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Because It's Worth It:

Why Schools Violate NCAA Rules and the Impact of Getting Caught in Division I Basketball

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The value of star college basketball players to their schools is examined using information known during the recruiting process (i.e., ex ante marginal revenue product). Under various regression models, five-star basketball players (those in the top few percent of college basketball players) are worth more than one million dollars per year to their schools, on average. Given the much smaller size of athletic scholarships (which are capped by NCAA rules), it is thus not surprising that many star athletes have been alleged in federal court proceedings in the Southern District of New York to have been paid under-the-table to attend certain schools.[1] However, even in the rare instance when those athletes and schools are caught by the NCAA and punished, the effect of the subsequent probation on their financial outcomes is statistically no different than comparable schools, thus providing no incentive to stop the underground payments. A discussion follows of the application of these findings to the recent FBI investigation (and resulting lawsuit involving James Gatto and others) of payments to star basketball players' families.

Keywords: Marginal Revenue Product, regression, NCAA, athletic scholarship, violation, probation, recruiting

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[1] See, for example, a summary of the allegations and testimony: https://www.newsobserver.com/sports/article208880939.html

In 2009, Utah State Athletic Director Scott Barnes noted the importance of Division I intercollegiate athletics to their affiliated universities with terminology that would be repeated by numerous other athletic directors and college presidents, “Athletics are the front porch of the university…It’s not the most important room in the house, but it is the most visible” (Longman, 2009, para. 18). The front porch of the university - particularly when the most prominent sports of men’s basketball and football are successful – can provide spillover effects for the entire institution including increased applications and overall enrollment, improved quality of incoming students (by overall grade point average and standardized test scores), enhanced donations and amplified perception of the institution by other university presidents (Anderson, 2017; Goff, 2000; Pope & Pope, 2009; Rascher & Schwarz, 2015).

Though Division I universities actively tout the importance of major college athletics as a marketing tool – frequently using this “front porch” metaphor (Bass, Schaeperkoetter & Bunds, 2015)[2] – they also serve to enhance the institutions’ direct bottom line. As noted by Schwarz (2016), the repeated commentary by universities and the National Collegiate Athletic Association (NCAA) that nearly every big-time college athletic department loses money, and has been doing so for a century or more, is largely false. Revenues for men’s basketball (a sport every Division I member offers) continue to grow rapidly. Since 1985, more than 85 schools have financially committed to enhance their investment in their sport programs by joining Division I, while very few have voluntarily chosen to drop their Division I affiliation. A number of reported expenses that universities claim are bankrupting college sports are typically simply intra-institutional transfers that have zero effect upon the financial bottom line of the college campus (Dosh, 2013; Goff, 2000).

Within this highly lucrative Division I basketball environment, the search for and acquisition of talented players is governed by the NCAA’s rules on recruiting and its grant-in-aid system that limits the compensation a college athlete can receive, even though many of those recruited athletes can provide hundreds of thousands or even millions of dollars in revenue for their institutions (Berri, 2018). NCAA rules are designed to prevent the use of financial inducements above the full cost of attendance (COA) scholarship, but cheating on the NCAA rules often occurs when athletes are recruited. For example, in 2015, Syracuse University was reprimanded by the NCAA for an ongoing series of violations committed by the head basketball coach, boosters, and a number of other university officials. More recently, in 2017 the Federal Bureau of Investigations announced an ongoing and wide-ranging probe that included the alleged payment of $100,000 to the family of star basketball recruit Brian Bowen to play for the University of Louisville. The trial that stemmed from those investigations ended in October 2018. Of note, there was evidence presented that payments were offered to high school star basketball players to attend certain universities, including Louisville, Kansas, North Carolina State, Arizona, Creighton, DePaul, and Oregon (McCann, 2018).

The NCAA retains an enforcement division that investigates recruiting violations, but it is not known to the public (and perhaps not to the NCAA itself) how effective enforcement activities are at curtailing violations of NCAA rules. For example, from 2005 to 2015 there were

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[2] For two examples of schools using this term see https://news.berkeley.edu/2018/08/23/new-athletics-director-sports-are-the-front-porch-of-uc-erkeley/ and https://blog.seattlepi.com/huskies/2011/04/27/new-uw-president-on-athletics-its-the-front-porch/

113 reported major violations on the NCAA's LSDBi database (across all sports). These violations resulted in a number of potential penalties, including vacating previous wins, limits on recruiting opportunities, curtailing of scholarships available to be offered to athletes, post-season bans, and individual censure of coaches and other athletic personnel. Specific to basketball recruiting, there were 33 recruiting violations from October 2006 through November 2017, or about three per year.

