The Costs of and Net Returns to College Major

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Abstract

Though undergraduate tuition generally varies little or not at all by field of study, instructional expenditures vary widely. This paper uses administrative student and expenditure data from Florida public universities to describe a) how the cost of producing graduates varies by major, b) how the inclusion of field-specific instructional costs alters the estimated net returns to different fields of study, and c) how major-specific instructional expenditures changed between 1999 and 2013. We find that the cost of producing graduates in the highest cost major (engineering) is more than double that of producing graduates in the lowest-cost major (library science). Measures of private return net of cost differ significantly from returns measured using labor market outcomes for a number of fields. On a per-graduate basis, low-cost but relatively high-earning fields like business and computer science offer higher net returns than higher-earning but higher-cost majors like engineering. On a per-dollar basis, differences between net returns and earnings returns are even more pronounced. Per-credit expenditures for undergraduate classes dropped by 16% in the Florida SUS system between 1999 and 2013. The largest drops occurred in engineering and health, growing fields with high individual-level returns, where per-credit spending fell by more than 40%. The observed changes have little relationship with average per credit costs or earnings effects.

1 Introduction

Both casual observation and detailed survey data indicate that post-college earnings for graduates vary widely by field of study. Though this is in part driven by differences in the mix of students majoring in different subjects, both observational evidence controlling in detail for student background and studies relying on quasi-experimental variation in student assignment to different majors indicate the major choice plays a causal role in earnings determination (Altonji,

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Blom, and Meghir 2012; Altonji, Arcidiacono, and Maurel 2016; Hastings, Neilson, and Zimmerman 2013; Kirkeboen, Leuven, and Mogstad 2014). State and national policymakers observing cross-field wage differentials have proposed policies encouraging students to pursue degrees in perceived high-return areas such as the STEM fields while suggesting that students think carefully before pursuing degree programs in liberal arts degrees with perceived low returns (Alvarez 2012; Jaschik 2014). The idea is that by choosing higher-earning degree programs, students will help raise the return on public and private investments in higher education.

While policy discussions tend to focus on labor market outcomes, pecuniary returns on educational investments depend not just on the revenue side (i.e., future earnings), but on costs. Though students' choices are simplified by the fact that at least until recently tuition costs have not varied, or have not varied that much, across fields (CHERI 2012; Ehrenberg 2012; Stange 2015), available evidence suggests that the costs of producing graduates or credit hours varies substantially by field (Johnson 2009; Conger et al. 2010). Some majors may lead to high earnings but be costly to produce, and offer lower net returns per graduate or per invested dollar than lower-earning but less costly majors. An understanding of *net* private returns may be valuable for policymakers seeking to maximize the efficacy of higher education spending.

This paper brings together evidence on major-specific earnings outcomes and production costs to provide what is to the best of our knowledge the first assessment of the net private returns to college major. We evaluate earnings outcomes using two data sources: administrative records of educational and early career labor market outcomes for a large sample of in-state, first-time-in-college students enrolling in the Florida State University System (SUS), and nationally representative data from the American Community Survey (ACS). Though we lack experimental or quasi-random variation in the assignment of students to college major, we do have access to a detailed set of control variables, including high school grades and college admissions test scores. We evaluate the costs of producing graduates and credits in different fields using publicly available administrative expenditure reports from SUS Board of Governors (FLBOG). These reports detail total and per-credit direct and indirect instructional expenditures within institution-major-course level cells. Majors are defined by two-digit CIP codes. We link the expenditure reports to microdata on student course-taking to compute total instructional expenditures over college careers for graduates and dropouts.

We use these data to consider two measures of net private returns. The first is the present discounted value (PDV) of net private returns per graduate by major. These values are potentially relevant for a university or policymaker trying to decide whether to open an additional spot in one major versus another. The second measure is the PDV of net private returns per dollar of incurred cost. This is potentially relevant for universities or policymakers with a fixed budget trying to decide which major or majors to expand.

We find that costs per credit and per graduate vary widely by field, and that measures of private returns net of cost are in many cases significantly different from returns measured using labor market outcomes only. Engineering majors are the most expensive, with total costs of $62,297. This compares to a median degree cost of $36,369 and a cost of $31,482 for business, the second cheapest major. The graduate-weighted standard deviation of distribution of the PDV of costs by major is $7,187 (in 2014 USD), roughly one quarter the size of the standard deviation of the PDV of earnings through approximately age 32 (the last year in which we observe earnings in the Florida data). Measuring returns on a per-graduate basis, we find that low-cost but relatively high-earning fields like business and computer science offer higher net returns than higher-earning but higher-cost majors like engineering. On the whole, however, differences in net returns across degree programs at the individual level are driven primarily by differences in earnings. The graduate-weighted correlation between net person-level PDVs through age 32 and estimates of log earnings effects is 0.95.

On a per-dollar basis, differences between net returns and earnings returns are more stark. High earning but high cost degree programs in Engineering and Health offer per-dollar returns that are similar to much lower earning but lower cost programs in fields like Education and Philosophy. High earning but low cost degree programs in fields like business and computer science have the highest net returns by this measure as well. The graduate-weighted correlation between per-dollar estimates of net PDVs and estimates of log earnings effects is 0.52.

We also consider students who did not graduate from college. Students who do not graduate incur substantial costs for each additional year they spend in college without realizing commensurate earnings returns. Compared to students who enroll in college and leave without graduating in their first year, students who leave without graduating after three or more years of college incur $28,276 in additional costs, while their earnings rise by $261 per quarter. The PDV of the additional earnings through age 32 is equal to 18.3% of the PDV of additional costs. Non-completers account for 17.2% of total costs in our sample.

The last component of our empirical work considers trends in field-specific per-credit expenditures over the 1999-2013 period. On average, per-credit expenditures dropped by 16% in the Florida SUS system over this period. Rates of decline are highly heterogeneous by field. The largest drops occured in engineering and health, growing fields with high individual-level returns. Per-credit funding in these fields fell by more than 40% over the period. Overall, costs per credit fell more in fields with large increases in credit hours. The changes have little relationship with average per credit costs and earnings effects. Our findings suggest that long-run declines in funding at the institution level affect fields asymetrically, and may alter the distribution of degree types in addition to overall completion rates (Bound and Turner 2007; Bound, Lovenheim, and Turner 2010).

The paper proceeds as follows. In Section 2, we discuss our contribution to existing work on the topic. In Section 3 we present a model of the tradeoffs facing policymakers deciding how to allocate program spots and funding across majors. In Section 4 we describe our data. Sections 5 and 6 present our findings, and Section 7 concludes.

2 Related literature

Our work builds on two important literatures.The first is the rapidly growing literature on return to education by field, surveyed by Altonji, Blom, and Meghir (2012) and Altonji, Arcidiacono, and Maurel (2016). A core challenge in this literature is to understand how the process by which students choose different fields affects observed earnings outcomes. A small set of studies, including Arcidiacono (2004) and Beffy et al. (2012), use a structural model of field choice and wages. A few other studies use plausibly exogenous variation in access to fields of study to identify returns. Hastings, Neilson, and Zimmerman (2013) and Kirkeboen, Leuven, and Mogstad (2014) use the fact that in Chile and Norway (respectively) determine admission to particular school/field of study combinations using an index of test scores and grades. This admissions structure provides the basis for a fuzzy regression discontinuity design. Findings from these studies indicate that access to different fields of study can have large effects on earnings outcomes.

In the absence of a good source of quasi-experimental variation, we follow the vast majority of studies that use multivariate regression with controls for student characteristics.[1] While omitted variables bias is always a concern, we do have access to high school transcript information and test scores. Consequently, our control set is richer than that of most previous studies. We find large differences in the returns across majors that follow the general pattern in previous studies (see ABM (2012) and AAM (2016)). Using the earnings regressions, we compute the present discounted value of earnings by field, relative to education. As we discuss in Section 4, we have some concerns about earnings outcomes measured using our Florida data because a) the data cover early career outcomes only, and b) we do not observe earnings outcomes for students who leave Florida. We therefore consider ACS estimates of earnings effects as well. These are very similar to estimates described in ABM, with the key difference being that we create more aggregated major categories to correspond more closely with what we observe in the Florida administrative records.

We also contribute to the important but much smaller literature on education production costs.

[1] Examples include Berger (1988), Chevalier (2011), Grogger and Eide (1995), Webber (2014), and Hamermesh and Donald (2008).

Bound and Turner (2007) and Bound, Lovenheim, and Turner (2010) show that changes (specifically, reductions) in per-student resources have played an important role in the decline in rates of college graduation since the 1970s. In research focusing on cost heterogeneity by major, Middaugh et al. (2003), Johnson (2009; 2013), and Conger et al. (2010) provide evidence that instructional costs vary across fields, and tend to be higher for STEM courses, as well as courses in instruction-intensive non-STEM fields like education, art, and nursing (Middaugh et al. 2003). Thomas (2015) uses data on course selection and instructor costs for particular courses to estimate a model of how universities allocate courses. His data are for the University of Central Arkansas. Our cost-side analysis most closely parallels Johnson (2009), who uses the same data on expenditures and course-taking in the Florida State University System. Our findings on the average and major-specific per-credit and per-graduate costs are very similar to his. In what follows we compare our results to his where applicable. Though our research focuses exclusively on Florida, evidence on costs from Ohio, New York, Illinois suggest that other states exhibit similar patterns of expenditure across field and trends over time (Conger et al. 2010).

Our main contribution is to a) highlight the importance of considering costs as well as earnings when evaluating the efficacy of field-specific educational investments, and b) bring these two strands of literature together to produce what to our knowledge are the first available measures of per-person and per-dollar net private returns. We also provide new evidence on heterogeneity in major-specific spending trends. Much previous work on major-specific spending has focused on snapshots of spending for particular cohorts of graduates. One exception, Conger et al. (2010), documents trends in major-specific spending in the SUS system over the 2002-2007 period, when both our data and theirs show little change in per-credit spending. Using a longer time window, we document a secular decrease in spending, with timing that coincides with economic downturns in in 2001 and 2008.

3 Private Incentives, Externalities, and Choice of Major

In this section we motivate our focus on instructional costs by laying out a simple model of optimal major choice from the point of view of both the individual and the social planner. Our focus is on how labor market returns, instructional costs, and tuition influence choice in an environment where taxation and education externalities cause the private and social values of majors to differ. We abstract from the extensive margin choice to attend college, as well as from the college completion margin.

Students choose majors to maximize utility. The utility from a given major depends on earnings returns, tuition, and the nonpecuniary benefits associated with its coursework and the occupations it leads to. Assuming additive separability, the utility U_i^f that student i receives from enrolling major f is

$$U_i^f = u_i((1-t)Y^f - \tau^f) + V_i^f \ , \tag{1}$$

where Y^f is the present discounted value of earnings for individuals who enroll in f, t is the tax rate on earnings, τ^f is the tuition in major f, and V_i^f is i's non-pecuniary utility from major f. We assume for simplicity of exposition that earnings and tuition do not vary across individuals within a major, and that tax rates are constant. The function u_i captures utility from the consumption of goods and services financed out of earnings net of tuition costs. V_i^f depends on preferences over subject matter and occupations, academic preparation, and ability.

