Supplemental Appendix for "Who Profits from Amateurism? Rent-sharing in Modern College Sports"

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I. Previous Research Studying College Sports

As described in the Introduction, there is some previous research examining related questions about the economic rents generated by college athletes. Of particular relevance to our questions regarding rent-sharing and potential compensation for athletes, a number of studies have attempted to calculate the marginal revenue product (MRP) for each football player. These efforts mostly follow the methods proposed by Scully (1974) and date as far back as Brown (1993), which attempts to calculate the MRP of elite college football players. Using a small sample of colleges, Brown (1993) finds that each NFL draft pick was associated with $500,000 in extra revenue for a college. Brown (2011) updates this estimate to include more colleges and finds that by 2005 an NFL draftee was worth around $1 million for a college on an annual basis. Lane et al. (2014) take a similar approach in estimating marginal revenue products of men's college basketball players. More recently, a series of papers have used recruiting rankings to estimate the MRP of college football and basketball players (Borghesi 2017; 2018; Bergman and Logan 2020). An advantage of this approach is that it leverages a metric of skill that is measured prior to an athlete entering college and is available for all players. These studies provide consistent evidence that the estimated MRP for players exceeds the scholarship value for all recruits of the quality that typically attend Power 5 colleges – with an even larger gap for the highest-skilled athletes. One difficulty in interpreting these studies is the potential for reverse causality – that is, do high-revenue colleges attract good athletes, or do good athletes increase revenues for colleges? Including college fixed effects can address this difficulty if the college-specific factors are time-invariant, but this reduces the estimated MRP by roughly 70 percent (Bergman and Logan 2020). Additionally, there are several time-varying factors such as new coaches or better facilities that could simultaneously increase revenue and attract higher-skilled athletes, which could bias estimates of the athlete's MRP.

Other authors have also attempted to calculate whether certain parts of the college sports value chain are capturing excess rents. These studies primarily focus on a single part of the value chain in isolation and lack the complete financial data that we have gathered in this paper. For example, (Leeds, Leeds, and Harris 2018) examine whether coaches obtain a greater share of the economic rents than would be expected given their on-the-job performance. Similar to our results, they find that coaches obtain a portion of the rents that exceed their on-the-job performance.

Finally, other authors have hypothesized that the existing system of rent-sharing results in a shifting of resources between athletes with meaningfully different economic backgrounds. Perhaps the clearest

example of this would be Sanderson and Siegfried (2015), who discuss this possibility in their argument for paying college athletes. However, we are not aware of existing research that empirically examines the distributional consequences of the existing rent-sharing system. We are able to directly address this question using our novel athlete-level data that matches high schools and hometowns to neighborhood socioeconomic characteristics.

II. Data Sources and Description

Athletic Department Finances

Our data on athletic department finances comes mainly from two sources: The College Athletics Financial Information database from the Knight Commission on Intercollegiate Athletics (Knight), and the U.S. Department of Education's Equity in Athletics Data Analysis (EADA) database. We also supplement this with data on total revenue, total spending, and institutional support from the USA Today NCAA Finances database, which is obtained through public records requests to colleges.

Colleges are required to report the EADA data to receive Title IV funding, so we observe this for all colleges in our sample. We observe revenue and expenses separately for each sport, covering the 2005-2006 through 2018-2019 school years. Schools also report additional "non-sport" revenue and expenses that are not allocated to a specific sport, which complicates some of our analysis. While the granularity and comprehensiveness of this data is ideal for our analysis, there are data quality concerns (Dosh 2017). We address these concerns and our approaches for handling them in Section III.A.1 and Online Appendix Section II.

The Knight data covers only 46 of the 65 colleges in our sample and covers the 2005-2006 through 2017-2018 school years. The Knight data is constructed as a synthesis of multiple data sources, but mainly comes from revenue and expense reports from public colleges and universities that are required to release financial statements. Therefore, these data provide the best information about colleges' financial constraints and budgeting. Unfortunately, the Knight data does not have sport-specific revenue and expenses, only school-year level aggregates for various categories.

Recruiting Class Rankings Data

We manually downloaded data from two websites: 24/7 (247sports.com) and Rivals (n.rivals.com). These websites provide detailed ratings of the recruiting classes each year for football and men's basketball. We collected data for football and men's basketball for the years 2011-2022 from 24/7, and we collected football ratings data from Rivals for the years 2002-2022.

We start from the school-year data used in Table 3 (which reports our main rent-sharing elasticity estimates), and we merge the ratings data onto this dataset. For the Rivals data, the data set is nearly complete and almost completely balanced, with only 3 school-year observations missing

from 2006-2008. The raw data contains information on the number of student-athletes committed to each team in a given year, the average player ranking (on a scale of 1-5 or 0-100 depending on the website), and a composite ranking that accounts for class size and quality.

We focus our analysis on a composite measure that is z-score standardized within a year, partly because Rivals changed its composite ratings measure in 2013, which is in the middle of our sample period. We match the recruiting data by year based on the year the recruiting classes would first enroll in college.

To validate that our recruiting ratings capture true variation in player quality, we correlate the 4-year lagged average standardized recruiting rating with each school-year's football power rating using the school-by-year college football power rating index from ESPN.com. We report the "binscatter" correlations in Online Appendix Figures OA.5, controlling for year fixed effects (Panel A) and controlling for school and year fixed effects (Panel B). Both figures show a strong correlation, which implies that stronger recruiting classes are associated with better on-field performance during the years that those recruited student-athletes are playing on the team. These correlations show that the recruiting ratings are proxy for underlying player quality.

As a result, the results in Table 6 showing a lack of correlation between changes in football and men's basketball revenue and changes in standardized recruiting rankings is consistent with limited bias in our primary rent-sharing elasticity estimates coming from endogenous changes in player quality.

Coaches' Salaries Data

The Knight data includes data on total salaries paid to all coaches and data on total salaries paid to all of the football coaches (i.e., all of the coaching staff). Non-football coach salaries are constructed by subtracting football coach salary spending from total coach salary spending for all colleges in the Knight dataset. Data from the Knight Commission draw upon publicly available tax documents, and therefore these measures may not include direct payments from non-university sources (for example, contracts between coaches and shoe companies). We supplemented this data with hand-collected data on football head coach salaries and identify all of the football head coaches during our sample period for all of the colleges in our data. We used two main sources:

1. 990 Tax Forms sourced from ProPublica. To gather football head coach salaries, we utilized ProPublica's Nonprofit Explorer site. We searched for each college or the coach's name, and we recorded the total compensation (base compensation, bonus and incentive compensation, other reportable compensation, retirement, and other deferred compensation, and nontaxable benefits) for the head football coach.

2. USA Today database. An alternative site that has salary information for college coaches is USA Today. To gather this data, we utilized the "total compensation" column. USA Today gathered this data by reaching out to all institutions requesting contract information for all forms of compensation and pay received by head football and basketball coaches. The years covered for football are 2006-2020 and for basketball, they are 2010-2019. The institutions were given the chance to review the figures, the review was conducted between September 29 to October 13, 2020. The dataset does not contain salary data for 2008, as USA Today did not collect data during this year, and compensation is missing from a few private universities and state schools that are covered under state law exempting them from releasing coach salary information. The description of total pay is as follows: "Sum of Actual School Pay and athletically related compensation received from non-university sources. (Effective Aug. 8, 2018, the NCAA reinstated a rule that requires athletics department employees to annually disclose athletically related income from non-university sources.)". This measure was utilized rather than actual school pay, as it was more highly correlated with the salary gathered from the 990 tax forms as shown in Online Appendix Figures OA.6 and OA.7. The USA Today total pay data was also utilized in Leeds et al. (2018) covering period 2006-2016.

Roster Data and Athlete Demographics

We collect roster data for each school and sport in our sample by scraping each school's athletics website in October 2018.[1] The format of the online rosters varies across colleges, but the hometown and previous school(s) attended of each athlete is typically listed. Online Appendix Table OA.18 shows sample statistics on the number of athletes[2] observed with each characteristic and the number matched to specific cities/counties and public high schools. We note that match rates at each step of the process are similar between revenue and non-revenue sports.

We match athletes to a Census Designated Place (CDP) and county using fuzzy text matching on the hometown field in each athlete's roster entry. We also match by hand any listed hometowns that appear in the roster data 10 or more times but are not matched by the algorithm.[3] The hometown matching works well, as we are able to match 93.4% of athletes where a U.S. state is listed to a county or CDP. Additionally, the total fraction of athletes that are not matched to a state is consistent with NCAA data on the foreign athlete share in the Power 5 conferences.

[1] An example is the Northwestern football team roster found here: https://nusports.com/sports/football/roster.
[2] The level of observation is technically athlete-sport as athletes that play multiple sports appear on the roster for each. Multi-sport athletes are rare, so we refer to the level as athlete for simplicity.
[3] This solves problems such as matching common alternative names, e.g. this matches all athletes with "Brooklyn, NY" listed as their hometown to the New York, NY CDP.

The high school matching is more difficult. While most athletes have a previous school attended field in their roster entry, the formatting of the entry often does not indicate whether this is the athlete's high school, or a previous college attended. Many athletes also attended private high schools, prep schools, or sports academies prior to enrolling in college rather than public schools. We again attempt to match athletes with a previous school listed through fuzzy text matching. For each athlete, we only search over the set of public high schools in the county or counties of the athlete's hometown. Therefore, the sample of athletes matched to a high school is necessarily a subset of the athletes with a matched hometown. We impose these search restrictions for two reasons. First, this improves match quality by reducing false matches from high schools in the same state with a similar name. Second, our empirical strategy is to aggregate Census tract data to form school-level sociodemographic measures, so it is necessary for the athlete to have attended a public school in their assigned district for these measures to be relevant.

We perform several validation tests on the high school match. From a random sample of 500 matches, we find the false positive rate to be less than 3%. We also check for a correlation between local private high school enrollment shares and the match rate in our sample. Appendix Figure OA.8 shows the fraction of athletes matched by binned private school share in their home county from the ACS. This suggests private school enrollment explains a significant amount of the unmatched athletes. Our final analysis sample results in 29,556 athletes matched to a CDP/county, with 16,794 of these athletes matched to a public high school.[4]

We compute statistics on student demographics by merging Census data on these geographic variables. First, census demographic data was downloaded from Social Explorer to gather information on mean and median household income (in 2018 dollars), proportion of population of various races and ethnicities, proportion of the adult population at various education levels, and proportion of the population living in poverty. All variables, but for mean household income, come from the 2000 Census SF3 and SF1 files, imputed to 2010 census tract geographies. The mean household income variable is derived by dividing aggregate household income by the number of households, in a calculation done by Social Explorer. Just 0.7% of the observations in the census dataset are missing, which is due to data suppression.

The tract-level census data is then merged and aggregated to the school level. First, we merge to a "school catchment area to tract" crosswalk.[5] 99.98% of schools have census information for at least one census tract in the catchment area, and 96.9% of schools have census information for all tracts. The dataset includes all schools that have census information for at least one tract. There are only two schools that don't match to the crosswalk file (accounting for the 0.02%),

[4] Clemson did not have previous school listed on any of the rosters, so the high school sample of colleges comes from only 64 colleges.

[5] These data were provided to us by Peter Bergman, with the original data coming from Maponics (2017).

because census data was missing for all tracts in that school's catchment area. Each census variable is then collapsed to the school level, weighted by relevant total. For example, household income is weighted by the number of households in the tract, whereas the education level for adults over 25 is weighted by the total number of adults over 25 in the tract.

As a final step, the now school-level demographic information is merged to the athlete roster data for athletes matched to a public high school. Of the 16,794 matched to a public high school, we successfully merge on the school-level demographics for 15,184 (90.4%). The unmatched are a result of either colleges missing from the crosswalk file because they were built after the crosswalk was created or because the school attendance zone data is unavailable, such as charter schools or a school district with fully open enrollment. We also merge college demographic data to each athlete from the Opportunity Insights college-level datasets (Chetty et al. 2020). For each school, the mean and median parent's income is reported. We can then report these summary statistics for colleges in the Opportunity Insight data generally, and compare them to the average household income and median household income from the athlete to census merged data above as a way of comparing athlete-specific parent income to the school's typical student's parent's income. Data is inflation-adjusted to 2018 dollars (adjusted from 2015 dollars).

III. Construction of Finances Analysis Sample

Sample and Variables

The EADA data covers academic years 2002-03 through 2018-19. We drop years prior to the 2005-2006 academic years due to data quality issues. We use the convention of our panel year referring to the end of the academic year, so 2006 corresponds to the 2005-2006 academic year and the 2005 fall football season. 64 of the 65 colleges in our sample are in the EADA data for every year in our sample. The exception is the University of Maryland, which does not report EADA or Knight data prior to 2009. Therefore, from the 65 schools and 14 years in our sample, we observe 907 of a possible 910 school-year observations. From the EADA data, we observe revenue and expenses for each school-sport-year as well as revenue and expenses not allocated to a specific sport for each school-year. Additionally, the EADA data reports the dollar value of "athletics-related student aid" that athletes receive in scholarships at the school-year level.