During the same time period, there were likely other recruiting violations that went undetected or a lack of sufficient evidence was uncovered to effectively go forward with an NCAA case (Solomon, 2016). For example, while the charges in federal court surrounding third-party payments only involve Adidas employees and consultants, the parties alluded to similar unspecified conduct by Nike and Under Armour.[3] While there is a dearth of research on the subject, Cullen, Latessa, and Johnson (2012) analyzed 648 surveyed athletes (about half of them men's Division I basketball players) and concluded that 38% of respondents violated NCAA recruiting rules. The more highly recruited athletes were more likely to have recruiting infractions and "given the prevalence of rule breaking, it is likely that *virtually every college athletic program contains student-athletes that have violated NCAA regulations*" (p. 690; emphasis in original). The authors also noted that "because these scandals have occurred for many years, cheating seems integral to the collegiate athletic enterprise" (Cullen et al., 2012, p. 669).

It is clear that the time has come for a renewed focus on NCAA rules violations, as the stakes are higher now given the much larger revenues generated. However, there is difficulty in conducting such research, as those involved have little incentive to provide the necessary information. Yet, previous literature paints a consistent picture of frequent rules violations. For example, Cullen, Latesa, & Byrne (1990), surveyed 192 head football coaches in Division I (both what is today called FBS and FCS football) and concluded that "more than 30% of programs committed serious violations on a regular basis and that almost half had committed at least one serious violation in the past 5 years" (p. 670). Sack (1991), in a survey of NFL players, found that around one-third had accepted prohibited benefits either while playing in college or during the recruiting process. The implication is that the NCAA detected and punished a very small fraction of the actual NCAA rules violations that occurred during the 1990s.

Why have NCAA member schools (or their stakeholders) historically been involved in violating the NCAA rules, especially if they know they may be punished? Two related hypotheses emerge. One is that the quality of the athletes that a school is able to attract by offering more than is allowed significantly exceeds the costs (excluding NCAA punishments and reputational harm) that flow from paying those athletes to attend the school. In other words, the value that the athlete provides to the athletic department as well as to the school in general via the front-porch effect, is substantial – it is "worth it" to break the rules if one does not believe one will get caught. A second, related hypothesis is more probabilistic – that the expected value of recruiting the higher quality athlete, even accounting for the additional costs that would flow from getting caught, exceeds the expected cost (true scholarship cost plus the probability of getting caught multiplied by the cost of the punishment) – it's "worth it" to break the rules even if you think you might get caught. Harris (2016) concurs: "By cheating and offering star [athletes] cash or in-kind benefits exceeding the NCAA-defined legal maximum, the schools can obtain more talented athletes and increase their winning percentages and their economic rent" (p.

[3] https://www.kansascity.com/sports/college/big-12/university-of-kansas/article220234535.html

417).[4] Similarly, Smith (2015, p. 97) shows that universities "suffer little economic or reputational damage when their athletic programs are penalized for violating Association rules."

Even though an exact estimate of the probability of getting caught is not known, a sufficient condition or corollary to the hypothesis is that even if a school gets caught and is punished it may be that the punishment has so little of a negative effect on the school that it is "worth it" anyway. In other words, even if one assumes the probability of getting caught is 100%, the benefits may still be seen to exceed the costs. That is, it may be "worth it" to break the rules even if one is certain one will get caught.

> Hypothesis 1: The economic value of a high quality athlete to a school is expected to exceed the true cost of the athlete to the school.
>
> Hypothesis 2: Even for schools that get caught and are punished for violating NCAA rules, they are no worse off financially after the probation is over than they would be otherwise.

Methods

Hypothesis 1

Are NCAA Division 1 basketball recruits expected to be worth more to their schools than they are expected to cost (leaving aside the question of punishment for violations), and by how much? Existing research typically assesses athlete value by means of the marginal revenue product (MRP), which estimates the incremental value (marginal product or MP) that an athlete has on the production of the product (the product is often defined as wins in these studies) multiplied by the marginal revenue (MR) of an additional unit of sales. This line of inquiry (with respect to college basketball) began with the seminal work of Brown (1994),[5] where he showed that star basketball players may be worth $1,000,000 per year to their universities. Brown and Jewell (2004) updated this work with similar results. Since Brown's work, others have extended the analysis beyond players who later played professionally. For example, Lane, Nagel, and Netz (2014) found, using data from 2001-2006, that the average Division I basketball player had an *ex post* (or realized) MRP of about $90,000 per year. Berri (2018) estimated that star basketball players at Duke University were worth more than $1 million per year in incremental value that they brought to the basketball program. More recent work has been done for college football as well (Goff, Kim, & Wilson, 2017).

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[4] The collusive scholarship limit produces a monopsony rent (or economic rent, i.e., super-competitive profit) from the athletes, which is transferred to the universities (Blair and Whitman, 2017; Harris, 2016).

[5] Across all sports, Gerald Scully was the pioneer of measuring player value when he published an article in the *American Economic Review* (Scully, 1974) looking at the value of Major League Baseball players. He determined that they were being paid about 20% of their MRP, and attributed that to the labor market in which they participated, which was under MLB's *reserve clause* preventing athletes from selling their services in an open market.

