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The Value of Using Early-Career Earnings Data in the College Scorecard to Guide College Choices

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ABSTRACT

Policymakers are increasingly including early-career earnings data in consumer-facing college search tools to help students and families make more informed postsecondary education decisions. We offer new evidence on the degree to which existing college-specific earnings data equips consumers with useful information by documenting the level of selection bias in the earnings metrics reported in the U.S. Department of Education's College Scorecard. Given growing interest in reporting earnings by college and major, we focus on the degree to which earnings differences across four-year colleges and universities can be explained by differences in major composition across institutions. We estimate that more than three-quarters of the variation in median earnings across institutions is explained by observable factors, and accounting for differences in major composition explains over 30 percent of the residual variation in earnings after controlling for institutional selectivity, student composition, and local cost of living differences. We also identify large variations in the distribution of earnings within colleges; as a result, comparisons of early-career earnings can be extremely sensitive to whether the median, 25^{th}, or 75^{th} percentiles are presented. Taken together, our findings indicate that consumers can easily draw misleading conclusions about institutional quality when using publicly available earnings data to compare institutions.

1. INTRODUCTION

Over the last decade, newly available labor market data has illuminated that the earnings of former college students vary considerably across higher education institutions. Policymakers at the state and federal level have responded to this information in two ways. First, by introducing legislation to hold colleges and universities accountable for the labor market outcomes of alumni,[1] and second, by incorporating labor market information into consumer-facing search tools so that students and families are equipped to make better decisions about their postsecondary plans.

We focus in this study on the extent to which earnings metrics included in consumer-facing search tools capture unbiased information on college quality. We do so by documenting the level of selection bias in the earnings measures reported in the U.S. Department of Education's College Scorecard (referred to as the Scorecard hereafter). The Scorecard is a web-based tool that reports earnings among federal financial aid recipients for over 4,000 institutions nationwide. It is the most comprehensive consumer-facing tool that reports earnings data by institution, and although the Scorecard does not assign quality ratings to institutions, it encourages consumers to compare institutions on the earnings of former students.[2]

Prior work on the appropriateness of using early-career labor market outcomes to evaluate higher education institutions and the role of major composition in explaining earnings differences across colleges has either examined aggregate earnings returns across institutions rather than returns for individual colleges and universities (Weber, 2014; Weber, 2016) or relied on small institutional samples or administrative data from a single state to examine earnings differences

[1] For example, several states including Florida, Texas, and Tennessee allocate a portion of state funding to public higher education institutions based in part on the earnings and job placement outcomes of former students (SHEEO, 2019; Snyder & Fox, 2016)

[2] From the home page on the Scorecard website, users can search for institutions by degree and program type, location, and size, among other features. By default, the resulting list of institutions that match the search criteria is sorted from highest to lowest salary.

across institutions (Cunha & Miller, 2014; Eide, Hilmer, & Showalter, 2015; Minaya & Scott-Clayton, 2016). As a result, we are not aware of any studies that have examined the determinants of earnings differences across the census of public and private, non-profit four-year degree-granting institutions in the United States or evaluated whether earnings data in the Scorecard enables students to accurately compare institutions. Recent evidence has also shown that the labor market returns to college are larger for some programs than others (Hastings, Neilson & Zimmerman, 2013; Hershbein & Kearney, 2014; Kirkeboen, Leuven & Mogstad, 2016), yet we believe we are the first to examine the degree to which earnings differences across colleges can be explained by differential selection into majors. In doing so, we shed light on the potential value to disaggregating earnings by college and program for consumers, which has been part of the long-term plan for the Scorecard since its inception and has received renewed attention since the President issued Executive Order 13864 in March 2019 directing the U.S. Department of Education to publish program-level earnings data for each college (Executive Office of the President, 2019).[3]

Using the universe of public and private, non-profit four-year institutions with available earnings data in the Scorecard dataset, we conduct several descriptive analyses to investigate this topic. First, we document the extent to which major composition varies across colleges and the relationship between major composition and median institution-level earnings. Second, we decompose the earnings variation across colleges into differences that can be explained by institutional selectivity, student demographics and socioeconomic status, local cost of living, and major composition. Third, we examine the sensitivity of college rankings to whether comparisons

[3] It is worth noting that by investigating the drivers of earnings differences across four-year institutions, we our focus on a set of institutions distinct from the certificate-granting institutions currently subject to federal Gainful Employment regulation. The selection mechanisms and relative importance of those mechanisms may well function differently in the four-year and less-than-four-year sectors.

are based on unadjusted versus regression-adjusted earnings metrics. Finally, after controlling for observable sources of selection, we investigate the sensitivity of using median earnings versus the 25th or 75th percentile of earnings to rank institutions. This last analysis reveals the extent to which comparing institutions using earnings data remains a complicated endeavor, even after the selection problem is addressed.

We find that more than three-quarters of the variation in median earnings across colleges is explained by factors we can observe, and accounting for differences in major composition explains over 30 percent of the residual variation in earnings after controlling for institutional selectivity, student composition, and local cost of living differences. Furthermore, we show that using earnings measures to evaluate college quality is extremely sensitive to the choice of metric used. For example, more than 70 percent of institutions move at least 10 percentiles in the earnings distribution after we control for observable selection factors. Even after controlling for selection, approximately 40 percent of colleges move 10 percentiles or more when either the 25th or 75th percentile of earnings is used instead of the median to rank institutions. Taken together, our findings indicate that choosing which metric(s) to present to consumers is consequential when comparing institutions on their early-career earnings performance.

We structure the remainder of this paper as follows. In section 2, we review the evidence base on the role of earnings information to inform student decision-making in college. We describe the Scorecard data and details of our empirical analysis in Section 3. We present our results in Section 4 and discuss the implications of our findings for research and policy in Section 5.

2. PRIOR EVIDENCE ON THE ROLE OF EARNINGS INFORMATION TO GUIDE STUDENT DECISION-MAKING

A large body of evidence indicates that labor market perceptions are consequential to human capital decision-making. Annual surveys routinely find that most incoming college students attend college to improve their labor market prospects (Eagan et al., 2017), and many individuals who would experience large returns to postsecondary education do not enroll because the returns are uncertain (Heckman, Lochner & Todd, 2006). Students also use expected labor market outcomes to inform their choice of major decisions, although to a lesser extent than perceived enjoyment and ability (Beffy, Fougere & Maurel, 2012; Wiswall & Zafar, 2015b; Zafar, 2011).

However, a key challenge to using labor market perceptions to guide human capital decisions is that many individuals are misinformed about the expected returns to different colleges and fields of study and the degree to which returns vary across colleges and majors. Several studies find that students make significant errors in estimating returns to majors and degrees (Baker et al., 2018; Betts, 1996; Dominitz & Manski, 1996; Arcidiacono, Hotz & Kang, 2012). For example, in a sample of community college students in California, Baker et al. (2018) find that more than half of students ranked the expected earnings of broad categories of majors inaccurately. Betts (1996) finds a similar degree of forecasting error among undergraduates at the University of California-San Diego on average. Evidence also suggests that lower income, lower ability, and less experienced students are most likely to hold biased expectations of their labor market returns (Attanasio and Kaufmann, 2012; Betts, 1996; Arcidiacono, Hotz & Kang, 2012; Zafar, 2011).

An upside to the pervasiveness of labor market misinformation is that students appear to respond when presented with new information. Using experimental research designs, Wiswall and Zafar (2015a; 2015b) find that providing undergraduates at New York University with public information on earnings caused students to revise their own earnings expectations at age 30 by $13,000 on average; students were also more likely to major in non-humanities fields relative to humanities fields upon receiving earnings information disaggregated by field of study. Hurwitz & Smith (2018) also find that when the earnings data in the Scorecard was first released in fall 2015, institutions that reported higher median earnings received more SAT score sends during the next admissions cycle. However, neither the availability nor use of new information will help students make more informed educational decisions if that information is inaccurate or too generic to guide decision-making.

