating variables are likely endogenous to performance-responsive revenue. Thus, I run two-stage least squares regressions for my entire panel, and for Power Five teams and non Power Five teams separately.

**5.1 Fixed Effects model**

The revenue of team *j* inseason *t* can be estimated as follows:

PerfomanceResponsiveRevenue*jt* = β0

+ β1ThreeStarsjt

+ β2FourStarsjt

+ β3FiveStarsjt

+ β4StadiumCapacityjt

+ β5StadiumYearsOpenjt

+ β6StadiumYearsSinceRenovationjt

+ β7CoachTotalExperiencejt

+ β8CoachSchoolExperiencejt

+ β9ConferenceCoachOfYearjt

+ β10NationalCoachOfYearjt

+ β11SRSj(t-1)

+ β12Unemploymentjt

+ β13Homegamesjt

+ εjt

+ αj (7)

As noted earlier, I include only revenue that is responsive to football team performance. This includes revenue from football ticket sales, donations to the football team, football concessions revenue, football sponsorship revenue, and revenue from camps. This addresses the revenue specification issue that was raised in Krautmann (1999). In order to account for labor quality (*L*), I use the variables *ThreeStars*, *FourStars*, and *FiveStars*. These variables indicate how many recruits of each star level committed to the team in the five years leading up to season *t*. The coefficients of these variables can be interpreted as the marginal value of a player of that star rating over a two-star player. Since previous studies have found high MRPs for elite college football players, I expect *FiveStars* to have a positive coefficient. Although I am agnostic as to whether the coefficients for *FourStars* and *ThreeStars* will be significantly different from zero, I expect *FourStars* to have a larger coefficient than *ThreeStars*.

To account for facilities quantity and quality (*F*), I use a team’s home stadium capacity (*StadiumCapacity*), the number of years a team’s home stadium has been open (*StadiumYearsOpen*), and the number of years since team’s home stadiumwent through a renovation or major expansion (*StadiumYearsSinceRenovation*). A team with a higher stadium capacity will have the ability to sell more tickets, so I expect *StadiumCapacity* to have a positive coefficient. Since older stadiums have attractive elements of history and tradition, I expect *StadiumYearsOpen* to have a positive coefficient. Assuming that renovations increase stadium quality, one should expect that stadiums that have not been updated recently would be of lower quality, and thus associated with lower revenue. Therefore, I expect that *StadiumYearsSinceRenovation* to have a negative coefficient.

To account for the coaching staff (*S*), I include variables representing the head coach’s number of years as the head coach of an FBS team (*CoachTotalExperience*), the head coach’s number of years as the head coach of his current team (*CoachSchoolExperience*), and whether the coach has ever received a conference or national coach of the year award (*ConferenceCoachOfYear* and *NationalCoachOfYear)*. I expect that both total head coaching experience and school-specific coaching experience will have a positive relationship with revenue, as more experience probably leads to better team performance, and thus more revenue. I expect both “coach of the year” variables to have a positive coefficient, as higher-skilled coaches have the potential to generate excitement about the team, and thus more revenue.

Finally, I include several variables to account for other factors that contribute to revenue generation. To account for past team performance, I use the lagged SRS. A team that performed well in year *t-1* is likely to have higher ticket sales and sponsorship revenue in year *t*, and thus higher revenue. I use *Unemployment* to account for the unemployment rate in the state that team *j* is located in during year *t*. I expect that as the unemployment rate increases, revenue will decrease. Lastly, I include the number of *Homegames* that team *j* plays in year *t*, as a team that plays more home games will have more opportunities to earn ticket and concessions revenue.