The Knight data covers the years 2005-2018, which gives us 13 years that match up with our EADA panel. 45 of the 65 colleges in our sample are covered by the Knight data in every year from 2006-2018, and the University of Maryland is present in the Knight data from 2009-2018. This gives 595 total observations in our Knight sample. The Knight data provides the best measure of total athletic department revenue and expenses, as well as several other revenue and expenditure categories. The revenue categories include ticket sales, donations, sponsorship and advertising, institutional support (student fees and general university/government funds), and a revenue category that includes NCAA and conference disbursements from postseason tournaments and TV contracts. The NCAA and conference disbursement variable is of particular interest for our empirical estimates of rent-sharing, as it accounts for a substantial amount of within-school variation in revenue. Both anecdotally and in the data, football and men's basketball appear to drive nearly all of these changes. The average of the NCAA and conference disbursement revenue category for colleges in the Big Ten conference increased from $41.7 million in 2016-17 to $56.8 million in 2017-18. For the University of Michigan, this change was almost identical from $43.2 million to $58 million over the same time. $51.1 million of this was from conference disbursements, with the significant increase attributed to new media rights deals for the conference's football and men's basketball games (Chengelis 2018). Figure 4 shows that within-school changes in NCAA/Conference/Bowl/TV revenue are correlated with contemporaneous changes in football, men's basketball, and "non-sport revenue" in the EADA data but not with revenue for other sports. Appendix Table OA.2 shows that the pass-through to non-sport revenue reflects differences in accounting practice, likely regarding how television revenue from football and men's basketball is categorized.

On the expenditure side, the Knight data has variables on total compensation for coaches and administrators, spending on facilities, and total student aid for athletes. The next sections describe various steps we take to clean the raw data before arriving at our analysis samples.

Sport Level Revenue Imputation

The first issue with the EADA data is the prevalence of school-sport-year observations where revenue and expenses are exactly equal to each other, mostly for sports other than football and men's basketball. While it is theoretically possible that colleges allocate spending to a sport to match its revenue and the true net income is zero, we find this implausible for several reasons. First, even if a sport is ex-ante budget neutral, revenue from ticket sales and various expenses like travel and medical care will vary over the course of the academic year. This makes it very unlikely that a sport is truly budget neutral *ex post*. Second, the zero net income sports are concentrated in school-year observations that typically report zero net income for a majority of their non-FB/MBB sports. Of the 907 total EADA school-year observations, 137 have a sport with zero net income and 121 of these have eight or more sports with zero net income. This again suggests colleges are misreporting revenue and/or expenses for these sports.[6]

The data suggests that net income is overstated in the years where net income is zero for these sports, and this is a result of revenue inflation rather than expense deflation. Appendix Figure OA.9 shows that the mass of school-sport-years at zero net income are in the right tail of the overall distribution of net income for these sports. Columns (4) and (5) of Appendix Table OA.25 show that occurrences of zero net income at the sport-level are not partially correlated with positive school-level shocks to revenue or profitability. Columns (1) - (3) of Appendix Table OA.25 show that at the sport-level, zero net income occurrences are partially correlated with large within-team increases in revenue and a nearly identical increase in net income, with virtually no change in expenses. This suggests that zero net income observations reflect artificial revenue inflation, and this inflation is meaningful in percentage terms of the average revenue for these sports.

To address this problem, we delete and then impute sport-level revenue and net income for all observations where net income is exactly or nearly zero. Revenue is imputed for all school-sport-year observations for non-FB/MBB sports[7] where the absolute value of net income as a fraction of sport-level expenses is less than 0.02. As women's sports account for a majority of non-FB/MBB sports at most colleges, we slightly broaden the criteria for imputation to capture data manipulation across multiple women's sports. We also impute revenue for women's sports where the absolute

[6] Berri (2018) points out that the "Revenue Theory of Cost" would also be consistent with instances of exactly zero net income in absence of data manipulation. While this seems plausible ex ante for the athletic department as a whole, we find our explanation of data manipulation more plausible for specific sports ex post net income.

[7] Zero net income for football and men's basketball is rare and appears to be in cases that understate true net income rather than overstate.

value of net income as a fraction of expenses is less than 0.1 and either total net income as a fraction of total expenses for all women's sports is also less than 0.1, or there are five or more women's sports in the school-year that have net income as a percentage of expenses less than 0.1. We exclude Stanford from these broader criteria, as their women's sports have net income around zero in almost every year of the data, implying it is not a result of manipulation.

For observations that meet the imputation criteria, the new imputed revenue and net income measures are created by the following procedure. First, we estimate separately for each sport s the regression

$$\ln(Rev_{jst}) = \alpha + \beta Impute_{jst} + \theta_j + \lambda_{jt} + \epsilon_{jst}$$

where j indexes colleges, t indexes years, Rev_{jst} is school-sport-year revenue as reported in the EADA data, $Impute_{jst}$ is a dummy for meeting the imputation criteria, θ_j are school-fixed effects, and λ_{jt} are conference-year fixed effects. For observations that meet the imputation criteria, we then delete revenue and replace it with

$$ImputedRev_{jst} = \exp\{\ln(\widehat{Rev_{jst}}) - \hat{\beta}\}$$

where $\ln(\widehat{Rev_{jst}})$ is predicted values and $\hat{\beta}$ is the OLS estimate from the above regression. Appendix Figure OA.10 shows the school-sport-year distribution of net income for non-FB/MBB sports after imputation. Sport-level net income and all school-level aggregate revenue and net income variables are then re-calculated using imputed sport-level revenue. School-level total revenue is not affected, as we make corresponding changes to the "non-sport" revenue of each school after every sport-level imputation. Overall, revenue is imputed for 9.6% of all school-sport-year observations.

Baylor, Boston College, Rutgers, and West Virginia do not have a sufficient number of years where no sports meet the imputation criteria to be suitable for our imputation procedure and are dropped completely from any analysis using the EADA data. This leaves a total of 851 school-year observations in the EADA analysis sample.

IV. Predicting Athlete Race

To impute race, we utilize the 'rethnicity' R package that predicts race based on first and last name (Xie 2022). The package utilizes a Bidirectional Long Short-Term Memory, a type of recurrent neural network commonly used for sequence prediction problems. The model was trained using Florida voter registration data, which contains names and the races of all Florida Voters. While this is a common dataset used in other race prediction packages (Sood and Laohaprapanon 2018; Imai and Khanna 2016; Parasurama 2021), Xie differs in that they under-sampled the majority class to create a balanced dataset focused on minorities. Race prediction packages often have lower recall rates when predicting minorities, as minorities are typically underrepresented in data leading to an algorithmic bias that focuses on the majority class. To alleviate this, 'rethncity' takes the smallest race group which contains around 104,000 observations, and randomly selects the same number of observations for each of the subsequent race categories: Asian, Black, Hispanic, and White. To assess the accuracy of the model the authors calculate the recall rate. Recall is one of the prevailing measures used in machine learning to determine how well a model is performing. The recall rate is a measure of the model's ability to correctly identify true positives. When compared to the Voter Registration data, the package's recall rate is 0.76 to 0.77 for Black names and 0.68. to 0.73 for White names, making it one of the superior prediction models when it comes to predicting minority names.

Incorporating this package into our analysis, we took two random samples. One random sample contained 153 college athletes across all sports and included male and female athletes. The other sample contained five randomly selected football teams for a total of 299 male athletes. To validate the data, we observed race based on publicly available roster photographs and then utilized the 'rethnicity' package. When running the 'rethnicity' package, we correctly identified the race of 0.72 of the football only sample, with a recall rate of 0.74 for Black athletes and 0.66 for White athletes. For the all-sports sample, the overall recall rate is 0.64, with 0.74 for Black athletes and 0.6 for White athletes. These numbers are in line with the recall rates found by Xie (2021) and are higher than other prediction models in the literature (Sood and Laohaprapanon 2018; Parasurama 2021).

V. NFL and NBA Collective Bargaining Agreements Excerpts

Below we include excerpts from the collective bargaining agreements of the NFL and NBA that describe the share of revenue designated for player salaries.

NFL

From Section 6(c)(ii) of the 2020 NFL-NFLPA Collective Bargaining Agreement:

"**Bands.** (A) If, in the 2020 League Year, the Player Cost Amount before application of the Stadium Credit is greater than 48.5% of Projected AR then the Player Cost Amount shall be reduced to 48.5% of Projected AR. If, in the 2020 League 96 Year, the Player Cost Amount is less than 47% of Projected AR, the Player Cost Amount shall be increased to 47% of Projected AR.
(B) If, in the 2021–2030 League Years, the Player Cost Amount before application of the Stadium Credit is greater than 48.5% of Projected AR then the Player Cost Amount shall be reduced to 48.5% of Projected AR. If, in any of these League Years, the Player Cost Amount is less than 48% of Projected AR, the Player Cost Amount shall be increased to 48% of Projected AR."

NBA

From Section 12(b)(3) of the 2017 NBA-NBPA Collective Bargaining Agreement:

"The Designated Share for each Salary Cap Year covered by the term of this Agreement shall equal fifty percent (50%) of BRI for such Salary Cap Year, provided that the Designated Share for a Salary Cap Year shall be increased or decreased in accordance with the following: (i) in the event that BRI for a Salary Cap Year exceeds the amount of BRI forecasted for such Salary Cap Year as set forth below, then the Designated Share for such Salary Cap Year shall equal fifty percent (50%) of the amount of BRI forecasted for such Salary Cap Year, plus sixty and one-half percent (60.5%) of the difference between the BRI for such Salary Cap Year and the BRI forecasted for such Salary Cap Year; and (ii) in the event that BRI forecasted for a Salary Cap Year as set forth below exceeds BRI for such Salary Cap Year, then the Designated Share for such Salary Cap Year shall equal fifty percent (50%) of the amount of BRI forecasted for such Salary Cap Year, less sixty and one-half percent (60.5%) of the difference between the BRI forecasted for such Salary Cap Year and BRI for such Salary Cap Year. Notwithstanding anything to the contrary in the foregoing, in no event shall the Designated Share for any Salary Cap Year be less than forty-nine percent (49%) of BRI or greater than fifty-one percent (51%) of BRI."

VI. Bowl Game Revenues and Media Rights

This section gives more details on bowl game revenues and media rights to provide more background on the instrumental variable described in the main text.

Conferences receive substantial payments when football teams qualify for post-season bowl games – and therefore by definition this revenue varies by year.[8] As an example of the sources of variation in these payments, consider the case of the Big Ten and Pac-12 conference in 2019. In that year, the Big Ten conference received an additional $6 million in payments because Ohio State earned a spot in the Fiesta Bowl and an additional $4 million for Penn State's berth in the Cotton bowl (Dosh 2019). These payments were in addition to the annual $40 million the conference receives each year as part of its ongoing contract with the Rose Bowl and its $66 million base payment from the College Football Playoffs (CFP). By contrast, in the same year teams in the Pac-12 had less successful seasons and did not receive invitations for any additional high-revenue bowl games. Therefore, the conference only received its regular $40 million for its contract to take part in the Rose Bowl and its $66 million CFP base payment from the College Football Playoffs. Given that the Big Ten shares all bowl revenue equally, this means each Big Ten athletic department received over $700,000 in additional revenue simply because of the successful seasons of the Ohio State and Penn State football teams. Conferences also receive payouts for participation in the annual "March Madness" men's basketball tournament – with part of the payments being based on the number of teams that qualify for the tournament.[9] In addition to payments related to the success of other teams, colleges also receive substantial payments from their conferences for media rights. These payments are not explicitly tied to the decisions of any one college and vary both over time and across conferences. In modern athletics, these media payments have grown substantially in value (Sanderson and Siegfried 2018).

VII. University of Utah Case Study

The supportive visual evidence leads us to interpret our panel fixed effects estimates as valid rent-sharing elasticity estimates. However, to further support the causal interpretation of our panel data estimates, we also report complementary results from an instrumental variables strategy that

[8] College football bowl games are post-season contests that are played primarily by NCAA FBS colleges. Bowl games pay the teams for participation, and the money is shared within the conference. Roughly half of all FBS colleges play in a bowl game each year.
[9] Conferences receive payments based on the success of their members in the men's postseason basketball tournament. Conferences earn "units" based on each stage of the tournament that their teams advance to. Each year's payments are based on a six-year rolling average of NCAA tournament performance.

exploits variation in revenues generated by the substantial transfers from conferences to athletic departments. As detailed in the main text, these revenues primarily accrue from payments to the conference resulting from bowl game participation by all members, NCAA tournament revenue, and revenue from media rights contracts (i.e. television rights). In this way, these revenues are generally[10] not directly related to the success of any individual college's team – but are clearly the result of that college participating in football and men's basketball.