In this study, we examine the extent to which data reported in the Scorecard provides students and families with accurate expectations of a college's contribution to early-career earnings. Unlike prior studies that have attempted to estimate the causal impact of colleges on early-career earnings in a value-added framework (Cunha & Miller, 2014; Dadgar & Trimble, 2015; Jepsen, Troske, & Coomes, 2014; Melguizo et al., 2017; Rothwell & Kulkarni, 2015), our goal in this paper is to examine descriptively whether the earnings data in the Scorecard provides consumers with useful information to guide application, matriculation, and major decisions. Our approach is similar in spirit to Minaya and Scott-Clayton (2018), who examine the sensitivity of institutional rankings to a variety of labor market metrics using state administrative data from Ohio. However, we build on their previous research and extend the literature in two ways. First, because of the breadth of coverage in the Scorecard data, we examine the utility of using earnings data to guide consumer decisions across the census of four-year public and private, non-profit degree-granting institutions in the United States with available earnings information. Second, we decompose the variation in median college earnings into different sources of selection to examine the relative importance of each source of bias, which Minaya and Scott-Clayton (2018) do not.[4] In doing so, we connect the literature on earnings heterogeneity over majors and the literature on measuring college quality by documenting the magnitude of bias in earnings differences across institutions due to differential selection into majors.

[4] Minaya and Scott-Clayton (2018) do examine the overall importance of controlling for student compositional differences across institutions, but they do not explore which sources of selection are most consequential.

3. EMPIRICAL ANALYSIS

3.1 *Data*

The College Scorecard is a publicly available dataset maintained by the U.S. Department of Education that provides a wealth of information on institutional characteristics for nearly all colleges and universities in United States. This data is also the source of the information displayed on the Department's consumer-facing website. Of particular interest for this study, the Scorecard makes available for the first time early-career earnings data maintained by the U.S. Department of Treasury for all students who received federal financial aid during college.[5] This information is aggregated to the institutional level and pooled across two consecutive entry cohorts of students.

The Scorecard includes several earnings outcomes for each institution. The dataset reports earnings over different time horizons, spanning from six to 10 years after students attended the college. For each of these time horizons, the Scorecard includes the mean, median, 25th, and 75th percentiles of the earnings distribution among students who are no longer enrolled in any postsecondary institution, regardless of their completion status.[6] In our empirical work, we focus on the median, 25th, and 75th percentile of earnings measured 10 years after enrollment for the 2003-04 and 2004-05 entry cohorts. This is the most recent set of pooled cohorts for which 10-year earnings outcomes are available. Earnings for those students are measured in calendar years 2014 and 2015, respectively, and reported in the Scorecard in 2017 dollars.

In addition to data on earnings, the Scorecard includes a rich set of institutional characteristics that we use to examine the degree of selection bias in earnings. To capture differences in selectivity across institutions, we use the average SAT score (or equivalent ACT-

[5] Earnings in the Scorecard is defined as the sum of wages and deferred compensation from all W-2 forms for each individual, plus any positive self-employment earnings from the Schedule SE.
[6] For select cohorts, the data also contains the 10th and 90th percentile of earnings.

concordant score) and admissions rate among fall 2004 applicants, and the share of students from the pooled 2003-05 cohort that sent their Free Application for Federal Student Aid (FAFSA) to five or more colleges.[7] We also rely on six measures of student body composition from the Scorecard, all of which are pooled across the 2003-05 entry cohorts. These elements are the share of students who are female, first-generation, and low-income (defined as having family income below $30,000), the share of students receiving a federal Pell Grant at any time in college, and the average family income reported separately for dependent and independent students.

The Scorecard also reports the share of degrees conferred in each field by institution and year. The dataset includes these measures for over 50 distinct fields of study (each denoted by a two-digit Classification of Instructional Program (CIP) code). We use the share of bachelor's degrees awarded to graduates in 2006-07 in our empirical work, which corresponds to entrants in 2003-04 who graduated in four years. For ease of interpretation, we construct six broad major categories from the CIP-level measures to investigate differences in earnings among college graduates by major. The categories we construct are similar to the groupings defined by Carnevale et al (2015); specifically, we collapse the field of study variables into teaching and serving, career-focused, quantitative STEM, non-quantitative STEM, business, and arts and humanities programs of study.[8] In Table 1, we provide a crosswalk between our major groupings and the CIP-level fields of study.

[7] Because the Scorecard is built from multiple underlying data sources, not all elements in the dataset are pooled across cohorts in the same way. In cases where data is reported separately for the 2003-04 and 2004-05 cohort rather than pooled across the 2003-05 cohorts, we use the data reported in 2004-05. We take this simpler approach, rather than constructing a pooled measure ourselves, because the year-over-year correlation of the annual measures is very high. For example, the correlation of SAT scores and admission rates in 2003-04 and 2004-05 is 0.97 and 0.92 in our sample, respectively.

[8] To examine the sensitivity of this aggregation decision, we also estimate results using the full set of CIP codes reported in the Scorecard. Selection into majors explains a larger share of the variation in median earnings across institutions when we account for major composition using the full set of CIP codes, which suggests that our decision rules for constructing meta-majors generates conservative estimates of the role of major composition in explaining earnings differences across institutions.

Finally, because many students attend college close to home and remain nearby after leaving (Kodrzycki, 2001; Hillman & Weichman, 2016; Ishitani, 2011), earnings differences across institutions may in part reflect geographical differences in living costs. We therefore use data from the American Community Survey to account for geographic differences in living costs that may contribute to earnings differences across colleges. Specifically, we use county-level estimates of the median monthly gross rent over the five years spanning 2012-2016 and match this data to institutions using county identifiers in the Scorecard dataset. Given that rental prices are the single largest component of the Consumer Price Index for urban consumers (Moretti, 2013), this measure is a reasonable proxy for local living costs.

3.2 *Sample*

We restrict our study sample to the 485 public and 886 private, non-profit four-year institutions that report earnings metrics for the pooled 2003-05 cohort.[9] This sample comprises nearly all public and private, non-profit four-year institutions in operation in 2003-04 and 2004-05 and captures aggregate earnings for over two million former students.[10] As a robustness check, we also present results from a sample that excludes 288 "specialty" institutions (defined as colleges that graduate 50 percent or more of degree-completers in a major category). This restriction allows us to examine whether major composition is an important determinant of earnings differences across institutions whose value proposition is not especially tied to the programs of study they offer.

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[9] We include institutions with missing covariate data in the analytic sample. We impute missing data by assigning an arbitrary constant value and interacting non-fully-populated covariates with a missing data indicator variable in our estimation models.

[10] Ninety-nine percent of all public and private, non-profit four-year institutions report non-missing median earnings for the pooled 2003-05 cohort, and ninety-eight percent report 25th and 75th percentile earnings metrics.

In Table 2, we present descriptive statistics for the full sample of institutions in our analysis (column 1) and separately for the subset of public (column 2) and private, non-profit institutions (column 3).[11] On average, the median 10-year earnings across colleges is $44,825 in the full sample. The average for public ($43,068) and private, non-profit institutions ($45,787) is similar, despite that fact that public institutions on average serve a larger share of traditionally disadvantaged students (e.g., 37 percent of students attending public institutions have family income below $30,000 compared to 28 percent of students attending private institutions). Although median earnings by sector are similar on average, there is considerable variation across institutions both within and across sector. The standard deviation of median 10-year earnings is $11,543, $9,219, and $12,536 across all, public, and private, non-profit institutions, respectively.

3.3 *Empirical Strategy*

We begin our empirical work by investigating the amount of variation in major shares across public and private, non-profit four-year colleges and universities in the United States. We then regress median earnings on the share of graduates in each broad category of major to begin to examine the relationship between variation in earnings and differences in major composition across institutions. Because changes in major composition are likely correlated with other sources of selection, we next estimate a series of linear regression models that additively adjust for additional compositional and cost-of-living differences across institutions. The most complete model we estimate is:

(1) $$\boldsymbol{Y_j = \alpha_0 + \gamma S_j + \delta D_j + \omega H_j + \beta M_j + \varepsilon_j}, \text{ where}$$

[11] For each variable, we report the number of non-missing observations in brackets if less than the full analytic sample.

$\boldsymbol{Y_j}$ denotes the median earnings 10 years following entrance to institution $\boldsymbol{j}$ among students who received federal financial aid. $\boldsymbol{S_j}$ is the vector of institutional selectivity measures composed of the admission rate, average SAT score of matriculated students, and percentage of students who sent their FAFSA to five or more institutions, which proxies for the number of colleges to which students attending institution $\boldsymbol{j}$ applied. $\boldsymbol{D_j}$ is the vector of average student demographic and socioeconomic characteristics that includes the percentage of dependent, female, first-generation, Pell Grant recipients, and low-income students, as well as the average income of dependent and independent students, respectively.[12] $\boldsymbol{H_j}$ controls for the median rental price over the five-year period from 2012-2016 in the county of each institution. $\boldsymbol{M_j}$ is the vector of major composition controls that captures the percentage of graduates at each institution majoring in the six broad major categories. In all estimates we report Huber-White robust standard errors.