Students rank fields based on their preferences, and choose the highest utility field available to them from some set of F majors, perhaps given some capacity constraints. We discuss these in more detail below. Note that students consider earnings Y^f and tuition τ^f, but not the costs of providing major f.

The social planner's problem differs from the individual's problem in three respects. First, the planner values Y^f, not just the after tax component. Second, the planner considers education production costs C^f, which may vary by major. Third, the planner considers the externalities associated with graduates in different fields. The value SU_i^f that the planner places on a degree in f for student i is

$$\begin{aligned} SU_i^f &= U_i^f + \lambda[tY^f + \tau^f - C^f] + EXT^f & (2) \\ &= u_i((1-t)tY^f - \tau^f) + V_i^f + \lambda[tY^f + \tau^f - C^f] + EXT^f & (3) \end{aligned}$$

In the above equation λ is the marginal utility generated by an extra dollar of goverment transfers and expenditures made possible by tax and tuition revenue. EXT^f is the net social externality associated with an extra graduate in field f.[2]

An instructive special case is when utility is linear in consumption, so that $u_i(Y^f(1-t) - \tau^f) = \theta_i[Y^f(1-t) - \tau^f]$. Assume the marginal utility of income does not vary, so that $\theta_i = \theta$. Since

[2] Lange and Topel (2006), Moretti (2004), and McMahon (2009) discuss the social benefits of higher education in general. Studies such as Currie and Moretti (2003) focus on effects on political participation and citizenship, on crime, and on parenting. There is much less evidence regarding differences across fields in externalities. Much of the policy discussion of field specific externalities centers on STEM education. For a recent example, see Olson and Riordan (2012).

a benevolent planner would choose taxes and transfers and public expenditures so that the marginal utility generated by expenditures matched the marginal benefit of private consumption, we set $\theta = \lambda$. Then i's utility from enrolling in f is

$$U_i^f = \lambda[(1-t)Y^f - \tau^f] + V_i^f,$$

and the planner's valuation simplifies to

$$\begin{aligned} SU_i^f &= \lambda[Y_i^f - C^f] + V_i^f + EXT^f \\ &= U_i^f + \lambda\left(tY^f + (\tau^f - C^f)\right) + EXT^f \end{aligned} \tag{4}$$

We make two observations based on this equation. First, the individual's preferences will be identical to the planners when $C^f - \tau^f = tY^f + EXT^f/\lambda$. Left unconstrained, individuals will choose the same allocation as the planner when tuition subsidies $C^f - \tau^f$ are sufficient to a) offset the wedge between individual and planner preferences created by the tax rate, and b) account for positive or negative externalities generated by enrollment. In the first part of our empirical work, we document differences in tuition subsidy levels by field of study. Second, the planner's valuation depends on $Y^f - C^f$, i.e. earnings net of costs for enrolled students. Our empirical work presents estimates of these quantities, which would determine planner preferences in the absence of externalities and non-pecuniary differences across majors.

Our empirical work also considers differences in per-dollar returns to field of study. To understand why this quantity is relevant for policy, consider a case in which student and planner preferences are as above, but where students cannot sort freely across fields. Specifically, each field has an allocation of N^f spots , with this enrollment cap binding in at least some fields. The corresponding budget limit is $B^f = N^f(C^f - \tau^f)$. Students are allocated to fields in a way that may depend on student preferences over fields and admissions' committee preferences over students. The idea of a hard cap on major-specific enrollment corresponds closely with institutional details in many non-US countries, such as Norway and Chile (see HNZ and KLM for more details). It is a reasonable approximation of US institutions that, e.g., establish minimum GPA standards for enrollment in some majors, or where lack of available seats in required courses leads to de facto limits on enrollment.

The planner has an opportunity to expand the budget in major f to allow for increased enrollment. For simplicity we assume that students who benefit from this expansion would otherwise have enrolled in a reference major g where tuition is equal to costs and where the capacity constraint is slack. Let D_{if} be an indicator function equal to 1 if i enrolls in f, and let

$$SU = \sum_i \sum_f D_{if} SU_i^f$$

be the sum of social utility over all students. Then, the gain in social utility from a marginal increase in B^f is given by

$$\begin{aligned} \frac{dSU}{dB^f} &= \frac{dSU}{dN^f} \times \frac{dN^f}{dB^f} = \frac{dSU}{dN^f} \times \frac{1}{C^f - \tau^f} \\ &= \frac{\lambda\left((Y^f - C^f) - (Y^g - C^g)\right) + (E^f - E^g) + \bar{V}^{fg}}{C^f - \tau^f}, \end{aligned} \tag{5}$$

where $\bar{V}^{fg} = E[V_i^f - V_i^g | i \in \text{marginal group}]$. Differences in returns net of costs are scaled by the net cost of producing majors in the destination field. We consider measures of earnings scaled by costs in section 5.5.

In practice, the social returns from marginally relaxing major-specific budget constraints will depend on the mix of majors from which students affected by the policy are drawn, and on students' relative skills in and preferences for those majors. HNZ (2013) and KLM (2016) explore these issues in detail.

4 Data

4.1 Cost data

Our cost data come from administrative expenditure reports compiled by the Board of Governors of the Florida State University System (FLBOG 2000-2014). The data span the 12 universities in the State University System.[3] These are four-year public institutions that primarily offer degrees at the bachelor's level or higher. The Florida College System, which includes mostly two-year institutions, is excluded. The reports document course taking and expenditures for the state university system as a whole and within groups defined by the intersection of college major and offering institution. Majors are identified at the two-digit CIP code level. This is a relatively

[3] Florida A&M, Florida Atlantic University, Florida Gulf Coast University, Florida International University, Florida Polytechnic University, Florida State University, the New College of Florida, the University of Florida, the University of North Florida, the University of South Florida, and the University of West Florida.

high level of aggregation: in 2000, there were 33 distinct major codes, of which 30 reported a positive number of undergraduate student credit hours. Examples include 'Engineering' or 'English Language and Literature.' A full list is provided in Table A-1. We use data obtained from the AY 1999-2000 through AY 2013-2014 versions of these reports.

Each report breaks down spending by course level and expenditure type. There are four relevant course levels for graduate and undergraduate education: lower undergraduate, upper undergraduate, masters' level courses, and doctoral courses.[4] Reports describe direct expenditures– primarily personnel– for instruction, research, and public service within institution-major cells. They also compute indirect costs for activities including academic advising, academic administration, financial aid, plant maintenance, library costs, and student services. They allocate these indirect costs to institution-major cells based on either student credit hours (for academic advising and student services) or faculty/staff person-years (for the other listed cost types). See Johnson (2009) for a more detailed description of these data.

Table 1 describes SUS expenditures by level and type for the 2000-2001 academic year. Instructional spending totaled just over $2 billion in that year, with direct spending accounting for 54% and indirect accounting for the rest.[5] Spending on undergraduate instruction made up 72% of total instructional spending, and direct expenditures accounted for 49.7% of the undergraduate instructional total. Together, these expenditures purchased a total of over 5.7 million student credit hours, equivalent to about 190,000 student FTEs at 30 credits per year. 37% of student credit hours were at the lower undergraduate level, 49% at the upper undergraduate level, and the remainder at the graduate level. Average per-credit spending was $357, with per-credit expenses increasing with course level. Non-instructional spending on research and public service added up to $486 billion.

How reliable are these cost measures? Johnson (2009) compares aggregate cost measures in the FLBOG expenditure reports to expenditure measures reported in IPEDS. The main difference between the two data sources is the FLBOG reports include only expenditures out of state appropriations and student fees. The reports do not include expenditures from other sources, like grants, contracts, or endowment income. Comparisons with IPEDS data indicate that the omission of these revenue sources may lead the expenditure reports to understate costs by 15-25%. It is also worth noting that although expenditure records do include operations and maintenance, they do not include the (amortized) costs of capital investment.

Our analysis hinges on comparisons of costs across majors. Existing evidence suggests that direct expenditures consist largely of instructor salaries (Johnson 2009; Middaugh et al. 2003).

[4]There are also separate codes for medical school courses and clinical education for medical residents.

[5]All dollar values reflect 2014 USD deflated using the CPI-U except where noted.

They will therefore allow for meaningful cross-major comparisons to the extent that either a) faculty and other instructors allocate their time to teaching in a manner consistent with the time breakdowns they report to (or are assigned by) universities, or b) differences between reported and actual time allocations are similar across majors. Comparisons will be uninformative if, e.g., both engineering and English professors report spending 40% of their time on teaching and 60% as research, but in practice English professors spend 80% of their time on research and only 20% on teaching while Engineering professors stay closer to the nominal allocation. The assumptions required to believe cross-major comparisons in indirect expenditures are more heroic. How to divide costs of building maintenance, academic advising, and similar activities across majors is not obvious. Allocating expenses based on student credit shares and faculty/staff person-year shares seems like an a priori reasonable strategy, but it will yield faulty comparisons if usage intensity of different resources varies by discipline.

Our analysis of per-credit expenditures will focus primarily on total instructional spending at the lower- and upper-undergraduate levels. This parallels our focus on undergraduate majors in the earnings analysis. When we compute costs per graduate, we use data on all courses taken by graduating students. We focus on total as opposed to direct instructional spending because we want our cost measure to come as close as possible to capturing cost levels across majors. This choice follows Johnson (2009), who notes that this is the approach taken by the FLBOG in internal cost calculations. The tradeoff is that indirect costs may be measured less accurately. We take some comfort in the fact that direct costs are very strong predictors of both indirect and total costs. In credit-weighted univariate linear regressions, direct costs explain 95.4% of the variation in total costs and 77.9% of the variation in direct costs. Similarly, changes in direct costs explain 91.3% of changes in total costs and 60% of changes in indirect costs. In sum, we view our cost measures as reasonable though imperfect first-order approximations of the production costs of different types of college credits.

4.2 Microdata extracts

We compute earnings and total spending for graduates using aggregated extracts and regression output drawn from administrative student microdata collected by the Florida Department of Education. We have data on the population of high school graduates from 15 Florida counties over six cohorts between 1995 and 2001. There are a total of 351,198 students in this sample. These data track students from high school, through any public college or university they may attend, and into the labor market. We focus on the subset of 57,711 students who enroll in the state university system in the year following high school graduation. Labor market data come from Florida Unemployment Insurance (UI) records and include in-state labor market outcomes only.

In addition to academic and labor market outcomes, these data include standard demographic variables like racial/ethnic background and free lunch status, as well as math and reading SAT scores for students who took those exams. See (Zimmerman 2014) for a more detailed description.