**5.2 Two-stage least squares model**

Because teams that generate more revenue will likely have higher recruiting budgets, and therefore a better ability to recruit highly-rated players, it is possible that a team’s past revenue is endogenous to variables accounting for labor quality (*L*). To account for this, I employ a two-stage least squares model with the same dependent variables as the fixed effects model and five instruments. The first instrument I use is *Population/D1Programs*, which is the year *t* population of the state team *j* is located in, divided by the number of Division I FBS football teams in that state. One could reasonably expect that teams with a high *Population/D1Programs* would have larger talent pool to recruit from. The second instrument I use is *HSGradPct*, or the percentage of adults aged 25-64 that have a high school diploma in the state of team *j*. It is possible that states with low *HSGradPct* prioritize athletic achievement, and thus teams in those states have access to better in-state talent. The third instrument I use is *ProTeamsPerMillion*, or the number of NFL, MLB, NBA, NHL teams in the same state as team *j* per million people in the state. It is possible that states with a higher ratio of professional teams per million people have a greater investment in athletics, and thus teams in those states will have access to more talented players. The fourth instrument I use is *SpringPractice*, which is a dummy variable that indicates if the state high school athletic association in the same state as team *j* allows a period of spring football practice. States that allow spring football practice likely develop higher skilled players, giving teams in those states a better talent pool to recruit from. The fifth instrument I use is *JuniorColleges*, or the number of junior college football teams in a state. The existence of junior colleges could give FBS football teams access to more high-skilled players.

Although I believe that my instruments satisfy the exclusion restriction, I am concerned that they are weak first-stage predictors because they vary so little within teams. Since prior work has found that weak instruments result in misleading inferences about parameter estimates (Bound, Jaeger, and Baker, 1993), I treat the fixed effects model as the main specification, and use the two-stage least squares model for comparative purposes.

**6 Results**

As outlined earlier, I ran a fixed effects model for my entire panel, exclusively Power Five teams, and exclusively non Power Five teams. Although the fixed effects models are my main specifications, I also ran two-stage least squares models for the same groups for comparative purposes. Regression results for all specifications can be found in Table 7.

The primary variables of interest in my models were the variables representing labor quality (*L*). Therefore, I am particularly interested in the coefficients for the *ThreeStars*, *FourStars*, and *FiveStars* variables. Since numerous studies have found that premium players had MRPs as high as one million dollars per year, I hypothesized that *FiveStars* would have a positive coefficient. The main specification produced a statistically-significant coefficient of about 1.4 million. This can be interpreted to mean that the marginal five-star player was associated with a $1.4 million increase in revenue over the marginal two-star player. This finding is roughly 40 percent higher than previous estimates of player MRP. Interestingly, the model generated a coefficient for *FourStars* that was not significantly different from zero, and a statistically significant coefficient for *ThreeStars* of about -184,000. These can be interpreted to mean that the marginal four-star player was not associated with a significantly different impact on revenue from the marginal two-star player, and that the marginal three-star player was associated with a $184,000 *decrease* in revenue compared to the marginal two-star player. This is a confusing finding that could be caused by a nonrepresentative sample, noisy data, or small sample size. At the very least, we should conclude that lower-rated players certainly do not generate nearly the MRP that five-star players do.

When these variables are broken down by Power Five status, we see different results for Power Five teams when compared to non Power Five teams. Similar to the main specification, for Power Five teams only we see that a marginal five-star player is associated with over $1 million in revenue increases compared to a marginal two-star player, but that there is no significant difference in revenue generation between a marginal four-star player and a marginal two-star player, and that the marginal three-star player is associated with a revenue loss in comparison to a two-star player. Meanwhile, non Power Five teams will not see a significant difference in revenue generation from adding any other player over a two-star player. All of this indicates that, because they have so much more to gain, Power Five teams have a much stronger financial incentive to obtain five-star players than non Power Five teams. This could be part of the reason that five-star players gravitate so strongly towards Power Five teams.

When we compare the main specification coefficients for the *ThreeStars*, *FourStars*, and *FiveStars* variables to the two-stage least squares coefficients, we see that the main specification performed better and generated estimates that are closer to MRP estimates from other studies. The two-stage least squares model associated the addition of a five-star player with a $2.9 million increase in revenue over a two-star player, which is a radical departure from estimates generated by other studies. However, this finding was not statistically significant. Neither of the coefficients for *ThreeStars* or *FourStars* were significantly different from zero, either.