An important issue with these *ex post* studies is that not everyone lives up to their *ex ante* potential. Some athletes get injured, some only pan out to be practice players, others redshirt their freshmen year (meaning that don't play in games until their sophomore year). In each of these cases, the measured value of these players is essentially $0, because the MRP method, as described, utilizes individual playing statistics, like points and rebounds, to generate wins, which then generate revenues. If a player is not playing in games, they do not generate any statistics. Lane *et al.* (2014) noted this failure in the *ex post* studies compared to the actual labor market for recruiting athletes, which is *ex ante* in nature in that colleges are recruiting athletes based on their potential, not on how they actually end up playing in the subsequent years, when they stated (p. 253):

> One explanation for the MRPs that are below the scholarship limit is that athletic scholarships are set ex ante, before the season and hence based on a student-athlete's expected performance, while the estimates of MRPs are ex post, based on the student-athlete's actual performance. Thus, ex post a player's MRP may be below his scholarship limit, while ex ante his MRP is above a scholarship limit.

Recent work by Borghesi (2018) begins to tackle this flaw in the existing literature by assessing the MRP impact of athletes based on *ex ante* assessment of athlete quality. Borghesi uses ratings of high school athletes from the rating service 24/7, maps those values to their expected impact on statistical measures of on-court value (i.e., how *ex ante* talent drives an *ex post* result, i.e., winning), and then follows the traditional path to map wins to MRP. Borghesi's models assume that all schools receive the same impact from a given athlete because each is a linear model without conference controls. But this fails to account for the fact that Power 5 schools generate about five times more revenue from basketball than the remaining schools in Division I. Also, Borghesi utilizes only the incoming freshmen and sophomore classes of recruiting data for a given school, implying that no juniors or seniors on a team matter to revenue. Berri (2018) showed that college athletes at the end of their college career are more valuable than at the beginning, which is not surprising. Finally, Borghesi includes measures of winning (RPI Rating, which is a ranking measure of the team based on how well it is performing) and athlete star rankings in the same models even though those athletes are the key factor in creating those RPI Ratings. In other words, there may be important collinearity between star ratings and RPI Ratings – collinearity issues from similar variables (Winning and RPI Ratings) have been shown to be significant in the past (Rascher & McEvoy, 2012). Unlike Borghesi (2018), this article does not use RPI Ratings, but instead uses only win-loss percentage to avoid one type of collinearity problem. Additionally, as described below, this article uses a two-stage model to account for the endogeneity and collinearity between win-loss percentage and star ratings.

Our study, therefore, accounts for these factors in two separate models. In the first, we test how *ex ante* athlete quality (as measured by star rankings) directly affects revenues. The baseline equation for this model is as follows:

$$MBBRev_{it} = \alpha + \beta_1 Stars_{it} + \beta_2 Conf_{it} + \beta_2 Year_t + \varepsilon_{it}, \tag{1}$$

where $MBBRev_{it}$ represents annual men's basketball revenue for school *i* in year *t*, α and β_n (*n*=1, 2, 3) are vectors of parameters to be estimated, $Stars_{it}$ represents the measure of talent for school i in year t, $Conf_{it}$ are conference indicator variables, $Year_t$ are year indicator variables, and ε_{it} is the error term. Sensitivity tests for how $Stars_{it}$ is defined are undertaken (as shown in Table 3). Further, the same models, but with logged $MBBRev_{it}$ are examined (Table 4).

In the second, we use a two-stage model which relates star ratings to winning (the marginal product part of MRP) and then winning to revenues (the marginal revenue part of MRP), an approach more commonly used with past studies, as previously discussed. The two-equation system representing the model is as follows:

$$WL_{it} = \theta_1 + \gamma_1 Stars_{it} + \gamma_2 Conf_{it} + \varepsilon_{it} \tag{2}$$

$$\ln(MBBRev)_{it} = \theta_2 + \gamma_3 \widehat{WL}_{it} + \gamma_4 Conf_{it} + \gamma_5 Year_t + \epsilon_{it}, \tag{3}$$

where WL_{it} is the winning percentage of team i in year t. Equation (3) is based on the triangular hierarchical structure of the two-stage model, with the fitted values from stage one (Equation (2)) as inputs into Equation (3). The other variables are similarly defined as in the previous model, Equation (1), with the θ and γ parameters to be estimated.

The models give broadly similar results, but we prefer the former because the latter approach limits a star athlete's impact on a team's revenues only through winning and not the possible effect of star power on fan engagement and general revenue generation. We also use a different functional form than Borghesi, log-linear, which allows for a more appropriate interactivity between the athletes' talent and the schools' revenue generation potential (a linear model is also included as a robustness check), reflecting the joint nature of the value-proposition. Finally, we use multiple years (five) of combined talent data in order to capture the performance of a star player within the context of the entire team.