Consider the case of bowl revenue. Conferences receive substantial payments when football teams qualify for post-season bowl games – and therefore by definition this revenue varies by year.[11] As an example of the sources of variation in these payments consider the case of the Big Ten and Pac-12 conference in 2019. In that year, the Big Ten conference received an additional $6 million in payments because Ohio State earned a spot in the Fiesta Bowl and an additional $4 million for Penn State's berth in the Cotton bowl (Dosh 2019). These payments were in addition to the annual $40 million the conference receives each year as part of its ongoing contract with the Rose Bowl and its $66 million base payment from the College Football Playoffs (CFP). By contrast, in the same year teams in the Pac-12 had less successful seasons and did not receive invitations for any additional high-revenue bowl games. Therefore, the conference only received its regular $40 million for its contract to take part in the Rose Bowl and its $66 million CFP base payment from the College Football Playoffs. Given that the Big Ten shares all bowl revenue equally, this means each Big Ten athletic department received over $700,000 in additional revenue simply because of the successful seasons of the Ohio State and Penn State football teams. Conferences also receive payouts for participation in the annual "March Madness" men's basketball tournament – with part of the payments being based on the number of teams that qualify for the tournament.[12] In addition to payments related to the success of other teams, colleges also receive substantial payments from their conferences for media rights. These payments are not explicitly tied to the decisions of any one college and vary both over time and across conferences. In modern athletics, these media payments have grown substantially in value (Sanderson and Siegfried 2018).

To demonstrate the importance of conferences in the revenue generated by football and men's basketball and to motivate our instrumental variables analysis, we first present a case study of the University of Utah – which moved from the relatively small Mountain West athletic conference to the larger and more financially sophisticated Pac-12 conference in 2012 (the decision was

[10] In some cases, the individual team that participates in or wins the bowl game will receive a larger sum of money than other teams in the conference that do not participate or win the bowl game, so this instrument still contains some components of revenue that are related to the individual school's current and lagged success. If current and lagged success are related to shocks the entire athletic department received and which lead to changes in spending, then this could constitute an exclusion restriction violation.
[11] College football bowl games are post-season contests that are played primarily by NCAA FBS colleges. Bowl games pay the teams for participation, and the money is shared within the conference. Roughly half of all FBS colleges play in a bowl game each year.
[12] Conferences receive payments based on the success of their members in the men's postseason basketball tournament. Conferences earn "units" based on each stage of the tournament that their teams advance to. Each year's payments are based on a six-year rolling average of NCAA tournament performance.

announced in June 2010). Figures OA.3 and OA.4 show the changes in revenue and spending from various categories from Utah's athletic department over this time period. For comparison we also provide the average for all other Power 5 teams over this time period. The top-left panel contains Utah's revenue from conference payments and shows a marked increase that begins immediately after its transition into the Pac-12 conference. Similarly, the top-right panel shows a swifter increase in revenue for football and men's basketball after joining the conference. Admittedly, this increase follows an already-increasing trend, but the figure shows clear "convergence" in football and men's basketball revenue for the University of Utah after joining the Pac-12. This trend reflects Utah's success in these sports, and it was arguably this success that made Utah an attractive target for moving to the Pac-12 in the first place.

All of the spending variables in Figures OA.3 and OA.4 follow the pattern established by our panel data estimates – i.e., increases in revenue generated by the activities of the football and men's basketball teams causing higher spending for all of the other sports, higher salaries for coaches and other personnel, and higher spending on facilities. While Utah is only a single case study of a college switching conferences, it provides visual and empirical evidence that supports our main panel data estimates. Additionally, the case study demonstrates the economic importance of conference payments, which motivates the instrumental variables analysis described in the main text.

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Online Appendix Table OA.1
Decomposition of NCAA/Conference/TV/Bowl Revenue by EADA Revenue Categories

	Dependent Variable is Revenue Category:						
	Total Revenue	All Sports Revenue	Non-Sport Revenue	Football	Men's Basketball	Other Men's Sports	Women's Sports
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total revenue from conference payouts, football bowls, and TV contracts	0.711	0.532	0.179	0.440	0.102	-0.027	0.018
	(0.111)	(0.106)	(0.105)	(0.091)	(0.026)	(0.012)	(0.018)

Notes: N = 569 for all regressions, and the unit of observation is a college-year. All variables are in 2018 dollars and measured in levels. The sample includes only non-revenue sports and covers 44 colleges from "Power 5" conferences in the Knight data between 2006 and 2018. Regression standard errors are shown in parentheses and are clustered by college. All regressions include college fixed effects and year fixed effects.

Online Appendix Table OA.2
Decomposition of NCAA/Conference/TV/Bowl Revenue: Heterogeneity by Non-Sport Revenue Share

	Dependent Variable: Revenue from						
	Total Revenue	All Sports Revenue	Non-Sport Revenue	Football	Men's Basketball	Other Men's Sports	Women's Sports
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total revenue from conference payouts, football bowls, and TV contracts	0.714	0.869	-0.155	0.826	0.088	-0.036	-0.010
	(0.144)	(0.132)	(0.133)	(0.112)	(0.033)	(0.015)	(0.023)
* 2nd Quartile Non-Sport Share	0.086	-0.188	0.274	-0.261	0.015	0.019	0.040
	(0.109)	(0.101)	(0.101)	(0.085)	(0.025)	(0.011)	(0.017)
* 3rd Quartile Non-Sport Share	-0.087	-0.246	0.160	-0.250	0.007	-0.020	0.016
	(0.115)	(0.106)	(0.107)	(0.090)	(0.027)	(0.012)	(0.018)
* 4th Quartile Non-Sport Share	-0.084	-0.602	0.518	-0.645	0.016	0.009	0.019
	(0.111)	(0.102)	(0.103)	(0.086)	(0.026)	(0.011)	(0.017)

Notes: N = 569 for all regressions, and the unit of observation is a college-year. All variables are in 2018 dollars and measured in levels. The sample includes only non-revenue sports and covers 44 colleges from "Power 5" conferences in the Knight data between 2006 and 2018. Regression standard errors are shown in parentheses and are clustered by college. All regressions include college fixed effects and year fixed effects. The main independent variable is interacted with dummies for quartile of college-level average of the share of EADA revenue that is categorized as “non-sport” across all years.

Online Appendix Table OA.3
Descriptive Statistics for Private and Public Schools

	All Schools		Private Schools		Public Schools	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
	(1)	(2)	(3)	(4)	(5)	(6)
Revenue:						
Total revenue	93.714	33.108	84.610	26.664	95.296	33.871
Total sport revenue	66.535	28.786	58.172	26.298	67.988	28.968
Total non-sport revenue	27.179	14.568	26.438	15.941	27.308	14.324
Men's Football + Men's Basketball revenue	59.499	26.685	49.097	22.159	61.307	27.003
Women's sports revenue	4.028	3.417	5.589	5.854	3.756	2.701
Other men's sports revenue	3.008	2.439	3.485	2.505	2.925	2.419
Expenses:						
Men's Football + Men's Basketball expenses	31.623	11.145	31.805	9.372	31.591	11.430
Women's sports expenses	15.201	5.031	16.663	4.983	14.947	5.000
Other men's sports expenses	8.029	3.531	8.675	3.208	7.916	3.574
Revenue - Expenses (Net Revenue):						
Men's Football + Men's Basektball	27.876	19.649	17.292	15.896	29.716	19.666
Women's sports	-11.173	4.578	-11.073	4.331	-11.191	4.622
Other men's sports	-5.021	2.570	-5.189	2.860	-4.992	2.517
Additional spending measures (from Knight commission):						
Salaries paid to all coaches	15.933	5.509	-	-	15.933	5.509
Salaries paid to football coaches	6.702	2.865	-	-	6.702	2.865
Total administrative compensation	16.533	6.923	-	-	16.533	6.923
Facilities spending	20.118	9.537	-	-	20.118	9.537
Total revenue from conference, bowls, TV	26.240	12.117	-	-	26.240	12.117
Total Number of Schools	61		9		52	
Total Number of School-Year Observations	851		126		725	

Notes: This table reports descriptive statistics for 61 (of the 65) schools in the "Power 5" athletic conferences. The data exclude 4 schools with sport-level accounting data that is not usable for the statistical analysis (Baylor, Boston College, Rutgers, and West Virginia). All values are in millions of (nominal) dollars, and cover year years 2006-2018. The school-level revenue and expenses data come from the EADA reports provided by the Department of Education. The salary, compensation, facilities, and conference revenue variables come from reports from the Knight commission, and cover 44 of the 65 Power 5 schools. See Data Appendix for more details. Columns 1 and 2 report the mean and median, respectively, for all schools in the sample. Columns 3 and 4 report the mean and standard deviation for private schools, and columns (5) and (6) report the mean and standard deviations for public schools. Data from Knight Commission are only available for public schools

Online Appendix Table OA.4
Heterogeneity of Rent-Sharing Elasticities Across Sports by Public/Private University

Dependent Variable is Total Expenses for:	Football and Men's Basketball	Women's Sports and Other Men's Sports	Women's Sports	Other Men's Sports
	(1)	(2)	(3)	(4)
Panel A: OLS Estimates Including School Fixed Effects and Year Fixed Effects				
Football and Men's Basketball Revenue + Total Non-Sport Revenue	0.828	0.424	0.416	0.439
	(0.090)	(0.071)	(0.078)	(0.093)
Football and Men's Basketball Revenue + Total Non-Sport Revenue * Private School	-0.095	-0.111	-0.081	-0.191
	(0.118)	(0.077)	(0.072)	(0.109)
R^2	0.894	0.941	0.934	0.934
Panel B: OLS Estimates Including School, Year, and Conference-by-Year Fixed Effects				
Football and Men's Basketball Revenue + Total Non-Sport Revenue	0.857	0.431	0.409	0.473
	(0.104)	(0.086)	(0.092)	(0.103)
Football and Men's Basketball Revenue + Total Non-Sport Revenue * Private School	-0.169	-0.150	-0.110	-0.249
	(0.098)	(0.065)	(0.068)	(0.085)
R^2	0.906	0.946	0.939	0.940

Notes: N = 851 for all regressions, and the unit of observation is a school-year. All variables are included in logs so that the coefficients can be interpreted as elasticities. The sample covers 61 schools in "Power 5" conferences between 2006 and 2018. The standard errors are clustered by school and are reported in parentheses.

Online Appendix Table OA.5
Wild bootstrap p-values for Table 3

Dependent Variable is Total Expenses for:	Football and Men's Basketball	Women's Sports and Other Men's Sports	Women's Sports	Other Men's Sports
	(1)	(2)	(3)	(4)
Panel A: OLS Estimates Including College Fixed Effects and Year Fixed Effects				
Football and Men's Basketball Revenue +	0.820	0.416	0.410	0.424
Total Non-Sport Revenue	(0.093)	(0.074)	(0.080)	(0.099)
Conventional p-value	[0.000]	[0.000]	[0.000]	[0.015]
Wild bootstrap p-value	{0.000}	{0.004}	{0.000}	{0.020}
R^2	0.893	0.941	0.934	0.933

Notes: N = 851 for all regressions, and the unit of observation is a college-year. All variables are included in logs so that the coefficients can be interpreted as elasticities. The sample covers 61 colleges in "Power 5" conferences between 2006 and 2019. The standard errors are clustered by college and are reported in parentheses, and the wild bootstrap p-values are based on 10,000 bootstrap replications and are clustered by conference.

Online Appendix Table OA.6
Wild bootstrap p-values for Table 4

Dependent Variable:	Total Salaries for Football Coaching Staff	Total Salaries for Non-Football Coaches	Administrative Compensation	Facilities Spending	Institutional Support
	(1)	(2)	(3)	(4)	(5)
Panel A: OLS Estimates Including College Fixed Effects and Year Fixed Effects					
Football and Men's Basketball Revenue +	0.397	0.311	0.452	0.861	-0.196
Total Non-Sport Revenue	(0.125)	(0.086)	(0.108)	(0.252)	(0.620)
Conventional p-value	[0.015]	[0.017]	[0.003]	[0.018]	[0.698]
Wild bootstrap p-value	{0.039}	{0.008}	{0.039}	{0.023}	{0.711}
R^2	0.764	0.896	0.902	0.779	0.855

Notes: N = 566 in columns (1)-(2), and N = 569 in columns (3)-(5), and the unit of observation is a college-year. All variables are included in logs so that the coefficients can be interpreted as elasticities. The sample covers 44 colleges in "Power 5" conferences between 2006 and 2018. The standard errors are clustered by college and are reported in parentheses, and the wild bootstrap p-values are based on 10,000 bootstrap replications and are clustered by conference.

Online Appendix Table OA.7
Rent-Sharing Elasticities As Shares

Effect on each group's spending:	Football and Men's Basketball	Women's Sports and Other Men's Sports	Women's Sports	Other Men's Sports
	(1)	(2)	(3)	(4)
Panel A: OLS Estimates Including College Fixed Effects and Year Fixed Effects				
Effect of Football and Men's Basketball + Total Non-Sport Revenue	0.306	0.113	0.074	0.039
	(0.035)	(0.020)	(0.014)	(0.009)
Panel B: OLS Estimates Including College, Year, and Conference-by-Year Fixed Effects				
Effect of Football and Men's Basketball + Total Non-Sport Revenue	0.318	0.117	0.073	0.043
	(0.039)	(0.024)	(0.017)	(0.010)

Notes: Results from Table 3 are transformed by multiplying the elasticities for each outcome by the ratio of the dependent variable share of athletic department revenue and the football and men's basketball revenue share of athletic department revenue (reported in Table 1). This transforms the elasticities into effects on spending in dollars for a one dollar increase in football and men's basketball revenue. Standard errors from the elasticity calculations are adjusted using the delta-method.