Variables accounting for facility quantity and quality (*F*) performed reasonably well in the main specification. Each additional year of home stadium age was associated with a $144,000 increase in revenue, while each additional year since a stadium renovation was associated with a $267,000 decrease in revenue. With p-values of 0.116 and 0.124, these parameters are sufficiently close to significance to give credence to my hypotheses that higher stadium age and more recent renovations are seen as a quality-enhancing characteristics. Interestingly, stadium capacity did not have a statistically significant impact on revenue. This is probably because most teams do not sell out their home stadiums, and the teams that do sell out their stadiums set ticket prices high enough that demand for tickets does not exceed the stadium capacity by much.

For variables relating to facility quantity and quality (*F*), we can again see differences between Power Five teams and non Power Five teams. Among only Power Five teams, each extra year of stadium age was associated with an increase in revenue of $2.66 million. It is doubtful that an extra year of stadium age is truly increases stadium quality that much, so there may be unaccounted factors that are biasing this estimate up. None of the variables relating to *F* were statistically significant for non Power Five teams. This could be because fans are most influenced to attend a non Power Five game by the talent level of the participating teams, and don’t care much about stadium quality.

Most variables related to coaching staff quantity and quality (*S*) did not perform as expected in my main specification. Most notably, coaches that won a conference or national “coach of the year” award were associated with $2.8 million and $6.3 million *less* in revenues than coaches who had not received those awards, respectively. This is the opposite of what I predicted, and indicates that these awards may represent coaches that was the beneficiary of a lucky season, rather than coaching acumen. Alternatively, this could indicate that fans have extremely high expectations for coaches that have won these awards, and refuse to attend games when coaches fail to meet their inflated expectations. It is also possible that coaches generally win these awards with non Power Five teams when they are competing against poor competition, but are not able to replicate that success when they move on the Power Five teams. Indeed, we see that the negative impact of having a coach that won a “coach of the year” award is far greater for Power Five teams than it was in the main specification: Power Five teams that had a coach who had won a conference or national “coach of the year” award were associated with roughly $6 million and $8 million less in revenues, respectively.

Other variables relating to *S* performed better than the “coach of the year” variables. In the main specification, each additional year of total head coaching experience was associated with an increase in revenue of roughly $384,000. This is probably because only skilled coaches are able to remain head coaches for long periods of time, and coaches who are unsuccessful wash out of the coaching profession or are demoted to assistant coach roles. This finding is especially strong for Power Five schools, where an additional year of total head coaching experience was associated with roughly $669,000 more in revenues.

I hypothesized that there may be a particular coaching quality related to the number of years that a coach had been the head coach at his current school. However, none of my models show a statistically significant relationship between head coach tenure at his current school and revenue. This could be because teams are constantly trying to hire the best coaches away from each other, and coaches never build much tenure at schools as a result.

In order to control for a team’s prior performance, I included the team’s lagged SRS. In my main specification, each additional point of lagged SRS was associated with an increase of roughly $142,000 in revenue. This gives credence to the idea that a successful season one year will increase revenues in the following year. Although this finding was statistically significant across my entire panel, it was not statistically significant among Power Five teams or non Power Five teams individually. This is probably due to the small sample size when running regressions on the split samples.

In order to account for general macroeconomic conditions, I included the unemployment rate of the state that each team was located in. This was a strong predictor in my main specification, as a one percentage point increase in the unemployment rate was associated with a $3.4 million decrease in revenue. Power Five teams were more sensitive to increases in unemployment compared to non Power Five teams, as a one percentage point increase in the unemployment rate was associated with a $3.1 million decrease and a $759,000 decrease in revenues, respectively. This is likely due to the fact that Power Five teams generate much more revenue than non Power Five teams in the first place. However, if we compare the estimated effect of a one percentage point change in the unemployment rate to the average yearly revenues within groups, we see that increases in the unemployment actually hurt non Power Five teams more than Power Five teams: an increase in the unemployment rate of one percentage point will reduce the average non Power Five team’s revenue by about 20%, all else equal, compared to about 10% for the average Power Five team, all else equal.

