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 in addition 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 Texas School Project (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). In 2016 14.9 percent of all people aged 35-39 and 63.9% of college graduates had an advanced degree.[1] The rapid growth of graduate education reflects the economy's increasing demand for a highly skilled labor force.

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

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[1] Calculated from US Census Bureau (2017), Table 1

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 have earned 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 specific degrees, such as an MBA (Arcidiacono et al, 2008) and or 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, and sample sizes are limited. 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 differ across schools and types of students and by full-time status. 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, social work and a set of health-related professional degrees that include the MD, pharmacy, and nursing. We also present estimates for a much larger set of degrees organized by broad CIP category. 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 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 that 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. An 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 contrast, FE only makes use of people with earnings observations both before and after graduate school to identify key return parameters. The fourth approach is to better define the comparison groups for the OLS and FEcg using 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.

Students also need to know the value of degrees from a given school. We 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 schools in the return to specific graduate degrees.

Because we consider a large number of fields, use multiple estimation methods, consider part-time/full-time status, produce estimates for demographic subgroups, and consider heterogeneity across schools, there is no easy way to summarize the findings. Instead, we provide a sense of the results by highlighting a subset of them. 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 returns differ substantially across the 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. Field differences in internal rates of return, which account for program length and require assumptions about tuition and earnings during graduate school, are much smaller than the log earnings differences but are still substantial. The values are 0.03 for social work, 0.06 for an MBA, 0.13 for electrical engineering, 0.17 for a JD and 0.20 for an MD.

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.

Part-time enrollment (defined based on average number of credits per semester) is very common in most fields, with law, medicine and pharmacy as important exceptions. Both OLS and FEcg estimates of the return are higher for full-time attendance, and the gap is large in some case, especially for FEcg. For example, the simple average of the full-time FEcg estimates for clinical psychology, social work, psychology and curriculum and instruction is 0.168, while the part-time average is 0.057. For an MBA, the values are 0.184 and 0.140. Hand in hand with differences in earnings effects is the fact that earnings during graduate school are substantial for many programs.

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 (GPA) on returns varies across fields. A point increase in college GPA increases the return to a JD by 0.173 (.018) and to an MBA by0.022 (0.008) It has a negative influence for education, social work, and clinical psychology. A possible interpretation is that pay scales in the industries and occupations that these degrees (eg., education) are more compressed than in most common counterfactual jobs for those pursuing these degrees.

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.

Finally, we estimate returns by college major (aggregated into 11 categories) for a set of graduate programs and find substantial heterogeneity. For an MBA, the FEcg estimates are only 0.119 (0.006) , 0.100 (0.013), and 0.071 (0.029) respectively for business, engineering, and computer science majors but exceed 0.22 for humanities, education, social science, and fine arts majors, which are lower paying undergraduate fields. We also find that the return a JD is higher for lower paying majors, although the relationship is less strong than for an MBA. The return to a master's in architecture is 0.151 (0.021) for an engineering major but 0.474 (0.077) for a fine arts major.

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. 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 this draft, we do not use information from the NSC, due to the lack of detailed enrollment information for out-of-state enrollment.

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. Foote and Stange (2019) study biases in estimates of effects of undergraduate degrees from particular institutions on earnings that arise from excluding individual who move out of state and find significant biases. Their results suggest that individuals with higher earnings and with degrees from state flagship universities such as the University of Texas at Austin are more likely to move out of state, although the problem is less severe for Texas. We suspect that our estimates of the return to law school and business school quality may be understated as a result. The fact that we restrict out analysis to individuals who attended high school in Texas may reduce the problem.[2]

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

[2]We plan to use data from various years of the National Survey of College Graduates (NSCG) and the National Survey of Recent College Graduates (NSRCG) to investigate the issue, building on AZ. 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, subject to sample size constraints.

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.[3]

Figure 1 displays the probability distribution of the elapsed time between wage observations and graduate school enrollment 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.[4] Figure 2 shows a similar pattern for the effective sample for the FE estimator.. Finally, Figure 3 provides similar information for MBA recipients for the FEcg sample. 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 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.[5] 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

[3]Since attending graduate school on a part-time basis is common, an alternative would be to include quarters above the \$3,000 minimum in the measure of experience, at least for part-time students. We have not tried this.

