Returns to Specific Graduate Degrees: Estimates Using Texas Administrative Records

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Abstract

We estimate causal effects of specific graduate degrees, such as an MBA or an MS in Electrical Engineering, on labor market outcomes. Moreover, we study how college major and characteristics of students and graduate schools influence the payoff to graduate education. We use alternative fixed effect regression models to control for endogenous selection into graduate programs and also use propensity score weighting to construct suitable control groups. We use a version of Dale and Krueger's strategy to estimate differences across schools in the value of specific degrees. Our analysis takes advantage of the size and richness of the TSP data, and the fact that it can be used to track students through high school, college, graduate school and the labor market.

1 Introduction

Graduate education has become an increasingly important part of higher education in the U.S. The number of new master's degrees awarded in 2013 is 14.7% of the number of 24-year-olds in the U.S. in 2013. In comparison, the statistic was 5.5% in 1985 (Altonji et al, 2016). The rapid growth of graduate education reflects the economy's increasing demand for a highly skilled labor force.

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Despite this rapid growth, there is very little research studying differences in earnings for *specific* graduate degrees, even at the descriptive level. Individual students and policy makers rely on average earnings of graduates. Such estimates, as well as simple regression estimates, have been shown to be highly misleading statistics for the returns to graduate degrees (Altonji and Zhong, 2020). For example, using data spanning the early 1990s to 2015, Altonji and Zhong find that on average, MBA degree holders earn $115,161, while graduates with a master's in education earn $66,306. The large earnings gap does not necessarily mean that individuals and policy makers should invest more in MBA programs, since students who enroll in MBA programs may earn more than students who enroll in education programs even without their graduate degrees. The earnings difference is due in large part to occupational preferences (business versus teaching) and prior education and work experiences.

A few studies have attempted to estimate the return to an MBA (Arcidiacono et al, 2008) and to an MD (Chen and Chevalier, 2012; Ketel et al, 2016), but much more work is needed. Altonji and Zhong (2020) (here after, AZ) provide causal estimates of the returns for a broad range of graduate degrees. Their main estimation strategy, which they call FEcg, is ordinary least squares regression with fixed effects for the combination of undergraduate major and the specific graduate degree obtained by the last time a person is observed. They use multiple waves of the National Survey of College Graduates and the National Survey of Recent College Graduates. While these data have many advantages, they have only limited information on family background and lack information on test scores and on academic performance in high school and in college. Furthermore, they do not identify educational institutions, so Altonji and Zhong could not estimate returns for specific schools or relate returns to measures of program quality.

In this paper, we exploit the richness of the Texas Schools Project (TSP) data to provide more credible estimates of the labor market returns to advanced degrees. We also study how the returns may differ across schools and types of students. To keep the paper manageable, we focus the discussion on a limited set of specific degrees defined at the 4 digit CIP level. These include the MBA, the JD, and master's degrees in computer science and in four subfields of engineering. We also consider education, psychology and social work and a set of health related professional degrees that include MD, pharmacy, and nursing. We also present estimates for a larger set of degrees organized by broad CIP category. Indeed, we view the paper as a step toward the goal of providing estimates of the return to specific graduate programs that are tailored to the college major, academic record and demographic characteristics of individual students, and are sufficiently credible to be useful in decision making.

We use several estimation strategies. The first is simply OLS regression with the extremely rich set of controls that are available in the Texas data. The second is regression with controls for person-specific intercepts (FE). The basic idea is to compare earnings of a person before and after they attend graduate school, focusing on the vast majority of individuals who work between college and graduate school. The third is regression with controls for the combination of undergraduate degree and graduate degree the individual has obtained by the time that she is last observed (FEcg). This approach was introduced by Altonji and Zhong, who provide a detailed discussion of its advantages and disadvantages. A major advantage of FEcg relative to the fixed effects approach is that it makes use of information on people with earnings observations only after graduate school or only before graduate school. In contrary, FE only makes use of people with earnings observations both before and after graduate school. The fourth approach is to better define the comparison groups for the OLS and FEcg by incorporating the probability of attaining a specific degree ("propensity scores"), such as an MBA, among the sample of individuals who either obtained that degree or did not go to graduate school. We use the propensity scores to re-weight the regression sample and as an additional control variable.

We also estimate school specific returns to a JD, an MBA, and degrees in Nursing, Pharmacy, Social Work and Psychology. To do so, we modify FEcg by drawing on Dale and Krueger's (2002) approach to estimating the return to college quality. Basically, we treat JDs from different schools as different degrees. We control for selection into different law schools using students' application and admission records, although we lack application and admissions data to private schools and out of state schools. For most of this analysis, we condition on obtaining a graduate degree in the specific field. We then regress the school specific returns on a measure of program rank from U.S. News & World Reports. To the best of our knowledge, we are the first to use this approach to estimate differences across school in the return to specific graduate degrees.

Because we consider a large number of fields, use multiple estimation methods, produce estimates for demographic subgroups, and consider heterogeneity across schools, there is no easy way to fully summarize the findings. Instead, we mention a subset of the results. Regardless of the estimation method, we find large effects of a JD degree on log earnings. The OLS and FEcg estimates are 0.514 and 0.565 respectively. The return rises with time since graduate school. The corresponding estimates for an MBA are 0.235 and 0.156. The OLS estimates are probably biased upward. The FEcg estimate of the return to civil engineering is 0.148. The values for electrical, computer, and mechanical engineering are 0.141, 0.079, and 0.227 and differ substantially across other engineering fields that we consider. For computer science, the return is 0.157. The returns to various master's degrees in education that we consider are relatively small. The FEcg estimate of the returns to social work and to psychology are 0.111 and 0.087 respectively, well above the OLS estimates. Weighing the evidence from the different estimation procedures, we find that the return to an MD degree is around 0.64. The return to a pharmacy degree is even larger.

Finally, we estimate returns by college major for a set of graduate programs.

For a few fields, we present estimates of how the return varies over the first ten years of post graduate school experience. We find substantial growth for an MD degree, which probably reflects the fact that most doctors work as residents for three or four years at relatively low pay after medical school. We also find significant growth for a JD degree and mechanical engineering, but little growth for computer science.

The return to most graduate degrees is higher for women than for men. We also find substantial differences across racial groups. We were surprised to find substantially lower returns for Asian Americans in most fields relative to non-Hispanic whites. The effect of college grade point average on returns varies across fields. Higher college GPA has a substantial positive influence on the return to an MBA and especially a JD degree, and a negative return for education, social work, and clinical psychology.

We find that the institution has a substantial effect on the return to an MBA. An increase of 10 places in the U.S. News & World report rankings increases the return by 0.021, which is substantial relative to the average return of 0.156. The average of the returns to a set of unranked MBA programs is negative. An increase of 10 places in the law school rankings increases the return by 0.026, compared to an average return of 0.565. In contrast, we do not find that the returns to nursing, social work, and psychology programs depend on the ranking.

The paper continues in section 2 with information about the data. In section 3 we present summary statistics. In section 4, we discuss the regression models and estimation methods used. In section 5, we present estimates of the return to graduate degrees, which are still preliminary. We close with a discussion of the next steps for the paper.

2 Data

We use administrative data from Texas for our empirical analysis. The data follows students from high school enrollment to college enrollment, advanced degree enrollment (if any), and employment, so long as these activities occur in Texas. The high school data is provided by the Texas Education Agency (TEA), the college data is provided by the Texas Higher Education Coordinating Board (THECB), and the employment and wage data is provided by the Texas Workforce Commission (TWC). The TWC data is drawn from unemployment insurance records. The data is also linked to 2008-2015 National Student Clearinghouse (NSC) data. Out-of-state enrollment and degree attainment of Texas high school graduates are observed between 2008-2015, and out-of-state enrollment of students who previously enrolled in Texas universities are also observed between 2008-2015. In the main analyses, we do not use information from the NSC, due to the lack of detailed enrollment information for out-of-state enrollment. We include additional analyses that make use of the NSC data in the appendix.

A limitation of the TSP data is that labor market outcomes can only be observed for people who work in Texas. For example, we do not observe the post medical school earnings of a student who graduates from an MD program in Texas and practices medicine in New York. Given the size of the Texas economy, we do not think that this limitation is severe.[1]

Wage observations are quarterly and are deflated to 2019 dollars. To account for sporadic unemployment episodes and to focus on returns for full-time work, we only keep wage observations that are (1) part of a sequence of four consecutive quarterly wage observations; (2) not during enrollment in graduate school; (3) at least three quarters after college; (4) either before graduate school or at least three quarters after advanced degree attainment; (5) not before college degree attainment; and (6) below \$250,000 and above \$3,000 (quarterly wage). An individual's work experience is calculated as the total number of qualifying quarterly wage observations up to the quarter of interest.

An important question concerns the distribution of the time between the year of the wage observation and the date of graduation. Figure 1 displays the probability distribution of the elapsed time between wage observations and graduate degree attainment for those who obtain a law degree in the effective sample for the FEcg estimator. One can see that the post-degree observations have a fairly wide distribution, with substantial mass between 10 and 18 years after law school. Figure 2 provides similar information for the effective sample for the FE estimator, and the patterns are broadly similar. Finally, Figure 3 provides similar information for MBA recipients. One can see that the distribution of time prior to attainment of the degree is more dispersed — people spend more time in the labor market before pursuing an MBA than before pursuing a law degree.

The TEA data contains rich information on students' high school enrollment, course selection, and standardized test scores, which provide valuable information on students' baseline abilities and academic interests. The attendance rate of a student is calculated as the fraction of school days for which a student was present. The courses a student takes in high school are classified into English, Math, Science, Social Studies, and Arts in accordance with the Texas Public Education Information Management System (PEIMS) service categorization codes. We also separately categorize students' enrollment in AP classes. Students' total credits accumulated in each category are calculated. While SAT and ACT test scores are available from college enrollment data, we use the state-wide high school assessment exams as our main standardized test scores. These exams are required for high school graduation and cover a wider population in our sample. The State of Texas Assessments of Academic Readiness (STAAR) is used for years 2012-2016, the

[1] In future robustness checks, we will use data from various years of the National Survey of College Graduates (NSCG) and the National Survey of Recent College Graduates (NSRCG) to conduct a parallel analysis, building on . The NSCG and NSRCG lack data on course curriculum and performance in high school, college, and graduate school and do not have test score information, but they do identify undergraduate major and graduate field. Because they are national samples and identify current state of residence and the state of the educational institution, we can examine how restricting the sample to those who work in Texas affects estimates.

Texas Assessment of Knowledge and Skills (TAKS) is used for years 2003-2015, and the Texas Assessment of Academic Skills (TAAS) is used for years 1994-2007. All three versions of the standardized tests have separate modules for mathematics, reading, and writing.[2] Students' performances in the separate modules, as well as their overall performances, are measured using their percentile ranking among their cohort peers.

The THECB data contains information on all students enrolled in undergraduate and graduate degree programs at public two-year, four-year, and health-related institutions since 1992 and at independent universities since 2003. Enrollment, major of study, semester credit hours, GPA, and degrees received are available for all cohorts of students. College major and graduate field are measured at the 8 digit CIP level. Below we aggregate college majors to the 47 2-digit CIP categories but use 4 digit graduate fields. Course-level schedule and performance information are available since 2011, but we have not used it so far because of the relatively short horizon. Information on students' parental income and parental education are contained in the students' financial aid files, which are available since 2001.

One of our analyses makes use of Dale and Krueger's (2002) idea of addressing selection into specific institutions by controlling for the programs a student applied to and was admitted to.[3] Students' admission records, which contains information on where students applied and were admitted to, is available for public universities since 2000 for both undergraduate and graduate programs. The application records are available even if students do not eventually enroll in the institution or are rejected by the programs. We lack application and admission data for out-of-state graduate programs and for private institutions in Texas.[4] For public institutions, we observe whether the student applied to an associate, bachelor's, master's, doctoral, JD, PharmD, DDS, OD, or DVM degree program. However, we do not observe what particular major(s) the student applied to or was admitted to. For example, we cannot distinguish an application for a master's in electrical engineering from an application for an MBA. Given the data limitations, the use of application and admission sets as an additional control is best suited to study the return to JD, PharmD, DDS, OD, and DVM programs. For master's programs such as an MBA or computer science, we assume that all applications were in the field of the program the student enrolled in. This assumption is broadly consistent with the application data available. In particular, we find that students who are observed earning a graduate degree in a particular field are highly unlikely to be observed applying to programs in a different application category.[5]

[2] In addition, TAKS and STAAR also have separate modules for science and social sciences, but we do not use them in our main specification because they are not available in TAAS.

[3] Dale and Krueger considered undergraduate degrees and did not consider field of study. To the best of our knowledge, we are the first to apply the idea to graduate degrees in specific fields.

[4] For students who attend private institutions, such as Rice University, we control for in-state public university application and admissions profiles and treat the school they attend as part of the profile.

[5] Among all individuals who are observed in the application files and have earned an MBA, 97% are observed applying to a master's degree program, but only 2% are observed applying to JD programs. Among all individuals who are observed in the application files and have earned a JD, 98% are observed applying to a JD program, but only 8% are observed applying to

Finally, we make use of the US News and World Report's graduate program rankings for various years in our analysis of differences in returns by program quality. In this draft, we use the average of all available ranking data from 1990 to 2017. Specifically, for a program that is ranked in the US News rankings in at least one year, we use the program's average ranking among the years in which the program is ranked. We do not make use of the years in which a program is not ranked because the number of ranked programs is not fixed across years. This means that being unranked conveys different information for different years. In the main analyses, we do not make use of programs that are unranked in US News rankings in all years when estimating the relationship between rank and returns. We do, however, report the average of the returns to unranked programs along with the returns to the ranked programs.

We use several different subsamples when estimating regression models of earnings. The choice depends on the model specification and estimation methodology. In addition, we explore robustness of results to alternative sample inclusion criteria.