In order to test Hypothesis 1, we utilized the star ratings of the athletes as generated by Rivals.com, which rates male high school basketball players who are being recruited by universities as either five, four, three, two, or zero stars, with five stars being the most highly rated.[6] These star ratings are used to predict the variation in team revenues (utilizing two different measures), controlling for conference and year fixed effects.[7]

In each of these studies, we are careful to control for the fixed effect of each school's conference affiliation. Conferences, such as the Southeastern Conference, generate a significant amount of revenue through conference media contracts, post-season championships, and distributions from the NCAA.[8] These conferences typically distribute the revenues equally (or

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[6] Rivals.com rarely utilizes a one-star ranking as part of its system.

[7] Team revenues are measured using two methods. Method 1 utilizes men's basketball revenues reported by universities to the U.S. Department of Education through the EADA (Equality in Athletics Disclosure Act) database. Method 2 uses these revenues, but also allocates the revenues that universities report as "unallocated by sport," using the proportion of men's basketball revenues to total allocated revenues.

[8] See, for example, the SECs federal tax return (Form 990) for fiscal year 2016, available at https://projects.propublica.org/nonprofits/organizations/630377461/201820329349301102/IRS990. In this year, the SEC reported $409 million in "TV/Radio Rights Fees" and $185 million in "Postseason events." The NCAA's most recent distributions report $36 million of distributions to the SEC. http://www.ncaa.org/sites/default/files/2011-12%2BDivision%2BI%2BTotal%2BRevenue%2BDistribution.pdf

nearly so) to all conference members (e.g., in 2016-17, the SEC distributed almost $600 million to its member schools, at approximately equal amounts),[9] which itself was an increase from the prior year.[10] Conferences tend to align themselves with similarly situated schools in terms of investments in athletics. Thus, much of what drives individual team revenues is its conference affiliation. Failing to control for this critical revenue driver can over-attribute incremental revenue gains to individual athletes.

The main independent variable, *Total Team Stars*, is simply the sum of the star ratings for the most recent five consecutive years. We use five consecutive years to account for the likely players that are actually on the roster. Of course there is a chance the higher rated athletes leave before the fifth year, meaning that a given team's five-year aggregate star count will tend to overstate the true team talent level; to the extent this occurs, the value of each star is under-stated. However, as a test for this potential bias, we explored alternative models that utilized indicator variables for each of the number of five-, four-, three-, and two-star athletes on the team. An assessment using the most recent four years of athletes' star data provides similar results.

Hypothesis 2

Hypothesis 2 is an extreme version of the simple notion that the expected result from violating the NCAA's recruiting rules is that the school's athletics department is no worse off financially than it was prior to the probation, even relative to comparable schools. In other words, while a school may grow its basketball revenues over time even while having faced probation, are those revenues keeping pace with where they would have expected to be if not for the probation? Therefore, the changes in revenues are compared to a control group, the other schools in the same conference, using a log-linear regression.

The regression model predicts logged basketball team revenue (or allocated basketball team revenue[11]) as a function of a probation indicator variable (for the year the probation began), lagged probation indicators (to account for the effect of previous years' probation), a probation severity variable (indicating the number of years the probation period lasted), and then some control variables: winning percentage, lagged winning percentage, conference fixed effects, school fixed effects (although never both at the same time), and year fixed effects. Specifically, the baseline model is as follows:

$$\ln(MBBRev)_{it} = \omega + \varphi_1 Prob_{it} + \varphi_2 Prob_{it-1} + \varphi_3 Prob_{it-2} + \varphi_4 Prob_{it-3} + \varphi_5 ProbSev_{it} + \varphi_6 WL_{it} + \varphi_7 WL_{it-1} + \varphi_8 Conf_{it} + \varphi_9 Year_t + \sigma_{it}, \quad (4)$$

[9] https://www.sbnation.com/college-football/2018/2/2/16964186/sec-revenue-distribution-2017
[10] See SEC Form 990, Schedule A. https://projects.propublica.org/nonprofits/organizations/630377461/201820329349301102/IRS990ScheduleA
[11] To allocate revenue, we assigned all revenue categorized as "institutional" (sometimes referred to as "unallocated by sport and/or gender" rather than sport-specific to sports proportional to the revenue the school has assigned on a sport-by-sport basis. We run this as an alternate dependent variable. See Section III, on data, below.

where $Prob_{it}$ is a probation indicator variable along with its lagged versions, $ProbSev_{it}$ is a measure of the severity of the probation. The other variables in Equation (4) are defined as above, and the parameters ω and φ are to be estimated.