[4]The figure shows some post law school earnings observations less than 3 years after enrollment. There are accelerated JD programs that only take 2 years. Even for standard JD programs, there are options for students to graduate early by enrolling during the summer.

[5]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.

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. We also have information on free/reduced lunch status for a subset of the sample. We do not use these measures in our main specification, but found that estimates are not very sensitive to controlling for family income using the subsample for which it is available.

2.1 Applications, Admissions and Program Quality Data

Our school specific estimates make 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.[6] Students' admission records, which contains information on where students applied and were admitted to, is available for Texas 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.[7] 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 very unlikely to be observed applying to programs in a different application category.[8]

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 by US News in at least one year, we use the program's average ranking over 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 changes over time. This

[6] 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.

[7] 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.

[8] 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% 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 master's degree programs.

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 by graduate degree type. To keep things manageable, we restrict our attention to 19 key graduate fields that we focus on 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. 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 3 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).

In general, post-graduate school earnings have a strong positive correlation with pre-graduate school earnings. But it is interesting that graduates from MD programs have the second lowest pre-graduate program income, although they earn the highest post-graduate program income (Column 1). This probably reflects the fact that some highly competitive graduate programs favor pre-graduate school experience in medicine related jobs that could have lower income. For example, some aspiring medical students will choose to work in Emergency Medical Services or in science labs for relevant experiences or in other lower income professions that could allow flexible schedules to prepare for the medical college admission test (MCAT).[9] This raises the possibility that pre-graduate school earningsdo not necessarily reflect the counterfactual incomes that an advanced degree graduate would have earned if she did not pursue a graduate degree. (See

[9]Appendix Table A2.4 (omitted this draft) reports the most common 2 digit industry before and after graduate school for each of the 19 fields, and well as the fraction of individuals who change. The pre and post industries are the same for all degrees except MD and social work. The most common 2 digit industry for future MDs is educational services.

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.

Annual earnings during graduate school also varies substantially across programs, from a low of $1,628 for MD to $59,324 for nursing. (We exclude observations for enrolled students in the earnings regression samples.) The value is $49,492 for an MBA but only $8,420 for a JD. These large differences across programs presumably reflect differences in the time requirements of enrollment, as well as the prevalence of programs that combine with work. Column 4 reports the fraction of people who attended graduate school part-time. In the absence of a part-time indicator we define part-time attendance based on when the individual obtained an average of less than 9 credits per semester enrolled. The 9 credit average may be too stringent, but one can see that the majority of students attend graduate school on a part-time basis. The fractions range from 0.92 and 0.914 nursing and for curriculum and instruction (respectively) to 0.08 for a JD. Below we compute one set of internal rate of return estimates including earnings while in school and using the average duration of enrollment. We compute another set assuming that the person is attending school full-time and not working. In section 5.3, we find that earnings effects of degrees obtained full-time are typically higher than returns to part-time degrees.

Table 1 also shows the average college major premium and industry premium of graduates from different degree programs.[10] Columns 5 and 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.

Column 6 and 7 show that higher paying graduate degrees are associated with higher industry premiums both before and after graduate school. There are substantial differences across fields in the gape between the pre-and post industry premium. In most cases, it is a small positive value. The exceptions are JD and MD degrees, for which the gains in the industry premium are 0.118 and 0.098 respectively.

In Table 2, we present demographic compositions and measures of high school and college academic performance for the 19 graduate fields we focus on. Column 1 of the table shows large variation in gender composition between programs. Between 76% and 90% of graduates from clinical psychology, curriculum and instruction (the most common education major), social work, psychology, and nursing programs are female. Women are underrepresented in engineering and computer science. The share of female graduates are also low in MBA and JD programs compared to the 59% share of female college graduates. Racial compositions

[10] To construct these, we first compute the earnings premium associated with each college major and 4 digit North American Industry Classification System (NAICS) industry code using a log earnings regression that includes college major dummies, industry code dummies, an indicator for whether the individual has 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.