Finally, I included a variable accounting for the number of home games a team played in a given season. I reasoned that since home games are opportunities to generate large revenues, a team that has more home games should generate more revenues. My models did not find a statistically significant relationship between the number of home games a team played and the revenue it generated. It is probably the case that time-invariant individual factors, such as fan base commitment to a team, are more important to revenue generation than the number of home games a team plays. Since I am using a fixed effects model, those time-invariant factors are controlled for, and thus the number of home games that a team plays does not have the effect on revenue that I hypothesized.

**7 Conclusions**

In this paper, I propose and develop a star-rating framework for the estimation of college football players’ marginal revenue products. The framework itself allows for the estimation of MRP for college football players of varied levels of productivity, which had previously not been accomplished in the literature. My pre-performance estimation of productivity has the added benefit of simulating the level of information that would be available to teams if they had to negotiate player salaries. Moreover, I addressed an issue raised by Krautmann (1999), who pointed out that MRP estimates should not be based on total team revenue, but the parts of revenue that are responsive to team performance.

My models produce five-star recruit MRP estimates of roughly $1.38 million annually, which is higher than comparable previous studies. When considering the value of an athletic scholarship at a typical public university, these estimates indicate that five-star athletes are experiencing up to 98% salary exploitation, as defined by Fort (2011, pp.285). The results also indicate that three and four-star players may not generate MRPs that are significantly different from replacement-level players, suggesting that NCAA rules effectively transfer wealth from five-star players to lower-rated players.

Future studies should improve on this work by generating more accurate estimates of the number of players of each star ranking that were on a team in a given season, leading to more accurate estimates. Future studies should also investigate more effective instruments for use in two-stage least squares regressions, possibly using proprietary data. Finally, future studies should introduce new variables that better account for coaching staff quality and quantity.

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**Appendices**

Table 1. Summary statistics, all schools.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Mean | Std. Dev. | Min | Median | Max |
| ThreeStars | 44.14 | 17.67 | 6 | 46 | 86 |
| FourStars | 14.15 | 16.14 | 0 | 9 | 62 |
| FiveStars | 1.26 | 2.52 | 0 | 0 | 16 |
| Lagged SRS | 1.79 | 10.25 | -23.53 | 2.17 | 24.51 |
| Unemployment | 7.94 | 1.93 | 3.27 | 7.82 | 13.5 |
| StadiumCapacity | 56468.02 | 22394.33 | 20000 | 55000 | 109901 |
| StadiumYearsOpen | 61.17 | 27.02 | 0 | 64 | 101 |
| StadiumYearsSinceRenovation | 7.06 | 5.76 | 0 | 6 | 27 |
| Homegames | 6.42 | 0.73 | 4 | 6 | 8 |
| CoachTotalExperience | 6.54 | 6.18 | 0 | 5 | 28 |
| ConferenceCoachOfYear | 0.53 | 0.50 | 0 | 1 | 1 |
| NationalCoachOfYear | 0.18 | 0.38 | 0 | 0 | 1 |
| CoachSchoolExperience | 3.76 | 4.45 | 0 | 2 | 27 |
| Population/D1Programs | 2376952.88 | 1460976.78 | 564376 | 1975239.8 | 8943010 |
| HSGradPct | 88.31 | 2.95 | 82 | 88.22 | 94.86 |
| ProTeamsPerMillion | 0.29 | 0.25 | 0 | 0.31 | 1.04 |
| SpringPractice | 0.58 | 0.49 | 0 | 1 | 1 |
| JuniorColleges | 1.81 | 3.37 | 0 | 0 | 14 |
| PerformanceResponsiveRevenue (thousands USD) | 20868.10 | 21085.03 | 454.22 | 14827.94 | 151379.85 |