We are primarily interested in two parameters from the estimation models. First, we report the adjusted R-squared statistic, which captures the percentage of variation in earnings across colleges explained by the set of included covariates. We compare how the adjusted R-squared changes across models to decompose the earnings variation across colleges into differences explained by institutional selectivity, student demographics and academic preparation, local cost of living, and major composition. Second, after estimating equation (1), we also calculate the residual for each college and compare where each institution falls in the distribution of unadjusted versus adjusted earnings metrics. This analysis sheds light on the extent to which selection leads to biased determinations about institutional quality when using earnings metrics to evaluate colleges.

[12] Although it may seem that several of these measures proxy for disadvantage and would therefore be highly correlated, in practice the maximum pairwise correlation is 0.62 in absolute value and most are less than 0.20, which justifies including each in the vector of student compositional controls.

4. RESULTS

4.1 *Variation in Major Shares across Colleges*

We begin to examine the role of major composition in explaining college earnings differences by investigating how major shares vary across four-year colleges and universities. In Figure 1, we plot the distribution of the percentage of graduates completing degrees in teaching and serving, career-focused, quantitative STEM, non-quantitative STEM, business, and arts and humanities programs of study. The left-hand spike in the curve representing career-focused majors indicates that at nearly all four-year institutions the share of graduates majoring in career-focused fields is less than 20 percent. However, major composition varies considerably across colleges with respect to the other five major categories. The standard deviation of the share of graduates with degrees in teaching and serving, quantitative STEM, non-quantitative STEM, business, and arts and humanities is 15.1, 12.2, 8.5, 14.7, and 18.7 percentage points, respectively.

In Figure 2, we graphically represent the association between changes in major composition and median earnings. The blue circles denote the coefficients from a linear regression of median earnings on standardized major shares, which have been normalized to have a mean of 0 and standard deviation of 1. Because the total of all major shares for each institution sum to one, we omit the teaching and serving major category from the estimating equation. The coefficients therefore represent the change in median earnings associated with a standard deviation increase in the share of degrees awarded in a given field rather than in teaching and serving. The red circles present analogous estimates from a model that also controls for institutional selectivity, student composition, and local living costs, which accounts for other observable differences across colleges correlated with major composition and earnings. The lines extending from the circle display the 95 percent confidence interval around each estimate.

The coefficients from the model without controls suggest that major composition and college earnings are only weakly correlated, apart from the share of graduates in quantitative STEM fields. The estimates on the career-focused, non-quantitative, business, and arts and humanities indicators are near-zero and not statistically significant. By comparison, the point estimate on quantitative STEM programs suggests that a standard deviation (i.e., 12.2 percentage point) shift in the share of graduates from teaching and serving to quantitative STEM fields is associated with a $5,000 increase in median earnings. Controlling for other observable differences between institutions attenuates the relationship between the percentage of quantitative STEM graduates and median earnings by approximately 50 percent, but the relationship remains positive and significant. Accounting for differences between institutions also reveals that the relationship between earnings and the share of graduates in non-quantitative STEM and arts and humanities majors is consequential. Our estimates imply that a one standard deviation shift in the share of graduates from teaching and serving to non-quantitative STEM and from teaching and serving to arts and humanities majors, respectively, is associated with a $1,207 and $3,739 decrease in median earnings.

4.2 *Accounting for the Variation in Earnings across Colleges*

To contextualize the relationship between college earnings and major composition, in Figure 3 we plot the R-squared from bivariate regressions of median earnings on each covariate we control for in equation (1). By comparing the R-squared on the major dummies to the R-squared on other selection factors, we begin to illustrate the importance of controlling for major composition when using early-career earnings to evaluate institutional quality. Because family income is highly predictive of educational and labor market opportunities (Belley & Lochner, 2007; Charles & Hurst, 2003; Chetty et al., 2017), it is not surprising that average family income of dependent students and the percentage of Pell students attending each institution are highly predictive of early-career earnings in our analysis. Each of these measures individually explains 40 percent of the variation in median earnings across institutions. The share of graduates in quantitative STEM programs is the seventh most highly predictive measure; it alone explains 18 percent of the earnings variation between colleges and accounts for a larger share of the earnings variation than many factors that researchers typically adjust for, including admission rates, and the percentage of female and first-generation students that institutions enroll. Furthermore, aggregating majors into broad categories understates the explanatory power of major composition. Using the full set of major CIP codes to account for differences in major composition across institutions explains 48 percent of the between-college variation in earnings.

Because many of the selection factors are correlated, the results in Figure 3 mask which predict median earnings over and above others. We therefore estimate regression models that additively adjust for each source of selection. Figure 4 shows the adjusted R-squared statistic from those models.[13] Moving from left to right, we first control for the set of institutional selectivity measures. We then build up to the model with full controls by successively adding the vector of student demographic and socioeconomic characteristics, median rental prices within the zip code of each institution, and major composition dummies to the model.

Between 75-80 percent of the variation in median earnings across institutions is explained by observable factors. Differences in institutional selectivity explain 45 percent of the variation, while controlling for student compositional differences in addition explains 61 percent of the variation. Adjusting for differences in local housing prices explains little of the residual earnings variation after we control for institutional selectivity and student composition. Whereas rental costs

[13] We report the coefficient estimates from the models in Table A1 in the appendix.

alone explain 13 percent of the variation in earnings, the adjusted R-squared only increases from 61 percent to 63 percent when we add rental costs to the model, which indicates that differences in local cost of living between colleges are highly correlated with differences in selectivity and student composition. In contrast, controlling for major composition continues to explain a substantial amount of the variation across colleges even after we account for differences in institutional selectivity, student composition, and local housing costs. The adjusted R-squared increases from 0.63 to 0.75 when we control for the percentage of graduates allocated across the six broad major categories. We are able to explain 80 percent of the variation in median earnings across institutions when we replace the broad major categories with the full set of major CIP categories. These results imply that ignoring major composition as a source of selection overstates the variation in median earnings that is potentially meaningful by as much as 33-44 percent.[14]

To investigate the influence of these controls on the rank order of colleges, in Figure 5 we plot the distribution of percentile differences between college rank orderings derived from unadjusted versus regression-adjusted median earnings. The results indicate that selection bias misleads consumers about college-specific contributions to future earnings. Seventy-two percent of institutions move 10 percentiles or more in the distribution and nearly one-quarter of colleges shift 40 percentiles or more after we control for the full set of selection factors. We document the sensitivity of controlling for selection further in Table 3. On average, institutions shift 17-25 percentiles between the unadjusted and regression-adjusted earnings distributions. Even after adjusting for institutional selectivity, student composition, and local cost of living differences, one-quarter of colleges shift 19 percentiles or more when we further control for major composition.

[14] This estimate represents the percent change in the share of unexplained earnings variation between the model that controls for differences in institutional selectivity, student composition, and housing prices and the model that additionally controls for differences in major composition.

In Appendix Figure A1 and Table A2, we show that major composition remains an important determinant of between-college variation in earnings in the sample that excludes specialty institutions. As shown in Figure A1, institutional selectivity, student composition, and local cost of living differences jointly explain an even larger share (77 percent) of the variation in median earnings across institutions in the conditioned sample. As a result, the adjusted R-squared increases by a smaller amount when we control for the percentage of graduates allocated across the broad major categories. However, the adjusted R-squared still increases by 9 percent in the conditioned sample, from 0.77 to 0.84, when we add the full set of major CIP codes to the regression model. Furthermore, in Table A2 we show that controlling for major composition leads to similar shifts in college rankings in the conditioned sample. The average rank difference derived from models that do and do not control for major composition is 13.6 percentiles in our main analytic sample and 11.6 percentiles in the conditioned sample.

