

**Alternative Approaches to Measuring MRP:
Are All Men's College Basketball Players Exploited?**

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Abstract: College men's basketball players have alleged that the NCAA's illegal cap on athletic scholarships leads to lower scholarships than would prevail in a free market. Recently, the NCAA increased the limit on athletic scholarships. We compare the marginal revenue product (MRP) of men's basketball players to athletic scholarship caps. We estimate MRPs using players' playing statistics; information on the distribution of pro salaries; and players' future draft status. We find that players' MRPs are greater than the athletic scholarship caps for about 60% of men's basketball players, not just the star players.

Keywords: marginal revenue product, basketball

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I. Introduction

In 2006, college men's basketball players sued the NCAA, alleging that the NCAA fixed the amount of athletic financial aid. At the time, the NCAA limited the total amount of financial aid received by a student-athlete to a full grant-in-aid (full GIA), which covers tuition and fees, room and board, and required textbooks. Though the case settled without changing the limit on athletic scholarships, the NCAA increased the scholarship limit in 2011 by \$2,000 to cover incidental expenses such as school supplies other than required textbooks and travel between the school and the student's home.

The case and recent rule change highlight the question, Do student-athletes contribute more to the school than they receive through athletic scholarships? We examine this question for Division I men's basketball players by estimating student-athletes' marginal revenue product (MRPs) using updated versions of two well-established approaches and one new approach.

In the first approach, we estimate MRP based on the student-athlete's playing statistics.¹ This approach produces a zero MRP estimate for student-athletes with no game play and, hence, no playing statistics. These student-athletes contribute to the team's performance despite the lack of game play by providing scrimmage players for the starters and providing replacement players should the starters be injured. Our second approach uses the distribution of NBA salaries in conjunction with the MRPs estimated using the first method to allow for the computation of MRPs for all team members, even those without playing statistics. The distribution of NBA

¹ This approach follows the methodology developed and applied to baseball by Scully, 1974.

salaries provides information about the distribution of pro MRPs. We use the shape of the distribution of pro MRPs to inform our calculation of college MRPs. . The final approach we implement uses information on student-athletes who are ultimately drafted by the NBA.² This method provides an MRP estimate for all subsequently drafted players.

Previous estimates of the MRP of student-athletes do not include school fixed effects. We estimate the MRP equations both with and without school fixed effects, and the results indicate that school fixed effects are jointly significant. MRPs estimated using school fixed effects are lower than those estimated without them, so previous MRPs may have been over-estimated.

There is broad similarity in the results across all three methods, but notable differences in the estimated MRPs as well. The average MRP for all men's basketball players is about \$90,000 with the Scully method and rises to almost \$120,000 when information on the distribution of pro MRPs is included, but the distribution of MRPs estimated by both approaches is similar. The average MRP for star players – those who were ultimately drafted by the NBA – ranges from \$150,000 to \$275,000 at schools with relatively low-revenue basketball programs and from about \$1 million to \$1.4 million at schools with high-revenue basketball programs. The methods using playing statistics show a significant range across MRPs for star players, while the Brown method gives a single MRP estimate for all players at low-revenue schools and another for all players at high-revenue schools.

We compare student-athletes' MRPs to the previous and current limits on athletic scholarships, as well as the cost of attendance (COA), which has been proposed as a limit on

² This approach follows the methodology developed by Brown, 1993.

athletic scholarships.³ We believe that we are the first to tackle the question of whether the revenue generated by all men's basketball players – not just the star players – is greater than the value of the scholarships that they receive. We find that about 60% of men's basketball players generated more revenue for their team than they received in the form of an athletic scholarship. With two exceptions, the MRP of every player who was ultimately drafted by the NBA was above the former and current scholarship limit.⁴

We proceed as follows. We first discuss the marginal benefits and costs of matriculating a student-athlete in Section II, as these are the determinants, in part, of the athletic scholarships offered by schools. We then discuss the estimation of MRPs using student-athletes' playing statistics in Section III; incorporating the distribution of pro salaries in Section IV; and using a student-athlete's future draft status in Section V. We compare the MRP estimates from the different methods in Section VI. In Section VII, we compare the MRP estimates to the previous, current, and proposed caps on athletic scholarships.

II. The Benefits and Costs of Student-Athletes

In a typical labor market, a profit-maximizing firm hires until the marginal revenue product (MRP) is equal to the marginal cost of the last worker hired. In terms of collegiate athletes, the “firms” “hiring” the student-athletes are non-profits with an objective other than profit-maximization. However, in maximizing the alternative objective, whatever it may be, the same economic principle applies: an athletic department or coach will take on a student-athlete

³ Most financial aid programs are based on a school's cost of attendance. The COA covers tuition, room and board, and books (these items make up the GIA) as well as incidental expenses. The COA includes the full estimate of the incidental expenses, while the new NCAA limit only allows scholarships to cover up to \$2,000 in incidental expenses. It is estimated that the estimated incidental expenses are \$2,500 to \$3,000 at most schools.

⁴ The exceptions are Joe Alexander at West Virginia and Dante Cunningham at Villanova, both based on freshman year only.

as long as his or her marginal contribution to the athletic department, team, or school is greater than the marginal cost of taking the player on.

However, the NCAA limits the amount of each athletic scholarship. If this restriction binds, student-athletes' marginal contribution will be greater than their marginal cost.

A. Student-Athletes Do More than Generate Revenue

The direct benefit that a men's basketball player brings to a school is to contribute to the winning ability of the team. Increasing the team's winning ability in turn translates into additional revenue for the school: men's basketball is one of the "revenue sports", in that it often generates net revenues for schools. Student-athletes themselves, or via their contribution to the winning ability of the team, may generate benefits to schools other than generating basketball revenues; for example, student-athletes' performance may increase a school's ability to recruit students and attract additional donations.

Given the difficulties in quantifying the non-pecuniary contributions of a student-athlete to the school, we limit our estimate of the marginal value of a student-athlete to his generation of team revenues. The contribution of individuals to their sport's revenues (their MRP) provides a lower bound on the marginal contribution that a student-athlete provides to a school.

B. The Cost of a Student-Athlete

The cost to a school of taking on another men's basketball player includes the marginal costs of educating, housing, training, and playing the student-athlete. The most direct cost to the athletic department is the value of his athletic scholarship. The player's athletic scholarship may not be a true reflection of the university's cost of educating and housing the player. A large portion of any scholarship is not a cash payment to the student-athlete, but a transfer from one university account to another to cover tuition, room and board, and, often, even books.

These “transfer prices” do not necessarily represent the actual marginal cost to the school for taking on another student. The marginal cost of another student may be considerably less than tuition,⁵ and the marginal cost of lodging for a student may also be less than the charge for room. The marginal cost of a student-athlete also depends on whether the student-athlete is an additional student or is replacing another student, and if replacing a student, whether that student would pay full price or receive financial aid from the school.

We do not have data to consistently and reliably adjust the scholarship to reflect the true marginal cost to the school of granting the financial aid to the student-athlete. In addition, it is typically the athletic department that determines whether to add a student-athlete, and under the accounting systems of most schools, the athletic scholarship is a reasonable proxy of the direct cost to the athletics department of adding a student-athlete to the team.