For the purposes of this study, key academic outcomes include course-taking behavior while in college and data on degree type, graduation date, and major. The microdata on college course-taking contain administrative course identifiers and a set of narrow subject descriptors that divide courses in 483 subject categories. We combine these records with publicly available administrative data that maps course identifiers to CIP codes (FLDOE 2011) and course levels (FLDOE 2015). We then merge on AY 2000-2001 SUS average per-credit cost data at the course level by two-digit CIP level. We match 96% of course to CIP codes and 74% to both CIP and course level.[6] We replace cost data for courses with missing level information with CIP-specific averages. We replace cost data for students with missing CIP codes with average per-credit costs across all majors and levels. We then compute total incurred direct, indirect, and total costs at the individual level, based on all courses each student takes within the state university system.

Our earnings data track students through early 2010, so the oldest students in the earnings records are 14 years past high school graduation, or approximately age 32. For each individual we compute mean quarterly earnings over the period eight or more years following high school completion, so the youngest individuals in our earnings outcome sample are approximately age 26. Our earnings specifications take either this variable or its log as the outcome of interest. Our earnings measure has a number of limitations in this application. First, as mentioned above, we do not observe earnings for individuals who leave Florida. We observe no earnings records for about 25% of individuals in our data. We discuss the relationship between earnings censoring and major choice in section 5.4. Second, it does not capture differential growth in earnings across majors over time. Two majors with similar average earnings over the immediate post-college period could have very different long-run trajectories. Third, because we cannot differentiate between non-employment and out-of-state migration, we cannot effectively compute labor force participation rates, which may differ by major. One factor that affects early-career labor force participation is enrollment in graduate school, which may differ by undergraduate field of study. When computing the present discounted value of cross-major earnings differences, we scale our estimated level effects by the number of elapsed quarters times 0.84, the labor force participation

[6] Note that our administrative course records date to the 2010s, while our microdata on student course-taking span the early 1990s through late 2000s. Merge rates are less than one because some courses offered in, say, 2000 do not appear in 2015 administrative data. Merge rates for CIP code are high because we observe narrow subject classification in both the administrative records and the course microdata. This allows us to merge CIP classifications to microdata at the subject level even where we do not observe a direct course match. Merge rates for level are relatively low because there is no level classification in the microdata, so we only observe level where we can precisely match a course from the late 1990s through mid 2000s to a course offered in 2011.

rate for college graduates aged 25-34 in 2005 (NCES 2015, Table 501.50).

We consider two samples of students in our earnings and cost analysis. The first consists of students who enroll in a state university in their first year following high school graduation and go on to complete a bachelor's degree program at a state university. We use data on these students for the cross-major earnings and cost comparisons. The second consists of students who satisify the initial enrollment criterion but do not graduate. We consider earnings and cost outcomes for these students in Section 5.6.[7]

To address concerns related to censoring and the lack of late- and mid-career data in the Florida earnings data, we supplement our earnings analysis with estimates of mid-career earnings from the ACS. We use data from the 2009 to 2012 ACS surveys, and estimate earnings value added specifications that control for gender, race, and labor market experience within the set of individuals aged 24 to 59 and earnings at least \$2000 per year. These estimates closely parallel those discussed in Altonji et al. (2012), except that we aggregate majors into coarser categories to correspond with two-digit CIP codes. We discuss results obtained using these data in parallel with our findings using the Florida data extracts.

5 Costs, returns, and net PDVS

5.1 Methods

Our analysis focuses on earnings and cost 'value added' specifications of the form

$$y_i = \theta^y_{f(i)} + X_i'\beta^y + e^y_i \tag{6}$$

and

$$c_i = \theta^c_{f(i)} + X_i'\beta^c + e^c_i \tag{7}$$

Equation 6 estimates the effects of college major, indexed by f, on earnings outcome y_i. We will consider specifications with both log earnings and earnings levels as the dependent variable. The X_i is a set of controls for individual and institutional characteristics. It includes race, gender, free lunch status while in high school, a dummy variable equal to one for students born

[7]Due to changes in data access policies, we no longer have access to the microdata used to estimate the earnings models and construct the cost estimates. Consequently, for part of the analysis we are limited to using data extracts based on the microdata. We were unable to compute summary statistics for our earnings and costs analysis samples.

in the US, a third degree polynomial in high school GPA, and third degree polynomials in SAT math and reading scores. It also includes sets of dummy variables for high school graduation cohort and the university a student attends. We estimate this specification within the sample of students who graduated from college. The coefficients of interest here are the $\theta^{y}_{f(i)}$, which correspond the effect of major on earnings conditional on other student observables. Although our control set is fairly rich, students may sort into majors in ways that are correlated with unobservable determinants of income levels. Students may also sort into majors on the basis of comparative advantage. We therefore interpret our estimates cautiously: they may not capture the earnings changes that would occur if students were arbitrarily selected to move from one degree to another.

Equation 7 has an identical control set, but takes as an outcome the total costs a student incurs while in college. We regression adjust costs as well as earnings to account for the fact that some students may take more or less expensive routes through college regardless of major. For example, students with lower high school grades may take more remedial courses.

We use estimated coefficients from versions of equations 6 and 7 where the dependent variables are earnings and cost levels to compute present discounted values of earnings and cost streams. We compute the present discounted value of a stream of earnings by a) multiplying the estimated quarterly earnings effects by four to get annual effects, b) scaling annual effects by 0.84 (the average rate of labor force participation amongst college graduates 25-34 in 2005) to approximate labor force participation rates, and c) computing the discounted value of a stream of payments of this size beginning in the eighth year following high school graduation and continuing until some stop-time T. We discount values back to the year before students begin college at interest rate of 5% per year. We consider two stop times: age 32 (14 years after HS completion), and age 45. The former corresponds to the limit of our support for earnings outcomes in the Florida data. We choose the latter to approximate earnings effects through mid-career. To compute the PDVs of college costs, we assign estimated total cost effects (the θ^{c}_{f}) evenly across the first four years following high school completion and discount back to the year of completion. This discounting will result in values that are too large for students who stay in college longer than four years, but too small for students who front-weight credits to their first few years of college.

5.2 Distribution of credits and graduates over majors

Figure 1 shows the shares of undergraduate credits by major for the 2000-2001 school year, sorted from smallest to largest share. In total, we observe cost data for 4.9 million student credit hours, or roughly 164,000 student FTEs. Business courses are the most common, accounting for 14.3% of all credit hours. The next most popular fields are social science and education, which make up 11.7% and 8.5% of credit hours, respectively. The most common type of STEM credit is math. Math courses make up 7.9% of all credit hours. Within the STEM category, math is followed by Engineering, Biology, and Computer Science, which each make up between 3.7% and 3.8% of all credit hours.

The distribution of degree programs for graduating majors strongly but not perfectly correlated with the distribution of credits. The lower panel of Figure 1 plots the log share of credits on the horizontal axis against the log share of graduates on the vertical axis. Most majors track the 45-degree line, which we plot for reference. A handful of majors– Math, Physical Science, Languages, and Philosophy– fall far below the line. Many students who take courses in these subjects do not major in them. The most common major, Business, accounts for nearly one quarter of all graduates.

5.3 Cost heterogeneity

As shown in the upper panel of Figure 2, spending per credit varies widely by field. Table 2 presents descriptive statistics about the distribution of costs over field, while Table 3 shows spending for each field individually. Per-credit spending on direct instruction in the highest-cost major, engineering, is $322, 272% higher than per-credit spending in the lowest-cost major, parks and recreation. It is 237% higher than the field with the second lowest cost, mathematics. Levels of total instructional spending are roughly twice as high, but both the ordering of degree programs and relative magnitudes of differences (in percentage terms) are quite similar. For example, the total cost per credit of an engineering course is $569, 209% more than the $184 per credit cost of a mathematics credit. Though STEM fields like Engineering, Health Sciences, and Engineering Technology are among the highest-cost fields, not all high-cost fields are STEM fields. For example, visual art, architecture, and library science all have above-average pre-credit costs. The (credit-weighted) interquartile range of the total cost per credit distribution is $120, or 43% of the median per-credit cost, and the standard deviation of per-credit cost distribution is $89.

The cost differences we observe suggest that some majors cross-subsidize others. Under the assumption that levels of institutional aid are consistent across majors, we can read off the relative net costs of credit hours in different majors to the institution by subtracting per-credit tuition from major-specific per-credit costs. Per-credit average in-state tuition in the State University System was $108 (2014 dollars) in the 2000-2001 academic year, including mandatory fees (FLBOG 2001). The upper panel in Figure 2 shows that tuition covers direct instructional costs in only a handful of majors, and does not cover total costs in any of them. Relative to tuition, the per-credit subsidy in engineering degrees was $461, compared to a $76 subsidy for mathematics credits. The credit-weighted average subsidy level is \$191 per credit. Relative to this average, classes in fields like business, psychology, and computer science cross-subsidize fields in engineering, health, education, and the visual arts.

We observe similar patterns across fields when assessing the costs on a per-graduate basis. Compared to an average total degree cost of \$39,184, engineering graduates incur costs of \$62,297 over their schooling career while graduates in business (the third lowest cost major) incur costs of \$31,482. The graduate-weighted interquartile range is \$11,511, equal to 32% of the median value. The graduate-weighted correlation between total per-credit costs and total incurred costs for graduates is 0.89, while the credit hour weighted correlation is 0.75. The values of total costs we compute are very similar to results reported for a subset of degrees in Johnson (2009) based on the 2003-2004 graduating cohort from the Florida SUS. For example, Johnson reports average total costs for graduates of 40,339 (after converting to 2014 dollars), similar to our estimate of \$39,184, and he reports average costs for engineering graduates of \$60,703, compared to our estimate of \$62,297.

5.4 Earnings heterogeneity

Earnings outcomes also differ across majors. Figure 3 and Table 4 show mean log earnings and regression adjusted log earnings differences. Values are expressed relative to the omitted education major. Without adjusting for student covariates, education majors earn an average of \$10,279 per quarter that they work, or roughly \$41,000 if they work for the entire year. This is 42.6 log points less than students in the highest-earning major, Engineering Technology, and 39.8 log points more than the lowest earning major, art. Value added measures that control for student observable characteristics yield similar patterns. Engineering technology majors earn 43.5% more than education majors with similar observable characteristics, while art and philosophy majors earn 37% less. Though STEM majors such as engineering technology, engineering, computer science, and health science are among the highest-paying majors, non-STEM majors like business are also high paying, while other STEM majors like biology, math, and the physical sciences offer lower returns. Overall, the graduate-weighted standard deviation of estimated earnings is effects is 0.17 log points, and the difference between the lowest- and highest-earning degrees is 80 log points, or 123%.