Online Appendix Table OA.8
Additional Rent-Sharing Elasticities as Share:
Salaries for Coaches, Administrative Compensation, and Facilities Spending

Dependent Variable:	Salaries for Football Coaches	Salaries for Non-Football Coaches	Administrative Compensation	Facilities Spending	Institutional Support	Surplus
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS Estimates Including College Fixed Effects and Year Fixed Effects						
Effect of Football and Men's Basketball + Total Non-Sport Revenue	0.031	0.034	0.087	0.203	-0.013	0.106
	(0.010)	(0.010)	(0.021)	(0.060)	(0.042)	(0.051)
Panel B: OLS Estimates Including College, Year, and Conference-by-Year Fixed Effects						
Effect of Football and Men's Basketball + Total Non-Sport Revenue	0.025	0.040	0.064	0.185	0.005	0.090
	(0.010)	(0.010)	(0.017)	(0.069)	(0.045)	(0.056)

Notes: Results from Table 4 are transformed by multiplying the elasticities for each outcome by the ratio of the dependent variable share of athletic department revenue and the football and men's basketball revenue share of athletic department revenue (reported in Table 1). This transforms the elasticities into effects on spending in dollars for a one dollar increase in football and men's basketball revenue. Column (6) reports elasticity estimates on the surplus (total revenue/expenses from EADA dataset), using the same panel regressions used in Table 4.

Online Appendix Table OA.9
Robustness to Lagged Effects, First Differences, and Lagged Dependent Variable

Dependent Variable is Total Expenses for:	Football and Men's Basketball	Women's Sports and Other Men's Sports	Women's Sports	Other Men's Sports
	(1)	(2)	(3)	(4)
Panel A: OLS Estimates Including College Fixed Effects and Year Fixed Effects **[Baseline Specification]**				
Football and Men's Basketball Revenue +	0.820	0.416	0.410	0.424
Total Non-Sport Revenue	(0.093)	(0.074)	(0.080)	(0.099)
R^2	0.893	0.941	0.934	0.933
Panel B: Lagged Effects of Revenue				
Football and Men's Basketball Revenue +	0.694	0.306	0.256	0.405
Total Non-Sport Revenue$_t$ (β_t)	(0.091)	(0.105)	(0.101)	(0.120)
Football and Men's Basketball Revenue +	-0.075	-0.036	-0.018	-0.055
Total Non-Sport Revenue$_{t-1}$ (β_{t-1})	(0.055)	(0.066)	(0.060)	(0.086)
Football and Men's Basketball Revenue +	0.133	0.128	0.113	0.151
Total Non-Sport Revenue$_{t-2}$ (β_{t-2})	(0.062)	(0.044)	(0.039)	(0.061)
Football and Men's Basketball Revenue +	0.016	0.076	0.094	0.055
Total Non-Sport Revenue$_{t-3}$ (β_{t-3})	(0.053)	(0.050)	(0.051)	(0.059)
Implied Long-Run Effect	0.768	0.474	0.446	0.556
($\beta_t + \beta_{t-1} + \beta_{t-2} + \beta_{t-3}$)	(0.115)	(0.095)	(0.090)	(0.130)
R^2	0.902	0.946	0.939	0.944
Panel C: First Differences				
Football and Men's Basketball Revenue +	0.762	0.256	0.212	0.304
Total Non-Sport Revenue	(0.086)	(0.080)	(0.086)	(0.092)
R^2	0.284	0.119	0.107	0.073
Panel D: Including Lagged Dependent Variable				
Football and Men's Basketball Revenue +	0.626	0.232	0.189	0.315
Total Non-Sport Revenue (β)	(0.073)	(0.052)	(0.047)	(0.072)
Lagged Dependent Variable (δ)	0.333	0.429	0.454	0.378
	(0.041)	(0.054)	(0.070)	(0.061)
Implied Long-Run Effect ($\beta/(1 - \delta)$)	0.938	0.407	0.346	0.507
	(0.100)	(0.087)	(0.083)	(0.106)
R^2	0.910	0.958	0.956	0.952
Panel E: Arellano-Bond Dynamic Panel Estimates				
Football and Men's Basketball Revenue +	0.814	0.287	0.198	0.405
Total Non-Sport Revenue (β)	(0.052)	(0.042)	(0.041)	(0.056)
Lagged Dependent Variable (δ)	0.171	0.458	0.483	0.373
	(0.043)	(0.052)	(0.049)	(0.055)
Implied Long-Run Effect ($\beta/(1 - \delta)$)	0.983	0.529	0.383	0.647
	(0.072)	(0.078)	(0.074)	(0.092)

Notes: The unit of observation is a college-year in all regressions. N = 851 in Panel A; N = 668 in Panel B; N = 790 in Panel C and Panel D; N = 729 in Panel E. All variables are included in logs so that the coefficients can be interpreted as elasticities. The sample covers 61 colleges in "Power 5" conferences between 2006 and 2019. The standard errors are clustered by college and are reported in parentheses. Panel A reproduces the main results from the baseline specification reported in Table 3. Panel B reports a specification which includes three lags alongside the contemporaneous revenue variable. The total effect of a change in revenue is then given by the sum of the lags. Panel C reports results from a first-differences specification with only year fixed effects instead of year and college fixed effects. Panel D adds a lagged dependent variable to the model estimated in Panel A. Panel E uses the Arellano-Bond estimator that instruments the lagged dependent variable with up to three additional lags (i.e., t-2 through t-4). In both Panel D and Panel the "long-run" effect is reported with standard calculated using the delta method.

Online Appendix Table OA.10
Instrumental Variables Estimates of Additional Rent-Sharing Elasticities

	Salaries for Football Coaches	Salaries for Non-Football Coaches	Administrative Compensation	Facilities Spending	Institutional Support
	(1)	(2)	(3)	(4)	(5)
Football and Men's Basketball Revenue + Total Non-Sport Revenue	0.818	0.309	0.683	1.472	-0.333
	(0.242)	(0.199)	(0.209)	(0.327)	(1.058)
First Stage F-statistic	37.88	37.88	37.34	37.34	37.34

Notes: N = 566 in columns (1)-(2), and N = 569 in columns (3)-(5), and the unit of observation is a college-year. All variables are included in logs so that the coefficients can be interpreted as elasticities. The sample covers 44 colleges in "Power 5" conferences between 2006 and 2018. This table reports IV estimates using instrument in Table 6 for the outcomes reported in Table 4. The standard errors are clustered by college and are reported in parentheses.

Online Appendix Table OA.11
Distinguishing Rent-Sharing from Skill-Upgrading
[Adding Conference-by-Year Fixed Effects to Table 7]

Dependent Variable:	Indicator for Change in Football Head Coach	Total Salaries for Football Coaching Staff	Football Head Coach Salary	Total Expenses for Football and Men's Basketball
	(1)	(2)	(3)	(4)
Panel A: OLS Estimates Including College, Year, and Conference-by-Year Fixed Effects				
Football and Men's Basketball Revenue +	-0.204	0.319	0.241	0.854
Total Non-Sport Revenue	(0.168)	(0.129)	(0.245)	(0.104)
R^2	0.146	0.795	0.786	0.905
Panel B: Adding College-by-Head-Coach Fixed Effects to Panel A				
Football and Men's Basketball Revenue +		0.254	0.010	0.797
Total Non-Sport Revenue		(0.087)	(0.313)	(0.094)
R^2		0.961	0.853	0.948

Notes: N = 851 in columns (1) and (4), N = 566 in column (2), and N = 463 in column (3) because of missing head coach salaries, and the unit of observation is a college-year. All variables are included in logs so that the coefficients can be interpreted as elasticities. The sample covers 44 colleges in "Power 5" conferences between 2006 and 2018. The standard errors are clustered by college and are reported in parentheses.

Online Appendix Table OA.12
Distinguishing Rent-Sharing from Skill-Upgrading
[Instrumental Variable Estimates of Table 7]

Dependent Variable:	Indicator for Change in Football Head Coach	Total Salaries for Football Coaching Staff	Football Head Coach Salary	Total Expenses for Football and Men's Basketball
	(1)	(2)	(3)	(4)
Panel A: IV Estimates Including College Fixed Effects and Year Fixed Effects				
Football and Men's Basketball Revenue +	-0.705	0.818	1.682	0.799
Total Non-Sport Revenue	(0.442)	(0.242)	(0.555)	(0.152)
R^2	0.060	0.754	0.687	0.891
Panel B: IV Estimates Including College, Year, and College-by-Head-Coach Fixed Effects				
Football and Men's Basketball Revenue +		0.602	1.681	0.874
Total Non-Sport Revenue		(0.176)	(0.534)	(0.148)
R^2		0.951	0.791	0.939

Notes: N = 851 in columns (1) and (4), N = 566 in column (2), and N = 463 in column (3) because of missing head coach salaries, and the unit of observation is a college-year. All variables are included in logs so that the coefficients can be interpreted as elasticities. The sample covers 44 colleges in "Power 5" conferences between 2006 and 2018. The standard errors are clustered by college and are reported in parentheses.

Online Appendix Table OA.13
Robustness to Alternative Measurement of Expenses and Spending

Data Source:	EADA	Knight	Knight	Knight
Dependent Variable is Total Expenses for:	Football and Men's Basketball	Football	Total Spending - Total Football Spending	Total Spending - (Salaries for Non-Football Coaches and Administrative Personnel + Facilities Spending + Total Football Spending)
	(1)	(2)	(3)	(4)
Panel A: OLS Estimates Including College Fixed Effects and Year Fixed Effects				
Football and Men's Basketball Revenue + Total Non-Sport Revenue	0.820	0.694	0.531	0.418
	(0.093)	(0.084)	(0.107)	(0.158)
R^2	0.893	0.879	0.936	0.786
Panel B: OLS Estimates Including College, Year, and Conference-by-Year Fixed Effects				
Football and Men's Basketball Revenue + Total Non-Sport Revenue	0.839	0.676	0.502	0.434
	(0.102)	(0.105)	(0.131)	(0.204)
R^2	0.903	0.893	0.941	0.812

Notes: N = 851 for column (1) and N = 569 for columns (2)-(3) and N = 564 in column (4), and the unit of observation is a college-year. All variables are included in logs so that the coefficients can be interpreted as elasticities. The sample covers 61 colleges in "Power 5" conferences between 2006 and 2019. The standard errors are clustered by college and are reported in parentheses.

Online Appendix Table OA.14
Robustness of Rent-Sharing Elasticities

	Dependent Variable is Total Expenses for:			
	Football and Men's Basketball	Women's Sports and Other Men's Sports	Women's Sports	Other Men's Sports
	(1)	(2)	(3)	(4)
Panel A: **Baseline results in Table 3**				
Football and Men's Basketball Revenue + Total Non-Sport Revenue	0.820	0.416	0.410	0.424
	(0.093)	(0.074)	(0.080)	(0.099)
R^2	0.893	0.941	0.934	0.933
N	851	851	851	851
Panel B: **Add College-Specific Linear Time Trends**				
Football and Men's Basketball Revenue + Total Non-Sport Revenue	0.698	0.233	0.241	0.227
	(0.081)	(0.099)	(0.100)	(0.119)
R^2	0.931	0.958	0.954	0.952
N	851	851	851	851
Panel C: **Restrict to Subsample with Knight Data**				
Football and Men's Basketball Revenue + Total Non-Sport Revenue	0.862	0.474	0.478	0.458
	(0.112)	(0.083)	(0.100)	(0.110)
R^2	0.891	0.937	0.927	0.931
N	569	569	569	569
Panel D: **Drop non-sport revenue from right-hand side**				
Football and Men's Basketball Revenue	0.427	0.168	0.176	0.154
	(0.075)	(0.043)	(0.045)	(0.060)
R^2	0.864	0.930	0.923	0.925
N	851	851	851	851
Panel E: **Main sample using non-imputed data**				
Football and Men's Basketball Revenue + Total Non-Sport Revenue	0.680	0.345	0.354	0.327
	(0.078)	(0.061)	(0.065)	(0.091)
R^2	0.885	0.939	0.933	0.930
N	851	851	851	851
Panel F: **Drop all colleges with imputed data**				
Football and Men's Basketball Revenue + Total Non-Sport Revenue	0.695	0.292	0.284	0.324
	(0.087)	(0.102)	(0.095)	(0.141)
R^2	0.883	0.938	0.937	0.929
N	851	851	851	851
Panel G: **Include Baylor, WV, BC, Rutgers**				
Football and Men's Basketball Revenue + Total Non-Sport Revenue	0.809	0.360	0.367	0.338
	(0.086)	(0.079)	(0.080)	(0.108)
R^2	0.890	0.939	0.932	0.929
N	907	907	907	907

Notes: This table reports robustness of Table 3; the unit of observation is a college-year. All variables are included in logs so that the coefficients can be interpreted as elasticities. The standard errors are clustered by college and are reported in parentheses. Panel B includes college-specific linear time trends to main specification. Panel C restricts the sample to colleges with additional variables on salaries and facilities spending. Thus, this panel reports rent-sharing elasticities for the sub-sample in Table 4 that correspond to outcomes in Table 3. Panel D drops non-sport revenue from the right-hand side. Panel E uses the non-imputed expenses and revenue variables. Panel F adds back in the 4 colleges that were dropped from the main analysis sample because of questionable sport-level accounting data and our inability to impute sport-level revenue reliably for these colleges. See the Online Appendix for more details on sport-level revenue imputation.