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, social work, education and public policy related programs. They are overrepresented in computer science, engineering, pharmacy, and medicine.[11] In terms of 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 and highest paying programs, including JD and MD.

Columns 7 and 8 present graduates' average percentile rankings in the standardized Texas high school assessment exams. Column 9 presents the average college GPA. Overall, graduates of higher earning programs have better high school and college academic performance, with the MDs leading the pack.

4 Econometric Specification and Methods

4.1 Overview and Notation

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 and 2 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

[11] In all discussion related to ethnicity, notice that international students are categorized as a separate group. For example, Asian students in the following discussion are US citizens or permanent residents of Asian ethnicity, and do not include international students from Asia.

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 $c \in \{1, ..., \mathcal{C}\}$ is an index of the undergraduate major. The index g denotes the type of graduate degree, with $g = 0, 1, ..\mathcal{G}$. 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 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. Our empirical analysis aims to estimate the causal effect of $G_{g(i)t}$ on $\ln w_{it}$.

We now turn to the econometric specifications and estimation methods. 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 and on whether the student attended on a part-time basis. We also allow additional interactions with student characteristics such as gender, race, and test scores. Finally, we consider program quality.

4.2 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

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

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 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 cubic function of age_{it} ($\alpha^c_{age_{it}}$), and c specific cubic in actual experience for males and females ($\alpha^c_{gen_i exp_{it}}$).

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

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

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.

The control vector X_{it} includes age, gender, race/ethnicity, a vector of high school standardized test scores, high school curriculum, high school attendance rate, college GPA, and college credits accumulated. Controlling for students' family income results in significant loss of sample size, and so family income measures are not included as controls in our main specifications. In all specifications, the effect of age is college major specific.[12]The labor market experience profile is also college major specific, with separate major specific profiles for men and women. Actual experience will be negatively correlated with $G_{g(i)t}$ because graduate school involves time away from the job market in many cases. Holding actual experience constant isolates the effect of the graduate degree on the intercept of the earnings equation. However, the estimates of γ^g will be net of any causal effects of $G_{g(i)t}$ on actual experience that operate through increased employment and may be less useful as simple summary of the net effect of going to graduate school on earnings. In Section 5.2.3 we discuss sensitivity to replacing the gender x c specific actual experience profiles with gender x c specific age profiles.

We provide FEcg and FE estimates using both the main sample and the sample that excludes "college

[12]We conduct sensitivity analyses in which we control for measures of parental income. We also separately conduct sensitivity analyses in which we allow the age profile to be a gender$\times$college major specific cubic. The analyses show that the results are not sensitive to the inclusions of family income as control and the more flexible age profile specification.

only" individuals who are not observed to go to graduate school (the "graduate school sample"). In both cases, the estimate of γ^g is based primarily 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. 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^g primarily 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 in the OLS and FEcg cases.

We refer readers to AZ for a detailed discussion of the assumptions under which FE and FEcg will identify treatment on the treated effects of graduate degrees (TT). We briefly summarize the discussion here. The first assumption is that the decision to go to graduate school is not induced by a transitory drop in earnings. If such transitory drops are an important factor in the decision to return to school, then earnings in the year or two prior to enrollment will tend to be an underestimate of what future earnings would be in the absence of graduate school. This would lead to upward bias in FEcg and FE (Ashenfelter, 1978). In Section 5.2 we explore the issue and conclude that transitory variation probably leads to a small upward bias in the estimates.

The second assumption is that ability and occupational preferences do not change between the time when earnings are observed before graduate school and when the decision to pursue a graduate degree is made. It is needed for pre graduate school earning to provide a reliable guide to counterfactual earnings in the absence of graduate schools. To see how it could fail, consider an education major who starts out as a teacher, concludes that she would prefer to work in business, but goes directly to business school rather than switching to a business occupation before starting an MBA. In this case FEcg and FE would use her earnings as a teacher, which would probably underestimate her counterfactual earnings in the absence of business school. If she left teaching and pursued a business career before going to graduate school and only earnings after the transition into her new career are used, then the assumption is satisfied. In practice, we use all earnings before graduate school (subject to sample selection criteria discussed above).