Our findings are qualitatively similar to those reported in Altonji et al. (2012) in that the gap between the highest- and lowest-earning majors is comparable in size to the college wage premium. However, our finding of fairly low returns (relative to education) in math and the physical sciences is inconsistent with results displayed there. This discrepancy may reflect real differences in program quality, labor market conditions, or student sorting in our data versus in the nation as a whole. However, it is also possible that our findings are an artifact of differential censoring across majors or of our focus on early-career outcomes. Table A-2 describes difference in rates of earnings censoring by major. To supplement our coefficient estimates, we present parallel estimates of equation 6 using nationally-representative ACS data for college graduates aged 24 to 59. These estimates control for gender, race, a third degree polynomial in age, and interactions between these variables. Figure A-1 plots the estimated coefficients from the Florida data on the horizontal axis against ACS coefficients on the vertical axis. The graduate-weighted correlation between the Florida and ACS estimates is 0.678. The most salient difference between the Florida estimates and the ACS estimates is that in the ACS data education is relatively low-earning degree program, while in Florida it falls in the middle of the earnings pack. Physical Science, Life Science, and Math majors also perform well in the ACS data relative to the Florida data. We will continue the comparison of Florida and ACS earnings estimates when comparing earnings to costs.

5.5 Net returns

Table 5 and Figure 4 compare regression-adjusted earnings and costs for graduates from different majors and compute present discounted values of net effects for graduates. We focus on levels specifications to facilitate simple comparisons between earnings and costs. We find that a) differences across major in net PDVs are primarily driven by earnings outcomes, but that b) differences in costs have a sufficiently large effect on PDVs to alter cross-degree rankings for a number of relevant comparisons.

Figure 4 compares value added measures of earnings effects (measured in levels) on the horizontal axis to returns net of costs through age 32 on the vertical axis. As with the earnings estimates above, we measure earnings level effects and net PDVs relative to the values observed for education, which we normalize to zero. Because the PDVs of earnings and costs are weakly correlated (the graduate-weighted correlation between these variables is 0.21), PDVs net of costs on average rise one-to-one with PDVs of earnings, closely tracking the 45-degree line, which we plot for reference. The highest-earning degrees, like engineering technology, engineering, and computer science, have the highest PDVs net of costs, while the lowest-earning degrees have the lowest net PDVs.

Deviations from the 45-degree line are driven by cost differences across degrees. One way to quantify the importance of these differences is to compare variation in costs to variation in the distribution of earnings. The graduate-weighted standard-deviation of the cost PDV distribution is \$7,187, roughly one quarter the size of the graduate-weighted standard deviation of the earnings PDV distribution (\$28,845). The graduate-weighted interquartile range of the cost PDV distribution is $10,582, and the difference between the highest and lowest-cost degree is $27,184. The former value is somewhat larger than the difference between the 10th and the 25th percentile of the distribution of earnings PDVs ($6,940) and somewhat smaller than the difference between the 25th and 50th percentile ($13,934).

It is also helpful to draw concrete comparisons between earnings and cost rankings of specific degree programs. For example, the PDV of early-career earnings is more than $32,000 higher for engineering majors than for business majors. However, higher costs for engineers lead these two majors to have PDVs that are close to equal. Similarly, business and health majors have earnings PDVs that are essentially the same, but lower costs for the business degrees lead to a higher net NPV. Shifting focus to the lower-earning degree programs, we can make similar comparisons. For example, English degrees have higher net NPV than physical science despite fairly similar earnings, because costs are much lower. Broadly speaking, we observe a relatively small number of degree programs where earnings are substantially higher than in Education. Using a difference of 10 log points as a cutoff, these degrees are in the fields of Health, Business, Computer Science, Engineering, Engineering Technology, and (somewhat surprisingly) Library Science. Cost differences are sufficient to reorder these programs relative to one another, but not to shift them to lower values than the set of lower-return programs.

If we believe that estimates of earnings and cost effects are causal, and that earnings effects are not heterogeneous across individuals, then the above discussion identifies the private return net of costs of adding an additional graduate in a given field. The effects of additional spending on a per dollar basis are also of interest. While the net private returns on per-degree basis are relevant for individuals who face the true costs of degree provision, or of policymakers maximizing the sum of net private returns who must choose how to allocate an additional graduate, net private returns on a per-dollar basis are relevant for policymakers trying to figure out how get the most net private value given a fixed budget for additional students.

To consider per dollar effects we first fix earnings and cost intercepts by conditioning a specific set of covariates. We consider the case of a Hispanic, female, US-born student from the Miami-Dade school district in the 2000 high school graduating cohort who attends Florida State, had unweighted high school GPA of 3.5, and scored 500 on the math and verbal sections of her SATs. We compute predicted PDVs of earnings and costs for this individual, based on estimated level effects from Table 5 and divide the earnings PDV by the cost PDV to get a per-dollar measure of the return to spending in each major. Figure 5 plots estimates of per-dollar returns by major through age 32 as a fraction of the per-dollar return to education on the vertical axis versus estimated log earnings effects on the horizontal axis. We normalize the return for the education major to zero. We report estimates for each major in Table 6.

The graduate-weighted correlation between per-dollar spending effects and estimated earnings effects is 0.5. Health and Engineering majors, where earnings returns are large on a per-graduate basis, have per-dollar returns similar to those observed in education, math, philosophy, and language degrees, where earnings are much lower. The degrees that fare best on a per-dollar basis are business and computer science, which are both high-earning and relatively cheap. These majors have per-dollar private returns that are 60% to 80% higher than in education degrees. The degrees that fare worst are Architecture, Art, and the Physical Sciences, which are fairly expensive and have relatively low earnings; these majors have per-dollar private returns that are 20% to 30% below that for education.

To supplement our analysis using earnings data from Florida, we consider measures of per-dollar returns computed using ACS earnings data. Paralleling Figure 5, Figure A-2 plots ACS estimates of log earnings effects on the horizontal axis earnings PDV per spending dollar on the vertical axis. We obtain per-dollar earnings PDV estimates using the procedure described above but substituting ACS earnings estimates for Florida earnings estimates. A similar pattern emerges in the sense that high-earning, low-cost degrees like business and computer science have the highest per-dollar PDVs. As in the Florida analysis, Health and Engineering degrees have fairly similar per-dollar PDVs to education despite much higher earnings. Degrees in Math and Social Science have higher per-dollar PDVs in the ACS data than in the Florida analysis.

5.6 Dropouts

The analysis above focuses on college graduates. Students who attend college but do not graduate incur costs as well, but may have very different labor market outcomes. Unfortunately, we do not observe declared major prior to graduation. Nor do we observe specific patterns of course-taking for non-graduates that might allow us to divide students by major prior to graduation. However, we are able to observe the total costs incurred by students who obtain varying amounts of course credits. Specifically, we observe results from specifications of the form

$$c_i = \theta_{t(i)} + X_i\beta + e_i \tag{8}$$

and

$$y_i = \theta_{t(i)} + X_i\beta + e_i \tag{9}$$

in the sample of students who enroll in a state university but do not complete their degree. Here y_i is earnings, again measured between eight and fourteen years following high school completion, c_i is total spending on courses taken by student i, $\theta_{t(i)}$ is a set of dummy variables corresponding to amounts of total completed credits, and X_i are the same set of individual covariates described in section 5.1. The categories indexed by t are divided into 24-credit bins. This is the minimum number of credits required to maintain full-time enrollment for two semesters, so we describe persistence in college for non-completers in terms of years. We focus on earnings effects in levels to make the comparison with costs more straightforward. Recall that earnings are measured on a quarterly basis.

Table 7 shows estimates of earnings and cost effects of the θ_t for students who persist through their second, third, and fourth or more year relative to those who drop out within the first year. Costs increase rapidly with additional years of attendance, rising by $5,419 in the second year to $11,915 in the third year, and to $28,276 for students who stay for three or more years but do not graduate. In contrast, earnings for non-completers do not rise much with additional years of attendance. We cannot reject the null hypothesis that non-completers who remain in college for two or three years have earnings equal to those who remain in college for only one year. Students who remain in college for three or more years earn $261 more per quarter than those who complete at most one year's worth of credits. However, the PDV of these earnings gains is $4,812 through age 32, 18.3% of the PDV of the additional costs these students incur.

One possible explanation for our finding of limited earnings gains per additional year of schooling in the dropout sample is that students who persist in an SUS institution but do not complete are likely to move out of state (for example, to complete college at a different institution). We note that a) this would not mechanically reduce estimated earnings effects, which are computed using earnings for stayers only, and b) rates of earnings censoring decline with additional schooling in the dropout sample. We display estimates of equation 9 with an indicator variable for missing earnings outcomes as the dependent variable in the third column of Table 7.

Dropouts account for a substantial share of overall costs in our data. Within our sample of students who enroll in college in the year following high school graduation, 38,336 students go on to graduate and are included in our analysis of college major returns, while 19,375, or one third of the total sample, do not receive a BA from any institution in the SUS. Based on average per-graduate expenditures of $39,184 and average per-dropout expenditures of $16,101, dropouts account for 17.2% of total expenditures in our sample. This estimate is similar to internal calculations conducted by the FLDOE and reported in Johnson (2009). These calculations found that 19.6% of costs for entering first-time-in-college students in the 2001-2002 school year accrued to students who had not graduated from any SUS institution by 2006-2007.

6 Trends in costs per credit

6.1 Overall trends in spending

Our analysis thus far captures a snapshot of instructional expenditures at a point in time. We next use our aggregate data on student credit hours and total expenditures for the 1999 to 2013 period to analyze trends in spending over time. Our goal is to understand how the allocation of resources and subsidies across majors changed over this period.

We begin by documenting overall trends in course-taking and spending. Figure 6 shows how total credits, total instructional spending, and average spending per student credit hour change over the 1999-2013 period. Total undergraduate credit hours rose by roughly 50% over the period, from approximately 4.6 million in 1999 to 7 million by 2013. This represents a rise from 150,000 FTEs to 233,000. Expenditures, shown in the middle panel, also rose, though less steadily and not as much. Total expenditures on undergraduate instruction rose roughly 25% from 1999 to 2013, from $1.4 billion to $1.7 billion. The result of these simultaneous trends was a 16% fall in per-credit spending over the period. It is worth noting that spending patterns correspond fairly closely to the business cycle, with large drops in average spending during recession periods in 2001 and 2007-2010.

6.2 Major specific trends

The allocation of student credit hours and expenditures also shifted between 1999 and 2013. Figure 7 breaks down enrollment and spending trends by major for 12 largest majors. Together, these 12 majors account for 75% of credits over the period. The upper panel of Figure 7 shows changes in within-year credit shares by major, normalizing to one a) total student credit hours in each year, and b) the 1999 share for each major. The middle panel shows shares of total within-year spending over the same period, again normalizing the 1999 spending share to one. The lower panel shows total per-credit expenditures by major relative to the 1999 per-credit spending level. Within each panel, we split the majors into high cost and low cost groups using a median split of average per-credit cost over the period.