Online Appendix Table OA.15
Athlete Race/Ethnicity in Revenue vs. Non-Revenue Sports

Panel A: Race/Ethnicity Shares for Revenue vs. Non-Revenue Sports

	Black (%)	White (%)	Other Race/Ethnicity (%)
Fotball and Men's Basketball	48.7	37.4	13.9
Other Sports	10.5	72.4	17.1
Total	19.6	64.0	16.4

Panel B: Share of Athletes in Revenue vs. Non-Revenue Sport by Race/Ethnicity

	Football or Men's Basketball (%)	Other Sport (%)
Black	59.3	40.7
White	13.9	86.1
Other Race/Ethnicity	20.2	79.8
Total	23.8	76.2

Notes: This table shows summary statistics of self-reported race/ethnicity of athletes for revenue and non-revenue sports. The data source is the NCAA Race and Gender Demographics Database from the 2016-2017 academic year. Sample is limited to athletes that are US residents and covers only the Power Five conferences. 99 percent of football and men's basketball players and 93 percent of other athletes are US residents. The full list of race/ethnicity groups in the NCAA demographics database are: "Black (Non-Hispanic)", "White (Non-Hispanic)", "Hispanic/Latino", "American Indian/Alaska Native", "Asian/Native Hawaiian/Pacific Islander", "Two or more races", and "Nonresident". "Nonresident" is excluded from the calculations above, and all categories except for the first two are grouped together in "Other Race/Ethnicity".

Online Appendix Table OA.16
Income Distribution Statistics by Sport for Other Race Athletes

	Other Race Athletes (Non-Black and Non-White)			
Sample of Athletes:	All Athletes	Football and Men's Basketball	Women's Sports	Other Men's Sports
Income				
Median Household Income	72,700	63,502	75,969	71,567
Mean Household Income	117,522	103,474	121,855	120,036
Percentile	0.62	0.54	0.65	0.62
Share in 1st Quartile	0.10	0.11	0.09	0.10
Share in 2nd Quartile	0.20	0.29	0.16	0.19
Share in 3rd Quartile	0.26	0.27	0.25	0.26
Share in 4th Quartile	0.45	0.34	0.50	0.45
Education				
Share with Grad School	0.14	0.11	0.15	0.14
Share with Bachelor's Degree	0.23	0.21	0.24	0.24
Share with Some College	0.29	0.30	0.29	0.29
Share with High School Degree	0.22	0.24	0.21	0.21
Share with Less than High School	0.12	0.14	0.11	0.11
Poverty Status				
Share in Poverty	0.08	0.09	0.07	0.07
Observations				
Share Athletes	1.00	0.20	0.50	0.29
Number of Schools	60	59	60	59
Number of Athlete-Sports	2,094	426	1,040	607

Notes: This table reports various statistics broken down by sport for athletes whose predicted race is neither Black nor White, using athlete-sport level data that combines the athlete's sport to census demographic information. The census information is linked through the athlete's high school's catchment area overlap with census tracts, and is aggregated to the high school level. Students who play multiple sports are represented in multiple rows in the data - once for each sport. Column one reports statistics for all student-sports, while columns two through five report statistics just for Football/Men's Basketball, Non- Football/Men's Basketball Sports, Women's sports, and Men's non-Football/Men's Basketball sports. The first set of statistics reported reflect median and mean household income. The next set of statistics shows the share of students in each quartile of the overall US household income distribution, created from 2000 Census SF3 files. The next set of statistics shows the proportion of the population associated with each high school of various educational attainments and various race/ethnicities. Finally, we report the number of colleges represented in the sample, as well as the number of athlete-sport rows. Income is reported in 2018 dollars.

Online Appendix Table OA.17
Neighborhood Characteristics for Athletes Using Hometown (City) Instead of High School

Sample of Athletes:	All Athletes	Football and Men's Basketball	Women's Sports and Other Men's Sports	Women's Sports	Other Men's Sports
Income					
Median Household Income	61,250	54,790	65,668	66,847	63,208
Mean Household Income	94,153	82,872	98,180	98,527	96,721
Average Hometown Income Percentile	0.54	0.46	0.57	0.57	0.55
Share in 1st Quartile	0.12	0.17	0.10	0.10	0.11
Share in 2nd Quartile	0.30	0.37	0.27	0.27	0.28
Share in 3rd Quartile	0.24	0.23	0.25	0.25	0.25
Share in 4th Quartile	0.34	0.23	0.38	0.39	0.36
Education					
Share with Grad School	0.14	0.12	0.15	0.15	0.15
Share with Bachelor's Degree	0.23	0.20	0.24	0.24	0.23
Share with Some College	0.27	0.28	0.27	0.27	0.27
Share with High School Degree	0.24	0.26	0.23	0.23	0.23
Share with Less than High School	0.12	0.14	0.11	0.11	0.11
Poverty Status					
Share in Poverty	0.13	0.15	0.12	0.12	0.12
Race/Ethnicity					
Share Black	0.14	0.20	0.11	0.11	0.11
Share White	0.74	0.67	0.76	0.76	0.76
Share Hispanic	0.13	0.14	0.12	0.12	0.12
Observations					
Number of Schools	61	61	61	61	61
Number of Athlete-Sports	27,737	7,297	20,440	11,874	8,199

Notes: This table reports various statistics broken down by sport, using athlete-sport level data that combines the athlete's sport to census demographic information. The census information is linked through the athlete's hometown overlap with American Community Survey cities, and is aggregated to the hometown level. Students who play multiple sports are represented in multiple rows in the data - once for each sport. Column one reports statistics for all student-sports, while columns two through five report statistics just for Football/Men's Basketball, Non- Football/Men's Basketball Sports, Women's sports, and Men's non-Football/Men's Basketball sports. The first set of statistics reported reflect median and mean household income. The next set of statistics shows the share of students in each quartile of the overall US household income distribution, created from 2010 American Community Survey files. The next set of statistics shows the proportion of the population associated with each high school of various educational attainments and various race/ethnicities. Finally, we report the number of colleges represented in the sample, as well as the number of athlete-sport rows. Income is reported in 2018 dollars.

Online Appendix Table OA.18
Hometown and High School Matching Statistics

	All Athletes	Football and Men's Basketball	Other Sports
# Observed in Online Rosters	35,721	8,461	27,260
# with Hometown Scraped	35,014	8,427	26,587
# with Previous School Scraped	32,520	8,102	24,418
# with Hometown in United States	31,644	8,139	23,505
# with Hometown Matched	29,556	7,730	21,826
# with High School Matched	16,794	4,455	12,339

Notes: This table shows the number of athletes in the rosters data that remain in each step of the matching process to hometowns and high schools.

Online Appendix Table OA.19
Census Summary Statistics

	Mean	Median	Standard Deviation
Income			
Median Household Income	59,385	53,680	34,124
Mean Household Income	84,478	74,587	40,683
Education			
Share with Grad School	0.09	0.06	0.08
Share with Bachelor's Degree	0.15	0.13	0.10
Share with Some College	0.27	0.27	0.08
Share with High School Degree	0.29	0.29	0.10
Share with Less than High School	0.20	0.17	0.14
Poverty Status			
Share in Poverty	0.13	0.10	0.12
Race/Ethnicity			
Share Black	0.13	0.03	0.22
Share White	0.75	0.85	0.26
Share Hispanic	0.13	0.04	0.21

Notes: This table lists summary statistics for all census variables reported in Table 7. The variables were pulled from Social Explorer 2000 Census on 2010 Geographies at the tract level for all census tracts in the US, and converted to 2018 dollars.

Online Appendix Table OA.20
Selectivity Tier List

Name	Tier	Tier Number
Duke University	Ivy Plus	1
Stanford University	Ivy Plus	1
Northwestern University	Other elite schools (public and private)	2
University Of California, Los Angeles	Other elite schools (public and private)	2
University Of Miami	Other elite schools (public and private)	2
University Of North Carolina - Chapel Hill	Other elite schools (public and private)	2
University Of Notre Dame	Other elite schools (public and private)	2
University Of Southern California	Other elite schools (public and private)	2
University Of Virginia	Other elite schools (public and private)	2
Vanderbilt University	Other elite schools (public and private)	2
Wake Forest University	Other elite schools (public and private)	2
Georgia Institute Of Technology	Highly selective public	3
Syracuse University	Highly selective private	3
Texas AandM University	Highly selective public	3
Texas Christian University	Highly selective private	3
University Of California, Berkeley	Highly selective public	3
University Of Florida	Highly selective public	3
University Of Georgia	Highly selective public	3
University Of Illinois System	Highly selective public	3
University Of Maryland System (Except University College) An	Highly selective public	3
University Of Michigan - Ann Arbor	Highly selective public	3
University Of Minnesota System	Highly selective public	3
University Of Maryland System (Except University College) And Baltimore City Community College	Highly selective public	3
University Of Texas At Austin	Highly selective public	3
University Of Wisconsin System	Highly selective public	3
Virginia Polytechnic Institute and State University	Highly selective public	3
Arizona State And Northern Arizona University And University	Selective public	4
Auburn University	Selective public	4
Florida State University	Selective public	4
Indiana University System	Selective public	4
Iowa State University Of Science and Technology	Selective public	4
Kansas State University	Selective public	4
Louisiana State University System	Selective public	4
Michigan State University	Selective public	4
Mississippi State University	Selective public	4
North Carolina State University	Selective public	4
Oklahoma State University	Selective public	4
Oregon State University	Selective public	4
Pennsylvania State University	Selective public	4

Purdue University	Selective public	4
Texas Tech University	Selective public	4
University Of Alabama	Selective public	4
University Of Arkansas	Selective public	4
University Of Colorado System	Selective public	4
University Of Iowa	Selective public	4
University Of Kansas	Selective public	4
University Of Kentucky	Selective public	4
University Of Louisville	Selective public	4
University Of Mississippi	Selective public	4
University Of Missouri System And Missouri University Of Sci	Selective public	4
University Of Nebraska System	Selective public	4
University Of Oklahoma	Selective public	4
University Of Oregon	Selective public	4
University Of South Carolina System	Selective public	4
University Of Tennessee System	Selective public	4
University Of Utah	Selective public	4
University Of Washington System	Selective public	4
Washington State University	Selective public	4
University Of Utah	Selective public	4
University Of Washington System	Selective public	4
Washington State University	Selective public	4
West Virginia University, West Virginia University Institute	Selective public	4

Notes: This table shows the tier of each college in our matched roster to Opportunity Insights dataset.

Online Appendix Table OA.21
Tract-Matched Mean and Median Household Income for Athletes by Selectivity Tier

Selectivity Tier	All Athletes	Football and Men's Basketball	Women's Sports and Other Men's Sports	Women's Sports	Other Men's Sports	Number of Colleges
Panel A: Tract-Matched Mean Houshold Income						
Ivy Plus	137,043	112,379	142,820	148,294	135,375	2
Other Elite Colleges and Universities	129,897	107,439	137,461	138,208	134,538	9
Highly Selective	115,872	101,358	121,107	122,705	118,861	15
Selective	104,795	96,680	107,716	109,257	105,277	33
All	112,272	99,753	116,676	118,086	114,160	59
Panel B: Tract-Matched Median Houshold Income						
Ivy Plus	84,304	60,535	89,586	92,891	82,010	2
Other Elite Colleges and Universities	73,447	59,086	81,196	83,338	75,449	9
Highly Selective	71,402	58,306	76,178	77,821	74,214	15
Selective	64,169	57,844	66,305	67,106	65,577	33
All	67,122	58,187	70,911	71,637	69,746	59

Notes: This table reports the census tract level median household income from the roster data, broken down by sport type and selectivity tier, where selectivity tier is defined by Opportunity Insights data. Ohio State University is not accounted for in the Opportunity Insights dataset. Income is reported in 2018 dollars.