3 Summary Statistics for the Main Sample

Table 1 displays information for the main regression sample on earnings and school performance by graduate degree type. To keep things manageable, we restrict our attention to 19 key graduate fields that we discussed in detail below. These are Clinical Psychology, Social Work, Education (Curriculum and Instruction), Psychology, Education Administration, Mathematics, Biology, Architecture, Public Administration (MPA), Nursing, Computer Sciences, MBA, Civil Engineering, Computer Engineering, Mechanical Engineering, Electrical Engineering, JD, PharmD, and MD. We present results for additional graduate fields in supplemental materials.[6] Throughout, the graduate fields are presented in the above order, which ranks the 19 graduate programs according to their post-graduate school earnings from low to high (Column 2 of Table 1). Graduates of engineering programs and health related programs (MD, PharmD, and Nursing) generally obtain higher incomes than graduates from education programs, psychology programs, and public policy related programs. On average, graduates from education and psychology programs earn less than the mean for entire sample, which is dominated by people who do not have a graduate degree (bottom row).

Interestingly, graduates from MD programs have the second lowest pre-graduate program income, although they earn the highest post-graduate program income. This probably reflects the fact that some highly competitive graduate programs favor pre-graduate school training in medicine related professions

master's degree programs.

[6] In future work we will explore separating out full-time graduate programs from part-time graduate programs, excluding observations on those who enrolled in part time programs from the analysis. We will also explore estimating returns to part-time programs. In both cases, we will experiment with allowing the period of enrollment in a graduate program to interact with the treatment effects on earnings relative to the counterfactual of not attending graduate school.

that could have lower income. For example, some aspiring medical students will choose to work in Emergency Medical Services for relevant experiences or in other lower income professions that could allow flexible schedules to prepare for the medical college admission test (MCAT). This raises the possibility that pre-graduate school earnings may not necessarily reflect the counterfactual incomes that an advanced degree graduate would have earned if she did not pursue a graduate degree. (See AZ for a discussion of the issue). In such cases, the OLS strategy can potentially identify more suitable counterfactual incomes compared to the FEcg and FE strategies. FEcg and FE both rely heavily on pre-graduate school earnings as a guide to their counterfactual incomes of graduate degree holders. The issue is probably most acute for medical degrees.

Table 1 also shows the average college major premium and industry premium of graduates from different degree programs. We first compute the earnings premium associated with each college major and North American Industry Classification System (NAICS) industry code by estimating a log earnings regression that includes dummies for college majors, industry code dummies, an indicator for whether the individual had a graduate degree (but not the field) and the controls for other student characteristics that we include in the regression models below. We then compute the average college major premium and industry premium of individuals with a given advanced degree. Columns 3 and 4 of Table 1 show that graduates of advanced degree programs with higher average earnings also tend to come from college majors with higher earnings potential and work in industries with higher earnings potential.

Columns 5-7 show average school performances of graduates from different programs. Columns 5 and 6 present graduates' average percentile rankings in the standardized Texas high school assessment exams. Column 7 presents the average college GPA of students from different graduate programs. Overall, graduates of higher earning programs have better high school and college academic performance, with the MDs leading the pack.

In Table 2, we present the demographic compositions of the 19 graduate fields we focus on. Column 1 of the table shows large variation in gender composition between programs. While close to or more than 80% of graduates from clinical psychology, education, social work, psychology, and nursing programs are female, women are underrepresented in engineering and computer sciences programs. The shares of female graduates are also low in MBA and JD programs compared to the share of female college graduates. Racial compositions also vary widely across graduate programs. For example, African American students are overrepresented in Clinical Psychology, Social work and Public Affairs and underrepresented in most STEM-related programs. Asian students are underrepresented in psychology, education and public policy related programs and overrepresented in computer science, engineering, pharmacy, and medicine.[7] In terms of

[7]In all discussion related to ethnicity, notice that international students are categorized as a separate group. For example,

socioeconomic status, column 6 of Table 2 shows that students from lower socioeconomic status backgrounds — students who qualified for reduced price or free meals in high school — are underrepresented in some of the most competitive advanced degree programs, including JD and MD.

4 Econometric Specification and Methods

The key challenge to estimating the returns to graduate education comes from the facts that people selectively choose whether to enroll in graduate school, and graduate programs make admissions decisions based on student characteristics that influence earnings. As Altonji et al (2016), and Table 1 document, people who enroll in particular graduate programs differ in many dimensions that affect labor market outcomes. These include ability, prior academic preparation, and occupational preferences. One can go part way toward addressing this problem by using the rich set of control variables that are available in the TSP data. These data are superior to the handful of other US data sets that identify graduate and undergraduate field, such as the NSF's National Survey of College Graduates (NSCG). However, bias from unobserved differences, particularly in occupational preferences, is still likely to be a serious problem.

We use five methods to tackle the endogenous selection into graduate programs. The first is simply OLS regression with a rich set of controls. The second is regression with controls for person specific intercepts (FE). The third is regression with controls for the combination of undergraduate degree and graduate degree the individual has obtained by the time that she is last observed (FEcg). The fourth approach is to better define the counterfactual groups for OLS and FEcg by using propensity scores for attainment of a specific degree, such as an MBA (versus no graduate degree), to re-weight the regression sample and as an additional control variable. We refer to these approaches as OLS-pw and FEcg-pw. To estimate school specific returns to particular graduate degrees, we draw upon Dale and Krueger's approach to modify FEcg.

Before turning to the econometric specifications, we need to introduce some notation. Let i index an individual student, and t index a time period t. Let w_{it} be earnings of individual i at time t. The variable $c \in \{1, ..., C\}$ is an index of the undergraduate major. We use g as the index of the type of graduate degree, with $g = 0, 1, ..G$. The value $g = 0$ is the case of no graduate degree. Throughout, we restrict our attention to individuals who already hold a bachelor's degree.

The variable $C_{c(i)}$ is a dummy variable that takes value 1 if individual i's college major is c, and 0 otherwise. Similarly, $G_{g(i)t}$ is a dummy variable that takes value 1 if individual i holds a graduate degree in field g at time t. The variable $G_{g(i)}$ is a dummy that equals 1 if i has a degree in g by the last time

Asian students in the following discussion are US citizens or permanent residents of Asian ethnicity, and do not include international students from Asia.

we observe her. The vector X_{it} is a collection of control variables such as gender, race, controls for past achievement in high school and college, age, and the year. The choice of X_{it} varies across models. Our main outcome variable is the natural log of w_{it}, which is real quarterly earnings in 2019 dollars. Following these notations, our empirical analysis aims to estimate the causal effect of $G_{g(i)t}$ on $\ln w_{it}$.

4.1 Econometric Specifications and Estimation Methods

This section draws heavily on AZ. We refer readers to that paper for a detailed discussion of the assumptions under which FE and FEcg will identify treatment on the treated effects of graduate degrees (TT). (In a future draft, we will provide a brief summary of the key assumptions). We work with both a simple additive regression specification and specifications that allow the return to a graduate degree to depend on c and/or on years of post graduate school experience. We also allow additional interactions with student characteristics such as gender, race, and test scores.

4.1.1 Average Returns without Degree-Specific Experience Trends

Our baseline specification assumes the effects of undergraduate major and graduate degrees are additively separable. It also assumes that the experience profile depends on the college major but not the graduate degree. The model is

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{C}(\alpha_0^c + \alpha_{\mathrm{age}_{it}}^c + \alpha_{gen_i exp_{it}}^c)C_{c(i)} + \sum_{g=1}^{G}\gamma^g G_{g(i)t} + X_{it}\beta + u_{it}. \tag{1}$$

The main parameters of interest are the γ^g, the returns to each graduate degree. OLS applied to the above equation treats the composite error term u_{it} as random. In the OLS specification, we use the full sample of individuals who at least earn a BA. Here, the implicit comparison group for individuals with an advanced degree in major g includes observations on individuals who never obtain an advanced degree as well as observations on individuals who eventually obtain an advanced degree but have not yet obtained the degree at time t. The effect of college major depends upon a c specific intercept (α_0^c), a c specific quadratic function of age_{it} ($\alpha_{age_{it}}^c$), and c specific cubic in actual experience for males and females ($\alpha_{gen_i exp_{it}}^c$). The error term u_{it} may be written as $u_{it} = e_i + \varepsilon_{it}$. We decompose person specific component e_i into its mean b_{cg} for persons who major in c and who eventually get a graduate degree in g and an orthogonal component v_i:

$$e_i = \sum_{c=1}^{\mathcal{C}}\sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)} + v_i \ . \tag{2}$$

The FE estimator treats e_i as a fixed effect and treats ε_{it} as random. It involves comparing the average wages of an individual before and after advanced degree attainment.

In the FEcg case, we add $\sum_{c=1}^{\mathcal{C}} \sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)}$ to (1) and apply OLS to

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{C} (\alpha_0^c + \alpha_{\text{age}_{it}}^c + \alpha_{gen_i exp_{it}}^c) C_{c(i)} + \sum_{g=1}^{G} \gamma^g G_{g(i)t} + X_{it}\beta + \sum_{c=1}^{C} \sum_{g=0}^{G} b_{cg} C_{c(i)} G_{g(i)} + \nu_i + \epsilon_{it}, \quad (3)$$

treating $v_i + \varepsilon_{it}$ as random. For the FEcg specification in equation (3), we follow AZ and restrict our sample to individuals who eventually earn advanced degrees in the baseline case. We refer to this sample as the "graduate school" sample. However, we also estimate a version using the full sample. In both cases, the estimate of γ^g is based on comparing the average wages before and after advanced degree among students who are in the same bachelor's degree major $\times$ advanced-degree type group.

So far, we have not investigated the possibility that the decision to go to graduate school is induced by a transitory drop in earnings. This would probably lead to upward bias in FEcg and FE (Ashenfelter, 1978). Arcidiacono et al do not find much evidence that this is a problem, but we intend to examine the issue in a future draft.

We provide FEcg and FE estimates using both the main sample and the sample that excludes "college only" individuals who are not observed to go to graduate school. As AZ point out, including the college only sample raises concerns about selection bias even with controls for $C_{c(i)} G_{g(i)}$. Furthermore, it is easier to interpret FEcg and FE as treatment on the treated estimates when only the graduate school sample is used. However, AZ also raise the possibility that imposing the assumption of parallel age and experience trends when it is false may lead to negative bias in estimates of the return to graduate school. A negative bias is more likely if the return to graduate school rises with post degree experience, and the BA only sample is excluded. The reason is that the common experience trend may pick up part of the shift in the experience slope following graduate school. This would lead to an offsetting negative bias in γ^g. We focus on the FEcg and FE results using the main sample in part for this reason but also to simplify comparison to OLS.

A second issue is whether or not to include those who go to directly to graduate school. Because FEcg and FE identify γ^gprimarily from a comparison of earnings before the graduate school with earnings after graduate school, one can argue that the case for interpreting them as treatment on the treated estimates is stronger if one excludes those who go to graduate school directly. To simplify comparisons among the estimators, we work primarily with the main sample and include these cases. They contribute to estimation of the age and experience profiles as well as the effects of time invariant controls the experience profiles in the OLS and FEcg cases.

4.1.2 Propensity Score Weighting

In OLS we assume that wages of those without a degree are good proxies for the counterfactual wages of those who do, conditional on the other controls. In both FE and FEcg specifications, we assume that the wage of an individual prior to graduate school enrollment is a good proxy for the counterfactual wage of the individual without a graduate degree, and that the age and experience profiles of those who do not go to graduate school are the counterfactual profiles for those who do. To construct better control groups for holders of degrees like an MD, we use a variation of OLS, which places additional weight on individuals who, given observable characteristics, have a high propensity to obtain an MD. To be more specific, we use a logit model to estimate the probability p_{ig^*} that an individual will eventually obtain an MD, or any other advanced degree, g^*:

$$p_{ig^*} = \Pr(g(i) = g^* | Z_i, g(i) = g^* \text{or } g(i) = 0); \tag{4}$$

where Z_i includes variables that are fixed for person i, many of which appear in X_{it}. For $g = g^*$, the probability is for individuals who either obtain g^* or do not attend graduate school in any field. We utilize the rich information available in the Texas administrative data, including GPA, college major, high school curriculum, high school GPA, high school standardized test scores, economic disadvantage status, ethnicity, and gender. We set p_{ig^*} to the predicted probability that i obtains degree g^*, and we compute corresponding probabilities for each degree g. We use p_{ig} to re-weight the sample and run a weighted least squares (WLS) regression separately for each advanced degree of interest, g. The specification is:

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{C} (\alpha_0^c + \alpha^c_{\text{age}_{it}} + \alpha^c_{gen_i exp_{it}}) C_{c(i)} + \gamma^g G_{gt} + X_{it}\beta + \beta_1^p p_{ig} + \beta_2^p p_{ig}^2 + u_{it} \ . \tag{5}$$

For the propensity weighted regressions, we use the sample of individuals who meet the other sample selection criteria and who either eventually obtained a degree in g or did not go to graduate school. That is, we estimate separate regressions for each advanced degree of interest, using the relevant p_{ig} for that regression as the weight and as a control. This is a way to address differences by graduate degree attainment in the effects of the control variables and experience profiles. However, unlike FE and FEcg, it does not address selection on unobservables. We also implement a propensity score weighted version of FEcg. The specification is the same as (5) but with $\sum_{c=1}^{C} b_{cg} C_{c(i)} G_{g(i)}$ added.

4.2 Average Returns with Advanced Degree-Specific Experience Trends

We also estimate models that relax the assumption that the returns to advanced degrees do not vary with years of potential experience after graduate school.

The OLS specification for returns with degree-specific potential experience trends is

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{C}(\alpha_0^c + \alpha_{\text{age}_{it}}^c + \alpha_{gen_i exp_{it}}^c)C_{c(i)} + \sum_{g=1}^{G}\gamma_{x_{it}}^g G_{g(i)t} + X_{it}\beta + u_{it} \tag{6}$$

where $\gamma_{x_{it}}^g = \gamma_0^g + \gamma_1^g x_{it} + \gamma_2^g x_{it}^2$, and x_{it} is years since graduate degree completion..