Course enrollment trends vary widely by major in both high- and low-cost categories, and are not strongly related to earnings or net PDVs we observe our analysis of microdata. The degrees with the greatest increase in credit share over the period were, in order, biology, health science, psychology, and engineering. Recall from Table 5 that health science and engineering were among the majors with highest NPVs, while biology and psychology were near the middle of the PDV distribution. The degrees with the largest losses over the period were, in order, education, computer science, and English. Computer science was among the highest-return degree programs in our data by any measure, while English and education were near the middle of the PDV distribution.

Changes in cost shares bear surprisingly limited relationships to changes in credit shares for many degree programs. Focusing on the middle panel of Figure 7, we see that while the 52% increase in credit share for biology courses was matched by a 41% increase in cost share, the 42% increase in health science credits did not correspond to any rise in cost share (in fact, there was a 3% decline in cost share over the period), while the 17% rise for engineering credits corresponded with a 17% decrease in cost share. Overall, a 10% within-major increase in credit hour share between 1999 and 2013 corresponded to a 5.8% increase in relative cost share, meaning that spending per credit share tended to decline in degrees with growing credit shares. On average, a 10% shift in enrollment share between 1999 and 2013 was met by a 3.5 percent decline in average costs per credit. The lower panel of Figure 7 explores this relationship in more detail. Some of the highest-growth fields saw the largest declines in spending per credit. Average spending per credit in engineering and health science fields fell by over 40% between 1999 and 2013. Conversely, the only field of the 12 considered here which had higher average spending per credit in 2013 than in 1999 was English literature, which saw one of the biggest declines in credit share.

7 Conclusion

This paper studies the differences in costs of producing course credits and graduates across majors and compares them to differences in earnings outcomes. We have two main findings. First, we find that costs per credit and per graduate vary widely by major. The average cost per graduate across all fields is $39,184; the standard deviation of costs is $7,187. This is equal to one quarter of the standard deviation of cross-major differences in earnings PDVs through age 32, sufficiently large to change relative rankings across fields in many cases. For example, business majors and health majors have approximately equal earnings through age 32, but the PDV net of costs is $25,000 higher for business majors due to lower costs. The importance of costs as a determinant of relative returns across majors is even more striking on a per-dollar basis. The mean PDV of earnings for an engineering major is similar to that for a much lower-earning education major per dollar of instructional cost. Earnings returns are highest on a per-dollar basis for fairly cheap but high-earning degrees like computer science and business. Second, we find that recent trends in per-credit spending differ dramatically by major. Per-credit spending fell 16% between 1999 and 2013, with especially rapid declines in majors with increasing number of credit hours.

These include high-return majors like engineering and health science, where per-credit funding fell over 40% over the period.

Our findings highlight the extent to which policies that fix tuition across majors create systems of cross-field cross-subsidies. A natural next question is how changes to this cross-subsidy system would affect the private and public returns to higher education. One approach would be to shift to major-specific tuition while keeping spending fixed (or not altering spending paths). As discussed in Stange (2015), Ehrenberg (2012) and CHERI (2011), increasing numbers of universities allow tuition to vary for at least some majors. While some universities use these policies to more closely match tuition to instructional costs in majors like nursing and engineering, others reduce tuition to encourage students to enroll in'high-need' majors regardless of costs. The majors labeled 'high need' are often STEM majors with fairly high costs as well. Our theoretical framework suggests (unsurprisingly) that measures of need based on private labor market outcomes should include differences in costs as well, and our empirical work suggests that cost considerations are quantitatively important, particularly for universities that are constrained by budget (as opposed to space). We also emphasize that private returns may not reflect public returns. An alternate approach is to reallocate spending across majors while keeping tuition as it is. The effects of such a policy depend on the relative returns to a dollar of spending across majors. Our findings suggest that average returns vary widely, but our estimates do not necessarily correspond to the effects of additional spending on the margin. Further research on the marginal effects of additional subject-specific dollars would be valuable here.

The most striking result presented in this paper may be the rapid decline in per-credit spending over the 2000s and 2010s. As we have noted, fast-growing, high-return fields saw the largest declines. Bound and Turner (2007) and Bound, Lovenheim, and Turner (2010) highlight the extent to which reductions in per-student resources at two-year colleges and less-selective four-year public universities depress college completion rates in the aggregate. The declines in median per-student expenditures they observe are on the order of 5% to 15% depending on institution type. Our findings suggest that these average declines may mask much larger declines in some majors than others, and that these large declines may occur in high-return areas. Overall declines in graduation rate may understate the degree to which declining investment reduces human capital accumulation, because the mix of graduates across fields may also be shifting.

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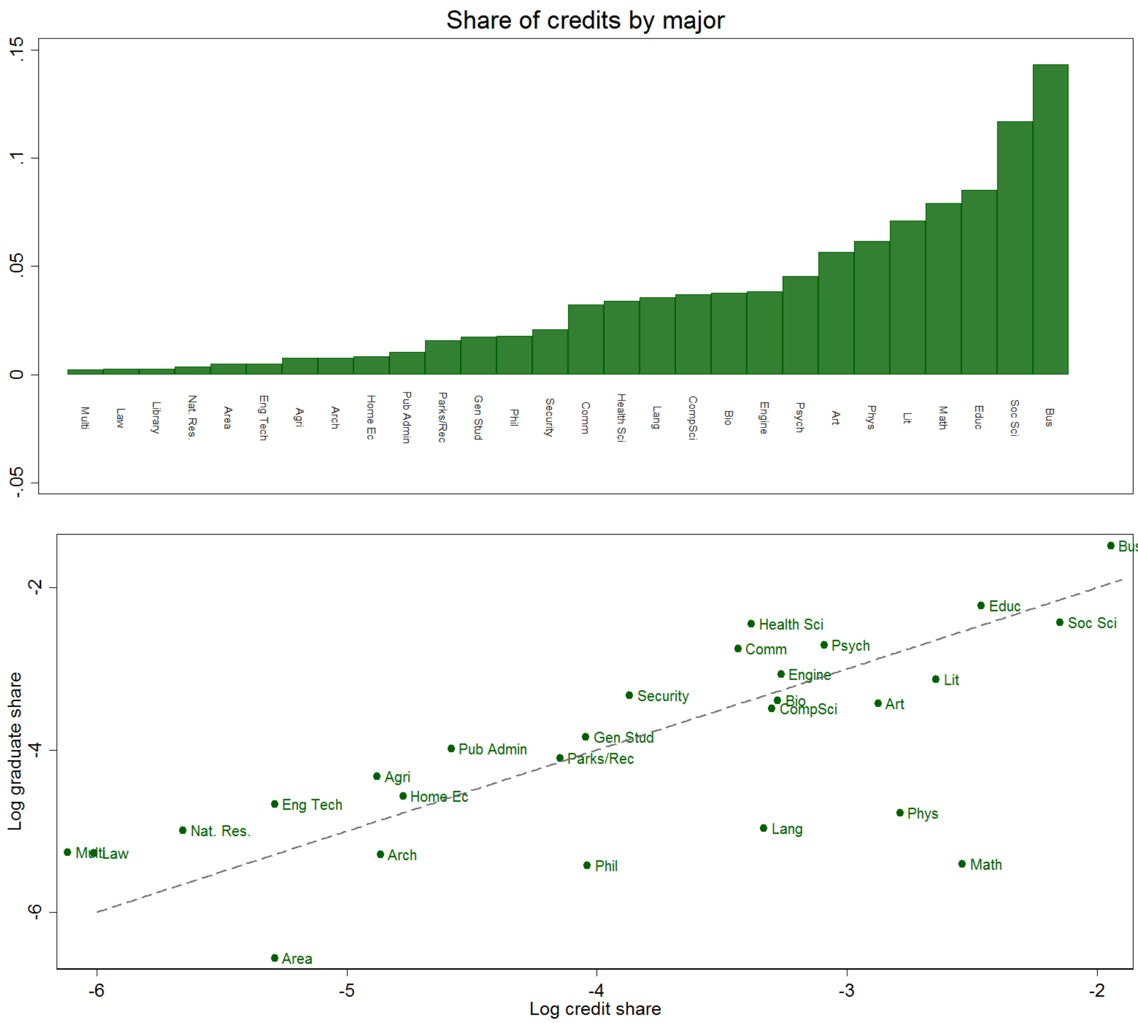
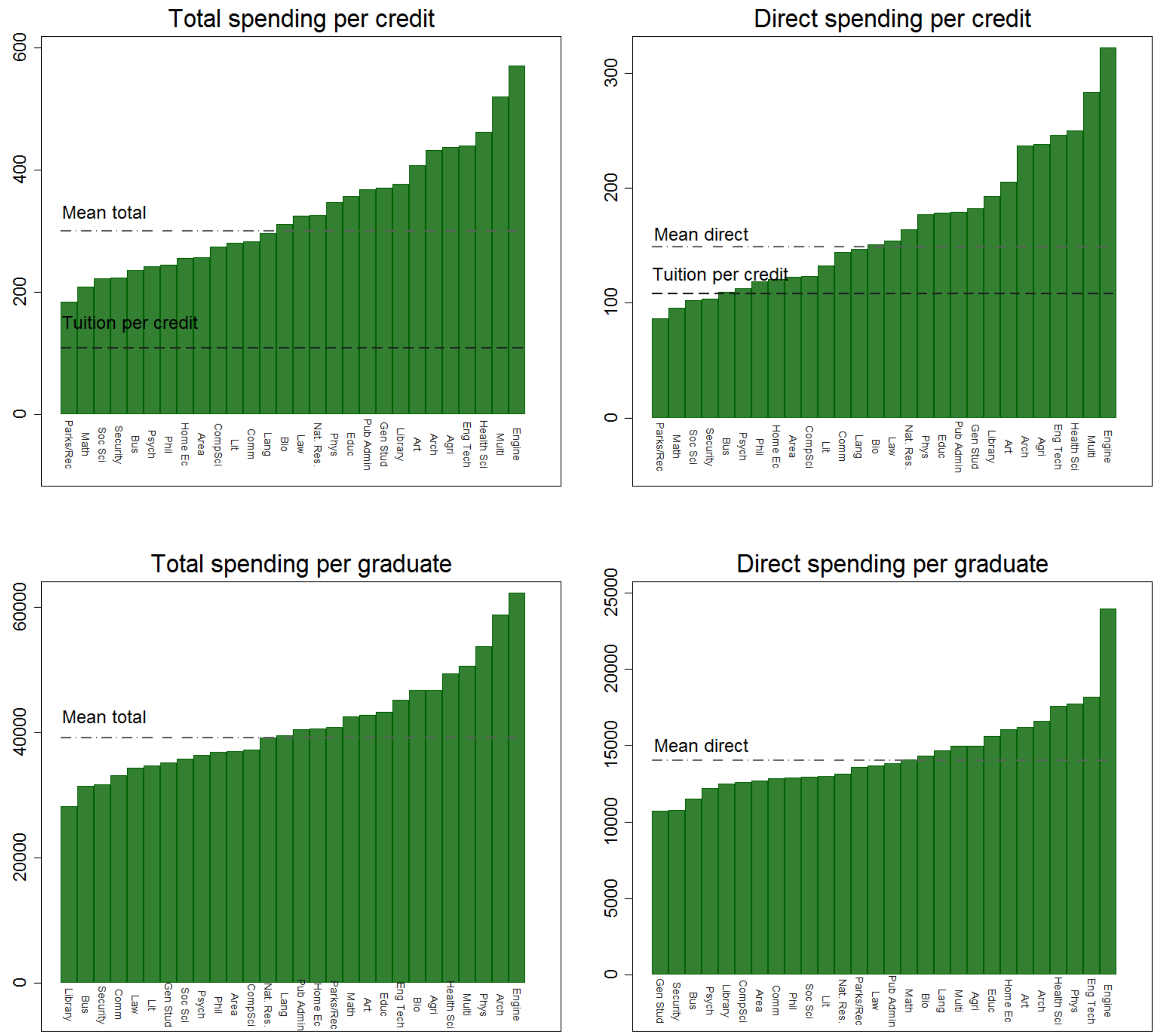
Tables and Figures