Online Appendix Table OA.22
Mean parent income compared to matched athlete household income by selectivity tier

	Mean Parent Income All Colleges	Mean Parent Income Power-5 Colleges	Tract-Matched Mean Income Athletes Only
Ivy Plus	453,395	517,865	137,043
Other elite colleges and universities	323,317	306,220	129,897
Highly selective	225,491	185,063	115,872
Selective	118,375	156,068	104,795
Nonselective Four-year not-for-profit	107,408		
Two-year not-for-profit	77,528		
Four-year for-profit	86,944		
Two-year for-profit	65,553		
All	112,702	197,374	112,272
Number of colleges	2,199	59	59

Notes: This table reports statistics from the roster data merged to Opportunity Insights data. In column 1, parent mean income from Opportunity Insights data is reported for all Opportunity Insights colleges. In column 2, the same parent mean income variable is reported for only those colleges that match to our dataset of Power-5 colleges. In column 3, we report a different income variable: aggregated census tract level mean household income matched to the athletes. Note that Ohio State University is not accounted for in Opportunity Insights, which is why the total number of colleges represented here is smaller. Income is reported in 2018 dollars.

Online Appendix Table OA.23
Median parent income compared to matched athlete household income by selectivity tier

	Median Parent Income All Colleges	Median Parent Income Power-5 Colleges	Tract-Matched Median Income Athletes Only
Ivy Plus	183,484	181,330	84,304
Other elite colleges and universities	156,747	158,638	73,447
Highly selective	125,650	125,439	71,402
Selective	89,405	108,210	64,169
Nonselective Four-year not-for-profit	72,910		
Two-year not-for-profit	65,346		
Four-year for-profit	62,457		
Two-year for-profit	50,586		
All	78,058	114,513	67,122
Number of colleges	2,199	59	59

Notes:This table reports statistics from the roster data merged to Opportunity Insights data. In column 1, parent median income from Opportunity Insights data is reported for all Opportunity Insights colleges. In column 2, parent median income is reported for only those colleges that match to our dataset of Power-5 colleges. In column 3, we report a different income variable: aggregated census tract level mean household income matched to the athletes. Note that Ohio State University is not accounted for in Opportunity Insights, which is why the total number of colleges represented here is smaller. Income is reported in 2018 dollars.

Online Appendix Table OA.24
Comparison of Coach Salaries as Percentage of Revenue to Executives

Year	Mean football coach salary (salary + bonus + benefits)	Mean football coach salary as a percent of athletic department revenue	Mean athletic department revenue	Mean executive annual compensation (salary + bonus) for top 5 executives	Mean executive total compensation for top 5 executives (salary, bonus, and all other compensation)	Mean executive annual compensation for top 5 executives as a percent of revenue (salary + bonus)	Mean executive total compensation for top 5 executives as a percent of revenue (salary, bonus, and all other compensation)	Mean Compustat Revenue	Amount Paid to Top 5 Highest Paid Coaches Per Athletic Department Revenue	Fraction of Total Coach Spending (Salary + Potential Bonus) Paid to Top 5 Highest Paid Coaches	Amount Paid to Top 5 Highest Paid Coaches	Total Amount Paid to All Coaches (USA Today Source)
2006	3,987,264	5.91%	73,733,936	870,227	2,089,639	0.64%	1.46%	180,100,496				
2007	4,307,838	6.04%	73,731,592	837,241	2,092,833	0.67%	1.57%	163,346,960				
2008	4,776,733	6.15%	80,915,568	820,729	1,607,907	0.60%	1.08%	170,467,008				
2009	5,212,583	6.70%	79,307,744	847,309	1,603,264	0.64%	1.13%	171,321,520				
2010	5,613,854	6.66%	86,618,136	868,189	2,006,583	0.65%	1.41%	169,535,472				
2011	6,149,183	7.14%	87,287,784	897,405	2,211,522	0.63%	1.50%	171,003,568				
2012	6,393,837	7.17%	91,443,248	959,268	2,218,529	0.68%	1.47%	176,345,552				
2013	6,911,888	7.31%	96,408,088	1,000,009	2,791,817	0.69%	1.72%	180,965,456				
2014	7,429,330	7.35%	103,527,920	1,004,085	2,822,460	0.64%	1.70%	185,798,080	5.56%	77.05%	5,756,020	7,359,422
2015	8,252,533	7.67%	108,509,912	1,021,075	2,600,460	0.68%	1.65%	186,857,488	6.39%	80.01%	6,866,978	8,547,747
2016	8,512,856	7.54%	114,256,016	1,065,870	2,657,195	0.65%	1.56%	186,731,824	6.41%	77.13%	7,357,490	9,502,495
2017	8,963,475	7.50%	121,125,824	1,067,099	3,076,713	0.70%	1.86%	189,693,376	6.46%	77.46%	7,735,860	9,890,424
2018	9,637,868	7.74%	126,613,248	1,123,794	3,911,580	0.62%	2.10%	206,204,192	6.59%	75.00%	8,324,252	11,031,487
2019				1,062,316	2,796,259	0.62%	1.80%	204,235,088		74.99%	8,853,779	11,800,828

Notes: This table compares annual average salaries of football coaches to business executives. Column 1 reports annual football coach salaries. Column 5 reports the total amount paid in salary and bonus for the top five most highly paid executives in the subset of the ExecuComp dataset that includes only firms whose revenue lies within the range of athletic department revenue in our sample. Column 6 reports the total compensation, including all forms of compensation beyond salary and bonus. Column 5 uses a broader measure of compensation including salary, bonus, other annual, total value of restricted stock granted, net value of stock options exercised, long-term incentive payouts, and all other compensation reported n the ExecuComp dataset.

Online Appendix Table OA.25
Zero Net Income Diagnostic Regressions for Non-Revenue Sports

	Dependent Variable:				
	Net Income (team)	Revenue (team)	Expenses (team)	Revenue (college)	Net Income (college)
	(1)	(2)	(3)	(4)	(5)
1(Team Net Income = 0)	0.738	0.729	-0.009	-0.887	-1.958
	(0.049)	(0.054)	(0.022)	(0.340)	(0.281)
Dependent Variable Mean	-0.25	2.31	2.55	85.94	2.59

Notes: N = 13,265 for all regressions, and the unit of observation is a college-sport-year. All dependent variables are in millions of 2018 dollars. The sample includes only non-revenue sports and covers 61 colleges in "Power 5" conferences between 2006 and 2019. Rutgers, Baylor, Boston College, and West Virginia are excluded from the sample, as they did not have sufficient variation in non-FB/MBB sport net income for our imputation procedure. Regression standard errors are shown in parentheses and are clustered by college-sport. The dependent variable mean is the mean conditional on a college-sport ever having zero net income but only for years where net income is not zero.

Online Appendix Table OA.26
Revenue and Expenses Share of Total Athletic Department Revenue

Salaries, Facilities Spending, and Total Institutional Support Share of (EADA) Total Athletic Department Revenue

[Panel C of Table 2 reproduced]

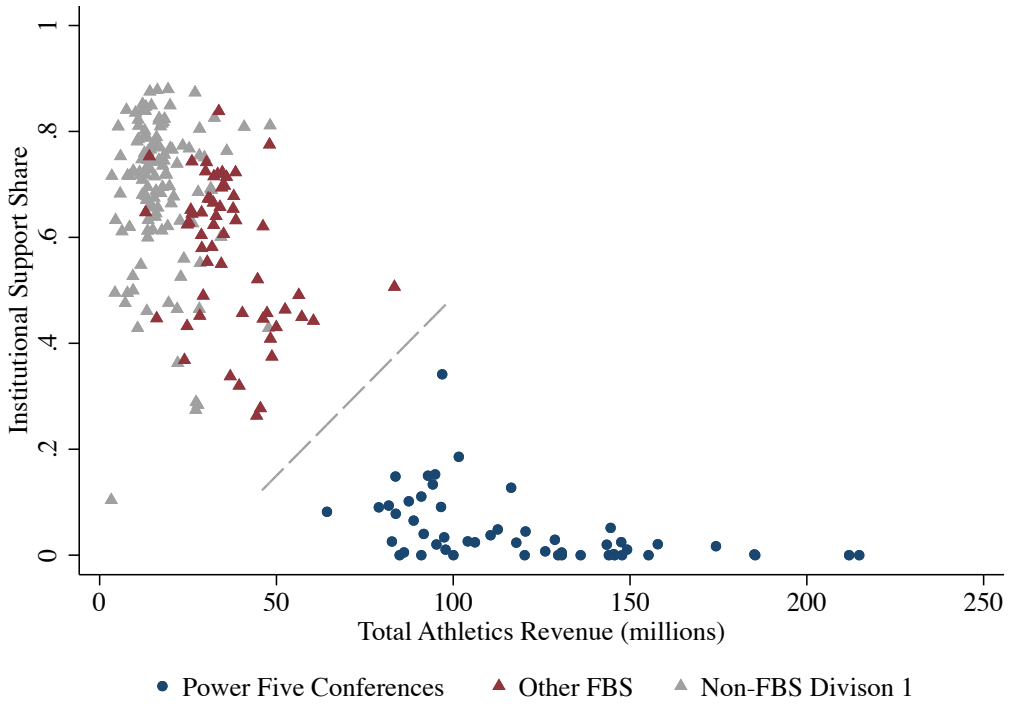
	Salaries for Football Coaches	Administrative Compensation	Facilities Spending	Total institutional Support
Average Share	0.073	0.179	0.218	0.063
Standard Deviation	(0.017)	(0.034)	(0.081)	(0.064)

Salaries, Facilities Spending, and Total Institutional Support Share of (Knight) Total Athletic Department Revenue

	Salaries for Football Coaches	Administrative Compensation	Facilities Spending	Total institutional Support
Average Share	0.070	0.172	0.206	0.061
Standard Deviation	(0.017)	(0.034)	(0.062)	(0.061)

Notes: This table reports average shares of total athletic department revenue are reported. The top panel reports the shares of spending on coaches, administrative compensation, facilities spending, and institutional support as shares of total athletic department revenue from EADA. However, since these spending variables come from data from the Knight Commission, the bottom panel validates the average shares by showing the analogous shares using total athletic department revenue measures from the Knight Commission, rather than EADA.

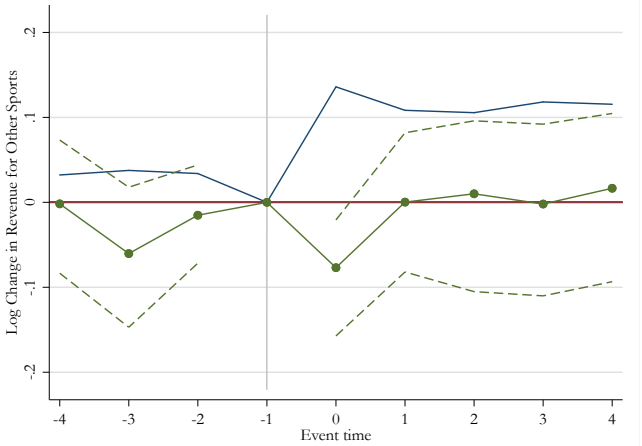
Online Appendix Figure OA.1: Athletic Department Financing for NCAA Division 1 Colleges and Universities, Separating Other FBS and Non-FBS Colleges and Universities, 2018



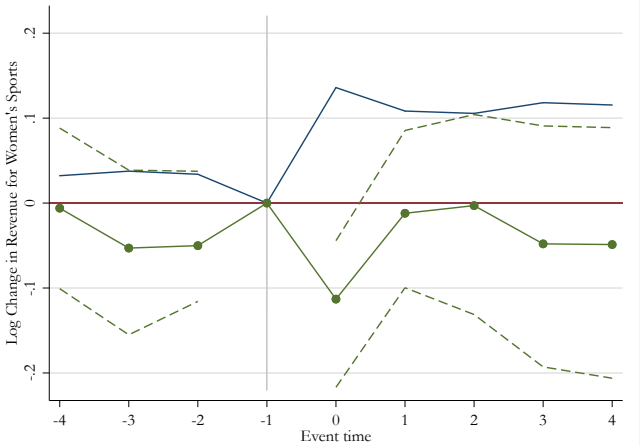
Notes: This figure reports an alternative version of Figure 1 that splits up the colleges not in the Power Five athletic conferences into other FBS colleges and non-FBS colleges. This division is not highly correlated with k-means clustering, unlike the division based on Power Five conferences, which is perfectly correlated with k-means clustering algorithm (see Figure 1 for more details).