4.3 *Sensitivity of College Rankings to the Choice of Earnings Metric*

The challenge of equipping consumers with useful earnings metrics is not isolated to the issue of selection bias. In addition to median earnings, the Scorecard reports the 25th and 75th percentile of 10-year earnings, although these metrics are not a part of the consumer-facing tool and instead reside in the college-specific data files. Determining which metric(s) to present is consequential, even after controlling for observable differences across institutions. We document this in Figure 6, which plots the distribution of percentile differences between college rankings derived from median versus 25th percentile of earnings measures. The gray bars in Figure 6 plot the distribution of percentile differences derived from unadjusted earnings measures and the red bars plot the analogous distribution based on regression-adjusted college residuals that account for selection bias. Similar to the results in Figure 5, institutions shift ranks considerably when evaluated on their median versus 25th percentile of earnings. The average absolute difference in percentiles between the regression-adjusted residuals is 10, with 41 percent of institutions moving at least 10 percentiles upwards or downwards in the distribution.[15] In addition, controlling for selection exacerbates the sensitivity of college rankings across measures. After the addition of controls, the distribution of percentile differences (depicted by the red bars) shifts even further to the right, indicating that colleges change ranks more on net when controls for selection are introduced.

5. POLICY IMPLICATIONS AND CONCLUSION

Pointing to the wide variation in average earnings between degree fields, the U.S. Department of Education has been collecting program-level earnings data since 2014 with the intention of providing students with a clearer sense of their expected earnings (US Department of Education, 2016). The President's recent executive order mandating the disaggregation of earnings data in the College Scorecard by institution and program provides new urgency around making this information publicly available. Our results suggest that disaggregating earnings by major is an important feature of the Scorecard's goal to equip consumers with useful information to guide college decision-making, at least among four-year institutions. We conclude that ignoring differences in major composition overstates the between-college variation in median earnings that is possibly attributable to institutions by over 30 percent.

However, our findings also suggest that the selection of students into institutions plays an important role in shaping future earnings profiles. We attribute no less than 45 percent of the variation in median earnings across colleges to other selection factors, most notably differences in

[15] We present analogous comparisons between median and the 75th percentile of earnings measures and between the 25th percentile and 75th percentile of earnings measures in Appendix Figure A2. We observe shifts in college rankings of similar magnitude in those analyses.

institutional selectivity and student demographic and socioeconomic characteristics. When not unaccounted for, the stratification of students across four-year colleges and universities can lead to very misleading conclusions about institutional quality based on early-career median earnings. On average, institutions shift 23 percentiles in the distribution of median 10-year earnings after accounting for differences in institutional selectivity, student composition, and local housing prices. This suggests that conveying accurate information to students and families on their expected returns to postsecondary education requires accounting for other sources of selection across colleges, most notably the types of students an institution serves and, to a lesser extent, where the college is located.

It is also worth noting that the amount of selection we observe in this study does not appear to be unique to four-year colleges and universities or to using earnings measures to compare institutional performance. For example, in their analysis of college effects on transfer credits across the 112-campus California Community College System, Kurlaender et al. (2016) find that the average college rank changed by 30 positions when controlling for student inputs. The large shift in rankings that we and other researchers observe suggests that accountability systems that reward or penalize colleges based on unadjusted outcome metrics may be unintentionally disadvantaging institutions that add substantial value to the welfare of their students.

Even after adjusting for differences in institutional and student characteristics, we find that using median, 25th percentile, or 75th percentile of earnings metrics to compare institutions can result in different conclusions about which colleges offer students the best earnings prospects. Taken together, our findings indicate that the interpretation and use of current outcomes to compare the performance of colleges is no straightforward task. Because institutional performance is multidimensional, quality rankings can change dramatically across measures, even among those that measure the same construct, and lead to misguided conclusions about effectiveness. As a result, improving the accuracy and efficacy of college search tools likely requires helping students and families understand and distinguish between multiple metrics, including those that account for selection bias that dramatically overstates earnings differences across colleges.

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Tables and Figures

Table 1. Classification of CIP field of study codes into broad major categories

Major Category	2-Digit CIP Name(s)	2-Digit CIP Code(s)
Quantitative STEM	Computer and Information Sciences, Engineering, Engineering Tech, Mathematics & Statistics, Physical Sciences, Architecture, Military Tech	04, 11, 14, 15, 27, 40, 41
Non-Quantitative STEM	Biological and Biomedical Sciences, Psychology, Agriculture, Natural Resources	01, 03, 26, 42
Business	Business	52
Arts, Humanities, and Liberal Arts	English Lang & Lit, History, Performing Arts, Philosophy, Theology, Liberal Arts, Area/Ethnic Studies, Foreign Language, Communications, Interdisciplinary	05, 09, 16, 23, 24, 30, 38, 39, 54
Career-Focused	Legal Professions, Personal & Culinary, Consumer Science, Construction, Mechanics, Precision Production, Transportation, Communication Tech	10, 12, 19, 22, 46, 47, 48, 49
Teaching and Serving	Education, Social Science, Public Admin, Law Enforcement, Library Science, Parks and Rec, Health Professions	13, 25, 31, 43, 44, 45, 51

Table 2. Summary statistics of the analytic sample

	(1)	(2)	(3)	(4)	(5)	(6)
	All Colleges		Public		Private, Non-Profit	
	Mean	SD	Mean	SD	Mean	SD
Average SAT score	1067	126	1032	103	1087	134
	[1201]		[433]		[768]	
Admission rate	67.9	18.5	70.3	17.4	66.6	18.9
	[1265]		[439]		[826]	
Share of students sending 5 FAFSAs	16.1	11.2	11.2	7.6	18.9	12.5
	[1342]		[481]		[861]	
Share of first-generation students	35.2	11.8	39.1	8.9	33.5	11.2
	[1322]		[482]		[840]	
Share of dependent students	27.5	19.1	28.3	15.5	27.1	20.8
	[1344]		[483]		[861]	
Share of low-income students	31.1	13.6	36.6	13.1	28.1	12.9
	[1371]		[485]		[886]	
Average family income of dependent students	$60,882	$15,757	$54,477	$13,464	$64,515	$15,756
	[1344]		[483]		[861]	
Average family income of independent students	$22,664	$8,524	$19,291	$4,012	$24,556	$9,719
	[1344]		[483]		[861]	
Share of Pell Grant recipients	52.4	16.1	60.0	14.4	48.3	15.5
	[1367]		[483]		[884]	
Share of female students	58.9	11.3	57.6	9.5	59.7	12.2
	[1345]		[485]		[860]	
Median rent in school county	$907	$260	$876	$238	$924	$270
	[1369]		[483]		[886]	
Median 10-year earnings	$44,825	$11,543	$43,068	$9,219	$45,787	$12,536
	[1371]		[485]		[886]	
25th percentile 10-year earnings	$28,418	$8,349	$27,261	$6,527	$29,059	$9,145
	[1355]		[483]		[872]	
75th percentile 10-year earnings	$64,641	$17,228	$61,750	$13,162	$66,242	$18,929
	[1355]		[483]		[872]	

Table 2, continued. Summary statistics of the analytic sample

	(1)	(2)	(3)	(4)	(5)	(6)
	All Colleges		Public		Private, Non-Profit	
	Mean	SD	Mean	SD	Mean	SD
Share of graduates in quantitative STEM majors	8.7	12.18	10.9	11.9	7.4	12.15
Share of graduates in non-quantitative STEM majors	12.4	8.5	12.5	6.5	12.3	9.5
Share of graduates in business majors	20.4	14.7	19.0	8.5	21.1	17.1
Share of graduates in arts and humanities majors	27.4	18.7	24.0	12.9	29.3	21.0
Share of graduates in career-focused majors	1.5	4.2	2.1	4.1	1.1	4.3
Share of graduates in teaching and serving majors	28.5	15.1	30.5	12.5	27.4	16.2
Observations	1,371		485		886	