Other costs of adding a student-athlete include the costs of the arena and training facilities, coaching, transportation, uniforms, etc. Many of the facilities are shared by other sports (e.g., weight rooms, arenas, support services, administration) and the facilities are often financed through sources not specifically attributed to men’s basketball. In addition, these latter costs sometimes are provided by sources other than the school via sponsorships and donations.

For all these reasons, we limit our estimate of the marginal cost of a student-athlete to his athletic scholarship.

C. Measuring the Benefits and Costs of a Student-Athlete

Colleges and universities must report revenues by sport to the Department of Education, which include “revenues from appearance guarantees and options, contributions from alumni and

⁵ Martin, 2004, states that “Increasing returns to scale and significant fixed costs in the intermediate term imply that marginal cost [of college education] is less than average cost.” The article goes on to provide statistics from 1,600 liberal arts colleges that report average tuition and fees at \$8,966, and a calculation of average marginal cost at \$3,347.

others, institutional royalties, signage and other sponsorships, sports camps, state or other government support, student activity fees, ticket and luxury box sales, and any other revenues attributable to intercollegiate athletics.”⁶ Allocation of these revenues across sports requires subjective decisions of the contribution of each sport, and are likely to differ from the revenues the sports generate through these items. To the extent that the data include revenues not generated by the basketball team (e.g., sports camps), the estimated MRP may be overstated. Likewise, to the extent that the data exclude revenues generated by the basketball team (e.g., sales of team jerseys), the estimated MRP may be understated. Nonetheless, the allocated revenue data are assumed to provide a reasonable, though imperfect, measure of the revenues generated by the team.

We measure the direct marginal cost to the athletic department of adding a student-athlete to the team with the maximum athletic scholarship. While we do not have data on the specific value of the athletic scholarship received by each student-athlete, most men’s basketball students receive the maximum allowable amount.⁷ Thus, the scholarship limit for men’s basketball players at each school is an upper bound on the scholarship received by each player.

D. Individual Effort in Team Sports

Estimating a student-athlete’s marginal revenue product (MRP) is complicated in the case of team sports in which players’ skills interact. To measure MRP, ideally one measures the full output of the player; in a team sport, a player’s performance not only directly impacts the team’s

⁶ U.S. Department of Education, 2006, Glossary of Terms, <http://www.ope.ed.gov/athletics/glossarypopup.aspx>. Although government support is included, in practice most schools receive no government support. See NCAA College Athletics Finance Database, <http://www.usatoday.com/sports/college/ncaa-finances.htm?csp=obinsite>.

⁷ We calculate the average number of full GIA athletic scholarships given to men’s basketball players at Division I-A schools (total scholarship expenditures divided by the number of scholarships given). Because the average number of full GIA scholarships and the number of student-athletes receiving scholarships are roughly the same, we conclude that most basketball players receive the maximum athletics scholarship allowed under the NCAA rules.

performance but also can help or hinder teammates' performance. Nonetheless, economists have measured the MRP of individual athletes who participate in team sports, including basketball, by using player performance as a reasonable proxy for the contribution of the player to team performance.⁸ MRP for college basketball has only, to the best of our knowledge, been measured for players who have ultimately been drafted by the NBA.

Measuring player performance is easier for some student-athletes and some positions than others. In particular, it is difficult to measure the value of scrimmage players. The scrimmage players often get little playing time (at the extreme, they may get no playing time and thus may have no performance statistics), though having a decent set of backup players to scrimmage against improves team performance. Young scrimmage players will also help in the preparation of the school's future team. In spite of their value to their school, these student-athletes will not have performance statistics in the year they do not play, and will therefore appear to have zero MRP.

III. Measuring MRP Using Players' Playing Statistics

The first approach we use is based on the work of Scully (1974). First, the team's win-loss percentage is regressed on measures of team performance. Second, the team's total revenues are regressed on the team's win-loss percentage, in addition to other determinants of revenues. Finally, an individual player's MRP is calculated as the product of the player's contribution to team performance, the marginal effect of team performance on the win-loss percentage, and the marginal effect of the win-loss percentage on team revenues. We discuss the

⁸ See, e.g., Brown, 1993 (football), 1994 (basketball), and 2004 (football and basketball); Chatterjee and Campbell, 1994 (basketball); Hadley et al., 2000 (football); Hofler and Payne, 1997 (basketball); Leonard and Prinzinger, 1984 (football); Scott, Long, and Somppi, 1985 (basketball); and Zak, Huang, and Siegfried, 1979 (basketball).

source of our data in Appendix A, and present descriptive statistics for the variables used in our study are included in Appendix B.

A. Step 1: The Win-Loss Regression

The team's win-loss percentage in a season is modeled as a function of team performance and the contribution of the coach. In mathematical terms,

$$\text{win-loss pct}_{it} = \alpha + \beta P_{it} + \gamma C_{it} + \delta X_{it} + \lambda T_i + \varepsilon_{it},$$

where i indexes the team and t indexes the season. The vector P represents the team's performance variables, the vector C represents the team's head coach's contribution towards winning, the vector X represents other determinants of the win-loss record, and the vector T represents team-specific fixed effects.

We use standard team performance statistics as explanatory variables for win-loss percentage:⁹ the number of blocks, steals, rebounds, and three-point shots per game and the percentage of goals and of free-throws made. The number of blocks, steals, and rebounds per game are measures of the team's defensive performance. In all cases, the expected coefficient is positive: the more blocks, steals, or rebounds, the better the defense and the more likely the team is to win. The other variables are measures of the team's offensive performance. The percentage of shots that are made (field goals or free throws) indicates the scoring skills of the players, so the higher these statistics, the more likely the team is to win.

We incorporate three variables to measure the head coach's contribution to team performance: a dummy variable indicating that there was a head coach change from the previous season ("new coach"); a dummy variable indicating that the head coach was ranked "coach of

⁹ Measures of team productivity typically include variables related to shooting, rebounds, assists, steals, blocks, turnovers, and fouls. See Berri, 1999; Chatterjee and Campbell, 1994; Hofler and Payne, 1997; Scott, Long, and Sompil, 1985; and Zak, Huang, and Siegfried, 1979. Our data do not include data on turnovers or fouls.

the year” in the current season;¹⁰ and a continuous variable bounded by zero and one indicating the coaches’ Division I win-loss record, for coaches who are currently ranked by the NCAA as one of the “winningest coaches.”¹¹

Coaches of the year and “winningest” coaches are particularly good and therefore their teams should have more success, resulting in a positive coefficient on these variables. We are agnostic as to whether the estimated coefficient on a coach change should be positive or negative. On the one hand, it may be positive because often coaches are changed when the team was doing poorly; thus, the new coach may be able to immediately increase the win-loss percentage. On the other hand, the appointment of a new coach may hurt team morale, and in the short-term there may be a reduction in the team’s win-loss percentage.¹²

We also include as explanatory variables the average rank index of opponents¹³ and the number of games for each team that were televised. We include the opponents’ rank index to measure the strength of opposition – the tougher the opposition, the lower the win-loss percentage, and thus a negative coefficient is expected. Televised games may induce more effort on the part of players, as televised games increase their exposure and may increase their chances of being drafted. This effect would also lead to a higher win-loss percentage.

¹⁰ A coach is a coach of the year if he was so designated by UPI, The AP, the U.S. Basketball Writers Association, the National Association of Basketball Coaches, Naismith, The Sporting News, CBS/Chevrolet, or Basketball Times.