Figure 1: Credits by major



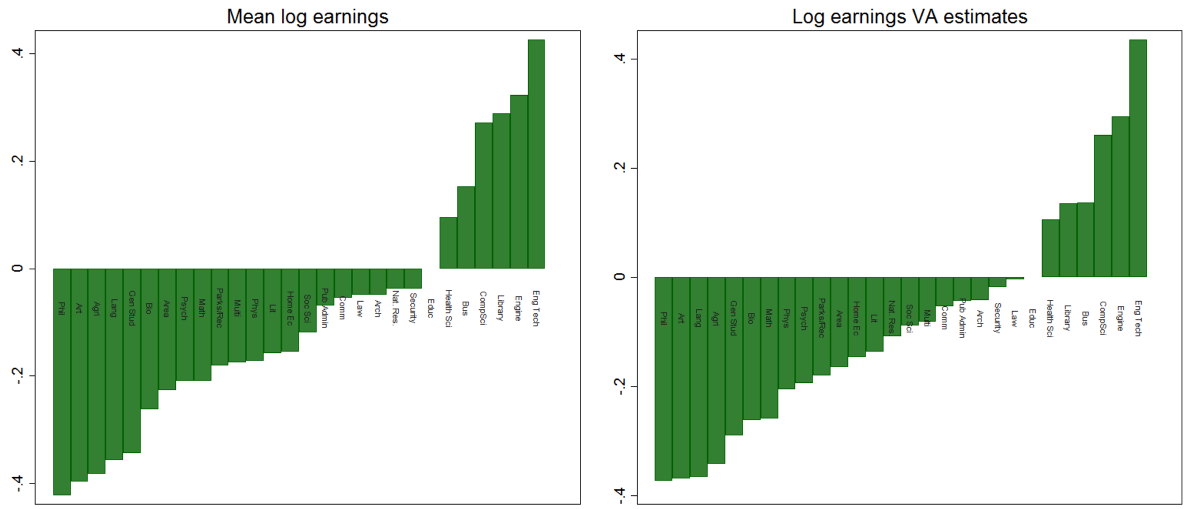
Upper panel: share of undergraduate-level credits by major in AY 2000-2001. Sample includes all Florida SUS institutions. Majors are divided by two-digit CIP code. Lower panel: log share of credits by major AY 2000-2001 on horizontal axis. Log share of graduates by major for AY 2000-2001. Source: authors' calculations from FLBOG expenditure and enrollment reports and graduate reports.

Figure 2: Costs by major



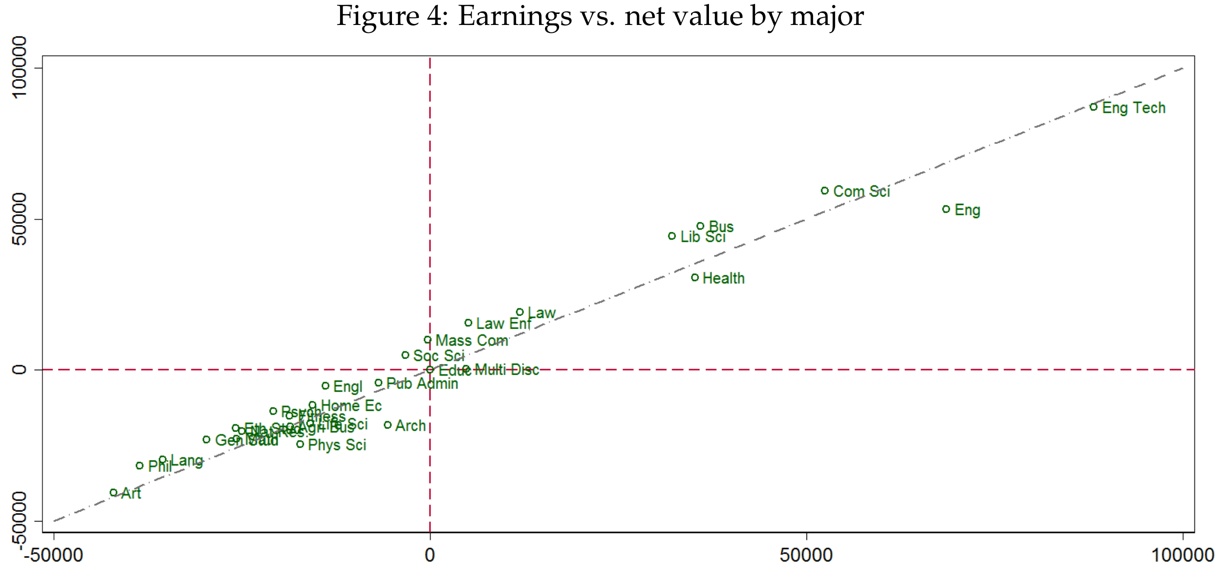
Upper panel: total and direct spending per credit by major, AY 2000-2001. Lower panel: total and direct spending per graduate. Upper panel uses administrative per-credit data for undergraduate-level credits averaged across SUS system. Tuition per-credit line represents (deflated) 2000-2001 in-state per-credit tuition and mandatory fees. 'Mean total' and 'Mean direct' lines are credit-weighted average of per-credit costs across majors. Lower panel: average total course costs for graduates in microdata extracts. 'Mean total' and 'Mean direct' lines are graduate-weighted cost averages.

Figure 3: Log earnings by major



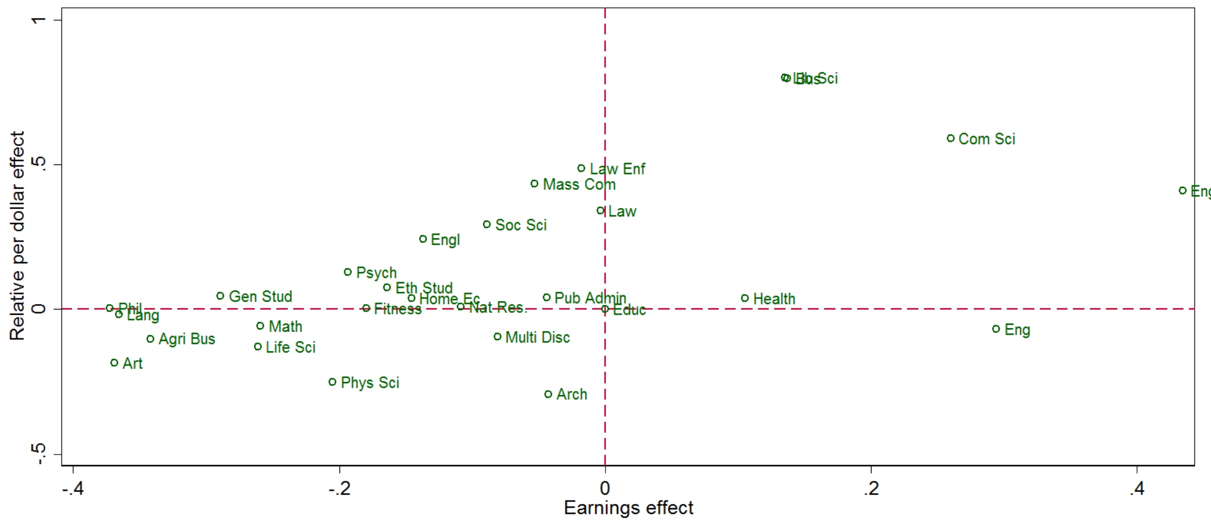
Raw and regression adjusted log mean earnings estimates for FL graduates in microdata extracts. Coefficient estimates expressed relative to omitted education category. N=28469 in left panel and 26189 in right panel.

Figure 4: Earnings vs. net value by major



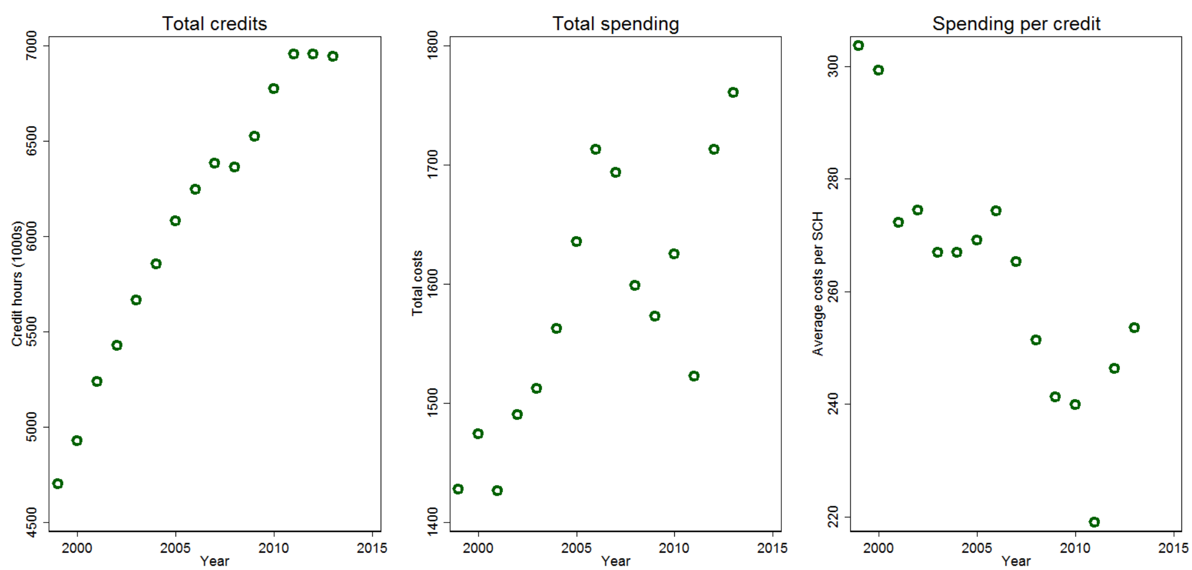
Horizontal axis: PDV of earnings effects through age 32 by major. Vertical axis: net PDV (earnings less costs) through age 32. Earnings and cost estimates come from equations 6 and 7 with quarterly and earnings and total costs as dependent variables. See section 5.1 for a discussion of PDV calculation in more detail.