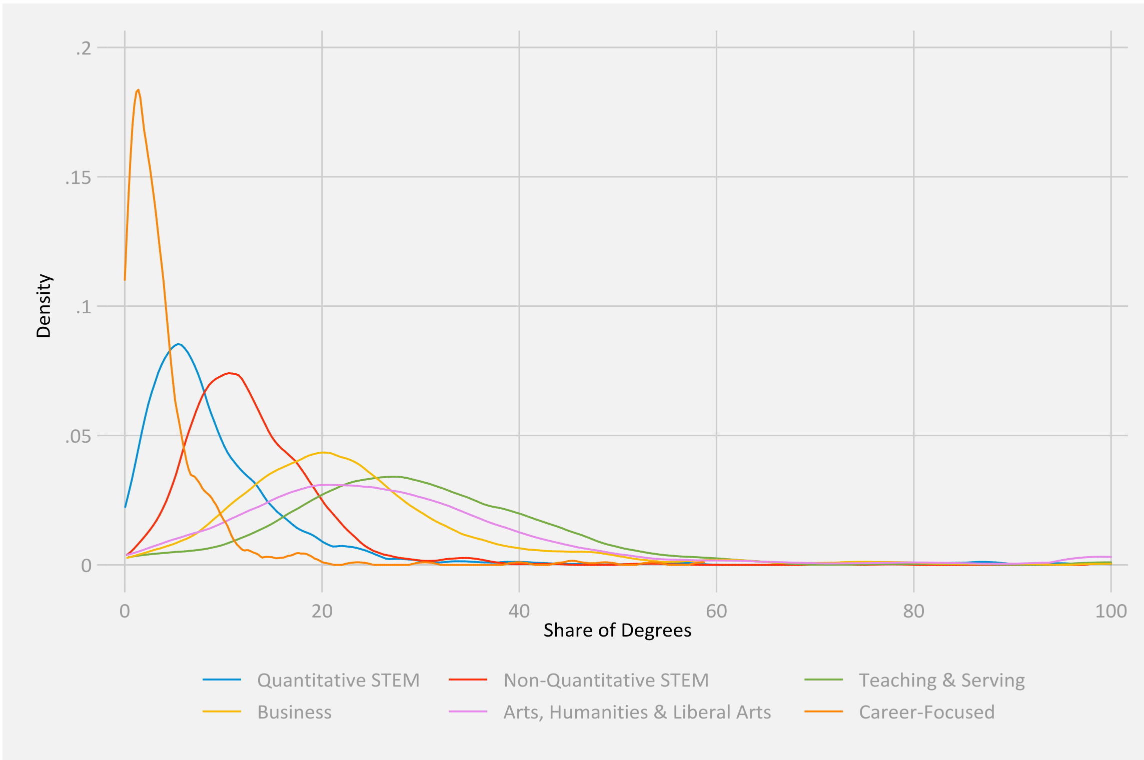
Notes: The sample is restricted to public and private, non-profit four-year colleges and universities with non-missing median 10-year earnings reported in the College Scorecard in 2013-14. Means and standard deviations are shown with the number of non-missing observations in brackets if less than the full sample.
Source: 2015-16 College Scorecard dataset.

Table 3. Changes in percentile rankings derived from unadjusted versus regression-adjusted median 10-year earnings distributions and correlations of regression-adjusted college rankings (N = 1,371)

	(1) Mean absolute change in percentiles	(2) 25th percentile of absolute change	(3) 50th percentile of absolute change	(4) 75th percentile of absolute change
A. Absolute change in percentiles relative to unadjusted earnings distribution				
Selectivity controls (M1)	17.35	5	13	24
+ Student composition controls (M2)	22.09	7	17	33
+ Local rental prices (M3)	23.46	7	19	36
+ Major shares (M4)	25.33	9	20	39
B. Absolute change in percentiles between M3 and M4				
	13.62	4	10	19
C. Spearman's rank correlations of college residuals across models				
	M1	M2	M3	
M1	1.000			
M2	0.756	1.000		
M3	0.710	0.948	1.000	
M4	0.550	0.739	0.779	

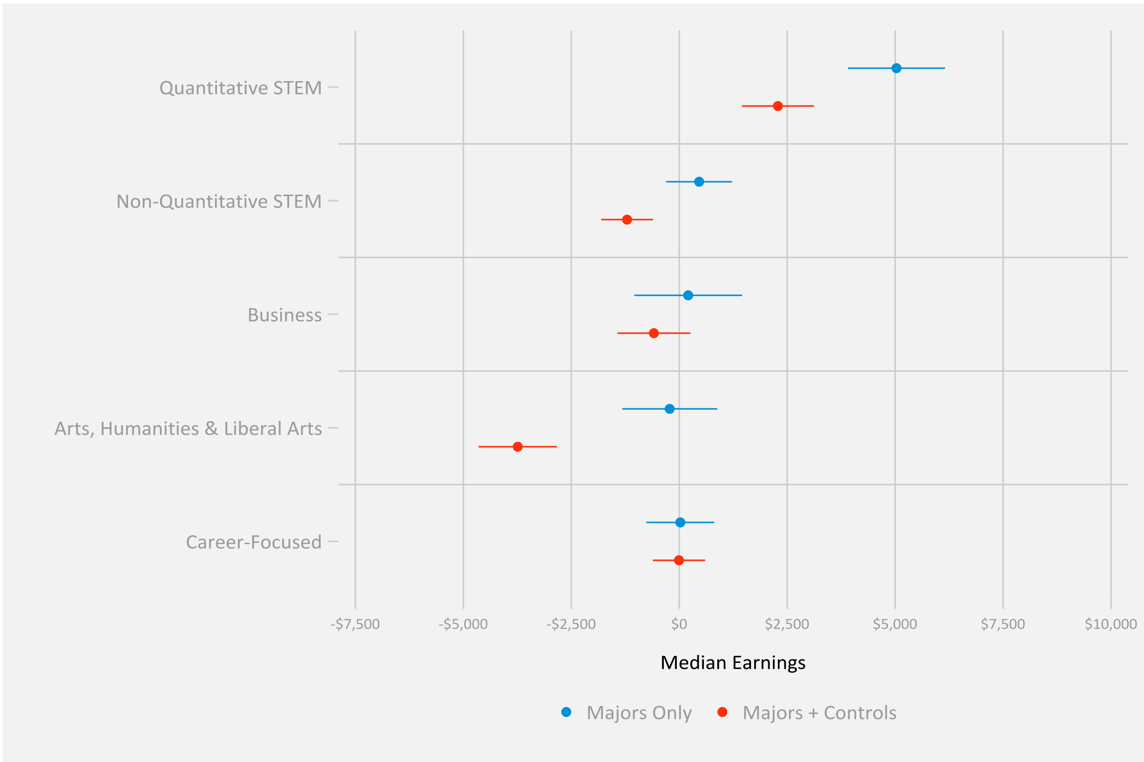
Notes: The sample is restricted to public and private, non-profit four-year colleges and universities with non-missing median 10-year earnings reported in the College Scorecard in 2013-14. Residuals are estimated from linear regression models. M1 controls for the admission rate, average SAT score of matriculated students, and the percentage of students who sent their FAFSA to five or more institutions. M2 controls for all M1 covariates plus the percentage of dependent, female, first-generation, Pell Grant recipients, and low-income students, as well as the average income of dependent and independent students, respectively. M3 controls for all M1 and M2 covariates plus the median rental price over the five-year period from 2012-2016 in the county of each institution. M4 controls for all M1, M2, and M3 covariates plus the percentage of graduates in each college majoring in the six broad major categories. See Table 1 for details of the majors included in each category.
Source: 2015-16 College Scorecard dataset.