¹¹ A “winningest coach” is one who has at least five years as a Division I head coach and has a win-loss record (for four-year U.S. colleges only) above 60%.

¹² We do not believe that endogeneity is an issue with the coach of the year and “winningest” coach variables. While the coach of the year is the coach of the team with the highest win-loss record for half the seasons in the sample, for four of the six seasons, more than one coach was coach of the year. Furthermore, many coaches have very similar win-loss records for a given year, and most of these coaches are not coach of the year. The determination of “winningest” coaches is the coach’s win-loss record for his entire career at four-year schools as long as he’s been head coach of a Division I team for at least five years. Thus, the current year’s win-loss record is a small determinant of “winningest” coaches.

¹³ The rank index for a team for each week is calculated as 26 minus the team’s rank. Thus, as the rank index of opponents increases, the better are the opponents faced by the team.

We run two versions of the win-loss equation, with and without team fixed effects. Most of the literature that measures productivity of teams does not include team fixed effects.¹⁴ We include team fixed effects to capture the myriad inputs into a winning team that are difficult to measure, such as the quality of the training facilities and academic support services available to student-athletes. The exclusion of these factors may bias the MRP estimates by attributing some of the win-loss percentage to the team's performance rather than, say, the school's superior facilities.

We estimate the model using ordinary least squares (OLS).¹⁵ We present the results with and without team fixed effects in Table 1.¹⁶

¹⁴ The only exception of which we are aware is Berri, 1999 (basketball).

¹⁵ The limited range of the win-loss percentage presents a potential econometric problem, since the assumption of the normal distribution of the error term under OLS requires that the dependent variable not be bound by zero and one. We also estimated the equation using a monotonic transformation of the win-loss percentage that is not bound by zero or one. The monotonic transformation is $lwl = \ln(\text{winloss} / (1 - \text{winloss}))$, where "ln" is the natural logarithm and "winloss" is the winloss percentage for each school-year pair. The results were not substantially affected by this transformation.

¹⁶ In addition to the two specifications we present, we explored others which varied in the included variables. All of them under-performed relative to the two that we present. These alternative specifications are available from the authors upon request.

Table 1: Scully Approach, Win-Loss Percentage Regression Results				
Dependent Variable: Team's Annual Win-Loss Percentage				
Independent Variables	No Team Fixed Effects		With Team Fixed Effects	
	Estimated Coefficients	Standard Errors	Estimated Coefficients	Standard Errors
Constant	-177.21 ^{***}	9.53	-162.56 ^{***}	11.30
Percentage Goals Made	343.57 ^{***}	15.23	318.29 ^{***}	16.82
Percentage Free Throws Made	51.24 ^{***}	10.12	61.46 ^{***}	10.65
Three Point Goals per Game	1.43 ^{***}	0.29	0.98 ^{***}	0.33
Blocks per Game	0.47	0.35	1.09 ^{***}	0.42
Steals per Game	1.19 ^{***}	0.26	1.90 ^{***}	0.28
Rebounds per Game	0.70 ^{***}	0.13	0.38	0.15
New Coach	-2.03 [*]	1.14	-1.66 [*]	1.02
Coach of the Year	16.30 ^{***}	3.47	12.72 ^{***}	3.16
“Winningest” Coach	7.74 ^{***}	1.38	3.52 ^{**}	1.66
Opponents' Average Rank Index	-0.26	0.29	1.12 ^{**}	0.45
Televised Games	0.27 ^{***}	0.05	0.19 ^{**}	0.05
Team fixed effects			included [†]	
Adjusted R ²		.55		.69
Number of Observations		1,044		1,044
*** Significant at the 1% level, ** at the 5% level, and * at the 10% level.				
† Jointly significant at the 1% level.				

In general, the variables are statistically significant and of the expected sign. In particular, the coefficients for the team performance variables are positive and generally significant, although the coefficients on blocks per game and on rebounds per game are insignificant in the version that excludes and includes team fixed effects, respectively. A coach change leads to a reduction in the win-loss percentage, but the presence of a “coach of the year” or a “winningest” coach increases the team’s win-loss record. The number of televised games

may be indicative of team spirit, which may explain why it increases the team's win-loss performance. The opponents' average rank index negatively impacts a team's win-loss performance in the version that excludes team fixed effects, as expected, but has no significant impact when team fixed effects are included.

The results support the inclusion of the fixed effects: the fixed effects are jointly significant and the adjusted R^2 increases substantially, from 0.59 to 0.72. Thus, unless otherwise indicated, we focus on the results from the version that includes team fixed effects.

B. Step 2: The Revenue Regression

The team's revenue is modeled as a function of team performance and demand. In mathematical terms,

$$\text{rev}_{it} = \alpha + \beta \text{TWL}_{it} + \gamma \text{D}_{it} + \delta \text{Conf}_{it} + \eta \text{Year}_i + \lambda T_i + \varepsilon_{it},$$

where i indexes the team and t indexes the season. The vector TWL represents the team's performance variables, D includes variables to measure other determinants of revenue, $Conf$ represents the team's conference, $Year$ represents the season, and T represents team fixed effects.

The vector TWL includes two variables. We include the win-loss percentage as a stand-alone variable and interacted with a dummy equal to one for teams with large revenues. The coefficient of the win-loss percentage in the revenue equation indicates the dollar increase in revenues given an increase in the team's win-loss percentage. We hypothesize that an increase in the win-loss percentage will not represent the same increase in revenues for a school that generates, say, \$0.5 million per year in revenues from men's basketball, as for a school that generates \$12 million. Therefore, we create a dummy variable equal to one if a team generates

more than \$10 million in a given year.¹⁷ This allows for the possibility that the effect of win-loss percentage on revenues is different for large teams. We expect the sign of the coefficient on both win-loss variables to be positive – the more games won, the more revenue the team earns, with the impact being larger at schools with more revenue.

To measure other revenue sources, we include variables (in the vector D) measuring the team's home-arena capacity and the capacity of opponents' arenas, a dummy equal to one if the team was sponsored by Nike, the team's rank index in the previous three seasons and the average rank index of opponents during the season (see footnote 13), and the number of games televised during the season.

We include arena capacity for the team and its opponents as determinants of ticket revenues; the more seats available, the more revenues that can be earned, and thus positive coefficients are expected. The Nike dummy is included because schools sponsored by Nike have access to the top high school recruits through their sponsorship deals and All-American camps.¹⁸ Recruiting top high school players should increase demand by fans to see games, increasing ticket and broadcast revenues.

We include the team's previous rank index to capture fan demand – teams that have been performing well (poorly) should encourage more (less) fan demand this year – and thus we expect a positive coefficient. We include the rank index of the opponents to account for the

¹⁷ The results for alternative definitions of large schools (i.e., schools with basketball revenues greater than \$8, \$9, \$11, or \$12 million) give similar results.

¹⁸ "Nike marketing consists of some 50 or 60 college sponsorships (though perhaps only half of these involve significant cash beyond the free outfitting), scores of individual athletes under promotional contracts, free sneaker deals with over 150 high schools and AAU (American Amateur Union) teams, summer sports camps for promising athletes, and sponsorships with professional teams in various sports." Zimbalist, 1999.

quality and/or entertainment value of the games. We expect that better opponents will lead to more demand, and thus expect a positive coefficient.¹⁹

Finally, we include the number of televised games as another indicator of demand, expecting a positive coefficient. More televised games generally lead to more broadcast revenues.