Sample Data

Hypothesis 1

The *Equity in Athletics Disclosure Act* requires universities to provide fairly detailed data to the U.S. Department of Education on athletics financials, headcount, etc. This source provides the information for the dependent variable, basketball team revenue, for 2008-09 through 2016-17. There are two measures of basketball team revenue. The first simply comes from what the schools self-report as basketball revenue.[12] The second starts with the self-reported figure but then takes the billions of dollars annually in Division I revenue that is not allocated by sport and allocates it to each sport based on how the sport-specific revenue is allocated (e.g., if a school's allocated basketball revenue comprises 42% of all revenue allocated to specific sports, we add 42% of the unallocated revenue to that self-reported figure). Much of this unallocated revenue is driven by big media deals, sponsors, and donors that would not lead to the large dollar amounts if not for the actual sports themselves. For example, in 2011-12, The Ohio State University reported over $19 million in donations to athletics, but only $170,068 was listed as being for football (with men's basketball at about $85,000). The remaining sports summed to less than $70,000.[13] It is clear this accounting bears no relationship to the economic reality; the existence of and success of the football team and (to a lesser extent) the men's basketball team drive a substantial portion of these millions in donations.

For our key variable of interest, we collected Rivals.com data on the star rating of each male basketball prospect from 2008-09 (labeled 2009) through 2016-17 (labeled 2017).[14] Only complete sets of data for each school were used, thus the result is a balanced panel data set for 172 schools in Division I. A summary of the data is included in Table 1.

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[12] In the recent *Alston v. NCAA* litigation, expert witness Daniel A. Rascher showed that EADA revenue for men's basketball was 99% correlated with the actual internal data submitted by schools to the NCAA, and a simple regression of the latter on the former revealed a coefficient of 1.03 with a t-statistic of over 282. See "Expert Report of Daniel A. Rascher on Economic Liability Issues for the Injunctive Classes," (March 21, 2017), available at https://drive.google.com/file/d/1KVvfZys5oBZSlGK-vk39zzpydM7UD3ls/view?usp=sharing

[13] Available at https://drive.google.com/file/d/16y7PC7oHdZAd-fD4Uf0W4cLceu7GP_Ky/view?usp=sharing, which was obtained via a freedom of information act request.

[14] Rivals data for years prior to 2008-09 utilized a different database structure and reporting system, thus complicating comparisons over periods pre- and post-2008.

Table 1. Summary of Data for Star Regression Model

Teams	172
Conferences	32
Years	2009-2017

Variable	Observations	Min	Max	Mean
Unallocated Revenue	1548	$231,984	$45,835,799	$6,112,427
Allocated Revenue	1548	$502,668	$60,623,444	$8,619,846
Aggregate Stars	860	0	135	34.3
Aggregate 5-star athletes	860	0	21	0.75
Aggregate 4-star athletes	860	0	16	2.4
Aggregate 3-star athletes	860	0	23	6.5

Hypothesis 2

The data on whether (and for how long) a school went on probation for a recruiting violation was gathered from the NCAA's own LSDBi major infractions database.[15] Each probation had to be analyzed to be sure that it related to a male basketball player recruiting violation. Twenty-seven schools were found to have gone on probation during the studied time period for a relevant reason (i.e., recruiting violations). Of these, two schools that went on probation twice during the relevant period were excluded, leaving 25 total schools.[16] EADA revenue data was collected for 2006-07 (labeled 2007) through 2016-17 (labeled 2017).[17] Win-loss records for basketball were gathered from sports-reference.com. A summary of the data appears in Table 2.

Table 2. Summary of Probation Regression Data

Teams	320
Conferences	35
Years	2007-2017
Schools on probation	25

Variable	Observations	Min	Max	Mean
Unallocated Revenue	3,498	$231,984	$45,835,799	$6,112,427
Allocated Revenue	3,498	$502,668	$60,623,444	$8,619,846
Win-Loss Record	3,498	0	0.97	0.51
Probation severity (years)	3,498	0	5	0.19

[15] https://web3.ncaa.org/lsdbi/
[16] In these two examples, the probation periods for a given school overlapped. Thus, it is difficult if not impossible to separate the effects of each individual probation from the cumulative impact. In other words, there is not a three-year period before and after probation that is unaffected by the other probation.
[17] EADA data pre-2006 follows a different reporting system than post-2006, making comparisons overtime problematic.

Results

Hypothesis 1

As shown below in Table 3, an individual point of star rating is worth almost one-quarter of a million dollars per year to the basketball program (when utilizing basketball revenue that includes the unallocated revenue), and about $160,000 when using the more narrowly defined basketball revenue. The goodness-of-fit (Adjusted R^2) is about 65%, with 860 observations in the model. When separate indicator variables are used to allow for piecewise non-linear impacts of star ratings (e.g., allowing a five-star athlete to be worth more or less than three-star plus two-star athletes), five-star athletes are worth about $1.5 million per year (nearly $1 million with the narrower dependent variable), with four-star athletes being worth somewhat less than $900,000 (or greater than $660,000 in the alternative model).