Figure 5: Earnings vs. net value by major



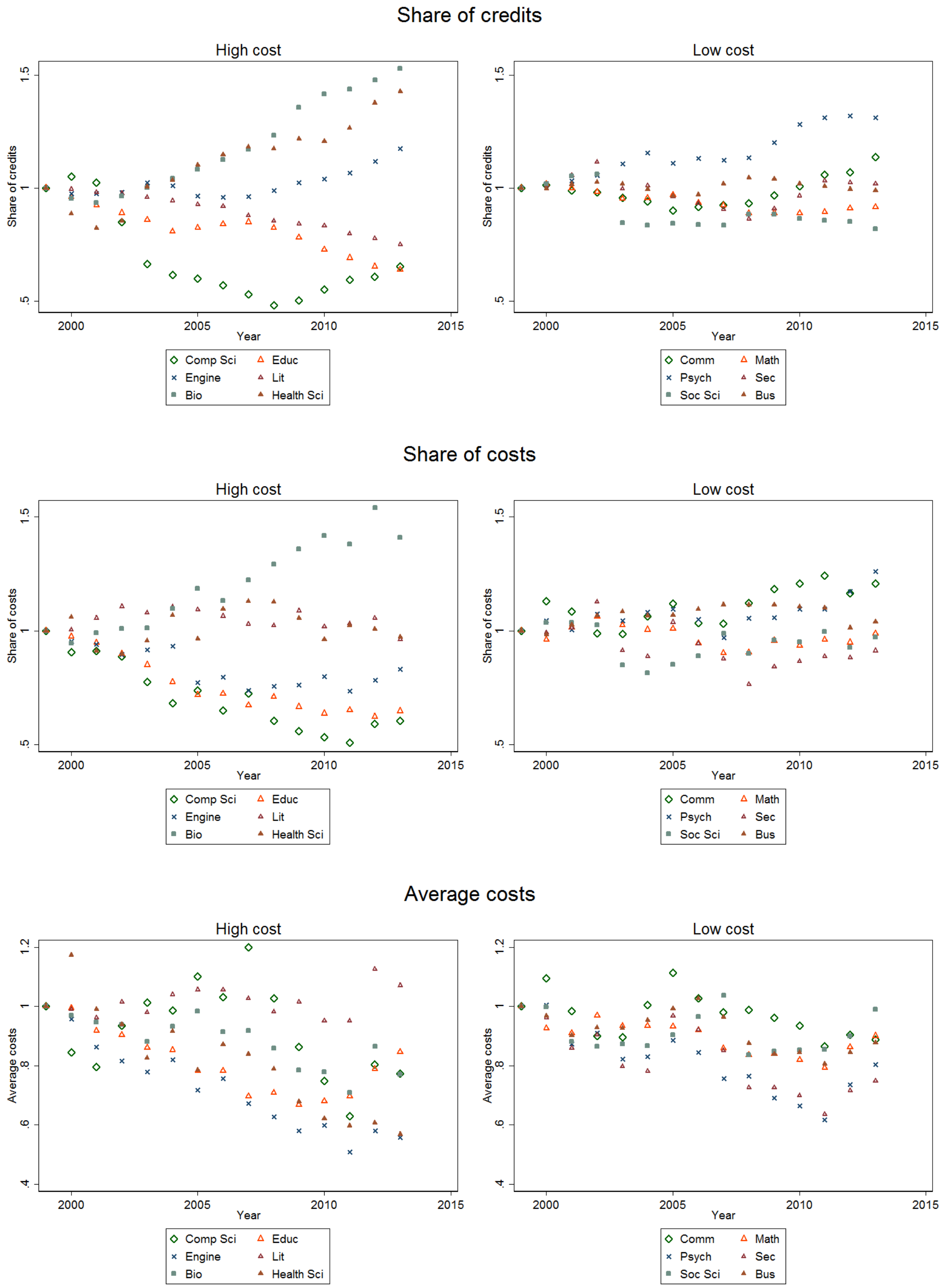
Horizontal axis: estimated log earnings effects from equation 6 relative to omitted education category. Vertical axis: ratio of earnings to cost PDVs relative to ratio for reference education category, conditional on $X_i = x$, i.e.: $\frac{EARNPDV_j(x)/COSTPDV_j(x)}{EARNPDV_{educ}(x)/COSTPDV_{educ}(x)} - 1$. See section 5.5 for more details on per-dollar effect calculations.

Figure 6: Trends in credits and spending



Trends in total credits, total expenditures, and per-credit expenditures over time. Undergraduate level credits only. Statistics computed over all SUS campuses. Credit hours reported in 1000s; total costs in millions of 2014 USD. Source: FLBOG expenditure reports.

Figure 7: Enrollment and spending trends by major



Enrollment and spending trends by major. Only 12 majors with highest number of credits included in graphs. Within each panel, the left graph displays the six majors with higher average per-credit costs over the period, and the right panel displays the six majors with lower average per-credit costs over the period. Upper panel: within-year share of credits by year, with each major normalized to a share of 1 in 1999. Middle panel: within-year share of total costs by year, with each major normalized to a cost share of 1 in 1999. Lower panel: average costs in each major relative to costs in 1999.

Table 1: Spending by type

Type	Direct	Indirect	Total	Credit hours	Direct PC	Indirect PC	Total PC
A. Instruction							
Lower	232	273	505	2147	108	127	235
Upper	502	467	969	2781	181	168	349
Graduate	371	199	570	803	462	248	710
All instruction	1106	939	2044	5731	193	164	357
B. Non-instruction							
Research	282	155	437				
Public Service	31	15	46				

Spending and credit hours by direct expenditure category in SUS system, AY 2000-2001. Units in left three columns are millions of USD. Units in credit hours column are 1000s of credits. Per-credit expenditures in dollars. Panel A: instructional expenditures by level and type. 'Upper' and 'Lower' are undergraduate leve expenditures. Panel B: non-instructional expenditures. See Section 4.1 for a discussion of direct and indirect expenditures.

Table 2: Spending variation by major

	Direct PC	Total PC	Direct per grad	Total per Grad
mean	149	299	14009	39184
sd	54	89	3013	8025
p5	95	209	10792	31482
p10	102	222	11501	31482
p25	109	236	11501	31689
p50	123	280	12958	36369
p75	178	357	15597	43200
p90	205	407	17600	49335
p95	250	461	18196	58764

Distribution of per-credit and per-graduate expenditures by major for SUS system AY 2000-2001. N=28. Graduate data from extract with N=38336. Left two columns are describe credit-weighted per-credit direct and total expenditures for undergraduate credits. Right two columns describe graduate-weighted direct and total per-graduate expenditures for graduates in microdata extracts.

Table 3: Spending by major

Major	Per credit Total	Per credit Direct	Per graduate Total	Per graduate Direct	Major	Per credit Total	Per credit Direct	Per graduate Total	Per graduate Direct
Fitness	184	87	40775	13587	Bio.	311	154	46735	14319
Math	209	95	42543	14077	Nat. Res.	326	164	39141	13137
Soc Sci	222	102	35744	12958	Gen. Stud.	370	177	35173	10743
Security	223	103	31689	10792	Educ.	357	178	43200	15597
Phil	245	109	36899	12873	Law	325	179	34338	13672
Home Ec.	255	112	40534	16074	Phys. Sci.	346	183	53716	17736
Bus.	236	119	31482	11501	Pub. Admin	368	193	40417	13823
Psych.	241	121	36369	12189	Art	407	205	42710	16222
Engl.	280	123	34656	12979	Agri. Bus.	437	237	46765	14986
Area Stud.	256	123	36951	12701	Arch.	432	238	58764	16599
Lang.	296	132	39448	14676	Eng. Tech.	439	246	45126	18196
Comp. Sci.	274	144	37236	12572	Health Sci.	461	250	49335	17600
Comm	282	147	33070	12841	Inter.	519	283	50569	14950
Lib. Sci.	376	151	28223	12480	Engine.	569	322	62297	23937

Per-credit and per-graduate total and direct expenditures by major. Credit data for SUS system, AY 2000-2001. Graduate data for microdata extract. Graduate data from sample with N=38336. For distribution summary statistics see Table 2.

Table 4: Earnings by major

Major	Mean	Log VA	Major	Mean	Log VA
Fitness	-0.182	-0.18	Law	-0.05	-0.003
Math	-0.21	-0.259	Nat. Res.	-0.038	-0.108
Soc Sci.	-0.12	-0.089	Phys. Sci	-0.173	-0.205
Sec.	-0.037	-0.017	Educ.	0	0
Bus.	0.153	0.137	Pub. Admin	-0.069	-0.044
Psych.	-0.21	-0.193	Gen Stud.	-0.345	-0.289
Phil.	-0.424	-0.372	Lib Sci	0.289	0.135
Home Ec.	-0.155	-0.145	Art	-0.398	-0.369
Area Stud.	-0.227	-0.164	Arch	-0.049	-0.042
Comp Sci	0.272	0.26	Agri	-0.383	-0.342
Engl.	-0.159	-0.137	Eng. Tech.	0.426	0.435
Comm	-0.055	-0.053	Health Sci	0.096	0.106
Lang	-0.357	-0.366	Inter.	-0.175	-0.081
Bio	-0.263	-0.261	Engine.	0.324	0.295

Unadjusted and regression adjusted log earnings by major. Expressed relative to omitted Education major. Standard deviation/IQR of log means: 0.189/0.312. Standard deviation/IQR of VA estimates: 0.174/0.274. Unadjusted means from regression sample with N= 28469, adjusted from sample with N=26189.