We include conference dummies to account for the different revenue-sharing policies specific to each conference.²⁰ We include year dummies to allow for the impact of general macroeconomic conditions, as well as to indicate any impact on demand from exogenous events (such as the winter Olympics in 2002).

Finally, we estimate the revenue equation with and without team fixed effects. Team fixed effects are appropriate if, for example, a school gets more institutional support (which may be in the form of student fees) or higher contributions to the athletics department if it is a big sport school. This degree of support might continue in years when the team is not doing so well (in terms of its winloss record). For example, the University of Michigan has one of the largest bases of alumni in the country and is a reasonably strong basketball school. UM could therefore raise more revenue than other schools, whether the team is currently doing well or not. All other variables are included when team fixed effects are included.

Table 2 presents the results for the OLS regressions.²¹

¹⁹ Of course, it may be that the relative quality of the teams is what drives demand; that is, there may be more demand to see a game between two top ranked teams or two unranked teams, where the outcome of the game is more uncertain, than to see a game between a top ranked team and an unranked team. We tried including the absolute value of the team's average rank and its opponents' average rank, but that variable was insignificant.

²⁰ For example, some conferences split gate revenues evenly; some split a minimum, with revenues above the minimum accruing to the home team; and some guarantee a minimum to the visiting team. These revenue-sharing rules thus impact the revenues earned by the school.

²¹ The limited range of the win-loss percentage presents a potential econometric problem, since the assumption of the normal distribution of the error term requires that the dependent variable not be bound by zero and one. We also estimated the equation using a monotonic transformation of the win-loss percentage that is not bound by zero or one.

Table 2: Scully Approach, Revenue Regression Results				
Dependent Variable: Team's Annual Revenues				
Independent Variables	No Team Fixed Effects		With Team Fixed Effects	
	Estimated Coefficients	Standard Errors	Estimated Coefficients	Standard Errors
Constant	-1,756,757 ^{***}	690,227	1,062,307	718,827
Win-loss percentage	1,430,498 ^{***}	337,644	508,049 ^{**}	250,165
Win-loss percentage × large school	6,245,516 ^{***}	374,829	2,426,866 ^{***}	307,855
Arena capacity	183.22 ^{***}	14.40	21.89	26.58
Opponents' arena capacity	52.09	64.25	-42.21	49.39
Nike school	-379,379 [*]	227,644	1,504,175 ^{***}	597,093
Past team index	107,294 ^{***}	15,474	76,949 ^{***}	21,038
Opponents' average index	59,486	80,284	33,567	46,029
# of games televised	27,609 ^{**}	11,924	25,161 ^{***}	6,833
Conference fixed effects	included [†]		included [†]	
Year fixed effects	included		included [†]	
Team fixed effects			included [†]	
Adjusted R ²	.85		.96	
Number of Observations	676		676	
*** Significant at the 1% level, ** at the 5% level, and * at the 10% level.				
† Jointly significant at the 1% level.				

The coefficient signs on the team performance variables are positive and significant, as expected – an increase in the win-loss record significantly (statistically and economically) increases a school's revenue. When team fixed effects are included, if the win-loss record increases by 10 percentage points (e.g., from 50% to 60%) at a school whose team generates less

The monotonic transformation is $lwl = \ln(\text{winloss} / (1 - \text{winloss}))$. The results were not substantially affected by this transformation.

than ten million in revenues a year, revenue increases by \$50,805. For a large school, the same increase in the win-loss record increases revenues by \$293,492.

A large difference arises between the versions excluding and including team fixed effects: the coefficients on the team performance variables are about a third in magnitude when team fixed effects are included. Team fixed effects are indicated; they are jointly significant at the 1% level and the adjusted R^2 increases substantially when they are included. The coefficients on the team performance variables are inputs into the calculation of players' MRPs. The difference in coefficient magnitudes translates into significantly higher estimated MRPs when team fixed effects are not included. However, including fixed effects also introduces the possibility of assigning to the school part of the revenue that comes from the players themselves. Inasmuch as individual performance affects team winnings and revenues not explained by the other variables and captured by the fixed effects, MRPs could be underestimated with the inclusion of fixed effects.

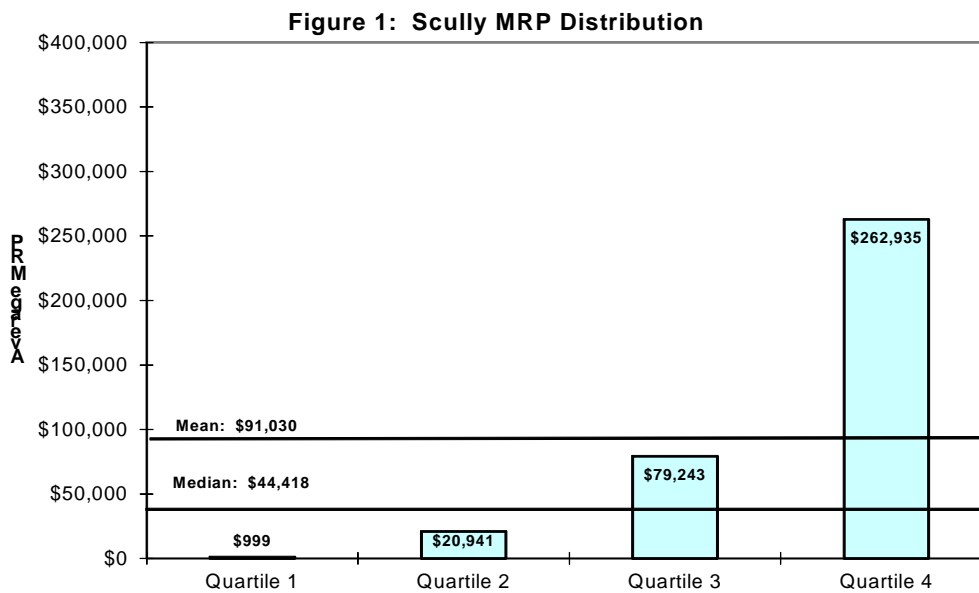
The other explanatory variables are generally positive, as expected, and significant. The capacity of opponents' arenas is insignificant, as is opponents' ranking index. Hence, it appears that team revenue is generated based on team performance and characteristics, regardless of opponents. The coefficient on the Nike dummy changes from negative to positive with the inclusion of team fixed effects. This suggests that in the version without team fixed effects, the Nike coefficient is conflating the effects of being a Nike team as well as school-specific revenue determinants.

C. Step 3: Estimating MRP

A player's MRP is the product of his contribution to team performance, multiplied by the effect team performance has on the team's win-loss percentage (given by the coefficients in the

win-loss regression), multiplied by the effect that the increase in the team's win-loss percentage has on revenues (given by the coefficients in the revenue equation).