Similarly, the FEcg specification is now:

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{C}(\alpha_0^c + \alpha_{\text{age}_{it}}^c + \alpha_{gen_i exp_{it}}^c)C_{c(i)} + \sum_{g=1}^{G}\gamma_{x_{it}}^g G_{g(i)t} + X_{it}\beta + \sum_{c=1}^{C}\sum_{g=0}^{G} b_{cg}C_{c(i)}G_{g(i)} + \nu_i + \epsilon_{it} \tag{7}$$

and the FE specification is:

$$\ln w_{it} = \alpha_1 + \sum_{g=1}^{G}\gamma_{x_{it}}^g G_{g(i)t} + X_{it}\beta + \alpha_i + \epsilon_{it}\,. \tag{8}$$

In the OLS, FEcg, and FE estimations with degree specific trends, we always use the full sample of individuals with college degrees. Once the assumption of constant returns is relaxed, the observations on individuals who do not attend graduate school are needed to identify the counterfactual earnings profile for those who do attend graduate school. [8]

4.3 Heterogeneity in Returns

Besides the average returns to advanced degrees, we are also interested in the heterogeneous returns by student characteristics such as gender, race/ethnicity, college GPA, and ranking of graduate program. To examine this, we estimate the OLS, FEcg, and FE models for each gender category and the main race/ethnic categories separately. For heterogeneity of returns by college GPA, the OLS specification is

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{C}(\alpha_0^c + \alpha_{\text{age}_{it}}^c + \alpha_{gen_i exp_{it}}^c)C_{c(i)} + \sum_{g=1}^{G}(\gamma_0^g + \gamma_1^g \text{GPA}_i)G_{g(i)t} + X_{it}\beta + u_{it}. \tag{9}$$

[8] Inclusion of the BA only observations reduces the reliance on the experience trend in earnings before and after graduate school for estimation of the experience profile in the absence of graduate school.

The parameter γ_1^g is the effect of a 1 point increase in grade point average on the return to $G_{g(i)}$. (The main effect of GPA_i is included in X_{it} in all specifications). Similarly, the FE-CG and the FE specifications are:

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{C}(\alpha_0^c + \alpha^c_{\text{age}_{it}} + \alpha^c_{gen_i exp_{it}})C_{c(i)} + \sum_{g=1}^{G}(\gamma_0^g + \gamma_1^g \text{GPA}_i)G_{g(i)t} + X_{it}\beta + \sum_{c=1}^{C}\sum_{g=0}^{G} b_{cg}C_{c(i)}G_{g(i)} + \nu_i + \epsilon_{it} \tag{10}$$

$$\ln w_{it} = \alpha_1 + \sum_{g=1}^{G}(\gamma_0^g + \gamma_1^g \text{GPA}_i)G_{g(i)t} + X_{it}\beta + \alpha_i + \epsilon_{it} \tag{11}$$

The control vector X_{it} includes age, gender, ethnicity, a vector of high school standardized test scores, high school curriculum, high school attendance rate, college GPA, college credits accumulated, and whether the student qualified for free or reduced price meals in high school. In all specifications, the effect of age is college major specific. The labor market experience profile is also college major specific, with separate major specific profiles for men and women.

4.4 Controlling for Application and Admissions Portfolios

We supplement the above approaches by using applications and admissions data to address selection bias into particular programs and particular institutions (Dale and Krueger (2002)).[9] We use the information in two ways, depending on data availability. First consider programs such as a JD, for which we can identify application and admissions results for programs in public institutions in Texas as well as identify the institution attended if the person did in fact go to law school. We add a fixed effect for each unique combination of Texas public law schools applied to and admitted to as an additional control in the FEcg specification. In our main specification we restrict the sample to people who eventually go to law school. The regression model becomes

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{C}(\alpha_0^c + b_{cg} + \alpha^c_{\text{age}_{it}} + \alpha^c_{gen_i exp_{it}})C_{c(i)} + \gamma^{gj}G_{gjt} + X_{it}\beta + \sum_{p} A^g_{ip} + \nu_i + \epsilon_{it}, \tag{12}$$

where G_{gjt} indicates having a degree from program g of institution j by time t. A^g_{ip} is an indicator for individual i having an application/admission portfolio $p \in P^g$. To construct the full set of dummies included in the set P^g, we consider three potential outcomes for a graduate program: did not apply, applied and rejected, and applied and admitted. Then we consider P as the exhaustive set of mutually exclusive portfolios

[9] Mountjoy and Hickman (2020) uses a similar approach and the Texas administrative data to study the returns to particular undergraduate institutions.

of all possible outcomes from all graduate degree programs of type g.[10]

To reduce dimensionality, we also consider a simplified portfolio of all possible application and admission outcomes by aggregating the potential outcomes. Specifically, here we will consider two potential outcomes for a graduate program: not admitted and admitted. In other words, the simplified portfolio controls do not distinguish between students who applied to but got rejected by a program and those who did not apply to the program.

Our options are more limited for master's programs because the type of master's program is not recorded in the application and admissions data. However, if we assume that all of the applications submitted by an individual who enrolls in a specific program type, say an MBA, are for MBA programs, then we have the possibility of controlling for the application and admissions set. However, we will only be able to identify application sets for people who actually enroll in MBA programs, and we restrict the estimation sample accordingly.

5 Results (preliminary)

We now turn to the estimates of the returns to graduate school. In section 5.1, we report estimates pooling all institutions. In section 5.2, we discuss estimates by demographic group and college GPA. In section 5.3, we report estimates of returns by US News and World Report ranking for a subset of the fields that we consider. In section 5.4 we present preliminary estimators of returns to graduate programs by undergraduate major but leave discussion to a future draft.

5.1 Estimates of returns to graduate degrees pooling all institutions

Table 3 reports estimates of returns for 19 of the 222 degrees for which we have computed estimates. For each degree, we report estimates for the specification in which the return varies with years of postgraduate school experience and the specification in which it is constant. The column headings list the estimation procedure and the sample used.[11] We report OLS, FEcg and FE estimates on the full sample of college graduates (Columns 1-3). We also report estimates for the FEcg and FE models using only individuals who have attained a graduate degree (Table A1). As we noted above, the additional observations in the full sample contribute to identification of the time trends and the experience and age profiles. For the OLS and FEcg models, we control for age, gender, ethnicity, a vector of high school standardized test scores, high

[10] We create separate fixed effects for a given combination of application and admissions outcomes involving Texas public law schools for students who attend particular Texas private law schools. We could handle out of state schools that identify field of degree in the same way but have excluded them so far.

[11] The sample sizes are reported at the bottom of the table.

school curriculum, high school attendance rate, college GPA, college credits accumulated, and college major. We also control for economic disadvantage, as measured by whether the student qualified for free/reduced price meals in high school. In this draft we have excluded parental education and parental income because these variables are only present in certain years. Keep in mind that both FEcg and FE account for fixed unobserved student characteristics and that time invariant student characteristics drop out of the FE models. The equations also control for year fixed effects, a college major specific quadratic in age, and a gender-college major specific cubic in quarters of actual work experience.[12] We use forty-seven 2 digit CIP categories for the college major controls and interactions, and use 4 digit CIP categories for the graduate degrees. The OLS, FE, and FEcg estimates are from models that include all 222 graduate degrees, not just the 16 that are reported in the tables. We present estimates for additional 4 digit CIP graduate degrees in Figures 4 to 11.

We also report OLS-pw and FEcg-pw estimates using equation 5 and equation 5 with control for $G_{g(i)}$ added (columns 4 and 5). For a given graduate degree the sample consists of individuals who obtain that degree plus the "BA only" sample consisting of individuals who never get a graduate degree. [13]

Columns 6, 7, and 8 display OLS, FEcg and FE estimates of γ^g_{1-10}, the average return over the first 10 years of postgraduate school experience. Figures 12 and 13 display the corresponding experience profiles and display how returns to specific graduate degrees change over years after graduation.

We follow standard practice in labor economics and use the word "returns" to refer to the estimates of the effects of the degrees on log earnings. But it is important to keep in mind that the length of the programs vary substantially, from one year for many masters programs to four years for an MD or a Doctor of Dental Surgery. In a future draft, we will present internal rates of return These are likely to differ less across programs of different lengths than the effects on log earnings.

5.1.1 Computer Science, Engineering, and Architecture

The estimates for a degree in computer and information sciences, general (CIP 1101) are 0.136 (0.023) using OLS, 0.157 (0.038) using FEcg, and 0.103 (0.034) using FE. The estimates of average returns over the first 10 years using the specifications with experience interactions are similar. These estimates suggest a healthy return to a master's in computer sciences, assuming that the degree takes one year. The estimates for

[12]Appendix Table A1 reports estimates excluding the polynomials in actual experience but including gender-college major specific cubics in age. The OLS, FEcg and FE estimates all tend to be smaller. The issue of whether or not to control for actual experience is not straightforward. When we do not control, we are picking up net effects of the degree and the lost actual experience obtaining a degree entails.

[13]We checked whether the difference between OLS and OLS-pw is due to weighting or to the change in samples by applying OLS using the same samples used for OLS-pw but without weighting. The change in OLS is less than $|.01|$ except in the engineering fields, for which the OLS estimates drop by between .017 and .021. The difference in the FEcg estimates on the full sample and the samples used for FE-cg are less than $|.003|$ in absolute value with the exceptions of MD (.018), Pharmacy (.030) and nursing (.006).

electrical engineering follow the same pattern across estimators but are about 0.03 log points smaller. The returns to civil engineering and mechanical engineering are more sensitive to the estimation procedure. The OLS estimates are -0.006 (0.014) and 0.042 (0.017) respectively, while the FE and FEcg estimates are 0.148 (0.027) and 0.094 (0.027) for civil and 0.227 (0.044) and 0.125 (0.039) for mechanical. It is interesting that for all three of these technical degrees the largest estimate is obtained using FEcg. Computer engineering, which is different from computer sciences, has the highest OLS estimate among engineering programs at 0.146, but the FEcg and FE estimates are lower at 0.079 and 0.021. We estimate that Architecture graduate programs generate a modest return of 0.076 using OLS and a healthy return of 0.177 using FEcg and 0.19 using FE.

Columns 4 and 5 report OLS-pw and FEcg-pw estimates. The OLS estimates are smaller in three of the four cases. For example, the return to computer science falls from 0.136 to 0.092. The FEcg estimates also drop by about .05 and are fairly close to the FE.

The estimates of γ^g_{1-10} are similar to the estimates of γ^g for all three estimators for all 4 fields. However, there is some variation in the path of the returns. Going forward, we will only mention the γ_{1-10} estimates when they differ substantially from those of γ^g. Figure 12 display the FEcg postgraduate school experience profiles (γ^g_x) for each of the degrees.[14] We find that the estimate for computer science, civil engineering, and electrical engineering are relatively constant. However, the returns to computer engineering and mechanical engineering increase from around 0.06 to about 0.10 and from about 0.15 to about 0.25, respectively.

Figure 4 displays the returns to the set of degrees that are classified in the category Computer and Information Sciences and Support Services (CIP 11) for some of the degrees, The figure also displays 90% confidence interval bands around the estimates.The highest returns are for computer systems analysis (CIP 1105), Computer information technology administration and management (CIP 1110), and Computer and information sciences, general (CIP 1101) which is the degree that we discussed in detail. Perhaps surprisingly, the return to a masters in computer science (CIP 1104) is among the smallest in the category. Note that the standard errors of the estimates are fairly wide in a couple of cases, and the corresponding point estimates should be considered cautiously.

Figure 5 displays the returns to the full set of engineering degrees. Both the OLS and the FEcg estimates are related to the average earnings level for the degree, but the relationship is much stronger for OLS. This suggests that actual earnings prior to obtaining a graduate degree are lower than the counterfactual earnings implied by ordinary least squares for degrees such as biomedical engineering, architecture, and environmental

[14] Keep in mind that we imposed a quadratic functional form on the (γ^g_x)

engineering.

5.1.2 Psychology and Social Work

We report estimates for a master's in psychology, clinical psychology (i.e., counseling psychology) and social work. The OLS estimates are close to zero for all three of these degrees. However, FEcg and FE show a return of 0.087 (0.026) and 0.060 (0.032) respectively for psychology, about 0.040 for clinical psychology, and about 0.10 for social work. Note that AZ find an even larger gap between the FEcg and OLS estimates for a combined social work and psychology category and the OLS estimate.

The OLS-pw estimates are above the OLS estimates, ranging from 0.029 for psychology to 0.111 for social work. Propensity weighting increases the FEcg estimate for clinical psychology from 0.042 to 0.094, but makes little difference for the other degrees. Restricting the sample to individuals who obtain a graduate degree substantially reduces both the FEcg estimates and the FE estimates (columns 9 and 10).

The top-middle panel of Figure 13 displays the experience profile of the return to a clinical psychology degree. There is not much variation in the returns over time. The figure shows an initial increase from 0.03 to about 0.05 and then declines to 0.02. Some of the movement might be an artifact of the quadratic functional form restriction on γ_x^g and/or sampling error.

Placing more of the weight on FEcg and FE, the estimates point to a modest return to graduate degrees related to clinical psychology, counseling and social work. AZ show that these degrees lead to relatively low wage occupations, but also are obtained by people who were working in relatively low-paying occupations. One can see this in the statistics presented in Table 1, which displays the sample mean of earnings for the years prior to graduate school.

Figure 6 displays OLS and FEcg estimates for the six psychology-related 4-digit CIP degrees for which standard errors of the OLS and FEcg estimators are both less than 0.103. (Again, these standard errors do not account for clustering at the individual level). One can see that there is a substantial range in the estimates. FEcg is above OLS in all cases, and the estimates tend to be increasing in the average earnings of graduate degree holders.

5.1.3 Medicine, pharmacy, and nursing

Next we consider three key health-related degrees, beginning with an MD. Not surprisingly, we find very large returns to an MD. The OLS estimate is 0.638 (0.01). The FEcg estimate is substantially higher at 0.784 (0.02), while the FE estimate is 0.594 (0.03). The fact that the vast majority of medical school school graduates participate in relatively low-paying residency programs for several years after graduate school means that initial earnings will understate career earnings of MDs. The FE estimator places more weight on these observations because the identifying variation comes from individuals who are observed working both before and after medical school. Propensity score weighting (and change in the sample) reduces the OLS estimate to 0.545 and the FEcg estimate to 0.525.