Table 5: PDVs by major

Major	Costs	Earn	Net PDV by: Age 32	Age 45	Major	Costs	Earn	Net PDV by: Age 32	Age 45
Fitness	-3.4	-18.7	-15.3	-31.2	Law	-7.1	11.9	19.1	29.2
Math	-2.8	-25.7	-23	-44.9	Nat. Res.	-4.7	-25	-20.3	-41.6
Soc Sci.	-8.2	-3.3	4.9	2	Phys. Sci	7.4	-17.3	-24.7	-39.5
Sec.	-10.6	5.1	15.6	19.9	Educ.	0	0	0	0
Bus.	-11.6	35.9	47.6	78.2	Pub. Admin	-2.5	-6.9	-4.4	-10.3
Psych.	-7.2	-20.9	-13.7	-31.5	Gen Stud.	-6.5	-29.7	-23.2	-48.4
Phil.	-6.9	-38.6	-31.7	-64.6	Lib Sci	-12	32.2	44.2	71.6
Home Ec.	-3.9	-15.6	-11.7	-25	Art	-1.3	-42.1	-40.8	-76.7
Area Stud.	-6.6	-25.8	-19.2	-41.2	Arch	12.7	-5.7	-18.4	-23.2
Comp Sci	-6.8	52.5	59.3	104	Agri	0.2	-18.6	-18.8	-34.7
Engl.	-8.7	-13.9	-5.3	-17.2	Eng. Tech	1.1	88.2	87.1	162.2
Comm	-10.4	-0.4	10	9.7	Health Sci	4.8	35.2	30.4	60.4
Lang	-5.8	-35.6	-29.8	-60.2	Inter.	4.5	4.8	0.3	4.3
Bio	1.8	-16	-17.8	-31.4	Engine.	15.5	68.6	53.1	111.5

PDVs of costs and earnings, and net PDVs by major. All estimates expressed relative to Education major, which is normalized to have earnings and cost PDVs of zero. See Section 5.1 for details on NPV calculation. Earnings PDV is computed through age 32. SD/IQR of cost pdv: 7.19/10.58. SD/IQR of age 32 earn PDV: 28.85/49.88. SD/IQR of age 45 earn PDV: 53.42/92.37.

Table 6: PDVs by major

Major	Earn PDV per dollar	Major	Earn PDV per dollar
Fitness	0.003	Law	0.342
Math	-0.056	Nat. Res.	0.009
Soc Sci.	0.294	Phys. Sci	-0.252
Sec.	0.486	Educ.	0
Bus.	0.799	Pub. Admin	0.04
Psych.	0.129	Gen Stud.	0.047
Phil.	0.004	Lib Sci	0.801
Home Ec.	0.038	Art	-0.185
Area Stud.	0.074	Arch	-0.292
Comp Sci	0.59	Agri	-0.101
Engl.	0.243	Eng. Tech	0.411
Comm	0.434	Health Sci	0.037
Lang	-0.018	Inter.	-0.095
Bio	-0.129	Engine.	-0.069

PDVs through age 32 of per dollar of spending as fraction of PDV per dollar in education major at fixed $X_i = x$. See section 5.5 for details on per-dollar spending PDVs.

Table 7: Earnings and costs for non-completers

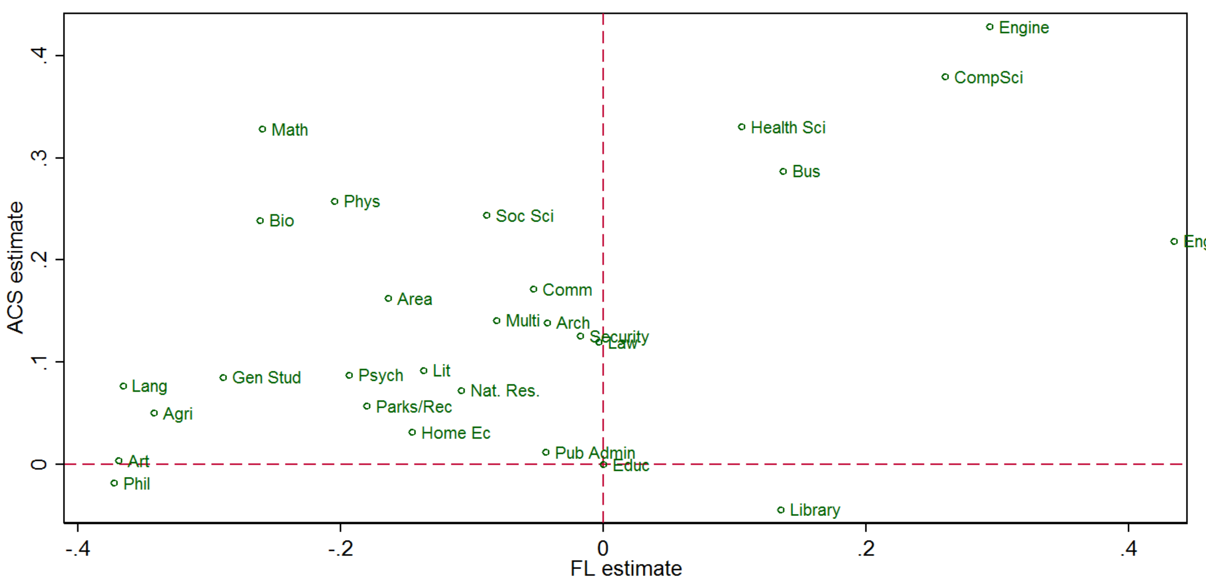
Spell length	Earnings	Costs	Censoring
1-2 years	-21	5419	-0.016
	(127)	(54)	(0.010)
2-3 years	141	11915	-0.033
	(143)	(72)	(0.011)
3+ years	261	28276	-0.084
	(130)	(161)	(0.010)

Earnings and costs for non-completers in extract data. Rows correspond to approximate lengths of enrollment before dropout. Earnings and cost columns present estimates of equations 3 and 4, respectively. Coefficients are expressed relative to omitted category of one or fewer enrollment years (within sample of students who enroll in university in year after high school completion). Earnings are quarterly earnings. Costs are total incurred costs. 'Censoring' outcome is a dummy equal to one if we do not observe mean earnings for a student. N=12,301 in earnings regression and 16,651 in cost and censoring regression.

Appendix

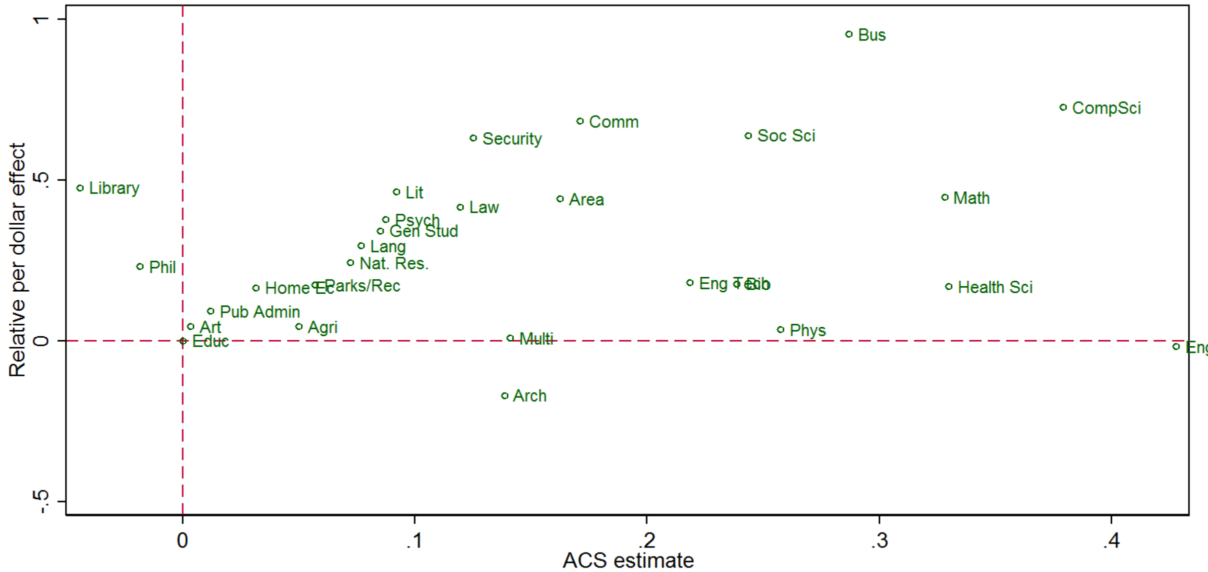
A Additional tables and figures

Figure A-1: ACS vs. FL major effect estimates



Estimated coefficients on for in ACS (vertical axis) versus FL (horizontal axis). Dependent variable is log earnings. ACS controls described in section 5.4 . FL controls described in section 4.1. FL N=38,336. ACS N=1,272,597. Degree weighted correlation between ACS and FL estimates is 0.678.

Figure A-2: Earnings PDVs per dollar in cost PDV using ACS earnings estimates



Horizontal axis: estimated log earnings effects from equation 6 in ACS data relative to omitted education category. Vertical axis: ratio of earnings to cost PDVs relative to ratio for reference education category, conditional on $X_i = x$, i.e.: $\frac{EARNPDV_j(x)/COSTPDV_j(x)}{EARNPDV_{educ}(x)/COSTPDV_{educ}(x)} - 1$. See section 5.5 for more details on per-dollar effect calculations.

Table A-1: Major classifications used in this paper

CIP code	Full name	Abbreviation
1	agribusiness and agric production	Agri
3	natural resources and conservation	Nat. Res.
4	architecture and environmental design	Arch
5	area and ethnic studies	Area
9	communications	Comm
11	computer and info sciences	CompSci
13	education	Educ
14	engineering	Engine
15	engineering technologies	Eng Tech
16	foreign languages	Lang
19	home economics	Home Ec
22	law	Law
23	english lang literature ltrs	Lit
24	liberal general studies	Gen Stud
25	library and archival science	Library
26	life sciences	Bio
27	mathematics	Math
30	multi interdisciplinary study	Multi
31	parks rec leisure fitness studies	Parks/Rec
38	philosophy and religion	Phil
40	physical sciences	Phys
42	psychology	Psych
43	protective services	Security
44	public administration and services	Pub Admin
45	social sciences	Soc Sci
50	visual arts	Art
51	health sciences	Health Sci
52	business and management	Bus

Table A-2: Censoring by fields

Major	Cens. rate	Major	Cens. rate
Fitness	0.076	Law	0.081
Math	0.1	Nat. Res.	0.113
Soc Sci.	0.103	Phys. Sci	0.234
Sec.	0.076	Educ.	0
Bus.	0.054	Pub. Admin	0.069
Psych.	0.1	Gen Stud.	0.108
Phil.	0.226	Lib Sci	0.228
Home Ec.	0.103	Art	0.185
Area Stud.	0.185	Arch	0.115
Comp Sci	0.053	Agri	0.125
Engl.	0.088	Eng. Tech	-0.01
Comm	0.1	Health Sci	0.035
Lang	0.171	Inter.	0.252
Bio	0.217	Engine.	0.127

Estimates of regressions of the form given in equation 6 with a dummy variable for presence in earnings data as the outcome. Estimates expressed relative to omitted education category. Censoring rate in education programs is 0.128. Estimates from regressions with N=38,336.