The player's contribution to team performance is obtained by multiplying each player's individual performance statistics by his weight in the team. We calculate the player's weight in the team as the ratio between the player's performance statistic and the team's performance statistic.²²



Summary information on the MRPs is contained in Figure 1 and Table 3. Figure 1 compares the average MRP by quartile, along with the mean and median MRPs. Table 3 gives summary information on the MRPs by position. MRPs range from \$0 to \$2.0 million. Estimated

²² E.g., to measure the player's contribution towards team blocks (or steals, rebounds, or three point attempts), we calculate the player's number of blocks per game and divide by the team's number of blocks per game. To measure the player's contribution towards the team's field goal and free throw percentages, we divide the number of goals made by the player by the number of goals made by the team. Suppose that a stylized two-person team makes two-thirds of its field goal attempts. Player A made 1 of those field goals out of 10 attempts, while Player B made 19 field goals out of 20 attempts. Then Player A contributed 1 field goal out of 30 team attempts, and Player B contributed 19 field goals out of 30 team attempts. Mathematically, $(1/30) + (19/30) = (20/30)$.

MRPs of \$0 arise for student-athletes who have no playing statistics, either because they had no game time or they did not shoot, block, rebound, or steal during their playing time. This applies to slightly over ten percent of player-year observations.

Position	Mean	Median	Std. Dev.	Min.	Max.	# of Obs.
Center	\$87,325	\$37,363	\$158,952	\$0	\$1,671,147	1,702
Forward	\$100,567	\$54,423	\$17,051	\$0	\$1,998,899	5,469
Guard	\$91,491	\$47,201	\$158,127	\$0	\$1,923,038	7,278

The highest MRPs (all above \$1.75 million) are for Kevin Durant, J.J. Redick, Hakim Warrick, Shelden Williams, and Tyler Hansbrough. Durant and Redick were both Naismith winners,²³ and all of these players ended up in the NBA. Durant was a second draft for the Seattle SuperSonics, and in 2010 he signed a five-year contract with the Oklahoma City Thunder worth \$86 million; and Redick was drafted by the Orlando Magic, and in 2010 signed him to a three-year, \$19 million contract. Warrick was drafted by the Memphis Grizzlies; Williams by the Atlanta Hawks; and Hansbrough by the Indiana Pacers.

IV. Estimating MRP using the Distribution of Pro Salaries

Using the Scully method, we cannot measure MRP for players for whom there are no player performance data, such as benchwarmers.

To estimate MRPs for these players, we incorporate information from the salary distribution of professional basketball players. If the market for professional players were perfectly competitive, pro players' salaries would approximate their MRP. While the market for

²³ This award is given to college basketball's top players. Players are chosen by a board that includes journalists, coaches, and administrators and incorporates fan votes.

pro basketball players is significantly closer to a free market than is the market for college players, it is not perfectly competitive. In particular, since the 1998-99 season, there has been a cap on the total wage bill per team as well as a cap and floor on individual player salaries.²⁴

The maximum player salary is a soft cap. For example, those players who already had salaries above the maximum were grandfathered in, and only the first season's salary is subject to the maximum for multi-year contracts (although there is a limit on the size of raises from year to year). In the first year under the new collective bargaining agreement (CBA), five pro players signed new contracts at the maximum and eight had salaries beyond the maximum because they were grandfathered in.²⁵ Approximately 1% of pro players' salaries were capped in the first year of the CBA. For the 2002-03 season, approximately 17% of players were at the salary floor.²⁶ While the salary caps and floor will mean that the salaries at the top and bottom end of the distribution somewhat understate and overstate those pro players' MRPs, we use the distribution of pro salaries as a proxy for the distribution of pro MRPs.

We then assume that the shape of the distribution of MRPs of pro players mirrors the shape of the distribution of MRPs of college players.²⁷ The implication is that, for example, if a benchwarmer center receives a salary that is 5% of the average NBA player, the benchwarmer's MRP is 5% of the average NBA player's MRP. We apply the shape of the pro salary distribution

²⁴ Staudohar, 1999. For players' minimum and maximum salaries, see NBA Salary Cap FAQ, <http://members.cox.net/lmcoon/salarycap.htm>.

²⁵ Hill and Groothuis, 2001, tables 1 and 2.

²⁶ From Patricia Bender at <http://www.Eskimo.com/~pbender/misc/salaries03.txt> 2009. This includes all players signed, even those signed for 10-day periods and those released in the middle of the season.

²⁷ We are not assuming the abilities of pro players are equivalent to the abilities of college players (hence the values of the MRPs for college and pro players are not assumed to be equal), nor are we assuming that a top-tier college player will be at the top end of the ability distribution when he goes to the pros.

to the average MRP of each school obtained from the previous approach to determine the individual MRP for all players, including those that have no performance statistics.²⁸

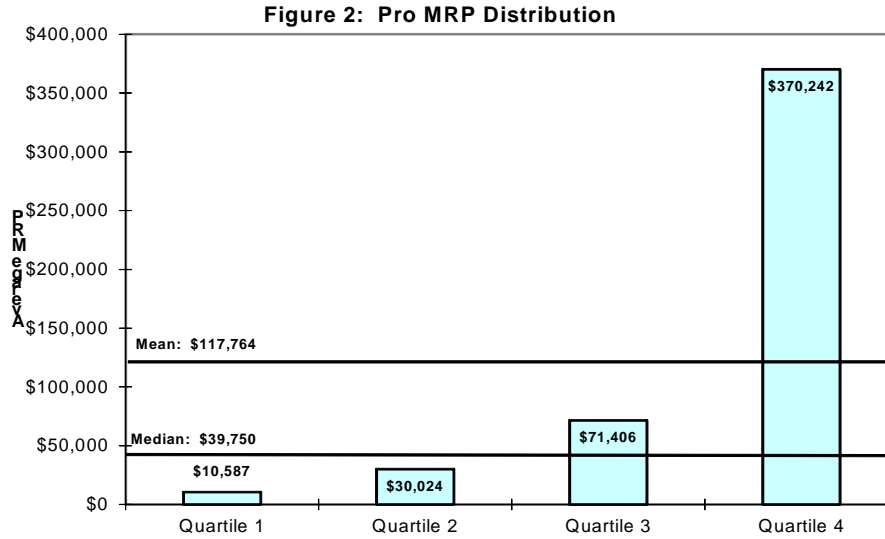
We rank professional basketball players in each position according to their annual salary, and calculate the ratio of the average salary in each decile of each position to the average of all professional player salaries. We then rank college players by position according to their estimated MRPs, including those players for whom MRP is estimated to be zero. We apply the position-decile-specific ratios from professional basketball players to student-athletes in the same position and the same decile to get modified versions of MRP.

For example, the average salary of the top decile of centers is 354% of the salary of the average professional basketball player. Then the new MRP estimate for the top decile of centers at the University of Michigan (Duke) is equal to 354% of the average MRP estimated at the University of Michigan (Duke) using the method described in Section III.²⁹ Thus, the top 10% of each position will have a different MRP than the bottom 10% of that position, and the top 10% of each position at one school will have a different MRP than the top 10% of that position at another school.

By employing this method, we are able to estimate MRPs for about 1,550 additional men's basketball player-years (or about 10% of our sample). We present the results in Figure 2 and Table 4.

²⁸ Krautmann, 1999, uses a similar approach for pro baseball. He uses information on free agents, who operate in a relatively free market, to calculate MRPs for reserve-clause players, who operate in a restricted market.

²⁹ This average MRP for each team includes the estimates of zero MRP for student-athletes without player statistics.



Comparing the earlier results given in Figure 1 and Table 3, we see that the minimum MRP is increased from \$0 to about \$3,500. The maximum MRP is also slightly higher, and the median MRP is about 30% higher. We discuss the differences further in Section VI.A.