When we allow the returns to depend upon years of postgraduate school experience, we obtain estimates of γ^g_{1-10} that are a bit below the estimates of γ^g. Interestingly, the FE estimate of γ^g_{1-10} rises to 0.738, which is close to the FEcg estimate. The narrowing of the gap between the two estimators may be due in part to the fact that γ^g_{1-10} weights the experience specific returns γ^g_x the same for the two estimators while $\hat{\gamma}^g$ reflects the sample distribution of the values of postgraduate school experience x. We graph the FEcg estimates of γ^g_x in Figure 12 (top-right panel). The returns rise dramatically with experience, from essentially zero in the first year to 1.4 after ten years.

The average returns for pharmacy, pharmaceutical sciences, and administration are broadly similar to the results for an MD, but are even larger (in log points) than the returns to an MD. The OLS, FEcg, and FE estimates are 0.751, 0.943, and 0.896. Propensity score weighting reduces these estimates by about 0.1 in the OLS and FEcg cases.

The return to a master's in nursing is more modest, but still substantial given that it requires less time. The OLS, FEcg and FE estimates are 0.377, 0.223, and 0.260, respectively. Propensity score weighting does not make much difference. It reduces OLS by about 0.02 and increases FEcg by 0.02. The estimates of γ^g_{1-10} are also similar.

Figure 7 displays estimates for a variety of degrees in the health professions and related programs category (CIP 51). Both OLS and FEcg increase with average earnings. The FEcg estimates range from a low of 0.17 for Dietetics to a high of 0.95 for Pharmacy. The FEcg estimates are higher than the OLS estimates in all cases except nursing.

5.1.4 Law (JD)

The OLS, FEcg and FE estimates of the return to a JD degree are 0.514, 0.565 and 0.453 respectively. Thus all three estimators point to a substantial return to a JD, even accounting for the fact that it is a three year course of study. We would expect the FE estimate to suffer from some downward bias to the extent that returns rise with time since graduate school, which is what we find (center-middle panel of Figure 13). The FEcg estimates of the experience profile of γ^g_x show an increase from 0.51 right after graduate school to 0.59 ten years out of law school. However, the estimates of γ^g and γ^g_{1-10} are very similar. Propensity score weighting has essentially no effect on the OLS estimate but leads to a modest increase in the FEcg estimate from 0.565 to 0.599.

5.1.5 MBA and other Business Degrees.

The OLS estimate of γ^g for an MBA degree is 0.235, which is well above the FEcg estimate of 0.156. The FE estimate is 0.194. In comparison, AZ obtained 0.282 (0.008) for OLS and 0.142 (0.021) for FEcg when they estimate on the full sample.When we follow AZ and exclude control for prior academic record and test scores the OLS estimate rises to 0.265. Propensity score weighting reduces the OLS estimates to 0.200 and leads to a smaller reduction in FEcg.

The estimates of γ^g_{1-10} are similar to the estimates of γ^g. The left-middle panel of Figure 13 shows that the return to an MBA rises from about 0.141 to about 0.171 ten years out of business school, displaying a modest increase in the return over time.

Figure 8 displays OLS and FEcg estimates of γ^g for 15 different business related masters degrees. Keep in mind that they are arranged from left to right in increasing order of average earnings. We find substantial differences across the degrees in returns, and these differences are positively related to average earnings levels. For example, the FEcg estimates of the return to a Masters in sales and marketing is only about 0.08, while the return to a Masters in finance is 0.250. It is possible that the length of time required to obtain these degrees varies, and that might be a factor in the differences in returns. We will investigate this in future draft. The relationship between average earnings and $\hat{\gamma}_g$ is weaker for the FEcg estimates, which tends to be below OLS.

5.1.6 Education and Education Administration

The return to a masters in curriculum and instruction, the most popular of the education related masters degrees, is small regardless of which estimator we use. This finding contrasts with AZ's results. They obtain 0.188 using FEcg and 0.102 using OLS. Salary schedules in many teacher contracts include a masters premium, so we would have expected a somewhat larger estimate than the one that we obtain.

Table 3 also reports estimates for Education Administration. The OLS estimates are around 0.070 (0.070) and the FEcg and FEcg-pw values and 0.054 (0.003) and 0.079 (0.003).

Figure 9 displays OLS and FEcg estimates for ten of the 4-digit CIP codes within the education category. The FEcg estimates are clustered around 0.03. The FEcg estimates are highest for special education, 0.056, and education administration, 0.052.

5.1.7 Public Administration

We focus on a masters in public administration (MPA, CIP 4404). The OLS estimate is 0.106 (0.005), while FEcg and FE are substantially higher: 0.168 (0.013) and 0.150 (0.012) respectively. The corresponding estimates of γ^g_{1-10} are similar, although the FE estimate moves toward the FEcg estimate. Propensity score weighting does not make much difference. Overall, the estimate suggests healthy return to an MPA, especially if one places more weight on FEcg.

Figure 10 displays OLS and FEcg estimates of γ^g for the 6 degrees that are classified in the Public administration two digit CIP category. (Social Work falls in this category, so we include it in the figure even though we discussed it along with psychology.) The highest return is to a masters in Public policy analysis. For that degree, the OLS, FEcg, and FE estimates are 0.188, 0.265, and 0.186 respectively.

5.1.8 Arts and Humanities

Figure 11 reports OLS and FEcg estimates of the return to a masters in Fine Arts, History, Music, Philosphy, and English. The FEcg estimates are clustered around 0. The OLS estimates are negative for all degrees except Music and average about -0.10.

5.1.9 Sensitivity of OLS to Controls for College Major, High School Record and Test scores, and College GPA

We are not aware of any other large US data sets that contain detailed information about prior academic record, test scores as well as college major. (The NSCG/NSRCG data used by AZ does have information about college major and information about GPA for a small part of the sample.) When we exclude controls for high school record, test scores and college GPA, the OLS estimates of the return to an MD and a JD rise by 0.112 and 0.08 respectively (not reported). The value for an MBA rises by 0.03. The return rises by between .032 and .059 for computer science and the engineering degrees that we've discussed. When the college major controls are also excluded, the OLS estimates typically rise by a small amount. The increase is largest for mechanical engineering (0.027). We conclude that failure to control for prior academic record and test scores can lead to substantial bias in OLS estimates of returns even if college major is controlled for.

5.2 Differences in Returns by Demographic Group and College GPA

In this section we present estimates by gender and by race/ethnic groups. we also examine how the estimates vary with college GPA.

5.2.1 Results for Males and Females

Table 4 presents OLS and FEcg estimates of γ^g for males and females separately. The FEcg estimates of the returns are higher for females in every case with the exception of electrical and computer engineering (heavily male fields), nursing (a heavily female field), and biology. The returns to a JD, MD and an MBA are all higher for women by 0.022, 0.026, and 0.011 respectively. The gap is particularly large for computer science, civil engineering, and psychology. In the latter case, the estimate is 0.118 for females and -0.014 for males. If one uses the graduate degree shares for men and women combined to construct an average return for FEcg, the value is 0.202 for females and 0.167 for males.

The fixed effects estimates also show gaps in favor of females for most degrees. We plan to examine gender differences in the implied counterfactual earnings of men and women and also explore the effects of obtaining a graduate degree on industry of employment as well as employment rates.

5.2.2 Results for Blacks, White Non Hispanics, Asians, and Hispanics

Column 1 and 2 of Table 5 presents OLS and FEcg estimates of returns for African Americans. We focus on the FEcg estimates, although sign of the difference across groups depends on the estimator to some extent. Columns 3 and 4 report results for white non-Hispanics. Columns 5 and 6 report results for Asians, and columns 7 and 8 report results for Hispanics. Standard error are fairly large for African Americans for the engineering degrees and computer science, which should be kept in mind. African Americans receive substantially larger returns to education and the engineering degrees. They receive substantially lower returns to a JD, a masters in psychology, an MD, and a nursing degree. They receive about the same return to a Masters in social work and to an MBA.

Hispanics receive substantially larger returns to engineering degrees and to MD. They receive substantially lower returns to a JD.

Asians receive substantially lower returns than whites to most degrees. The gaps are particularly wide in engineering. For example, the return to mechanical engineering is 0.191 for non-Hispanic whites and -0.013

Asians. for civil engineering the values are 0.153 (0.036) and -0.044 (0.064). Asians also receive substantially lower returns to JD, psychology, social work, pharmacy, and nursing degrees. . We are puzzled by these results and will investigate further in a future draft.

5.2.3 The effect of GPA on returns

Table 6 estimates of the coefficientγ_1^g on the interaction between $G_{g(i)t}$ and college GPA_i. (We do not have data on graduate school GPA.) The interactions represent the effect of a one-point increase in GPA compared to the average college GPA of graduate degree holders, which is 2.99. The standard deviation of GPA varies by graduate field but a typical value is about 0.5. The effect of GPA varies quite a bit across fields. The FEcg coefficient estimates are -0.074 (0.010) for curriculum and instruction, -0.053 (0.006) for education administration, -0.048 for clinical psychology, and about -0.05 for the health related degrees. Positive interactions are more likely for the highest paying fields. It is large and positive (0.173) for a JD degree and (0.113) for a mechanical engineering. Part of effect for a JD degree may be the return to attending a higher quality law school, which we document in Section 5.3. The interaction is only 0.022 (0.008) for an MBA.

We should point out that the size of the interaction varies somewhat across estimation procedures.

5.3 Estimates by Program Rank

In this section we explore the effects of program rank on returns for a subset of fields — MBA, JD, Nursing, PharmD, Social Work, and Psychology. These are the graduate degrees for which there are significant numbers of ranked graduate programs in Texas. We examine the effect of program rank on returns in two steps. First, we estimate school specific returns to each degree using FEcg following the specification in section 4.4. Second, we calculate each graduate program's average ranking using the Us News and World Report rankings for various years. As discussed in section 2, we only use programs that have non-missing ranking for at least one year. We then estimate regressions of the school-specific returns on average rankings.

Returns to degrees are larger for higher ranking programs for MBA and JD programs. In the MBA case, the return increases by 0.021 for a 10-spot increase in program ranking. In comparison the average return to and MBA is 0.156. Thus, a 10-spot increase in program ranking increases returns to MBA by around 13%. The coefficient is significant at the 5% level. We find that the average of estimates of the returns to the unranked MBA programs in the sample is negative: -0.14.

The returns to a JD increases by 0.026 for a 10-spot increase in program ranking. In comparison the average returns to JD is 0.566. A 10-spot increase corresponds to a 5% increase in returns. The coefficient is significant at the 1% level.

In comparison, the returns to nursing, social work, and psychology are not significantly related to program ranking, and the return to PharmD is in fact higher for lower ranking programs.

We also produce estimates taking advantage of the fact that we observe whether an individual has applied to a JD program. This permits us to expand the sample to include individuals who have applied to JD programs but have not attained JD degrees. We then repeat the procedure as above. Using this empirical specification and sample selection, we estimate that a 10-spot increase in program ranking increases returns to JD by 0.022 , which is very close to our original estimate.

One potential explanation for the significant value of higher ranking programs for MBA and JD graduates compared to the lack thereof for the other programs, is that a large share of graduates from MBA and JD programs enter professional services occupations, where prestige and pedigree may be more highly valued. In future drafts, we will further investigate the root cause of this discrepancy between fields.

5.4 Returns to Graduate Degrees by Undergraduate Major

We are in the preliminary stage of estimating models that allow the return to a specific advanced degree to depend on the undergraduate major. We separately estimate the FEcg model for students who obtain college degrees in 10 broad categories of college majors, although we plan to explore use of more disaggregated categories in a future draft.

Table 7 reports preliminary FEcg estimates by college major categories. We do not report estimates with standard errors in excess of 0.08. There is a tendency for the return to an MBA, a JD, and MD, which have high average earnings, to be larger for lower paying college majors.

6 Conclusion / Research Agenda

Our results are still preliminary, and so it seems more appropriate to conclude with a research agenda. First, we will complete the analysis of the return to specific graduate degrees by college major. Second, we will check robustness to controlling for undergraduate institution. Third, we will examine internal rates of return and the net present discounted value to some of the key degrees, using the data to identify typical program length. Because people are only observed up to about 18 to 20 years after completing graduate school, we will have to make assumptions about the shape of the experience profile of returns to graduate school beyond that value. Fourth, we will explore the structure of the relationship among the alternative estimators of γ^g and γ^g_c that we use. Fifth, we will examine the contribution of detailed industry to the return to graduate education.

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Tables and Figures

Table 1: Summary Statistics — Earnings and Academic Performance

Grad Program	Wage		Premium		High School Test Score		College
	Pre Grad	Post Grad	College	Industry	Math	Reading	GPA
Clinical Psychology	46372.96	54307.72	0.00	-0.01	75.99	76.11	3.11
Social Work	41467.92	55304.36	-0.04	0.01	74.46	74.83	3.14
Curriculum and Instruction	47764.48	58578.76	0.02	-0.01	78.28	77.55	3.14
Psychology	42487.48	60966.88	-0.03	-0.01	79.34	79.15	3.15
Edu Admin	49390.36	68711.32	0.02	-0.01	78.68	76.57	3.02
Mathematics	50313.88	68906.24	0.11	-0.01	88.56	82.23	3.32
Biology	41103.20	70323.88	0.13	0.03	82.47	81.58	3.16
Architecture	46184.00	70373.28	0.05	0.10	83.12	79.19	3.20
MPA	52132.80	77285.72	0.05	0.04	76.91	77.89	3.02
Nursing	70140.64	105347.08	0.21	0.15	81.00	80.11	3.31
CS	69903.52	108771.92	0.25	0.18	89.47	85.36	3.37
MBA	71815.80	109902.60	0.16	0.17	82.61	79.90	3.07
Civil	63717.40	110127.36	0.43	0.18	89.12	83.91	3.27
Computer Engineer	80264.00	111738.88	0.35	0.22	89.17	84.44	3.33
Mech	70182.72	116761.52	0.44	0.23	89.06	83.41	3.32
Elec	82840.92	129746.24	0.43	0.25	89.13	83.42	3.35
JD	55438.80	129818.00	0.08	0.23	86.93	87.80	3.38
PharmD	50040.68	129885.40	0.14	0.08	88.00	82.83	3.33
MD	46966.56	178923.80	0.14	0.15	91.87	89.25	3.69
All College Grad	77449.78	-	0.10	0.09	79.26	77.38	2.98

Notes: This table reports the summary statistics related to students' earnings and academic performances by the type of graduate degrees attained. Average college and industry premiums are calculated by taking the sample average for each graduate degree of the college and industry premiums. These are the coefficient estimates of college and industry dummies in ln earnings regressions as specified in Section 3. High school math and reading scores are measured by students' percentile rankings in Texas state's senior year standardized exams.