Table 3. Star Model Estimating Value of Basketball Players to their Schools

OLS Model
*p-values in parentheses * p<0.05 ** p<0.01 *** p<0.001*

Dependent Variable	MBB Revenue with Allocation				MBB Revenue without Allocation			
Aggregate Stars	242,971.8***				158,664.3***			
Aggregate Stars (3-5)		246,963.0***				161,634.3***		
Number 5-Star Athletes			1,593,263.2***	1,639,251.3***			981,792.0***	998,555.4***
Number 4-Star Athletes			870,416.2***	900,418.3***			661,631.0***	672,567.3***
Number 3-Star Athletes			11,314.4	71,883.3			409.5	22,487.8
Number 2-Star Athletes				-87,450.1				-31,877.0
Conference Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-1,111,928.3	-373,052.6	6,220,867.0***	6,068,592.1***	-814,574.9	-347,709.5	3,914,512.2***	3,859,005.4***
N	860	860	860	860	860	860	860	860
adj. R-sq	65.9%	66.4%	75.5%	75.5%	64.8%	65.3%	73.0%	72.9%

The log-linear model (Table 4) allows for the impact to be non-linear and vary with the size of the basketball program. In other words, higher-revenue programs likely benefit more in terms of incremental dollars than smaller-revenue programs, and this analysis allows for that assumption. The Adjusted R^2 are substantially higher in these models (over 85%, thus 10-20 percentage points higher than the levels models), indicating that the data are non-linear in nature and so the log-linear approach is appropriate. The results indicate that each star is associated with an increase of 1.6% in revenue (and the coefficient is statistically significantly different from zero). A 5-star athlete tends to be associated with about 7-8% more revenue per year, which can take on quite a range across the varying levels of revenue associated with different calibers of men's basketball programs.

Table 4. Log-Linear Model Estimating Value of Basketball Players to their Schools

Log-Linear Model
p-values in parentheses ** p<0.05 ** p<0.01 *** p<0.001*

Dependent Variable	Log MBB Revenue with Allocation				Log MBB Revenue without Allocation			
Aggregate Stars	0.0161***				0.0164***			
Aggregate Stars (3-5)		0.0162***				0.0166***		
Number 5-Star Athletes			0.0728***	0.0803***			0.0666***	0.0788***
Number 4-Star Athletes			0.0578***	0.0626***			0.0600***	0.0679***
Number 3-Star Athletes			0.00881***	0.0186***			0.0108***	0.0270***
Number 2-Star Athletes				-0.0141*				-0.0233***
Conference Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	15.21***	15.26***	15.59***	15.57***	14.71***	14.76***	15.08***	15.04***
N	860	860	860	860	860	860	860	860
adj. R-sq	85.9%	86.1%	87.2%	87.3%	85.9%	86.2%	86.8%	87.1%

As a consistency check, we also developed a two-stage model that takes the more traditional approach, first measuring the impact of star ratings on winning (controlling for fixed effects) and then using the fitted values from that analysis to estimate the effect of winning on team revenue (again, controlling for fixed effects). The results of this model are shown in Table 5. The key variables in both models are statistically significant. An additional star rating in the first-stage model is statistically related to changes in winning, which in turn are associated with changes in logged revenues, such that one more star ratings point is associated with 1.6% increase in revenues, very similar to the more direct models in Table 4.[18]

Table 5. Two-stage Talent to Winning and Winning to Revenue Model

Estimation	Coefficient	Adjusted R^2	N
Stage 1: Regression of win-loss record on number of stars	0.0034***	0.1545	850
Conference indicator variables	Yes		
Stage 2: Regression of logged team revenue (allocated) on Stage 1 win-loss fitted values	4.775***	0.8576	850
Conference and year indicator variables	Yes		

[18] A model that measures the effect of both winning and star ratings in the same regression (with appropriate fixed effects) has similar findings, but the coefficient on star ratings drops from about 1.6% to about 1.3%, from the mild collinearity between the two variables.

Hypothesis 2

It is clear that teams that go on probation nevertheless continue to grow their revenues. For example, simply comparing basketball team revenue from the three years prior to going on probation with the same measure three years after the start of probation shows that revenue grew (for the 17 schools with data in the prior and post three years) from about $8 million per year to $12 million per year. In other words, these seven years (including the year that probation began) show a very large increase in revenue *despite* being on probation for the last three years of the period. Of course, schools not on probation also saw revenue increases, therefore, an econometric model that accounts for typical growth in revenues is analyzed.

The four models displayed in Table 6 measure the impact of probation on basketball team revenues by including a probation indicator and its one-, two-, and three-year lags, a probation severity variable, win-loss percentage (and its lag), and year fixed effects, and either conference fixed effects or school fixed effects.[19] As with the star model above, the logged models tend to have high goodness-of-fit (86% to 97%). None of the probation indicator variables, or the probation severity variable, are significantly different from zero. Winning and its lag are highly significant (and the fixed effects, though not shown below, are also significant). When probation is defined as 0 prior to the first year of probation and as 1 during each of the years after probation (and there are conference fixed effects), there is a positive and statistically significant impact of about 10%. That is, we see teams on probation with higher revenue than would otherwise be the case in years after probation. Given that the variable is not significant when controlling for team fixed effects, this may be detecting specific teams that grow revenue substantially after probation. The nature of the variable is such that it gives equal weight to all years after probation, thus providing a blunter instrument than in the previous models with individual probation year indicators.