Position	Mean	Median	Std. Dev.	Min.	Max.	# of Obs.
Center	\$128,355	\$53,340	\$277,349	\$3,837	\$1,777,842	1,702
Forward	\$124,909	\$45,789	\$281,768	\$3,404	\$2,038,780	5,469
Guard	\$117,503	\$40,248	\$271,884	\$3,568	\$1,882,623	7,278

V. Estimating MRP using a Player's Future Draft Status

For men's basketball players who are ultimately drafted into the NBA, we can also estimate MRP using the method developed in Brown (1993). We estimate a model of team revenue as a function of the number of star players (players who were ultimately drafted) in their roster in each year and other determinants for revenue, as follows:

$$rev_{it} = \alpha + \beta Drafted_{it} + \eta Drafted \times Large_{it} + \gamma D_{it} + \delta Conf_{it} + \eta Year_i + \lambda T_i + \varepsilon_{it},$$

where i indexes the team and t indexes the season. The variable *Drafted* represents the number of players ultimately drafted by the NBA for all teams, while the interacted variable *Drafted* \times *Large* represents the number of players ultimately drafted by the NBA for schools that had annual basketball revenues greater than \$10 million.³⁰ The vector D includes other determinants of revenue for the team; the vector *Conf* represents the team's conference; the vector *Year* represents the season; and the vector T represents team fixed effects.

The variables of interest are *Drafted* and *Drafted* \times *Large*. The coefficient on the number of drafted players (*Drafted*) indicates the dollar increase in revenues given an additional player with enough talent to be drafted by the NBA at a low-revenue school, and the sum of the coefficients on the two variables indicates the dollar increase at a large-revenue school. Thus, the coefficient on *Drafted* is the MRP for star players at low-revenue schools and the sum of the coefficients on *Drafted* and *Drafted* \times *Large* is the MRP for star players at high-revenue schools.

To control for other revenue sources, we include the same variables as in the Scully approach: the team's home-arena capacity and the capacity of opponents' arenas, a dummy equal to one if the team was sponsored by Nike, the team's rank index in the previous three seasons and the average rank index of opponents during the season, and the number of games televised during the season. These variables are all expected to have the same impact as before. Again we estimate the equation with and without team fixed effects.

The number of players drafted is endogenous, correlated with unobserved factors that also affect revenue.^{31,32} In particular, teams with higher revenues are likely to spend more on

³⁰ The results are similar when a large basketball program is defined as revenue greater than \$8, \$9, \$10, \$11, or \$12 million.

³¹ Endogeneity is confirmed with both Durbin and Wu-Hausman test statistics.

recruiting and attract better players who will later be drafted.³³ To correct for the biases caused by the endogeneity in the draft variable, we employ two-stage least squares (2SLS). The excluded instruments are: the win-loss ratio; the numbers of points, goals, three-point goals, blocks, rebounds, steals, and assists per game; the percentages of goals and free throws made; whether the team was a contender or loser in the previous season; whether the head coach was new, a coach of the year, or a “winningest” coach; and a measure of the market opportunities for the school.³⁴ The R^2 s for the first stage regressions are about 0.80, and a test of the over-identifying restrictions confirms the validity of the instruments.

The results from the 2SLS Brown regression are presented in Table 5.

³² The winloss variables included in the revenue equation when estimating the MRP using the Scully approach could also be subject to a similar simultaneity issue. However, the Durbin and Wu-Hausman tests do not reject the null hypothesis of exogeneity.

³³ NCAA rules limit recruiting activities under bylaw 13, but there is still variation in recruiting expenditures within the limits (and plenty of allegations of expenditures outside the limits).

³⁴ The variable to measure market opportunities is based on Brown, 1993. We use a weighted average of population in 20-, 40-, and 60-mile diameters around the college, divided by the number of college and pro basketball teams within 60 miles.

Independent Variables	No Team Fixed Effects		With Team Fixed Effects	
	Estimated Coefficients	Standard Errors	Estimated Coefficients	Standard Errors
Constant	-951,442	1,006,758	1,110,477	1,001,891
# Drafted Players	987,237***	266,165	270,880	217,462
# Drafted × Large School	1,002,362**	518,525	918,065**	363,964
Arena capacity	217***	23	320***	43
Opponents' arena capacity	6	95	-71	55
Nike school	-690,575	573,910	-811,771	1,610,127
Past team index	25,671	43,049	79,917***	29,716
Opponents' average index	-5,499	124,194	103,086**	48,040
# of games televised	45,208**	21,343	15,174	10,052
Conference fixed effects	included [†]		included [†]	
Year fixed effects	included		included [†]	
Team fixed effects			included [†]	
Adjusted R ²	.77		.97	
Number of Observations	507		507	
*** Significant at the 1% level, ** at the 5% level, and * at the 10% level.				
[†] Jointly significant at the 1% level.				

Some striking differences are apparent in comparing the results excluding and including fixed team effects, as was true for the revenue equation for the Scully approach. The team fixed effects are jointly significant, and significantly increased the adjusted R². The magnitude of the MRP estimate for players from low-revenue schools falls from almost \$1 million to a bit over \$0.25 million, and becomes significant only at the 21.3% level. The additional MRP that accrues to high-revenue schools from an additional drafted player is about the same with or without team

fixed effects, about \$1 million.³⁵ One interpretation is that without fixed effects a lot of the school-specific variation was being attributed to the “performance” variables, and the number of drafted players is now more precisely proxying for performance. Alternatively, because some of the fixed effects are correlated with the other regressors, the estimated coefficients may conflate the influence of the regressors and of the fixed effects.