Figure 1. Kernel density plots of the percentage of graduates completing bachelor's degrees in teaching and serving, career-focused, quantitative STEM, non-quantitative STEM, and arts, and humanities majors at public and private, non-profit four-year colleges and universities



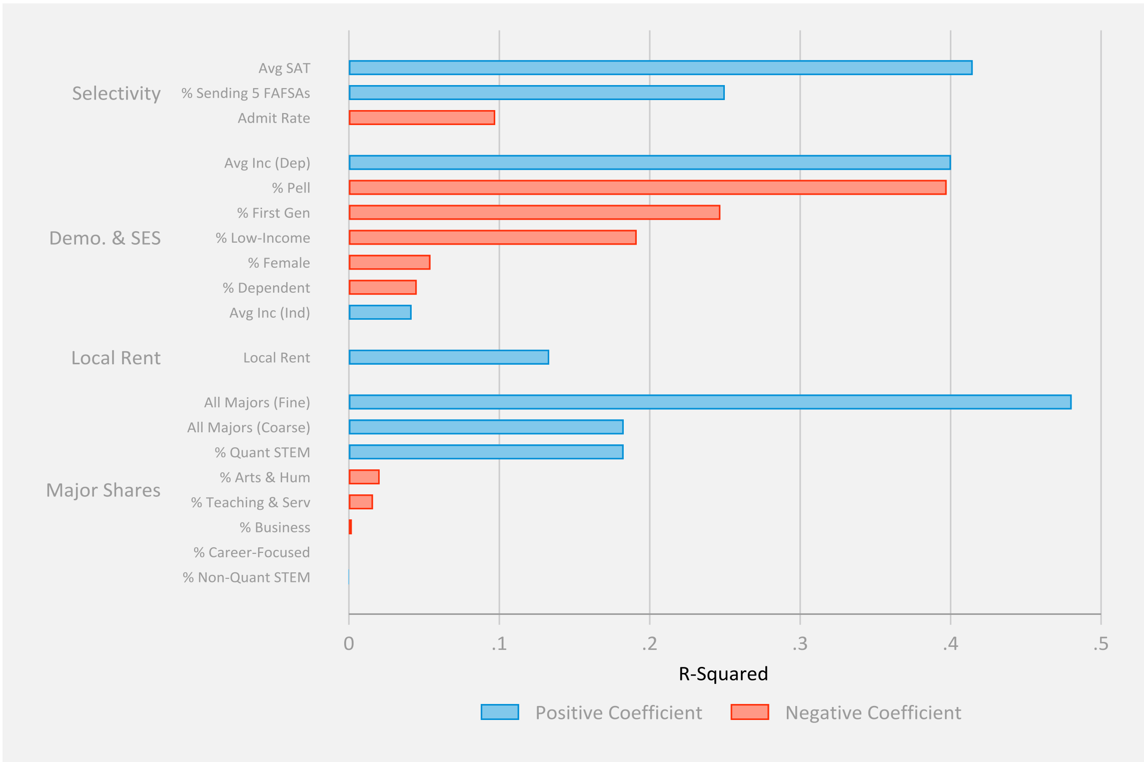
Notes: The sample is restricted to public and private, non-profit four-year colleges and universities with non-missing median 10-year earnings reported in the College Scorecard in 2013-14. See Table 1 for details of the majors included in each category.
Source: 2015-16 College Scorecard dataset.

Figure 2. Estimates of the relationship between changes in the composition of graduates across majors and median 10-year earnings



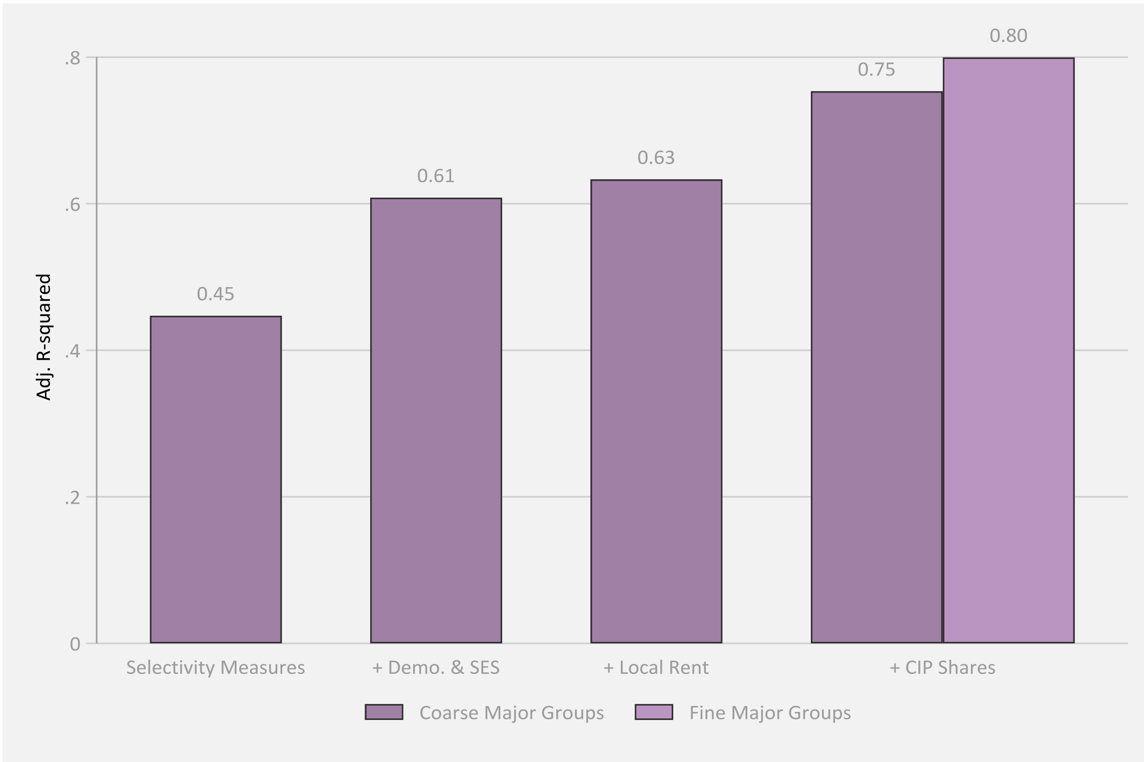
Notes: The sample is restricted to public and private, non-profit four-year colleges and universities with non-missing median 10-year earnings reported in the College Scorecard in 2013-14. See Table 1 for details of the majors included in each category. Each point plots the coefficient from a linear regression of median earnings on standardized major shares (mean = 0, standard deviation = 1), with teaching and serving majors as the omitted category. The standard deviation of each major share category is as follows: Quantitative STEM = 12.2, Non-Quantitative STEM = 8.5, Business = 14.7, Arts & Humanities = 18.7, and Career-Focused = 4.2. Estimates with covariates control for institutional selectivity, student composition, and local living costs. See Table 3 for the specific list of covariates included in each set of controls. The lines extending from each circle denote the 95 percent confidence interval around the estimate derived from Huber-White robust standard errors.
Source: 2015-16 College Scorecard dataset.

Figure 3. The percentage of between-college variation in median 10-year earnings individually explained by each observable selection factor



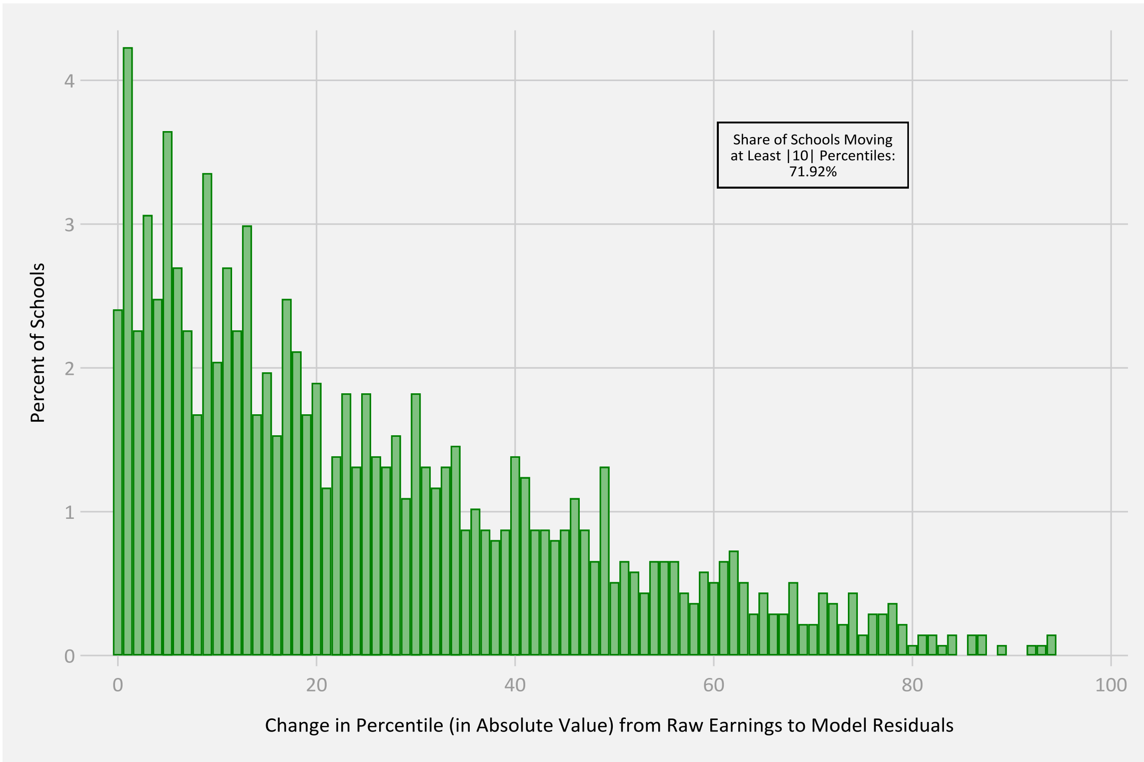
Notes: The sample is restricted to public and private, non-profit four-year colleges and universities with non-missing median 10-year earnings reported in the College Scorecard in 2013-14. See Table 1 for details of the majors included in each category. Except for the "All Majors" predictors, each bar reports the r-squared from a bivariate linear regression of median 10-year earnings on the individual predictor. The "All Majors" bars (coarse and fine) report the adjusted r-squared from multivariate linear regressions.
Source: 2015-16 College Scorecard dataset.