Table 2: Summary Statistics — Demographics

Grad Program	Share					
	Female	Asian	African American	Hispanic	Anglo	Free/ Reduced Meal
Clinical Psychology	0.87	0.02	0.19	0.20	0.59	0.17
Social Work	0.90	0.03	0.18	0.24	0.55	0.20
Curriculum and Instruction	0.86	0.02	0.10	0.35	0.53	0.18
Psychology	0.76	0.04	0.12	0.25	0.59	0.16
Edu Admin	0.69	0.01	0.14	0.28	0.57	0.17
Mathematics	0.48	0.06	0.05	0.27	0.62	0.09
Biology	0.57	0.06	0.06	0.21	0.67	0.14
Architecture	0.30	0.05	0.06	0.20	0.69	0.11
MPA	0.55	0.02	0.17	0.31	0.50	0.21
Nursing	0.86	0.07	0.12	0.19	0.62	0.15
CS	0.20	0.22	0.02	0.14	0.63	0.12
MBA	0.46	0.09	0.12	0.19	0.60	0.12
Civil	0.23	0.07	0.02	0.19	0.72	0.14
Computer Engineer	0.17	0.27	0.04	0.14	0.54	0.13
Mech	0.13	0.05	0.03	0.22	0.71	0.15
Elec	0.14	0.25	0.04	0.17	0.55	0.14
JD	0.47	0.06	0.07	0.16	0.71	0.06
PharmD	0.64	0.33	0.09	0.17	0.41	0.16
MD	0.48	0.24	0.05	0.16	0.54	0.09
All College Grad	0.59	0.06	0.09	0.23	0.62	0.15

Notes: This table presents the demographic composition of the main graduate programs of interest. The share of each ethnicity group is the share out of the four main ethnicity groups — African American, Anglo, Asian, Hisanic. International students are not included in any of these categories. Share of free/reduced meal students is calculated using students' high school records.

Table 3: Average Returns to Graduate Degrees

Dependent Variable	Log Quarterly Wage							
	Additive Model					With Post-Adv Exp Interaction		
Specification	OLS	FEcg	FE	OLS PS	FEcg PS	OLS 1-10 Yrs	FEcg 1-10 Yrs	FE 1-10 Yrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Clinical Psychology	0.009	0.040	0.042	0.052	0.094	0.008	0.041	0.041
	(0.006)	(0.007)	(0.006)	(0.009)	(0.011)	(0.009)	(0.010)	(0.009)
Social Work	0.041	0.111	0.097	0.111	0.117	0.043	0.114	0.092
	(0.005)	(0.008)	(0.009)	(0.009)	(0.010)	(0.005)	(0.008)	(0.009)
Curriculum & Instruction	0.032	0.019	-0.005	0.076	0.029	0.027	0.016	-0.024
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
Psychology	-0.010	0.087	0.060	0.029	0.098	-0.008	0.093	0.064
	(0.019)	(0.026)	(0.032)	(0.019)	(0.027)	(0.018)	(0.025)	(0.033)
Edu Admin	0.070	0.054	0.033	0.115	0.079	0.073	0.058	0.032
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mathematics	-0.084	0.023	-0.061	-0.102	0.021	-0.083	0.026	-0.059
	(0.020)	(0.023)	(0.024)	(0.031)	(0.034)	(0.020)	(0.023)	(0.025)
Biology	-0.006	0.130	0.112	-0.016	0.151	-0.010	0.157	0.168
	(0.017)	(0.026)	(0.031)	(0.019)	(0.028)	(0.015)	(0.025)	(0.032)
Architecture	0.076	0.177	0.19	0.069	0.179	0.075	0.177	0.196
	(0.009)	(0.019)	(0.023)	(0.013)	(0.023)	(0.009)	(0.019)	(0.024)
MPA	0.106	0.168	0.150	0.110	0.187	0.107	0.172	0.168
	(0.010)	(0.0127)	(0.012)	(0.014)	(0.017)	(0.010)	(0.013)	(0.013)
Nursing	0.377	0.223	0.260	0.355	0.249	0.394	0.242	0.293
	(0.007)	(0.008)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)
CS	0.136	0.157	0.103	0.092	0.104	0.140	0.164	0.107
	(0.023)	(0.038)	(0.034)	(0.028)	(0.043)	(0.021)	(0.038)	(0.035)
MBA	0.235	0.156	0.194	0.194	0.132	0.238	0.162	0.210
	(0.004)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
Civil	-0.006	0.148	0.094	-0.071	0.086	-0.012	0.147	0.098
	(0.014)	(0.027)	(0.027)	(0.017)	(0.030)	(0.014)	(0.027)	(0.027)
Computer Engineering	0.146	0.079	0.021	0.127	0.008	0.146	0.080	0.018
	(0.024)	(0.033)	(0.032)	(0.031)	(0.040)	(0.023)	(0.033)	(0.033)
Mechanical Engineering	0.042	0.227	0.125	0.010	0.164	0.042	0.231	0.127
	(0.017)	(0.044)	(0.039)	(0.020)	(0.047)	(0.017)	(0.043)	(0.040)
Electrical Engineering	0.124	0.141	0.072	0.052	0.109	0.117	0.139	0.072
	(0.014)	(0.021)	(0.023)	(0.018)	(0.025)	(0.013)	(0.021)	(0.023)
JD	0.514	0.565	0.453	0.498	0.599	0.514	0.568	0.464
	(0.008)	(0.012)	(0.015)	(0.013)	(0.021)	(0.007)	(0.012)	(0.015)
PharmD	0.751	0.943	0.896	0.644	0.880	0.746	0.971	0.893
	(0.010)	(0.020)	(0.023)	(0.016)	(0.026)	(0.010)	(0.020)	(0.024)
MD	0.638	0.784	0.594	0.545	0.525	0.578	0.761	0.738
	(0.009)	(0.019)	(0.033)	(0.019)	(0.029)	(0.007)	(0.018)	(0.029)
Sample Size	15664350	15664350	15664350	*	*	15664350	15664350	15664350

Notes: This table reports the average returns estimates using various estimation strategies. Robust standard errors are clustered at the individual level, and are reported in parentheses. All OLS and FEcg specifications control for a cubic in age, gender, ethnicity, a vector of high school standardized test scores, high school curriculum, high school attendance rate, college GPA, college credits accumulated, and economic disadvantage status, as measured by whether the student qualified for free / reduced price meals in high school. In all specifications, the effect of age is college major specific. The labor market experience profile is a cubic and with separate major specific profiles for men and women. Regressions reported in columns (1)-(3) and columns (6)-(8) use the full sample of individuals who have a college degree and have non-missing values for all control variables. Columns (4) and (5) present propensity score weighted regression results, so these estimates are not from a single regression. Rather, each estimate comes from a separate regression that uses the sample of holders of that particular degree and individuals who have no graduate degrees.

Table 4: Gender Heterogeneity in Returns fo Graduate Degrees

Dependent Variable	Log Quarterly Wage			
Gender	Female		Male	
Specification	OLS	FEcg	OLS	FEcg
	(1)	(2)	(3)	(4)
Clinical Psychology	0.022	0.051	-0.049	0.024
	(0.006)	(0.007)	(0.021)	(0.026)
Social Work	0.059	0.119	-0.116	0.090
	(0.006)	(0.008)	(0.018)	(0.027)
Curriculum & Instruction	0.056	0.030	-0.077	0.002
	(0.005)	(0.006)	(0.015)	(0.027)
Psychology	0.014	0.118	-0.086	-0.014
	(0.022)	(0.027)	(0.032)	(0.050)
Edu Admin	0.105	0.068	-0.010	0.027
	(0.003)	(0.003)	(0.006)	(0.006)
Mathematics	-0.019	0.024	-0.149	-0.002
	(0.026)	(0.029)	(0.030)	(0.036)
Biology	0.033	0.110	-0.076	0.141
	(0.021)	(0.031)	(0.028)	(0.044)
Architecture	0.135	0.182	0.034	0.161
	(0.015)	(0.034)	(0.012)	(0.024)
MPA	0.130	0.171	0.069	0.163
	(0.013)	(0.015)	(0.018)	(0.022)
Nursing	0.371	0.220	0.456	0.290
	(0.008)	(0.009)	(0.023)	(0.024)
CS	0.217	0.270	0.117	0.110
	(0.050)	(0.078)	(0.025)	(0.042)
MBA	0.238	0.160	0.226	0.149
	(0.005)	(0.006)	(0.006)	(0.006)
Civil	-0.015	0.250	-0.010	0.108
	(0.033)	(0.067)	(0.016)	(0.030)
Computer Engineering	0.145	0.018	0.138	0.084
	(0.051)	(0.091)	(0.027)	(0.037)
Mechanical Engineering	0.040	0.254	0.031	0.204
	(0.055)	(0.118)	(0.018)	(0.046)
Electrical Engineering	0.216	0.035	0.102	0.137
	(0.040)	(0.043)	(0.015)	(0.023)
JD	0.553	0.577	0.465	0.545
	(0.011)	(0.017)	(0.011)	(0.017)
PharmD	0.757	0.939	0.715	0.940
	(0.013)	(0.027)	(0.015)	(0.028)
MD	0.693	0.784	0.569	0.758
	(0.011)	(0.025)	(0.013)	(0.028)

Notes: This table reports the average returns estimates for the female and male samples separately, using FEcg and FE specifications. Robust standard errors are clustered at the individual level, and are reported in parentheses. All FEcg specifications control for age, ethnicity, a vector of high school standardized test scores, high school curriculum, high school attendance rate, college GPA, college credits accumulated, and economic disadvantage status, as measured by whether the student qualified for free / reduced price meal in high school. In all specifications, the effect of age is college major specific. The labor market experience profile is also college major specific.

Table 5: Race and Ethnic Group Heterogeneity in Returns to Graduate Degrees

Dependent Variable	Log Quarterly Wage							
Ethnicity	African American		Anglo		Asian		Hispanic	
Specification	OLS	FEcg	OLS	FEcg	OLS	FEcg	OLS	FEcg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Clinical Psychology	0.040	0.038	-0.008	0.052	-0.074	-0.004	0.050	0.038
	(0.012)	(0.013)	(0.008)	(0.009)	(0.038)	(0.056)	(0.013)	(0.014)
Social Work	0.082	0.123	0.008	0.110	0.006	0.031	0.085	0.129
	(0.012)	(0.016)	(0.009)	(0.012)	(0.031)	(0.047)	(0.009)	(0.013)
Curriculum & Instruction	0.084	0.014	0.013	0.023	-0.041	-0.072	0.065	0.015
	(0.014)	(0.018)	(0.007)	(0.008)	(0.027)	(0.028)	(0.007)	(0.010)
Psychology	-0.005	0.023	-0.001	0.167	-0.226	-0.041	0.002	0.062
	(0.035)	(0.050)	(0.028)	(0.041)	(0.115)	(0.156)	(0.027)	(0.043)
Edu Admin	0.132	0.065	0.043	0.052	0.022	0.005	0.116	0.061
	(0.007)	(0.008)	(0.004)	(0.004)	(0.022)	(0.027)	(0.005)	(0.006)
Mathematics	0.155	0.203	-0.098	0.005	-0.153	0.032	-0.025	0.024
	(0.070)	(0.095)	(0.027)	(0.032)	(0.091)	(0.124)	(0.029)	(0.031)
Biology	-0.053	0.030	-0.001	0.133	-0.051	0.264	0.034	0.149
	(0.065)	(0.103)	(0.022)	(0.035)	(0.055)	(0.074)	(0.032)	(0.048)
Architecture	0.108	0.112	0.073	0.170	0.064	0.302	0.067	0.137
	(0.033)	(0.093)	(0.011)	(0.023)	(0.052)	(0.102)	(0.019)	(0.039)
MPA	0.106	0.153	0.135	0.184	-0.099	-0.094	0.102	0.163
	(0.021)	(0.029)	(0.015)	(0.021)	(0.072)	(0.084)	(0.018)	(0.020)
Nursing	0.365	0.097	0.390	0.256	0.289	0.186	0.373	0.218
	(0.020)	(0.022)	(0.010)	(0.011)	(0.025)	(0.029)	(0.014)	(0.016)
CS	0.079	-0.172	0.130	0.180	0.054	0.087	0.240	0.220
	(0.089)	(0.076)	(0.030)	(0.055)	(0.056)	(0.058)	(0.047)	(0.078)
MBA	0.219	0.140	0.244	0.160	0.203	0.135	0.209	0.147
	(0.011)	(0.012)	(0.005)	(0.006)	(0.012)	(0.014)	(0.008)	(0.010)
Civil	0.248	0.541	-0.032	0.153	-0.099	-0.044	0.074	0.207
	(0.090)	(0.108)	(0.016)	(0.036)	(0.042)	(0.064)	(0.042)	(0.057)
Computer Engineering	0.071	-0.057	0.122	0.065	0.168	-0.121	0.234	0.275
	(0.127)	(0.110)	(0.029)	(0.038)	(0.055)	(0.055)	(0.081)	(0.090)
Mechanical Engineering	-0.104	0.167	0.047	0.191	-0.002	-0.013	0.054	0.329
	(0.170)	(0.174)	(0.022)	(0.049)	(0.060)	(0.125)	(0.031)	(0.081)
Electrical Engineering	0.280	0.288	0.110	0.152	0.101	0.029	0.183	0.222
	(0.108)	(0.118)	(0.017)	(0.025)	(0.030)	(0.040)	(0.034)	(0.068)
JD	0.369	0.397	0.540	0.593	0.422	0.455	0.441	0.502
	(0.028)	(0.037)	(0.009)	(0.015)	(0.028)	(0.041)	(0.019)	(0.027)
PharmD	0.699	0.893	0.734	0.932	0.605	0.790	0.870	1.115
	(0.032)	(0.068)	(0.016)	(0.029)	(0.018)	(0.042)	(0.023)	(0.036)
MD	0.679	0.678	0.665	0.824	0.452	0.645	0.698	0.823
	(0.033)	(0.062)	(0.012)	(0.027)	(0.018)	(0.043)	(0.020)	(0.047)

Notes: This table reports the average returns estimates for the main ethnicity categories separately, using FEcg and FE specifications. Robust standard errors are clustered at the individual level, and are reported in parentheses. All FEcg specifications control for a cubic in age, gender, a vector of high school standardized test scores, high school curriculum, high school attendance rate, college GPA, college credits accumulated, and economic disadvantage status, as measured by whether the student qualified for free / reduced price meal in high school. In all specifications, the effect of age is college major specific. The labor market experience profile (a cubic) is also college major specific, with separate major specific profiles for men and women.