[19] An analysis in levels (not logs) had an Adjusted R^2 that was 20 percentage points lower than the logged models.

Table 6. The Effect of Probation on Basketball Revenues

*p-values in parentheses *p<0.05 **p<0.01 ***p<0.001*

Dependent Variable	Log MBB Revenue with Allocation			
Probation Indicator	0.110	-0.0977		
Prob Indicator Lagged 1 Year	0.0128	-0.0365		
Prob Indicator Lagged 2 Years	0.0760	-0.00838		
Prob Indicator Lagged 3 Years	0.102	0.0330		
Probation Before-After (After=1)			0.102**	0.0540
Probation Severity	-0.0337	0.0224	-0.0242	-0.0140
Win-Loss %	0.500***	0.0996***	0.500***	0.107***
Win-Loss % Lagged 1 Year	0.507***	0.0828**	0.516***	0.0967***
Conference Fixed Effects	Yes		Yes	
Team Fixed Effects		Yes		Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Constant	15.25***	14.84***	15.16***	14.73***
N	2544	2544	3180	3180
Adjusted R-squared	0.855	0.966	0.851	0.958

Discussion and Conclusion

To put the current results into context, during the recent federal fraud trial against Adidas executive James Gatto, evidence was presented that a number of five-star high school men's basketball players (Brian Bowen, Silvio De Sousa, Billy Preston, and Dennis Smith[20]) were offered tens or hundreds of thousands of dollars to attend certain schools (McCann, 2018). A question the jury was faced with was whether it was reasonable to assume the efforts of the defendants was designed to harm the schools (by putting them at risk of NCAA penalties) or help the schools (by delivering them the ability to generate marginal revenue). That is, not whether harm might be a side effect of the alleged scheme, but if its purpose was to harm the schools. While the jury was not provided with an actual economic framework for their analysis, this task was essentially the same as asking whether the *ex ante* value of a five-star athlete, less the true cost of the scholarship, less the expected cost of any punishment, was positive or negative. Of the four schools originally involved (University of Miami, University of Kansas, University of Louisville, and North Carolina State University), the University of Miami is the most expensive

[20] The allegation originally included Nassir Little, but his name was struck from the case by agreement of the parties after no evidence was presented as to his (or his family) having received any money.

at approximately $68,000 per year for a full athletic scholarship. Based on the findings in the present study, a five-star athlete would be expected to generate incremental revenue worth many multiples more than a full athletic scholarship, as shown in Table 7.

Table 7. 2016-17 COA vs. Ex-Ante Five-Star Athlete MRP Comparison

School	2017 MBB Program Revenue	Five-Star effect	Ex-ante MRP of a Five-Star Athlete	Tuition & Fees	Room & Board	Misc.	Books	Total COA
Kansas	$18,266,319	8.19%	$1,496,258	$28,239	$9,610	$3,070	$1,080	$41,999
Louisville	$43,960,492	8.19%	$3,600,958	$26,286	$8,130	$5,432	$1,200	$41,048
Miami (FL)	$10,868,814	8.19%	$890,303	$47,004	$13,310	$3,062	$930	$64,306
NC State	$14,611,434	8.19%	$1,196,874	$26,399	$10,635	$2,442	$1,082	$40,558

Note: assumes out-of-state tuition & fees; on-campus room & board, misc expenses
Source: IPEDS

This may not be surprising given the rarity of five-star rated basketball players coming out of high school and their obvious likelihood of positive on-court impact in a college program. If we make the extremely conservative assumption that no five-star athlete leaves college prior to completing his eligibility (i.e., if we pretend one-and-done and other early departures do not exist), at most 133 (2.4%) of the 5,484 men's Division I college basketball players playing during the 2017 season would have been five-star recruits, based on the total number of five-star recruits from 2013-2017. Of course, because many five-stars do leave after one or two years, this is an over-estimate of their frequency.