Online Appendix Figure OA.2: Difference-in-difference representation of revenue for other sports

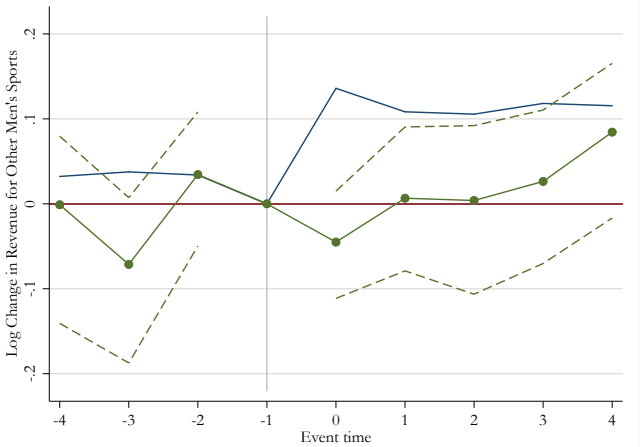
Panel A: Revenue for Women's Sports and Other Men's Sports



Panel B: Revenue for Women's Sports

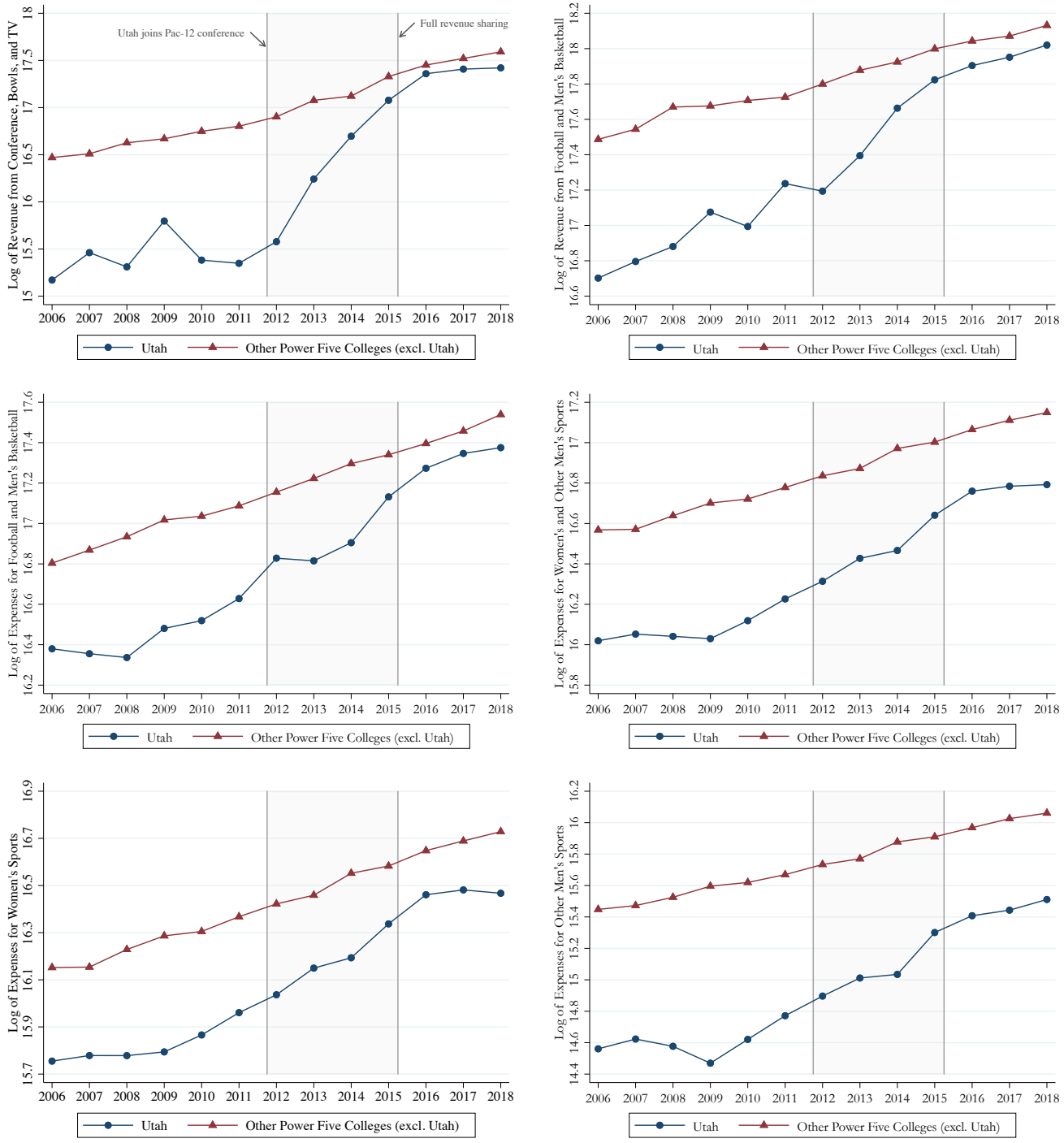


Panel C: Revenue for Other Men's Sports



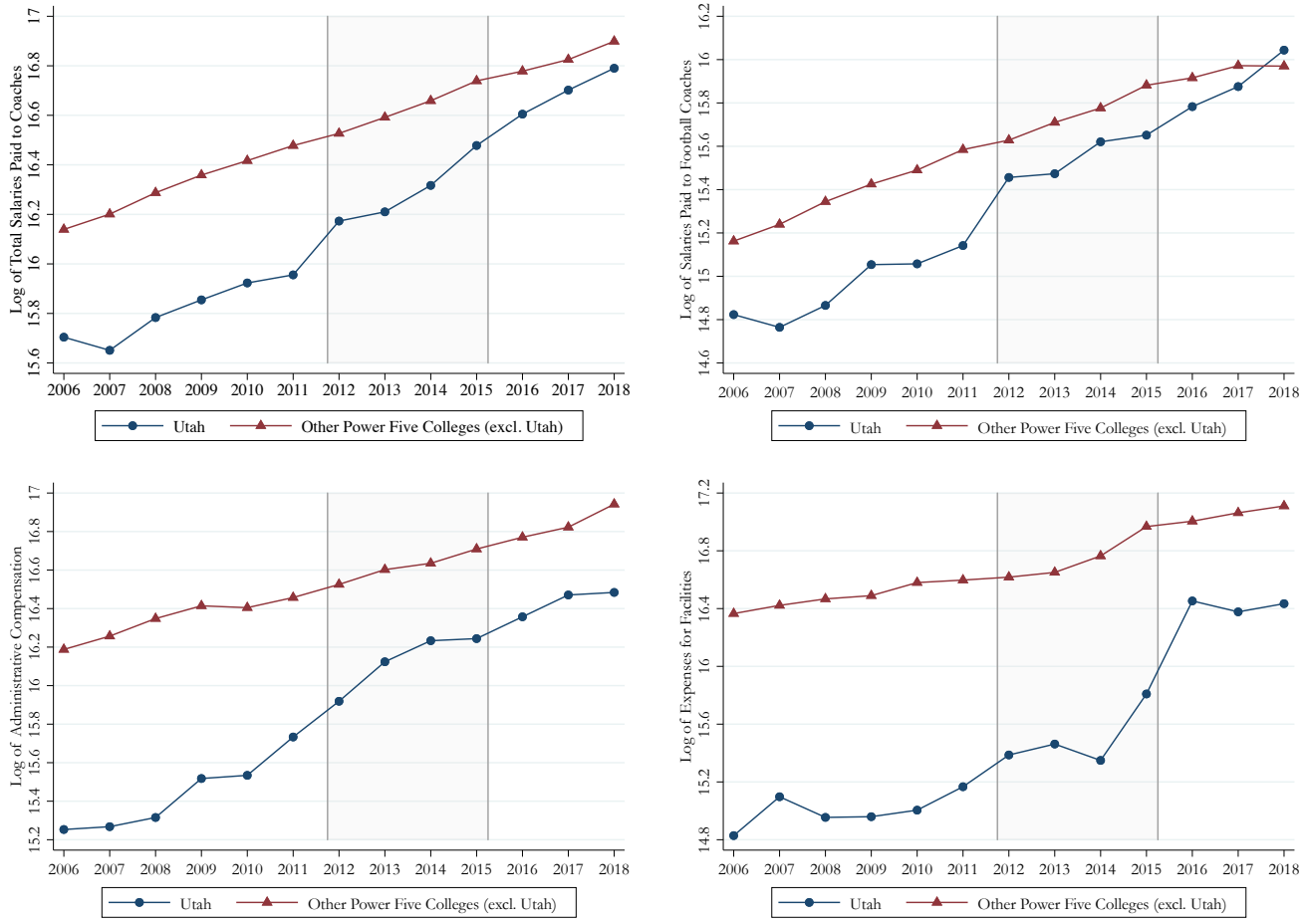
Notes: This figure reports a difference-in-difference representation of the rent-sharing elasticities reported in Table 3. See notes to Figure 4 for more details.

Online Appendix Figure OA.3: Rent-Sharing in the University of Utah Case Study



Notes: This figure reports raw trends in outcomes comparing the University of Utah to all of the other "Power 5" colleges in our analysis. Beginning in 2012, Utah moved from the Western Athletic Conference (not a "Power 5" conference) to the Pac-12 (which is one of the "Power 5" conferences). Over the next 3 years, the conference payments to Utah were "phased in".

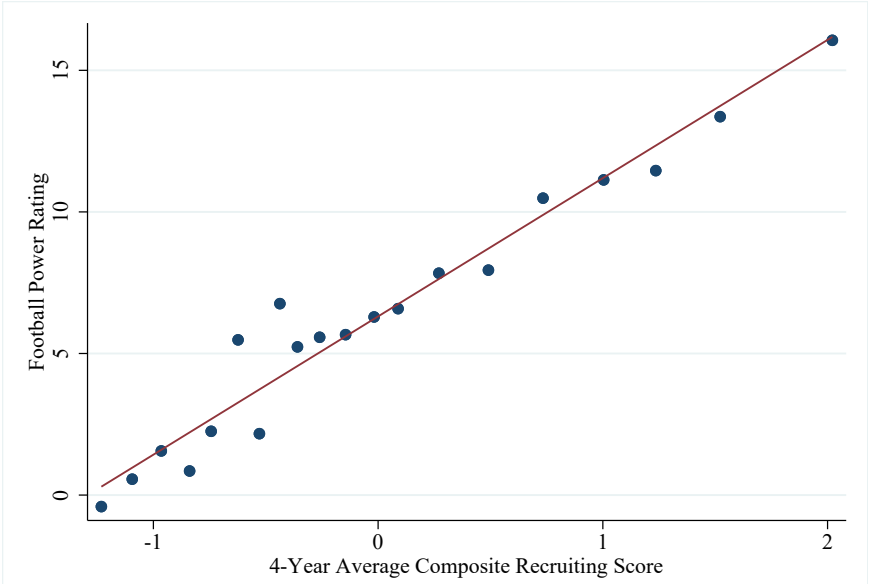
Online Appendix Figure OA.4: Additional Outcomes for University of Utah Case Study



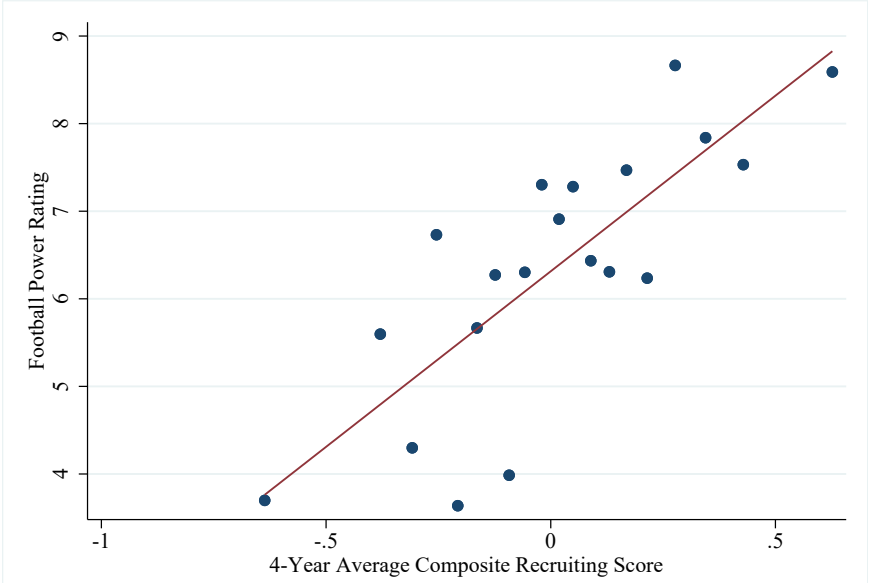
Notes: This figure reports raw trends in outcomes comparing the University of Utah to all of the other "Power 5" colleges in our analysis. See notes to Figure OA.9 for more details on this case study.