Table 6: The Effect of GPA on the Return to Graduate Degree

Dependent Variable	Log Quarterly Wage	
Specification	OLS (1)	FEcg (2)
Clinical Psychology # GPA	-0.033 (0.013)	-0.048 (0.012)
Social Work # GPA	-0.067 (0.011)	-0.066 (0.011)
Curriculum and Instruction # GPA	-0.049 (0.010)	-0.074 (0.010)
Psychology # GPA	-0.007 (0.041)	-0.004 (0.029)
Edu Admin # GPA	-0.029 (0.006)	-0.053 (0.006)
Mathematics # GPA	-0.044 (0.039)	-0.033 (0.039)
Biology # GPA	0.014 (0.035)	-0.013 (0.033)
Architecture # GPA	-0.002 (0.019)	-0.008 (0.019)
MPA # GPA	-0.005 (0.019)	-0.012 (0.019)
Nursing # GPA	-0.058 (0.018)	-0.056 (0.018)
Computer Sciences # GPA	0.028 (0.050)	0.038 (0.044)
MBA # GPA	0.016 (0.008)	0.022 (0.008)
Civil Engineering # GPA	0.005 (0.038)	0.014 (0.036)
Computer Engineering # GPA	-0.011 (0.060)	-0.012 (0.056)
Mechanical Engineering # GPA	0.098 (0.040)	0.113 (0.039)
Electrical Engineering # GPA	-0.002 (0.032)	-0.002 (0.030)
JD # GPA	0.180 (0.018)	0.173 (0.018)
PharmD # GPA	-0.042 (0.026)	-0.041 (0.026)
MD # GPA	-0.040 (0.029)	-0.044 (0.028)

Notes: This table reports the estimates of γ_1^g, the effect of GPA has on return to graduate degree g, using OLS, FEcg, and FE specifications. See (10) and (11). International students are excluded. Robust standard errors are clustered at the individual level, and are reported in parentheses. All OLS and FEcg specifications control for age, gender, ethnicity, a vector of high school standardized test scores, high school curriculum, high school attendance rate, college GPA, college credits accumulated, and economic disadvantage status, as measured by whether the student qualified for free / reduced price meal in high school. In all specifications, the effect of age is college major specific. The labor market experience profile is also college major specific, with separate major specific profiles for men and women. The regressions reported use the full sample of individuals who have a college degree and have non-missing values for all control variables.

Table 7: Returns to Graduate Degrees by College Major Areas

	College Major Area									
Grad Program	Engineer	CS	Comm	Humanities	Edu	Social Sciences	Natural Sciences	Health	Fine Arts	Business
Clinical Psych	-0.054	-	-0.013	0.012	0.085	0.090	-0.113	0.132	-0.048	-0.040
	(0.027)	-	(0.019)	(0.011)	(0.021)	(0.007)	(0.025)	(0.022)	(0.023)	(0.017)
Education	0.134	0.069	0.115	0.012	0.104	0.019	-0.068	0.037	0.076	0.006
(Curriculum)	(0.028)	(0.059)	(0.018)	(0.008)	(0.015)	(0.011)	(0.012)	(0.031)	(0.021)	(0.014)
Edu Admin	-0.007	0.034	0.018	0.051	0.093	0.042	-0.008	0.119	0.022	0.017
	(0.011)	(0.044)	(0.009)	(0.005)	(0.008)	(0.006)	(0.008)	(0.013)	(0.008)	(0.006)
Biology	0.209	-	-	-0.021	-	-0.007	0.144	0.018	-	-
	(0.069)	-	-	(0.075)	-	(0.053)	(0.012)	(0.057)	-	-
Architecture	0.159	-	0.343	0.285	-	0.208	-	-	0.464	0.056
	(0.013)	-	(0.052)	(0.069)	-	(0.055)	-	-	(0.050)	(0.060)
MPA	0.191	-	0.131	0.163	-	0.219	0.186	0.064	0.229	-
	(0.032)	-	(0.020)	(0.016)	-	(0.009)	(0.037)	(0.030)	(0.044)	-
Nursing	0.178	-	0.482	0.290	0.623	0.389	0.235	0.242	-0.144	0.357
	(0.056)	-	(0.061)	(0.040)	(0.076)	(0.021)	(0.018)	(0.003)	(0.078)	(0.036)
MBA	0.111	0.066	0.193	0.215	0.271	0.235	0.229	0.162	0.258	0.118
	(0.005)	(0.011)	(0.008)	(0.008)	(0.026)	(0.005)	(0.008)	(0.009)	(0.016)	(0.002)
Computer	0.126	-0.009	-	-	-	-	0.089	-	-	-
Engineering	(0.025)	(0.022)	-	-	-	-	(0.061)	-	-	-
Mechanical	0.197	-	-	-	-	-	0.256	-	-	-
Engineering	(0.015)	-	-	-	-	-	(0.063)	-	-	-
Electrical	0.107	0.065	-	0.698	-	-	0.282	-	-	-
Engineering	(0.010)	(0.029)	-	(0.078)	-	-	(0.052)	-	-	-
JD	0.426	0.484	0.663	0.631	0.758	0.583	0.556	0.474	0.660	0.522
	(0.016)	(0.033)	(0.015)	(0.010)	(0.062)	(0.008)	(0.022)	(0.056)	(0.028)	(0.009)
PharmD	0.889	0.739	1.245	1.084	-	1.262	0.965	0.810	-	0.817
	(0.040)	(0.065)	(0.074)	(0.062)	-	(0.057)	(0.012)	(0.037)	-	(0.031)
MD	0.472	0.752	-	0.750	-	0.967	0.800	0.716	0.808	0.695
	(0.023)	(0.070)	-	(0.029)	-	(0.032)	(0.011)	(0.035)	(0.057)	().035)
Average	0.224	0.178	0.342	0.331	0.322	0.374	0.280	0.277	0.351	0.272

Note: This table reports the returns to graduate degrees for separate college major categories, using FEcg specification. Each column is estimated using FEcg on the subsample of individuals who have college degrees in the corresponding category. Engineer includes engineering subfields and architecture; CS includes computer sciences majors; Comm includes communication majors; Humanities include gender studies, language and linguistics, english, liberal arts, philosophy, theology, and history majors; Edu includes education subfields; Social Sciences include law, psychology, public administration, and social sciences majors; Natural Sciences include biology, mathematics, and physics majors; Health include all health-related majors; Fine Arts include all visual and performing arts majors; and Business includes all business, management, and related majors. Robust standard errors are clustered at the individual level, and are reported in parentheses. All specifications control for age, gender, ethnicity, a vector of high school standardized test scores, high school curriculum, high school attendance rate, college GPA, college credits accumulated, and economic disadvantage status, as measured by whether the student qualified for free / reduced price meal in high school. In all specifications, the effect of age is college major specific. The labor market experience profile is also college major specific, with separate major specific profiles for men and women.

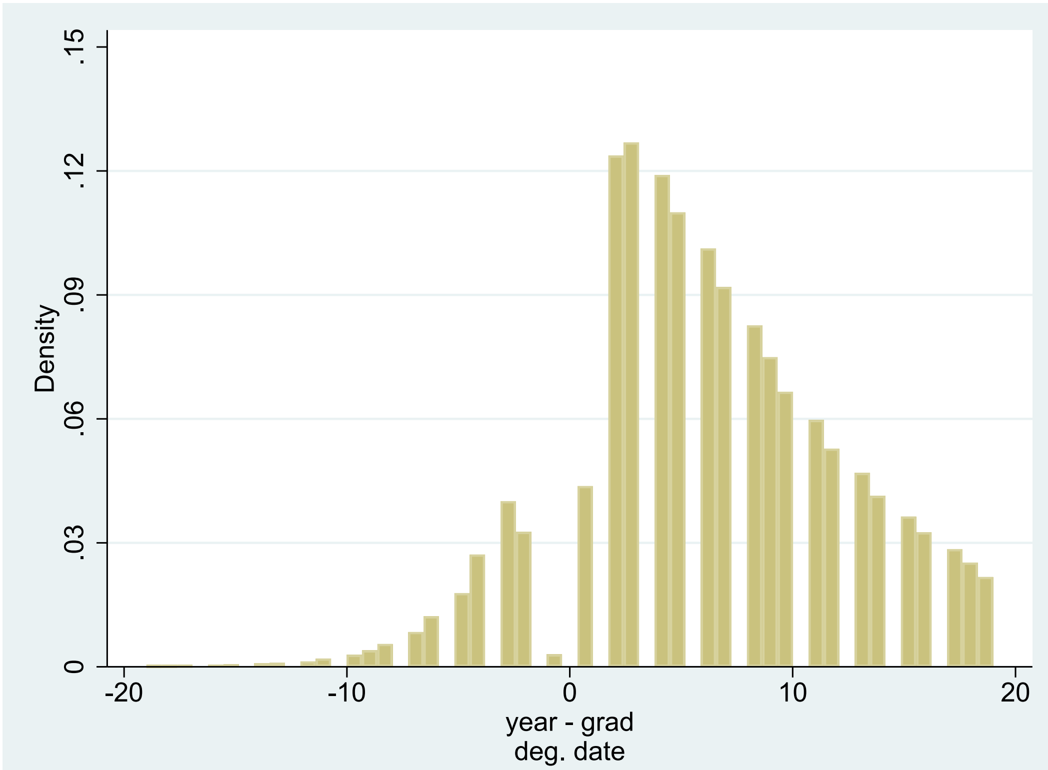

Figure 1: Distribution of Year -Minus Graduate Year in the Regression Sample — JD Degree Holders

Notes: This figure shows the distribution of the time between each wage observation and the year of graduate degree attainment for those who obtain a JD degree and for whom we also know undergraduate major.

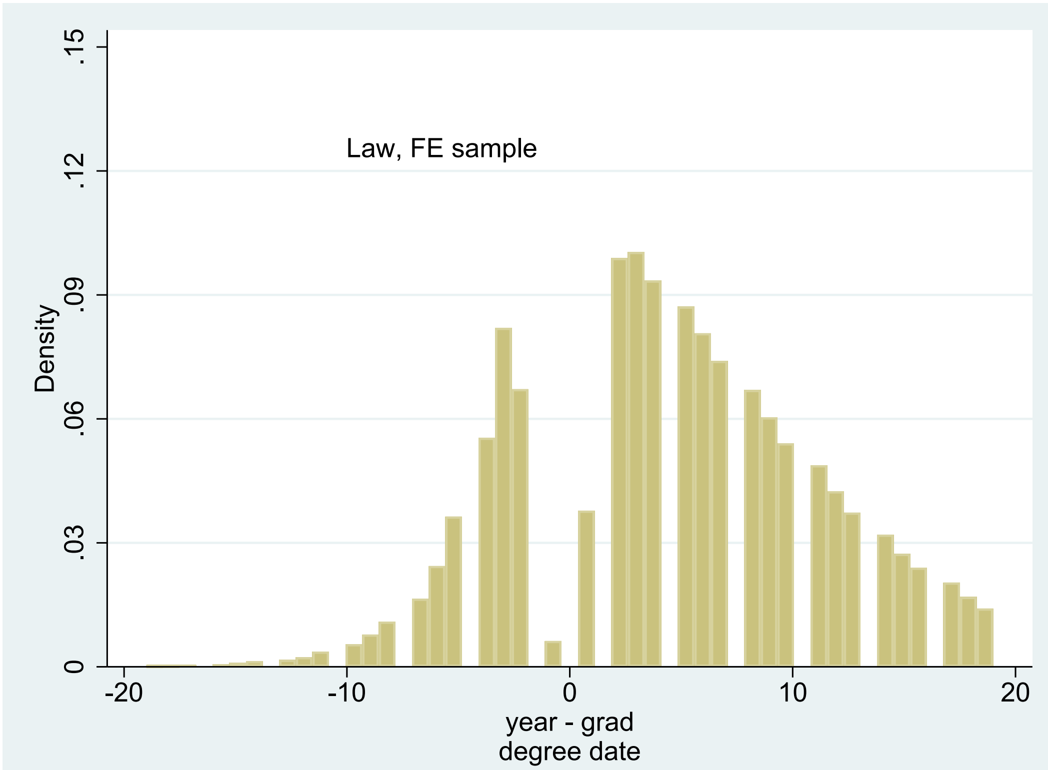

Figure 2: Distribution of FE Sample Around Graduation — JD Degree Holders

Notes: This figure shows the distribution of the time between each wage observation and graduate degree attainment for JD degree holders for whom we also know their undergraduate major and observe both before and after graduate school.