As another consistency check, our *ex ante* valuations ought to correspond, at least on average, to the *ex post* studies that utilize playing statistics in college to estimate marginal revenue product. Again, the *ex post* studies look at how a player actually performed as opposed to how they would have been expected to perform during the recruiting process coming out of high school, and so we should expect the over- and under-performers to balance out in the long-run average. Berri (2018) applied his *ex post* model to the players on Duke University's 2014-15 team. Focusing on the five-star athletes on that team (Tyus Jones, Jahlil Okafor, Justise Winslow, and Rasheed Sulaimon), one can see in Table 8 that his findings are similar to those here with those five-star athletes having been expected to generate incremental revenue of around $2.8 million, and the actual output at an average of $2.4 million. We should note that Rasheed Sulaimon was dismissed from the team during the middle of the 2014-15 season (for non-basketball reasons) and thus had much lower playing statistics, but when given a chance to play a full season elsewhere (University of Maryland), he performed at a high level. The average without Sulaimon is just over $3 million. The aforementioned Borghesi (2018) study found that five-star recruits generated about $625,000 in incremental annual revenue, on average at any Division I school, which is much lower than the findings here. The main reason for the difference is that Borghesi's study included about 220 Division I schools that are outside of the Power 5 conferences (and looked at an average across all schools in the data), while this analysis included a much more even mix of Power 5 and non-Power 5 schools (and allowed the average value to vary based on team revenue in some iterations of the model). In fact, the average revenues of Power 5 basketball programs are just over 5 times larger than the average revenues of the schools outside of the Power 5, thus five times $625,000 is much closer to the findings in the current study. Furthermore, Borghesi's study used data that somewhat spanned an earlier time period.

Table 8: MRP estimates from Berri (2018) and Rivals star-rating model

Duke 2014-15 Team Revenues	$33,772,145
Star-rating incremental value (%)	1.64%

Player	Stars	Ex-post MRP Estimate (Berri)	Ex-ante MRP Estimate (Rascher)
Tyus Jones	5	$3,755,823	$2,766,395
Jahlil Okafor	5	$3,082,682	$2,766,395
Justise Winslow	5	$2,323,924	$2,766,395
Rasheed Sulaimon	5	$252,831	$2,766,395
Average		$2,353,815	$2,766,395

Rivals.com
EADA
Berri, David. Sports Economics, p 310. Worth Publishers (Macmillan Learning) 2018.

Setting aside the revenue potential of a five-star athlete, one also must consider whether the listed price of a scholarship accurately reflects the marginal cost to a university. Generally speaking, there is evidence in the literature that much of the scholarship cost is simply a transfer within the university or the actual wholesale/out-of-pocket cost to providing it is less than the list price (Goff, 2000; Goff, Kim & Wilson, 2017). For instance, given that the school is already offering classes to a large, diverse undergraduate student body, the marginal cost of adding one athlete to various classrooms is likely low, perhaps nearly zero. Similarly, depending on capacity, the cost to a school of allowing an athlete to sleep in a dorm room may be quite low, though for a school with dorms that are otherwise full, there would be an opportunity cost if there is an otherwise full-paying student who is crowded out from that dorm room. Otherwise, the cost is quite small. For example, during the 2017 academic year, the University of Louisville was only 91% full in its dorms,[21] meaning that it had hundreds of empty spaces, and the incremental cost of housing one more athlete was likely negligible. The result is that many schools will need to find only a small positive expected value from an athlete to exceed these negligible costs, making the incentive to disregard NCAA recruiting rules more enticing.

It is not surprising that various authors over the years (Cullen et al., 2012; Harris, 2015; & Sack, 1991) have found recruiting violations to be far more prevalent than the few that are actually investigated, decided and punished by the NCAA. Given the extraordinarily high

[21] "Just the Facts" (2017-18) reports Louisville's "Student Housing Occupancy Rate" at 91%. Available at http://louisville.edu/oapa/institutional-research-and-planning/quick-facts/2018JusttheFactsFINALada.pdf

potential of elite athletes to generate incremental revenue for schools, especially those in the top revenue-producing conferences, and the presented probation regression results, it appears the historical level of NCAA punishments are clearly not harsh enough (or not relevant) to cause the sort of financial harm needed to deter schools from violating NCAA rules. In fact, for schools that commit NCAA rules violations *and are caught*, they are no worse off after their probation than their competitors who were not punished. The present findings confirm previous literature. For example, Fleisher, Goff and Tollison (1992) found that teams improved their winning on the football field even after getting caught and punished for violating NCAA rules. More recently, Smith (2015; p. 97) found that there was “little economic or reputational damage” for colleges and universities post-probation.

The results of this study should not be taken as an endorsement of increasing NCAA infraction punishments. Such a conclusion would not follow from these data, because this analysis does not assess whether NCAA efforts to deter this conduct is actually in the public interest. Many authors (e.g., Leeds, Leeds, & Harris, 2017; Sanderson & Siegfried, 2015; Santesteban & Leffler, 2017) have concluded that the surplus extracted from athletes because compensation is prevented from approaching the athletes’ MRP is primarily transferred to coaches, administrators, and other service providers, rather than being utilized to serve some public good.

Given this, increased enforcement is not a wise prescription, especially in light of the ineffectiveness of the system in preventing what appears to be a widespread underground economy in which money is inefficiently funneled from shoe firms (and perhaps other sponsors) to members of an athlete’s family or circle of advisors. However, until the rational solution – ending the prohibition of market-based compensation for athletes – is adopted, what is clear is that rational actors will continue to violate irrational rules because these rules do far too little to deter the conduct in question.

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