Online Appendix Figure OA.5: Correlation Between Recruiting Ratings and Football Power Ratings

Panel A: Binscatter Controlling for Year Fixed Effects



Panel B: Binscatter Controlling for School and Year Fixed Effects

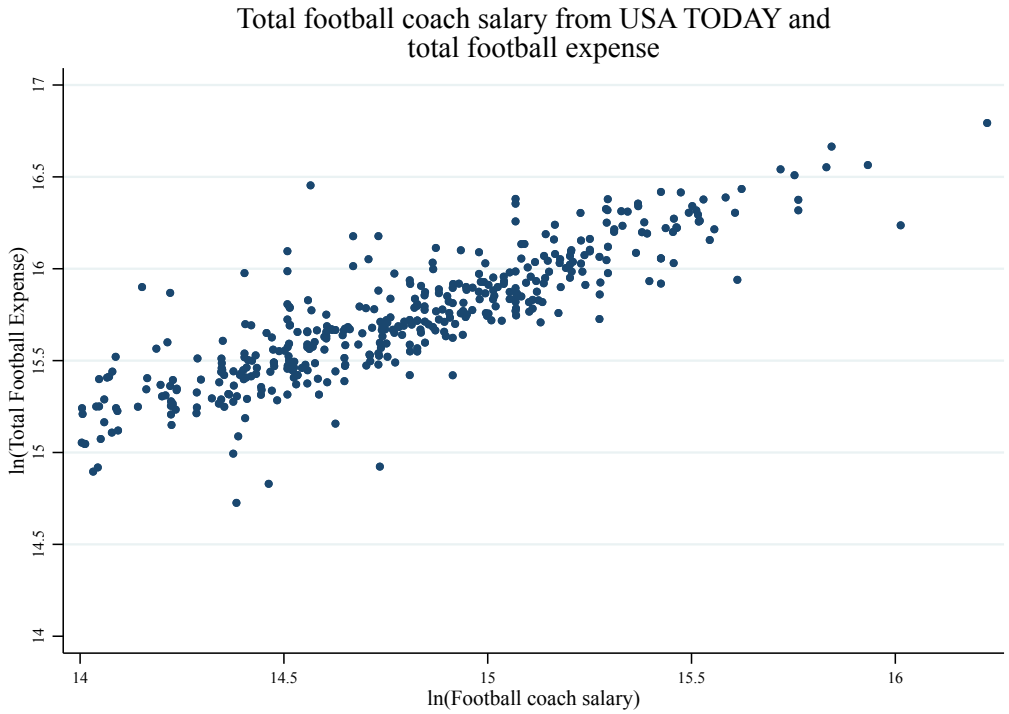


Notes: To verify that our recruiting ratings capture true variation in player quality, we correlate the 4-year lagged average standardized recruiting rating with each school-year's football power rating using the school-by-year college football power rating index from ESPN.com.

Online Appendix Figure OA.6: Correlation Between Football Head Coach Salaries in 990s and USA Today database

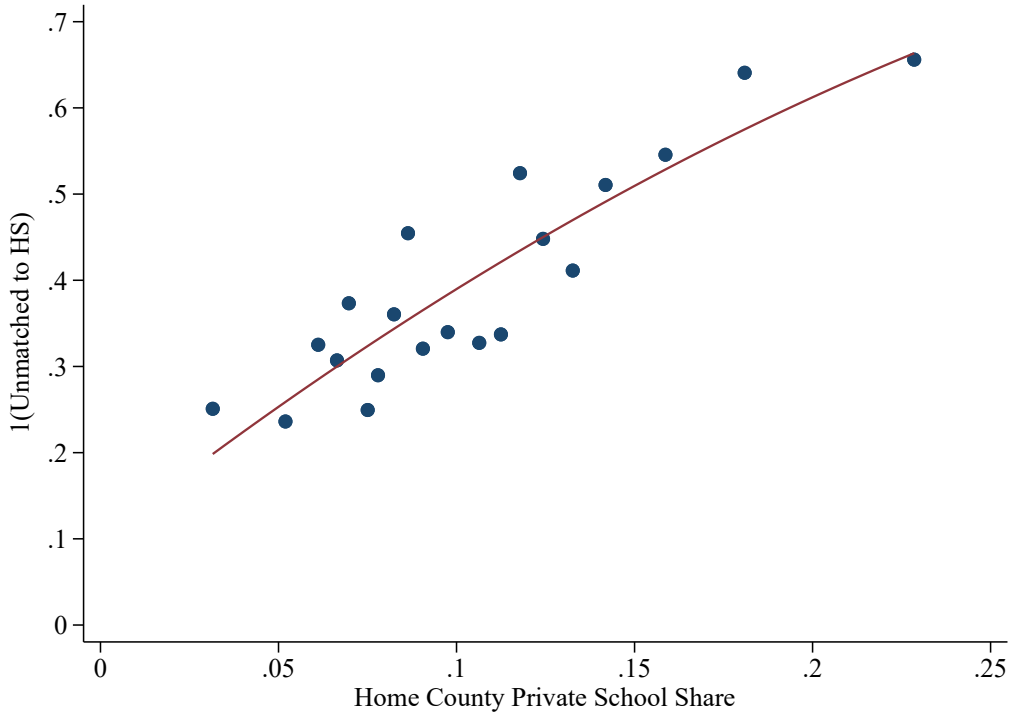
Notes: This figure reports the association between the football head coach salary measured in USA Today database and the football head coach salary measured in the 990s collected from ProPublica.

Online Appendix Figure OA.7: Correlation Between Football Head Coach Salaries and Total Salaries Paid to the Football Coaching Staff



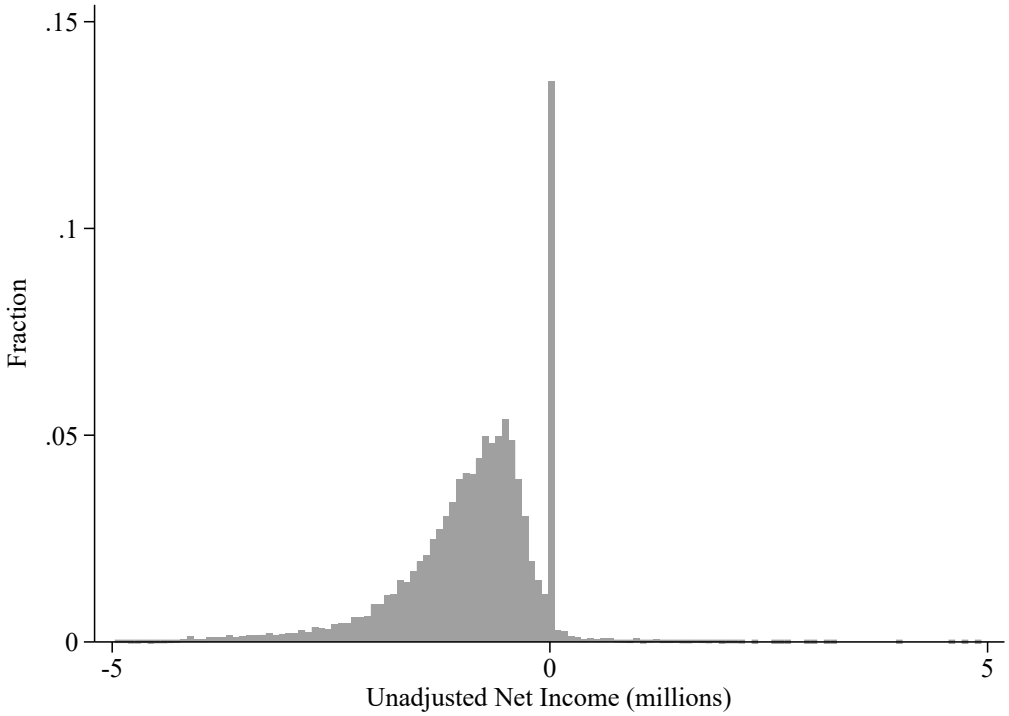
Notes: This figure reports the association between the football head coach salary measured in USA Today database and the total salaries paid to the football coaching staff measured in the Knight data.

Online Appendix Figure OA.8: Relationship Between High School Match Rate and Private High School Attendance



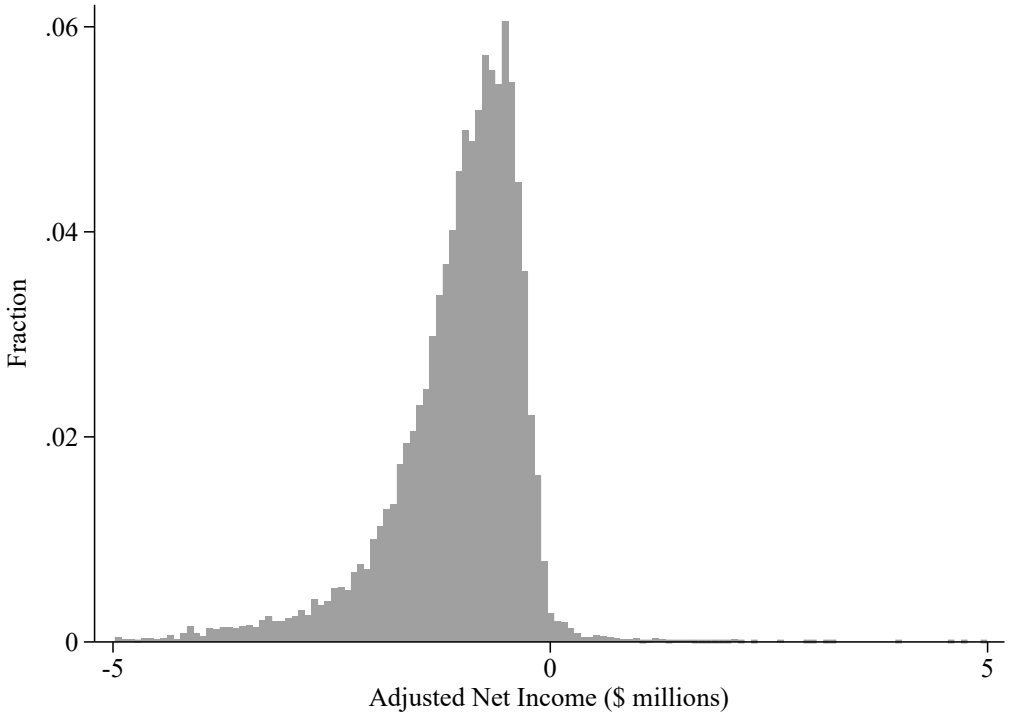
Notes: This figure shows a binned scatter plot of an indicator for whether an athlete is matched to a public high school in our matching process on the fraction of students that attended a private high school in the athlete's home county. The sample covers athletes that are matched to a home county and that have some information related to previous schools attended in their online roster entry. The variable for home county private school share comes from the 2017 5-Year American Community Survey, and is the fraction of 15-17 year old students that attend a private school in each county.

Online Appendix Figure OA.9: Distribution of Unadjusted Sport-Level Net Income for Non-Revenue Sports



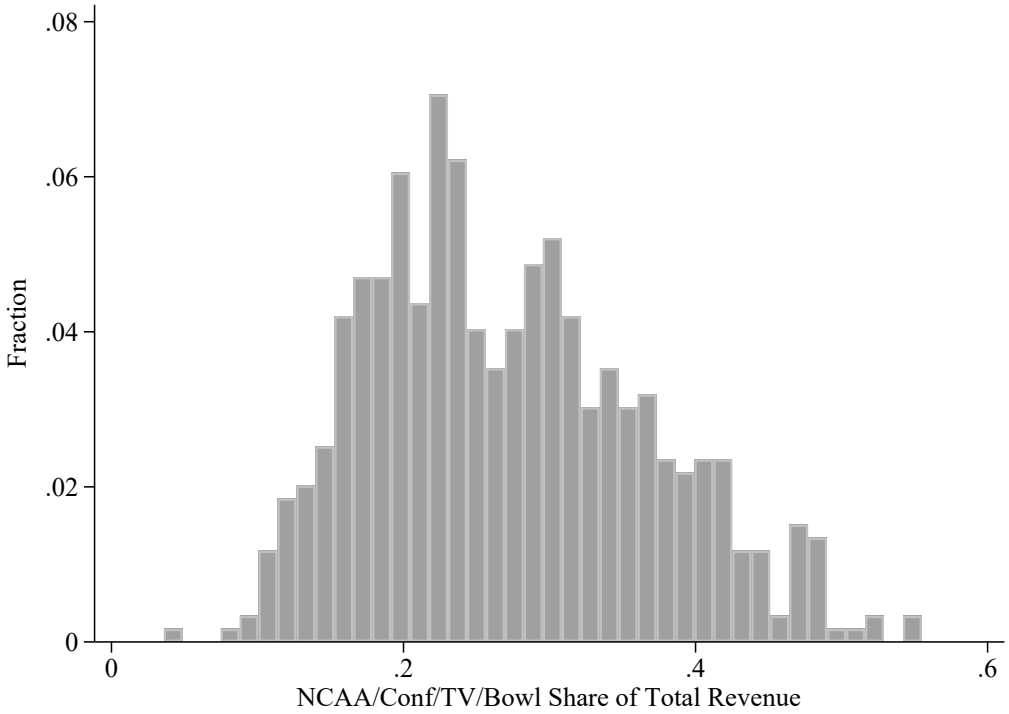
Notes: This figure shows the distribution of reported net income in the EADA data at the school-sport-year level. This covers the full sample of Power Five colleges across the full sample period of 2006-2019 and all sports other than football and men's basketball. The x-axis is in millions of 2018 dollars. The bin width is $75,000.

Online Appendix Figure OA.10: Distribution of Post-Imputation Sport-Level Net Income for Non-Revenue Sports



Notes: This figure shows the distribution of net income in the EADA data at the school-sport-year level after our revenue imputation procedure. This covers the full sample of Power Five colleges across the full sample period of 2006-2019 and all sports other than football and men's basketball. The x-axis is in millions of 2018 dollars. The bin width is $75,000.

Online Appendix Figure OA.11: Instrument Share of Total Revenue



Notes: This figure plots the distribution of the share of total revenue (as measured in the Knight data) our instrument accounts for in the data. The unit of observation is a school-year. The sample covers all 46 Power Five colleges in the Knight data and all years over the period 2006-2018.