VI. Comparison of MRP Estimates

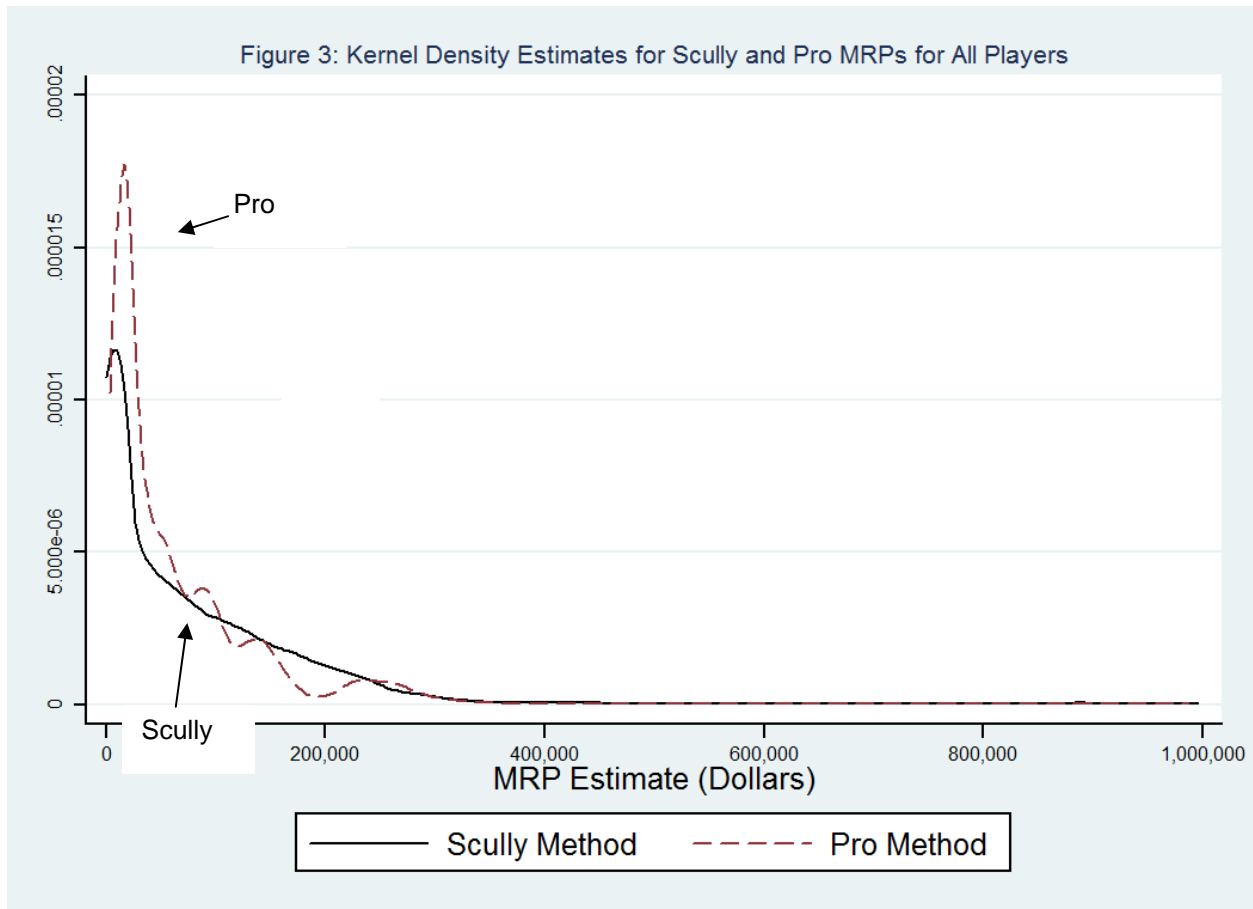
A. All Men’s Basketball Players

We are able to estimate MRPs for all men’s basketball players using the Scully method and a variation incorporating information on the shape of the pro salary distribution. To illustrate differences in the entire distribution of MRP estimates, we graph the kernel density of the MRP estimates for the Scully and pro methods in Figure 3.³⁶ From the graph, we can see that the distribution of the Scully estimates are shifted leftwards (towards zero) relative to the pro estimates.

³⁵ The results for alternative definitions of large schools (i.e., schools with basketball revenues greater than \$8, \$9, \$11, or \$12 million) give similar results when fixed effects are excluded or included.

³⁶ Kernel densities are constructed with a commonly used technique for smoothing density functions that would normally be portrayed in histograms. The smoothness of the kernel density function is inversely proportional to the width of the bandwidth being used. In our case, we use a bandwidth around MRP values of \$10,000.

For legibility reasons, we limit the graphical presentation to only those MRP estimates that are less than \$1 million. Over 95% of the MRPs are included in the graph. The two densities are largely coincident beyond \$1 million, except that the density using the pro method is slightly higher than the Scully method for MRP estimates around \$1.25 million.



B. Star Men's Basketball Players

We use all three methods – Scully, pro, and Brown – to calculate the MRP for basketball players who are subsequently drafted by the NBA. We compare the MRP estimates for these players in Table 6.

Table 6: MRP Estimates for College Players who are Drafted by the NBA

	Mean	Median	Std. Dev.	Minimum	Maximum
Low-Revenue Schools					
Scully	\$181,192	\$182,868	\$83,709	\$0	\$411,292
Pro	\$155,7242	\$142,021	\$81,817	\$5,886	\$351,763
Brown	\$270,880	\$270,880	n/a	\$270,880	\$270,880
High Revenue Schools					
Scully	\$970,164	\$957,292	\$435,923	\$85,748	\$1,923,038
Pro	\$1,403,265	\$1,420,504	\$247,848	\$405,376	\$2,038,780
Brown	\$1,188,945	\$1,188,945	n/a	\$1,188,945	\$1,188,945

At low-revenue schools, the Brown MRP is significantly higher than the Scully or pro MRP. At high-revenue schools, the Scully MRP is significantly lower and the pro MRP significantly higher than the Brown MRP. The Scully approach incorporates players' playing statistics, while the Brown approach uses a binary signal for athletic skill (the player is good enough that he is subsequently drafted by the NBA, or he's not). The latter may capture a player's "athleticism" that contributes to revenues in a way that is not captured by his playing statistics. For example, Denard Robinson may attract additional revenue beyond his contribution to a win due to the fact that people want to see star athletes. In addition, a star player may affect other players' playing statistics to a greater extent than a non-star player. In that case, the Scully and pro approach may attribute some of the star player's contribution to winning the game to other players.³⁷ At low- and high-revenue schools, we see that the Brown approach masks a significant range in MRPs.

VII. Players' MRP versus Athletic Scholarship Caps

³⁷ We thank an anonymous reviewer for these points.

We compare players' MRPs, a lower bound on a player's marginal contribution to a school, with an upper bound on the athletic scholarship received by players.³⁸ We are able to compare MRPs to the original athletic scholarship cap (the GIA (grant-in-aid)), the new cap (covering GIA plus up to \$2,000 for incidental expenses), and COA (proposed cap, covers total estimated incidental expenses), for slightly more than 15,000 player-year combinations.

Recall that we do not observe the actual scholarship received by each student-athlete, but we know the maximum scholarship received is equal to the cap. If the student-athlete's MRP is above his scholarship limit, then the MRP is also definitely above the actual scholarship received by the student-athlete. Similarly, we cannot observe the full marginal value that the player contributes to the school. The MRPs are underestimates of the marginal value of the student-athlete to the schools, because they only capture the direct revenue impact.

Based only on the direct revenues the student-athletes bring to the schools, the results show that the Scully MRP for approximately 60% of players is greater than any of the scholarship caps considered (see Table 7). These numbers increase slightly when MRPs are estimated by taking into account information on pro salaries. Thus, even with the recent increase of the limit on athletic scholarships, the majority of players would still produce more revenue for the school than the maximum possible value of his scholarship; in some cases, as much as a eighty times the value of his scholarship.

³⁸ The athletic scholarship is not the only benefit a player receives from a school; he also receives an education, training, and experience. For some athletes, an athletic (or other) scholarship is a necessary condition for him to be able to attend a particular school. In that case, the scholarship money undervalues the difference the scholarship makes in the athlete's future earnings. On the other hand, not all athletes graduate (the average graduation rate for men's basketball players entering in 1997 to 2000 is 61%), and that is partly due to the demands of playing on the team and possibly student-athletes attending schools that are academically beyond their abilities. In addition to educational benefits, training and experience increase the likelihood that a student-athlete will play professionally, although only a very, very small number of men's college basketball players go on to play professionally. Because of the difficulty of placing a value on these effects, we limit our comparisons to the direct pecuniary gains to student-athletes, in the same way that we limit ourselves to the direct pecuniary costs to the schools in granting athletic scholarships.