Table 2. Summary statistics, Power Five teams.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Mean | Std. Dev. | Min | Median | Max |
| ThreeStars | 52.95 | 12.90 | 20 | 54 | 86 |
| FourStars | 21.37 | 15.95 | 0 | 16 | 62 |
| FiveStars | 1.93 | 2.92 | 0 | 1 | 16 |
| Lagged SRS | 6.20 | 8.28 | -14.87 | 6.06 | 24.51 |
| Unemployment | 7.82 | 1.94 | 3.27 | 7.76 | 12.58 |
| StadiumCapacity | 68544.68 | 17710.13 | 32740 | 64150.5 | 109901 |
| StadiumYearsOpen | 70.00 | 26.01 | 1 | 83 | 101 |
| StadiumYearsSinceRenovation | 6.44 | 4.97 | 0 | 6 | 25 |
| Homegames | 6.70 | 0.61 | 5 | 7 | 8 |
| CoachTotalExperience | 7.78 | 6.33 | 0 | 6 | 28 |
| ConferenceCoachOfYear | 0.63 | 0.48 | 0 | 1 | 1 |
| NationalCoachOfYear | 0.24 | 0.43 | 0 | 0 | 1 |
| CoachSchoolExperience | 4.35 | 4.95 | 0 | 3 | 27 |
| Population/D1Programs | 2689560.61 | 1611197.94 | 742609.25 | 2202384 | 8943010 |
| HSGradPct | 88.67 | 2.88 | 82 | 88.91 | 94.04 |
| ProTeamsPerMillion | 0.32 | 0.25 | 0 | 0.31 | 1.04 |
| SpringPractice | 0.59 | 0.49 | 0 | 1 | 1 |
| JuniorColleges | 1.98 | 3.52 | 0 | 0 | 14 |
| PerformanceResponsiveRevenue (thousands USD) | 30226.52 | 20838.28 | 4445.43 | 24237.83 | 151379.85 |

Table 3. Summary Statistics, non Power Five teams.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Variable | Mean | Std. Dev. | Min | Median | Max |
| ThreeStars | 28.09 | 13.37 | 6 | 25 | 69 |
| FourStars | 0.99 | 1.76 | 0 | 0 | 9 |
| FiveStars | 0.02 | 0.15 | 0 | 0 | 1 |
| Lagged SRS | -6.23 | 8.49 | -23.53 | -6.155 | 18.69 |
| Unemployment | 8.15 | 1.89 | 4.13 | 7.83 | 13.5 |
| StadiumCapacity | 34477.70 | 9681.36 | 20000 | 30850 | 65857 |
| StadiumYearsOpen | 45.10 | 20.75 | 0 | 45 | 82 |
| StadiumYearsSinceRenovation | 8.19 | 6.86 | 0 | 6 | 27 |
| Homegames | 5.91 | 0.64 | 4 | 6 | 8 |
| CoachTotalExperience | 4.29 | 5.20 | 0 | 2 | 23 |
| ConferenceCoachOfYear | 0.36 | 0.48 | 0 | 0 | 1 |
| NationalCoachOfYear | 0.06 | 0.24 | 0 | 0 | 1 |
| CoachSchoolExperience | 2.69 | 3.09 | 0 | 2 | 14 |
| Population/D1Programs | 1807726.86 | 895300.36 | 564376 | 1599070.25 | 4837659.75 |
| HSGradPct | 87.66 | 2.97 | 82 | 87.5 | 94.86 |
| ProTeamsPerMillion | 0.25 | 0.23 | 0 | 0.31 | 0.79 |
| SpringPractice | 0.55 | 0.50 | 0 | 1 | 1 |
| JuniorColleges | 1.51 | 3.07 | 0 | 0 | 14 |
| PerformanceResponsiveRevenue (thousands USD) | 3827.41 | 3684.98 | 454.222 | 2640.90 | 23819.12 |