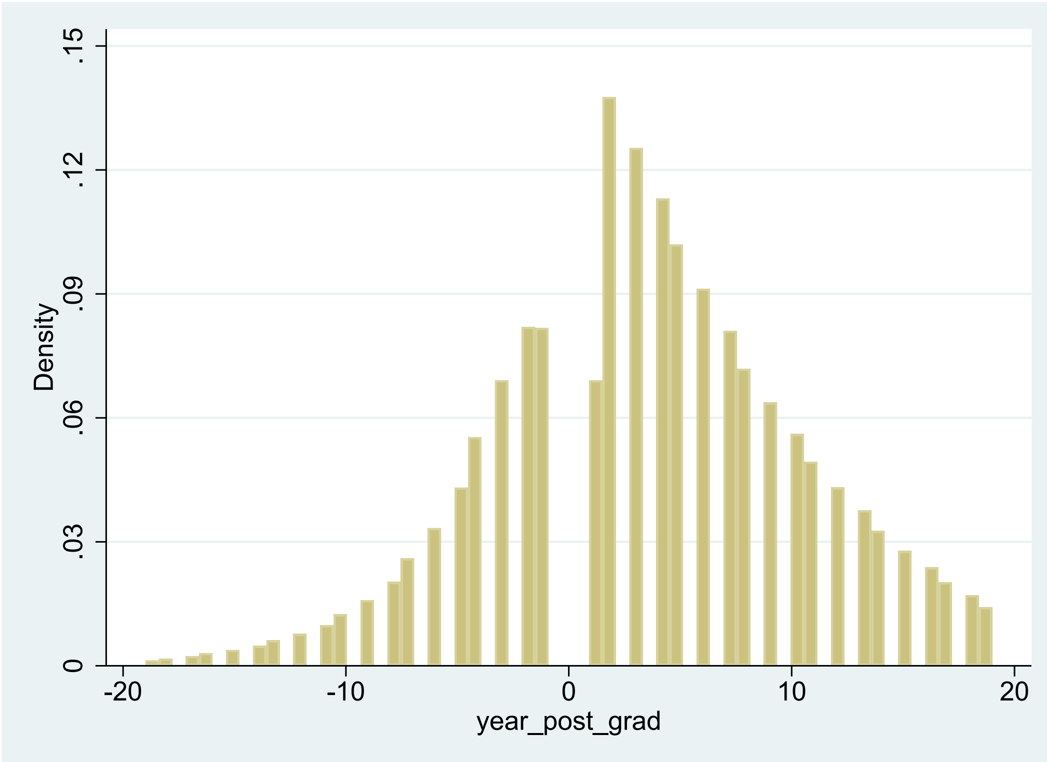

Figure 3: Distribution of FEcg Sample Around Graduation — MBA Degree Holders

Notes: This figure shows the distribution of the time between each wage observation and graduate degree attainment for MBA degree holders for whom we also know their undergraduate major.

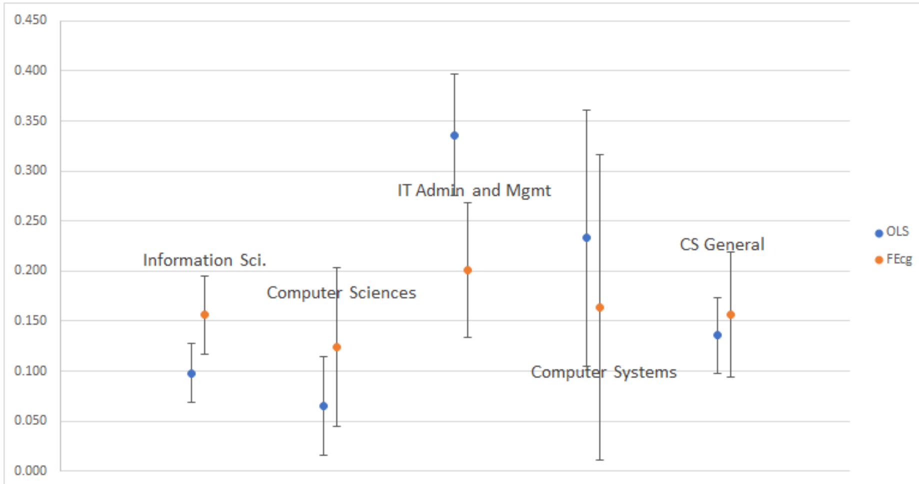

Figure 4: Additional Average Returns Estimates — Computer Sciences

Notes: This figure reports the OLS and FEcg estimates of average returns to a set of computer sciences graduate degrees. Point estimates of OLS and FEcg are shown in blue and orange dots, and 90% confidence interval bands are shown with the wicks around the point estimates. These estimates come from the same regressions as those reported in columns (1) and (2) of Table 3.

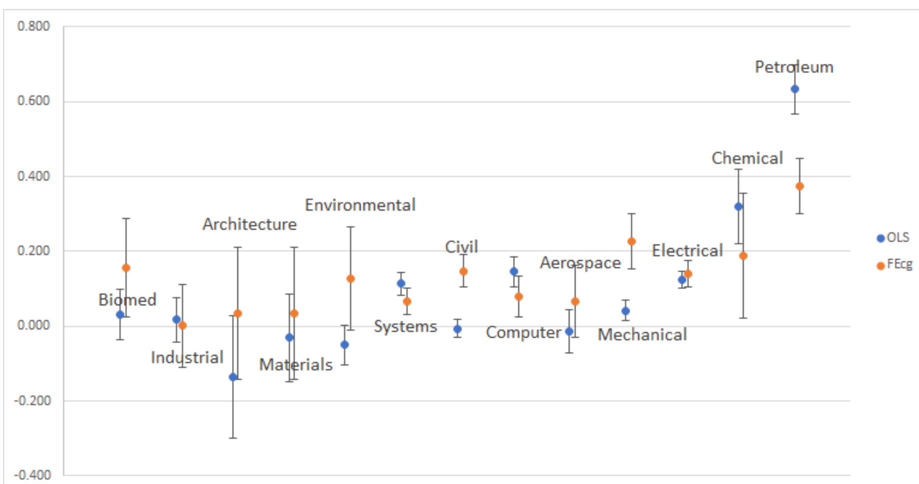

Figure 5: Additional Average Returns Estimates — Engineering

Notes: This figure reports the OLS and FEcg estimates of average returns to a set of engineering graduate degrees. Point estimates of OLS and FEcg are shown in blue and orange dots, and 90% confidence interval bands are shown with the wicks around the point estimates.. These estimates come from the same regressions as those reported in columns (1) and (2) of Table 3.

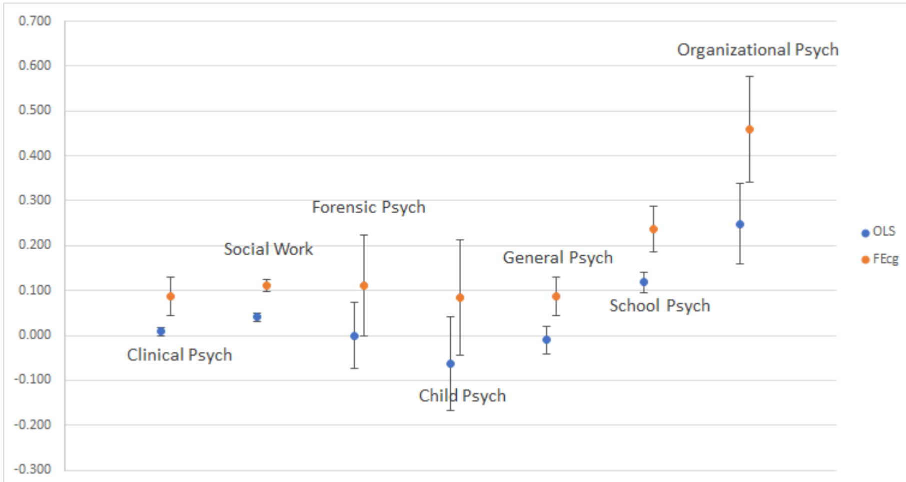

Figure 6: Additional Average Returns Estimates — Psychology

Notes: This figure reports the OLS and FEcg estimates of average returns to psychology-related graduate degrees. Point estimates of OLS and FEcg are shown in blue and orange dots, and 90% confidence interval bands are shown with the wicks around the point estimates. These estimates come from the same regressions as those reported in columns (1) and (2) of Table 3.

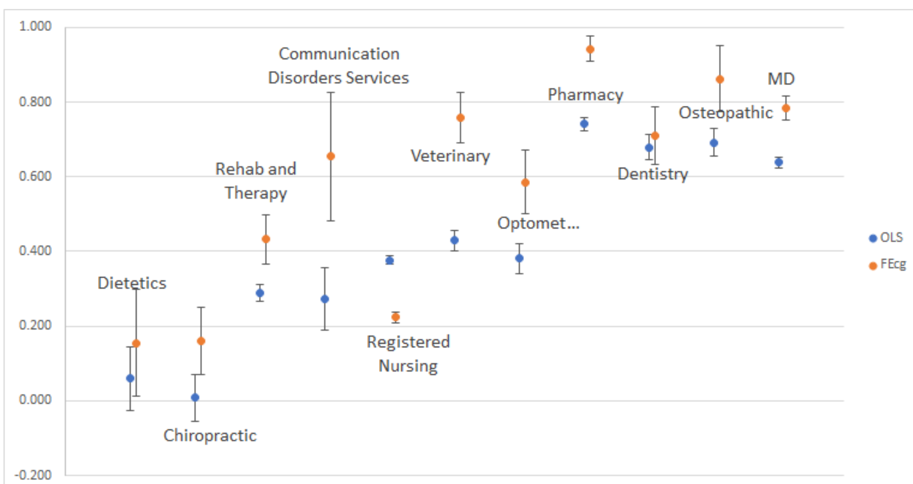

Figure 7: Additional Average Returns Estimates — Health

Notes: This figure reports the OLS and FEcg estimates of average returns to a set of health-related graduate degrees. Point estimates of OLS and FEcg are shown in blue and orange dots, and 90% confidence interval bands are shown with the wicks around the point estimates. These estimates come from the same regressions as those reported in columns (1) and (2) of Table 3.

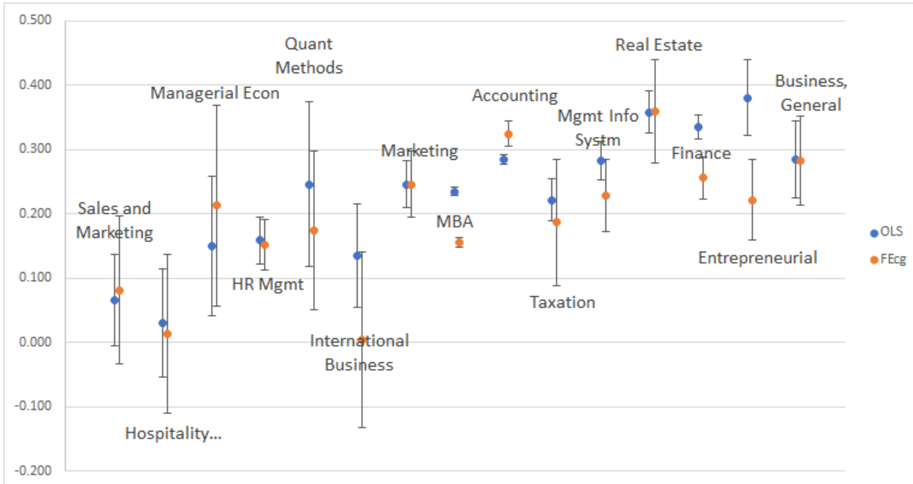

Figure 8: Additional Average Returns Estimates — Business

Notes: This figure reports the OLS and FEcg estimates of average return to a set of business-related graduate degrees. Point estimates of OLS and FEcg are shown in blue and orange dots, and 90% confidence interval bands are shown with the wicks around the point estimates. These estimates come from the same regressions as those reported in columns (1) and (2) of Table 3.

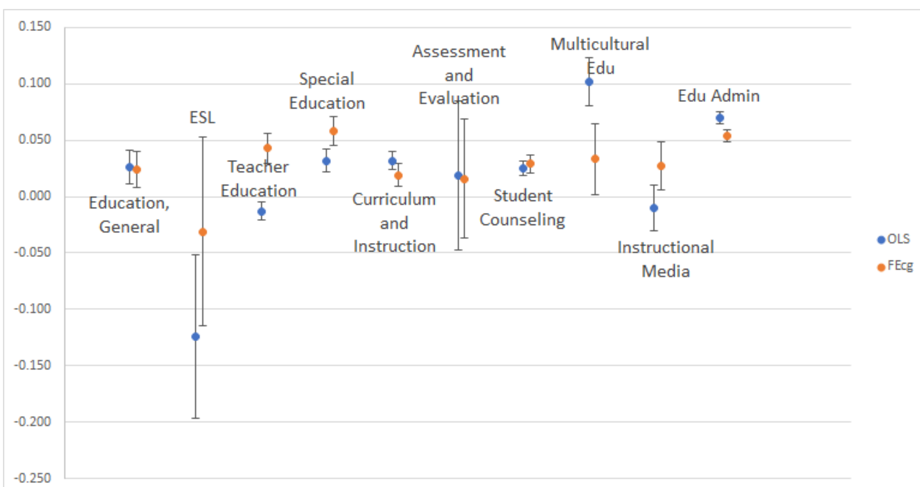

Figure 9: Additional Average Returns Estimates — Education

Notes: This figure reports the OLS and FEcg estimates of average returns to education-related graduate degrees. Point estimates of OLS and FEcg are shown in blue and orange dots, and 90% confidence interval bands are shown with the wicks around the point estimates. These estimates come from the same regressions as those reported in columns (1) and (2) of Table 3.

Figure 10: Additional Average Returns Estimates — Public Policy

Notes: This figure reports the OLS and FEcg estimates of average returns to a set pf public policy-related graduate degrees. Point estimates of OLS and FEcg are shown in blue and orange dots, and 90% confidence interval bands are shown with the wicks around the point estimates. These estimates come from the same regressions as those reported in columns (1) and (2) of Table 3.