Figure 4. The percentage of between-college variation in median 10-year earnings jointly explained by observable selection factors



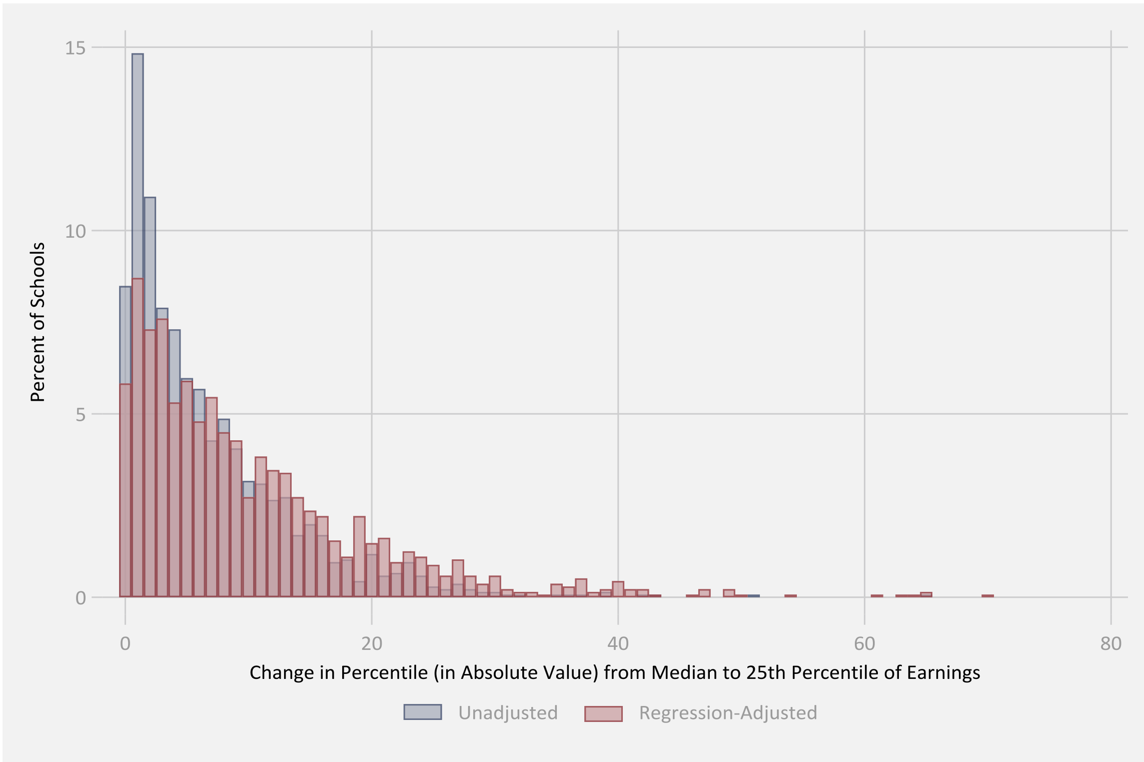
Notes: The sample is restricted to public and private, non-profit four-year colleges and universities with non-missing median 10-year earnings reported in the College Scorecard in 2013-14. Each bar denotes the adjusted r-squared from a linear regression of median 10-year earnings on the set of denoted predictors. See Table 3 for the list of covariates included in each model. See Table 1 for details of the majors included in each coarsened major category. The model that controls for "fine" major categories replaces coarsened major categories with two-digit CIP codes.
Source: 2015-16 College Scorecard dataset.

Figure 5. Distribution of percentile ranking differences between unadjusted and regression-adjusted median 10-year earnings



Notes: The sample is restricted to public and private, non-profit four-year colleges and universities with non-missing median 10-year earnings reported in the College Scorecard in 2013-14. Residuals are estimated from a linear regression that controls for institutional selectivity, student composition, local cost of living, and major composition. See Table 3 for the list of covariates included in the estimation model.
Source: 2015-16 College Scorecard dataset.

Figure 6. Unadjusted and regression-adjusted distributions of percentile ranking differences between median and 25th percentile earnings metrics



Notes: The sample is restricted to public and private, non-profit four-year colleges and universities with non-missing median 10-year earnings reported in the College Scorecard in 2013-14. Residuals are estimated from a linear regression that controls for institutional selectivity, student composition, local cost of living, and major composition. See Table 3 for the list of covariates included in the estimation model.
Source: 2015-16 College Scorecard dataset.

Appendix

Table A1. Parameter estimates from linear regression models of median 10-year earnings that additively control for institutional selectivity, student composition, local housing costs, and major composition (N = 1,371 institutions)

	(1)	(2)	(3)	(4)
Average SAT score	4703.81	2886.86	3165.42	2336.63
	(284.96)	(407.18)	(405.70)	(328.92)
Admission rate	-22.34	-40.25	-32.56	-36.04
	(15.37)	(13.88)	(13.05)	(10.55)
Share of students sending 5 FAFSAs	198.32	205.26	140.78	132.14
	(26.74)	(27.16)	(27.53)	(21.91)
Share of first-generation students		66.28	97.05	26.67
		(42.28)	(42.36)	(35.86)
Share of dependent students		63.27	65.51	56.73
		(22.60)	(20.76)	(22.13)
Share of low-income students		204.21	117.13	101.04
		(63.02)	(58.52)	(48.64)
Average family income of dependent students		225.68	88.20	43.52
		(54.08)	(50.84)	(41.86)
Average family income of independent students		101.21	195.74	127.98
		(44.09)	(41.91)	(34.38)
Share of Pell Grant recipients		-309.45	-297.60	-259.97
		(73.30)	(66.82)	(49.34)
Share of female students		-239.06	-242.68	-72.57
		(34.91)	(33.87)	(25.74)
Median rent in school zip code			8293.11	9818.87
			(984.95)	(876.94)
Share of graduates in quantitative STEM majors				2285.68
				(425.22)
Share of graduates in non-quantitative STEM majors				-1207.48
				(305.80)
Share of graduates in business majors				-587.54
				(430.98)
Share of graduates in arts and humanities majors				-3739.76
				(463.50)
Share of graduates in career-focused majors				-6.14
				(309.32)
Adjusted R-Squared	0.45	0.61	0.63	0.75