Table 7. Regression Results

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Variable  (Cohort) | FE  (All teams) | TSLS  (All teams) | FE  (Power Five) | TSLS  (Power Five) | FE  (Non Power Five) | TSLS  (Non Power Five) |
|
| ThreeStars | -183.6\*\* | -187.0 | -480.4\*\*\* | 142.9 | -43.8 | -175.4\* |
| (-2.17) | (-1.34) | (-3.44) | (0.98) | (-1.21) | (-1.88) |
| FourStars | -160.47 | -623.6 | -15.67 | -159.1 | -73.1 | 649.6 |
| (-0.92) | (-1.35) | (-0.07) | (-0.26) | (-0.22) | (0.70) |
| FiveStars | 1383.1\*\* | 2860.2 | 1063.9 | 1908.2 | 481.8 | -5885.9 |
| (2.26) | (1.21) | (1.48) | (0.72) | (0.22) | (-0.50) |
| Stadium Capacity | 0.15 | 0.80\*\*\* | 0.02 | 0.75\*\*\* | 0.25 | 0.23 |
| (0.85) | (6.0) | (0.08) | (5.07) | (0.88) | (4.49) |
| Stadium Years Open | 144.01 | 29.5 | 2658.3\*\* | -31.6 | -18.7 | -25.8 |
| (1.58) | (1.44) | (2.07) | (-1.1) | (-0.52) | (-1.82) |
| Stadium Years Since Renovation | -266.9 | -77.8 | -62.07 | 114.5 | 58.7 | -58.7 |
| (-1.54) | (-0.72) | (-0.28) | (0.84) | (0.52) | (-0.98) |
| Coach Total Experience | 383.5\*\* | 73.57 | 668.7\*\* | 188.5 | 21.7 | -141.9\* |
| (2.23) | (-0.22) | (2.54) | (0.84) | (0.34) | (-1.75) |
| Coach School Experience | 74.6 | -43.19 | -256.16 | -225.1 | 65.4 | 141.6 |
| (0.77) | (-0.22) | (-0.71) | (-1.03) | (0.59) | (1.18) |
| Conference COY | -2821.4 | 2538.9 | -5995.0\*\* | 2174.8 | 57.5 | -701.4 |
| (-1.60) | (1.63) | (-2.24) | (1.03) | (0.08) | (-0.83) |
| National COY | -6259.9\*\*\* | 300.58 | -8034.4\*\* | -15.1 | -2857.9\*\* | 825.9 |
| (-2.60) | (0.13) | (-2.53) | (-0.01) | (-2.06) | (0.40) |
| Lagged SRS | 142.4\* | 491.71\*\* | 107.84 | 396.0 | 39.0 | 217.5\*\*\* |
| (1.71) | (2.19) | (0.81) | (1.27) | (1.25) | (3.35) |
| Unemployment Rate | -3405.3\*\*\* | -2025.0\*\*\* | -3073.6\*\* | -2625.0\*\*\* | -758.7\*\*\* | -477.6\*\*\* |
| (-9.57) | (-6.17) | (-2.20) | (-6.86) | (-5.00) | (-2.37) |
| Home games | -792.23 | 184.33 | -100.7 | -1676.9 | -248.3 | 1253.7\*\* |
| (-0.90) | (0.13) | (-0.08) | (-1.15) | (-0.69) | (2.22) |
| Observations | 378 | 378 | 244 | 244 | 134 | 134 |
| R-square | 0.32 | 0.83 | 0.45 | 0.87 | 0.37 | 0.65 |
| Note: Parameters in thousands of US dollars. T-statistic in parentheses. | | | | | | |
| \*p < 0.10. \*\*p < 0.05. \*\*\*p < 0.01. | | | | | | |

1. Football Bowl Subdivision (FBS) is a newer classification that applies to universities that were previously classified as NCAA Division I-A. [↑](#footnote-ref-1)
2. Professional teams located in Washington, DC are counted for both Maryland and Virginia. [↑](#footnote-ref-2)