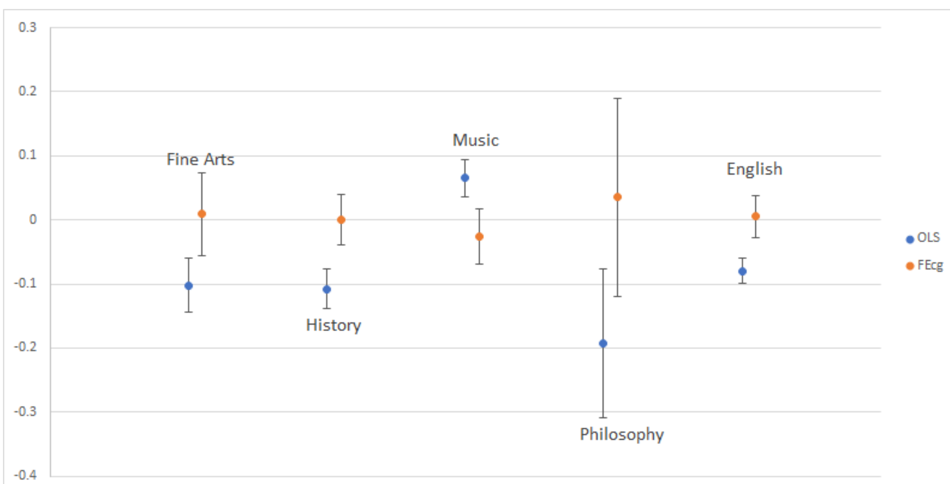

Figure 11: Additional Average Return Estimates — Arts and Humanities

Notes: This figure reports the OLS and FEcg estimates of average return to a set of arts and humanities graduate degrees. Point estimates of OLS and FEcg are shown in blue and orange dots, and 90% confidence interval bands are shown with the wicks around the point estimates. These estimates come from the same regressions as those reported in columns (1) and (2) of Table 3.

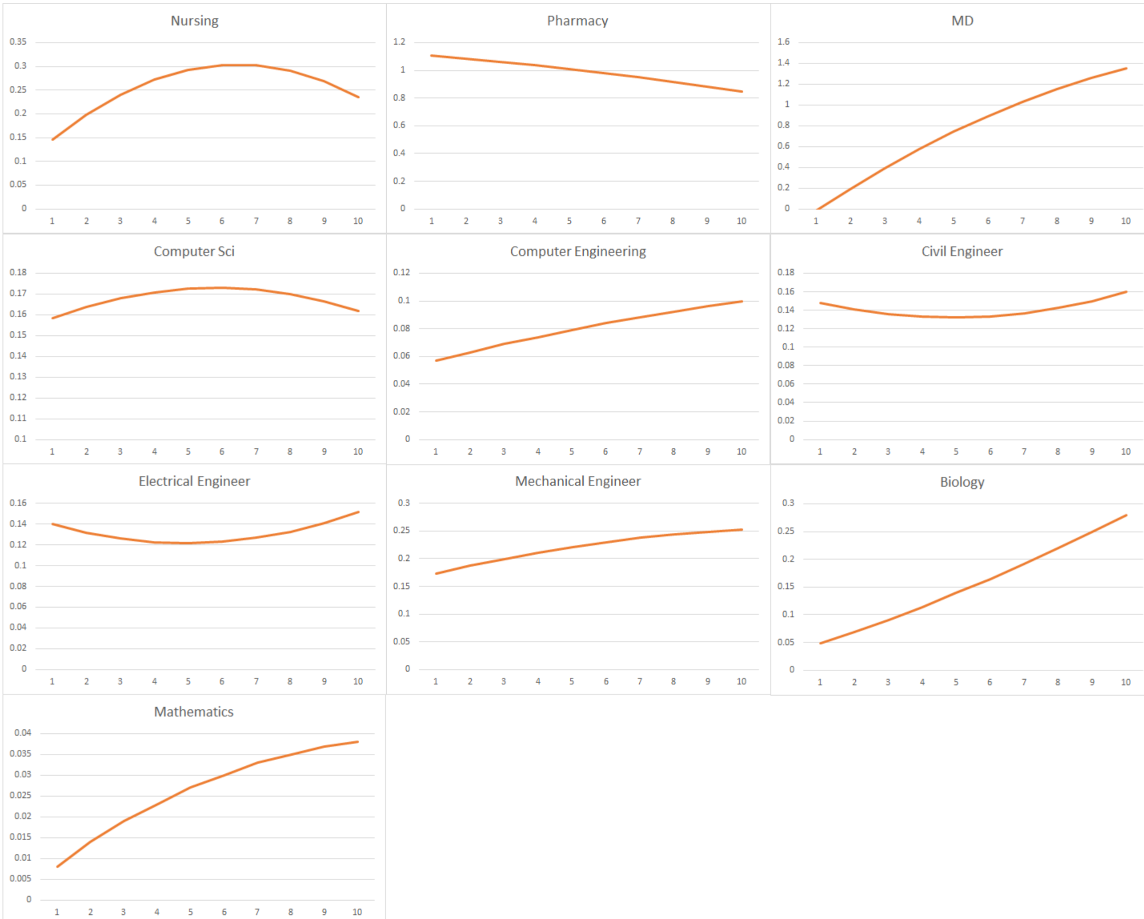

Figure 12: Graduate Degree Returns by Post Graduate School Experience — STEM Degree

Notes: This figure reports estimates of γ_{gx}, the return to the graduate degree after x years of post graduate school experience for a set STEM-related graduate degrees, up to 10 years. We estimate an FEcg model with graduate degree specific experience trends following the specification in equation (7). The estimates of $\gamma_{gx}$the first 10 years of experience after graduation are then calculated as the linear combinations of terms associated with the graduate degree of interest.

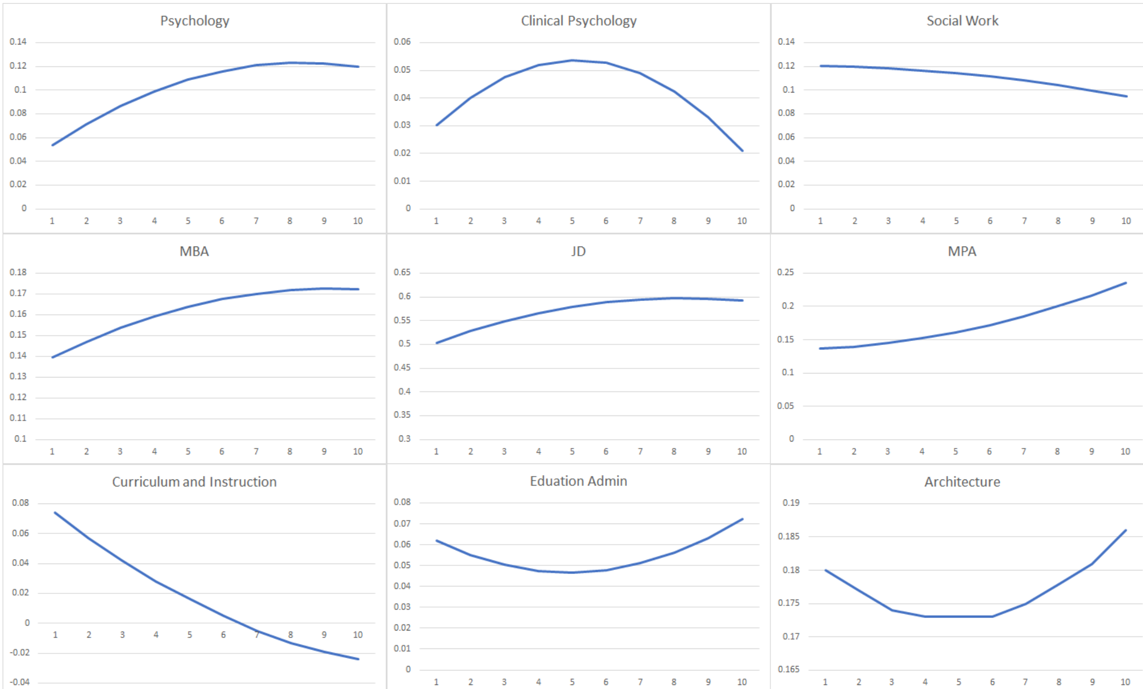

Figure 13: Graduate Degree Returns by Post Graduate School Experience — Non-STEM

Notes: This figure reports estimates of γ_{gx}, the return to the graduate degree at x years of post graduate school experiencethe trends of returns to various Non-STEM graduate degrees over the first 10 years after graduation. We estimate an FEcg model with graduate degree specific experience trends following the specification in equation (7). The estimates of γ_{gx} for the first 10 years of experience after graduation are then calculated as the linear combinations of terms associated with the graduate degree of interest.

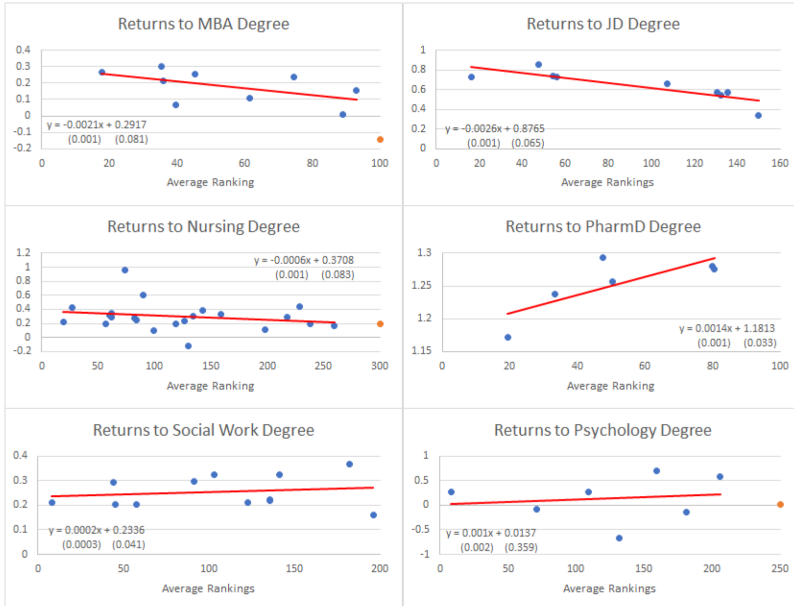

Figure 14: Returns by Program Ranking

Notes: This figure reports the relation between the returns to individual graduate programs and the programs' ranking for each type of degree Each blue point in the figure corresponds to the returns to one individual graduate program, which is estimated following the FEcg specification in equation (12). The orange dots in the returns to MBA, Nursing, and Psychology panels are the average returns to unranked programs in those fields. The trend lines are calculated using the estimated returns to ranked programs only. The regression coefficient estimates and the standard errors are reported in the panels.

Appendix A: Additional Tables and Figures

Table A1: Average Returns with Graduate School Sample Only

Dependent Variable	Log Quarterly Wage				
Specification	FEcg Grad Only (1)	FE Grad Only (2)	OLS No Actual Exp (3)	FEcg No Actual Exp (4)	FE No Actual Exp (5)
Clinical Psych	0.028 (0.007)	0.001 (0.006)	-0.029 (0.006)	0.008 (0.007)	-0.025 (0.006)
Social Work	0.108 (0.008)	0.064 (0.009)	0.012 (0.006)	0.093 (0.009)	0.021 (0.009)
Curriculum and Instruction	0.007 (0.006)	-0.050 (0.006)	0.018 (0.005)	0.012 (0.006)	-0.061 (0.005)
Psychology	0.083 ().026)	0.014 (0.032)	-0.062 ().020)	0.062 (0.027)	-0.029 (0.033)
Edu Admin	0.042 (0.003)	-0.010 (0.004)	0.086 (0.003)	0.049 (0.003)	-0.058 (0.012)
Mathematics	0.027 (0.023)	-0.083 (0.024)	-0.154 (0.021)	-0.009 (0.026)	-0.123 (0.025)
Biology	0.083 (0.026)	0.042 (0.033)	-0.087 (0.017)	0.083 (0.027)	0.048 (0.031)
Architecture	0.175 (0.020)	0.174 (0.027)	0.018 (0.010)	0.142 (0.021)	0.043 (0.024)
MPA	0.164 (0.013)	0.122 (0.013)	0.075 (0.011)	0.147 (0.014)	0.080 (0.012)
Nursing	0.192 (0.010)	0.171 (0.010)	0.349 (0.008)	0.212 (0.009)	0.190 (0.0008)
Computer Sciences	0.171 (0.039)	0.108 (0.034)	0.105 (0.024)	0.165 (0.040)	0.053 (0.034)
MBA	0.149 (0.005)	0.167 (0.005)	0.205 (0.004)	0.124 (0.005)	0.100 (0.004)
Civil Engineering	0.148 (0.027)	0.095 (0.028)	-0.054 (0.014)	0.147 (0.029)	0.031 (0.027)
Computer Engineering	0.085 (0.033)	0.025 (0.031)	0.106 (0.025)	0.076 (0.036)	-0.047 (0.033)
Mechanical Engineering	0.222 (0.044)	0.120 (0.038)	-0.027 (0.018)	0.217 (0.046)	0.069 (0.038)
Electrical Engineering	0.142 (0.022)	0.080 (0.023)	0.083 (0.015)	0.110 (0.022)	0.028 (0.023)
JD	0.562 (0.012)	0.411 (0.015)	0.418 (0.008)	0.487 (0.013)	0.278 (0.015)
PharmD	0.893 (0.020)	0.815 (0.024)	0.643 (0.010)	0.875 (0.021)	0.757 (0.024)
MD	0.735 (0.019)	0.515 (0.033)	0.506 (0.009)	0.696 (0.020)	0.412 (0.033)
Sample Size	3140885	3140885	15664350	15664350	15664350

Notes: This table reports the average returns estimates using various robustness check specifications. Robust standard errors are clustered at the individual level, and are reported in parentheses. All OLS and FEcg specifications control for a cubic in age, gender, ethnicity, a vector of high school standardized test scores, high school curriculum, high school attendance rate, college GPA, college credits accumulated, and economic disadvantage status, as measured by whether the student qualified for free / reduced price meals in high school. In all specifications, the effect of age is college major specific. The labor market experience profile is a cubic and with separate major specific profiles for men and women. Regressions reported in columns (1) and (2) restricts the main FEcg and FE analyses to the subsample of individuals who have earned graduate degrees. Columns (3)-(5) use the full sample but replace actual observed experience of individuals with the age profile of an individual.