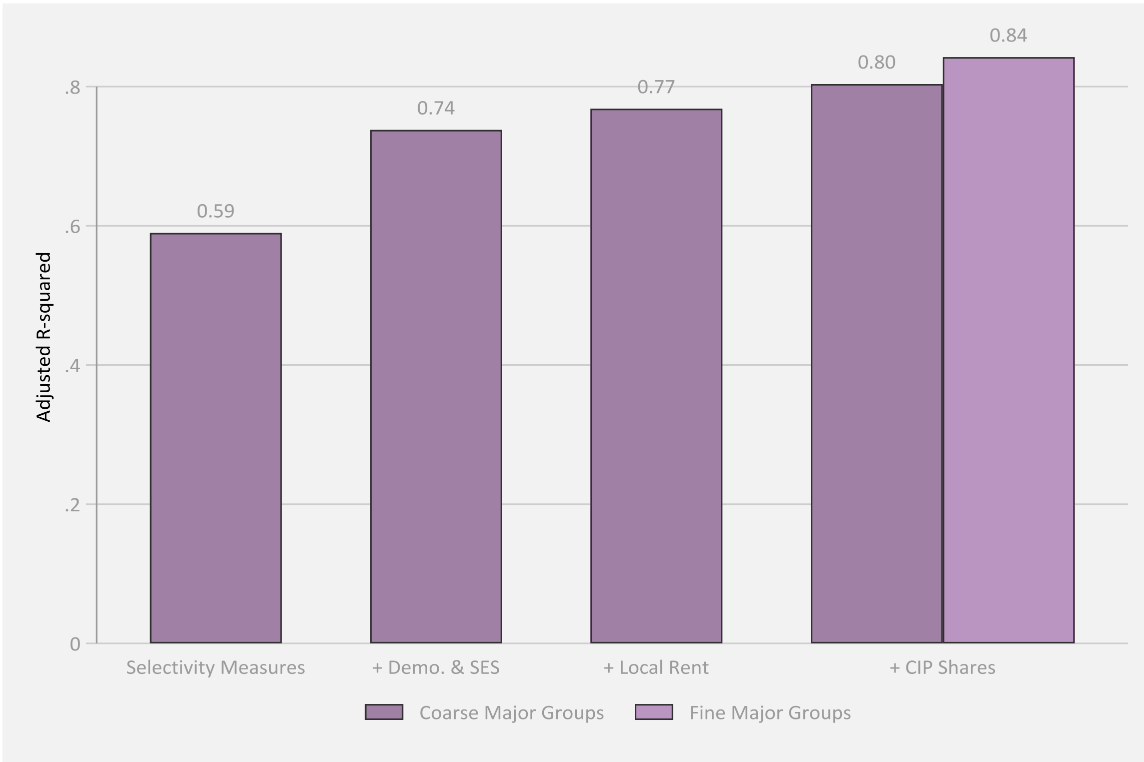
Notes: The sample is restricted to public and private, non-profit four-year colleges and universities with non-missing median 10-year earnings reported in the College Scorecard in 2013-14. The omitted major category is teaching and service programs. See Table 1 for details of the majors included in each category. All models also include a constant. Robust standard errors are reported in parentheses.
Source: 2015-16 College Scorecard dataset.

Table A2. Changes in percentile rankings derived from unadjusted versus regression-adjusted median 10-year earnings distributions, excluding specialty institutions (N = 1,083)

	(1) Mean absolute change in percentiles	(2) 25th percentile of absolute change	(3) 50th percentile of absolute change	(4) 75th percentile of absolute change
A. Absolute change in percentiles relative to unadjusted earnings distribution				
Selectivity controls (M1)	17.56	6	13	25
+ Student composition controls (M2)	22.56	8	18	33
+ Local rental prices (M3)	23.86	8	19	36
+ Major shares (M4)	24.55	8	20	37
B. Absolute change in percentiles between M3 and M4				
	11.59	4	9	17

Notes: The sample is restricted to non-specialty public and private, non-profit four-year colleges and universities with non-missing median 10-year earnings reported in the College Scorecard in 2013-14. Specialty institutions are defined as those that graduated 50 percent or more of graduates in a broad major category. See Table 1 for details of the majors included in each category. Residuals are estimated from linear regression models. See Table 3 for the specific list of covariates included in each model.
Source: 2015-16 College Scorecard dataset.

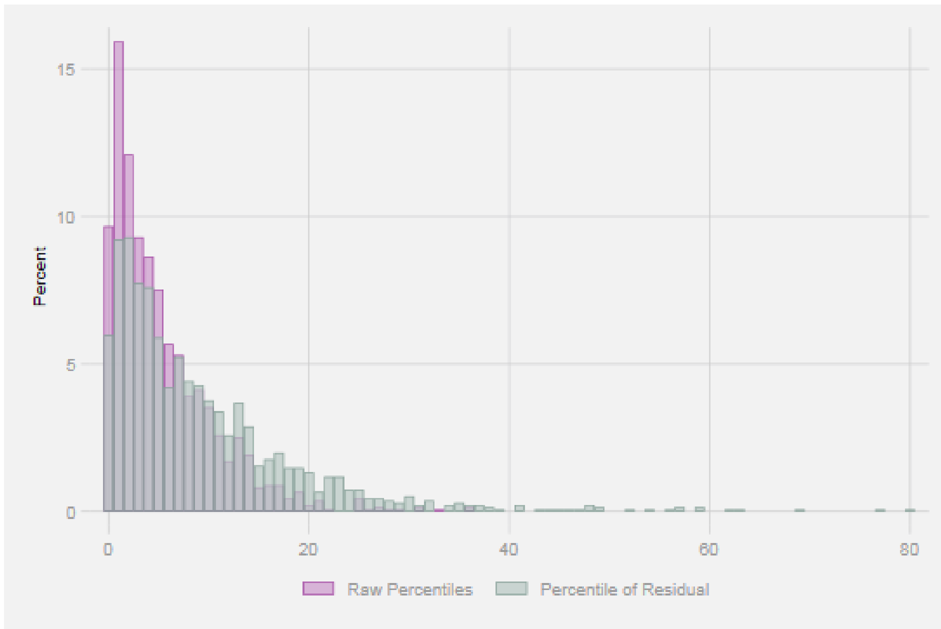
Figure A1. The percentage of between-college variation in median 10-year earnings jointly explained by observable selection factors, excluding specialty institutions (N = 1,083)



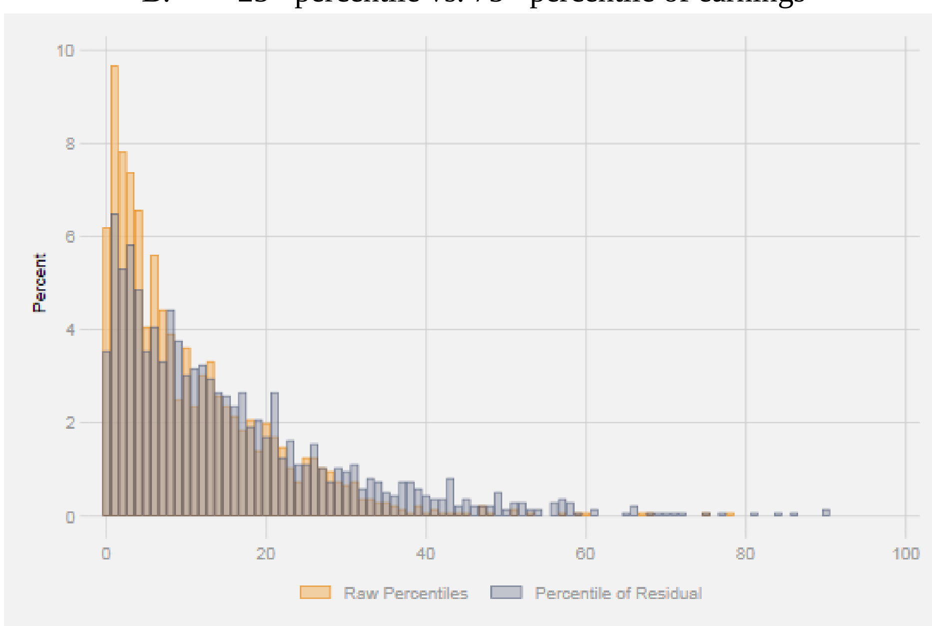
Notes: The sample is restricted to non-specialty public and private, non-profit four-year colleges and universities with non-missing median 10-year earnings reported in the College Scorecard in 2013-14. Specialty institutions are defined as those that graduated 50 percent or more of graduates in a broad major category. See Table 1 for details of the majors included in each coarsened major category. Each bar denotes the adjusted r-squared from a linear regression of median 10-year earnings on the set of denoted predictors. See Table 3 for the list of covariates included in each model. The model that controls for "fine" major categories replaces coarsened major categories with two-digit CIP codes.
Source: 2015-16 College Scorecard dataset.

Figure A2. Unadjusted and regression-adjusted distributions of percentile ranking differences between alternative earnings metrics

A. Median earnings vs. 75th percentile of earnings



B. 25th percentile vs. 75th percentile of earnings



Notes: The sample is restricted to public and private, non-profit four-year colleges and universities with non-missing median 10-year earnings reported in the College Scorecard in 2013-14. Residuals are estimated from a linear regression that controls for institutional selectivity, student composition, local cost of living, and major composition. See Table 3 for the list of covariates included in the estimation model.
Source: 2015-16 College Scorecard dataset.