Estimating Method:	Scully	Pro
% of MRPs > GIA	58%	60%
% of MRPs > new cap	59%	61%
% of MRPs > COA	60%	63%

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. While coaches adjust their expectations based on a player's high school record, suppose that the average MRP of current players is a reasonable proxy for each player's *ex ante* MRP. We find that the average MRP, our hypothetical proxy for each player's *ex ante* MRP, is above the original and current scholarship limit for every school in our sample.

Finally, consider the MRP estimates for the college players who are ultimately drafted by the NBA. Regardless of the method used to estimate drafted players' MRPs, virtually all estimates are greater than the player's original or new cap on athletic scholarships.³⁹ Thus, all drafted players contribute more revenue to their school than they receive in athletic scholarships.⁴⁰ On average, the MRPs are over ten times greater than the GIA received by the

³⁹ The exceptions are Joe Alexander at West Virginia and Dante Cunningham at Villanova, both based on freshman year only.

⁴⁰ The question of whether college athletes generate more revenue than they receive in financial aid has been tackled before for men's basketball players who are subsequently drafted by professional leagues. Brown, 1994, finds that star college men's basketball players on average generate between \$871,310 and \$1,283,000, while he estimates the typical scholarship at roughly \$20,000.

player. Based on the Scully method, the maximum difference is over fifty times greater than the GIA.

VIII. Conclusion

We estimate MRPs based on the student-athlete's playing statistics, as well as using a variation that incorporates pro salary distribution data. We find that about 60% of men's basketball players have a monetary contribution to the school that is greater, often substantially greater, than the value of the scholarship the player received. We conclude that most men's college basketball players are paid less – often substantially less – than their monetary benefit to the college for which they play.

Second, we estimate MRPs for college players who are ultimately drafted by the NBA based on a player's performance statistics, incorporating the distribution of pro salaries, and by directly estimating the effect of the presence of future drafted players on revenues earned by the team. We find that virtually 100% of drafted players contribute more revenues to their school than they receive in the form of scholarships; the degree to which schools “profit” from these star players ranges from \$7,000 to \$1.8 million, with an average of about \$400,000.

Finally, we compare the MRPs estimated using the different methods. For all men's basketball players, we find broadly similar results when using playing statistics whether or not the distribution of pro salaries is incorporated. For drafted players, we find some difference in the mean MRP similar across the three methods, although the mean MRPs are in the same ballpark regardless of the method used to estimate MRP. The difference in the three methods is more obvious in terms of the variation in MRPs. In particular, the Brown approach, by construction, provides a single MRP estimate for all drafted players at low-revenue schools and a second single MRP estimate for all drafted players at high-revenue schools, regardless of

position or quality of the player. The MRPs as estimated by the Scully and pro methods show a range in estimated MRPs, from about \$5,000 to over \$400,000 at low-revenue schools and from \$100,000 to \$2 million at high-revenue schools.

We have implemented three methods for measuring MRP. Each method gives somewhat different numerical results, but the conclusion that stems from each one is the same: a majority of men's college basketball players contribute more to their schools' revenue than what they get from the schools.

Appendix A: Data Sources

Win-loss data: NCAA, <http://web1.ncaa.org/stats/StatsSrv/careerteam>.

Basketball team revenues: U.S. Department of Education's Office of Postsecondary Education's Equity in Athletics Data Analysis Cutting Tool Website.

Players' performance statistics: NCAA, <http://web1.ncaa.org/stats/StatsSrv/careerteam>. Team performance statistics are calculated by summing individual players' statistics.

Coach of the year and winningest coach: NCAA, Basketball Records Book.

Number of games that were televised: ESPN, 7 August 2007, Men's College Basketball Team Schedules, <http://sports-ak.espn.go.com/ncb/teams>.

Arena capacity: NCAA, undated, Archived Team-By-Team Final Statistics, <http://web1.ncaa.org/stats/StatsSrv/careersearch>.

Nike schools: nikebiz.com, undated, If Your School's Name is on the Front of the Product, You Might Want to Know about the Names Behind It, <http://www.nike.com/nikebiz/nikebiz.jhtml?page=25&cat=collegiat>.

Population: U.S. Census Bureau

Draft: www.nbadraft.net.

GIA and COA: Department of Education, National Center for Education Statistics, IPEDS (Integrated Postsecondary Education Data System) data, <http://nces.ed.gov/ipeds/>.

Appendix B: Descriptive Statistics

Data used in all regressions are at the year/team level. Due to differences in data availability, years included vary by regression.

1. Scully Approach Win-Loss Percentage Regression

The Scully Approach Win-Loss Percentage regression includes data for 2001 – 2006. The number of schools included varies by year due to changes in NCAA division status and data availability.

Year	Number of Teams Included
2001	170
2002	172
2003	172
2004	172
2005	178
2006	180

Variables included in Scully Approach win-loss percentage regression:

	Obs	Mean	Std. Dev.	Min	Max
Win-loss percentage	1044	0.55	0.17	0.07	0.95
Percentage Goals Made	1044	0.44	0.03	0.37	0.53
Percentage Free Throws Made	1044	0.69	0.04	0.57	0.80
Three Point Goals per Game	1044	6.38	1.27	2.72	13.93
Blocks per Game	1044	3.52	1.22	0.80	10.79
Steals per Game	1044	6.98	1.46	3.73	23.36
Rebounds per Game	1044	32.18	3.31	21.39	81.93
New Coach	1044	0.11	0.31	0	1
Coach of the Year	1044	0.01	0.10	0	1
“Winningest” Coach	1044	0.18	0.30	0	0.82
Opponent Average Index	1044	1.66	1.45	0	6.65

2. Scully Approach Revenue Regression

The Scully Approach Win-Loss Percentage regression includes data for 2001 – 2004. The number of schools included varies by year due to changes in NCAA division status and data availability.

Year	Number of Teams Included
2001	169
2002	169
2003	170
2004	168

Variables included in Scully Approach revenue regression:

	Obs	Mean	Std. Dev.	Min	Max
Revenue	676	\$3,593,735	3,376,319	\$99,687	\$18,523,619
Win-loss percentage	676	0.55	0.17	0.07	0.95
Win-loss percentage \times large school	676	0.05	0.18	0.00	0.95
Arena capacity	676	11,070	5,062	1,200	33,000
Opponents' arena capacity	676	11,095	2,616	5,461	16,755
Nike school	676	0.08	0.28	0	1
Past team index	676	1.69	4.22	0	23.055
Opponents' average index	676	1.70	1.52	0	6.65
# of games televised	676	5.05	7.51	0	36

3. Brown Approach Regression

The Brown Approach regression includes data for 2002 – 2004. The number of schools included varies by year due to changes in NCAA division status and data availability.

Year	Number of Teams Included
2002	169
2003	170
2004	168

Variables included in Brown Approach regression:

	Obs	Mean	Std. Dev.	Min	Max
Revenue	507	\$3,727,093	3,473,307	\$99,687	\$18,523,619
# Drafted Players	507	0.69	1.15	0	7
# Drafted \times Large School	507	0.18	0.75	0	6
Arena capacity	507	11,068	5,064	1,200	33,000
Opponents' arena capacity	507	11,080	2,629	5,461	16,755
Nike school	507	0.08	0.28	0	1
Past team index	507	1.74	4.19	0	23.06
Opponents' average index	507	1.69	1.48	0	6.65
# of games televised	507	6.74	8.00	0	36

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Notes