The next three assumptions are required to guarantee that the experience profiles of college graduates and those who obtain an advanced degree are parallel. The need for parallel profiles stems from the fact that we do not observe counterfactual earnings for years after graduate school. The first assumption is that on average earnings growth driven by changes in occupations and jobs in response to new information about ability and preferences does not depend on graduate school attendance (conditional on college major). The second is that earnings growth within occupation is the same for all occupations conditional on college major and ability. This is strong but is needed because graduate school has a causal effect on occupation paths. The third assumption is that the contribution of occupational progression to earnings growth would have been the same (conditional on college major) if the person did not go to graduate school. The parallel experience profile assumptions are strong. In section 4.3 we add g specific experience profiles to the model.

4.2.1 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 a better control group for holders of a specific degree, such as an MD, we use a variation of the OLS approach that places additional weight on individuals who, given observable characteristics, have a high propensity to obtain an MD. To be more specific, consider the specific graduate degree $g(i) = g$. We use a logit model to estimate the probability p_{ig} that an individual will eventually obtain an advanced degree in g versus not get a graduate degree in any field:

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

where C_i is the vector of college major dummies and X_i includes all time invariant elements of X_{it}. For $g(i) = g$, p_{ig} is the probability of obtaining g for the population of individuals who either obtain g ($g(i) = g$) or do not go to graduate school in any field ($g(i) = 0$). We use the estimates of p_{ig} from (4) to re-weight the sample and run a weighted least squares (WLS) regression to estimate γ^g. The specification is

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{\mathcal{C}} (\alpha_0^c + \alpha_{\text{age}_{it}}^c + \alpha_{gen_i exp_{it}}^c) C_{c(i)} + \gamma^g G_{gt} + X_{it}\beta + \beta_1^p p_{ig} + \beta_2^p p_{ig}^2 + u_{it} \ ; g(i) = g \text{ or } 0. \quad (5)$$

For each degree, we estimate (4) to obtain p_{ig} and estimate (5) using the relevant p_{ig} 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.[13] For this reason, we also implement a propensity score weighted version of FEcg. The specification is the same as (5) but with $\sum_{c=1}^{\mathcal{C}} b_{cg} C_{c(i)} G_{g(i)}$ added.

4.3 Average Returns with Advanced Degree-Specific Experience Profiles

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 graduate degree-specific potential experience profiles is

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

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..

The corresponding FEcg specification is

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

The corresponding FE specification is

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

In the OLS, FEcg, and FE estimations with degree specific trends, we always use the full sample of individuals with college degrees.[14] FEcg and FE require the assumption that for each college major c the

[13] We include p_{ig} and p_{ig}^2 to provide additional robustness to bias from nonlinearity in the effects of the controls beyond what is provided by propensity score weighting. Note also that if the regression model is correctly specified, the terms can also serve as a control function for the effects of selection on time invariant unobservables. See ___. However, we discount this interpretation because identification of β_1^p and β_2^p is based on functional form restrictions rather than the exclusion of determinants of p_{ig} from (5)

[14] Once the assumption of constant returns is relaxed, the observations on individuals who do not attend graduate school

counterfactual earnings profile of those get a degree in g are parallel to those who do not go to graduate school.

4.4 Returns by Gender, Race/ethnicity and Grades

Do returns to advanced degrees vary by gender and race/ethnicity? To examine this, we estimate the OLS, FEcg, and FE models for each gender category and the main race/ethnic categories separately. We examine heterogeneity in returns by college GPA using the OLS specification

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

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, we add interactions between GPA_i and $G_{g(i)t}$ to the FE-CG and the FE specifications.

4.5 Program Specific Returns: Controlling for Application and Admissions Portfolios

To study returns to specific programs, 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)).[15] We use the information in two ways, depending on data availability. First consider programs such as a JD, for which we observe applications and admission results for programs in public institutions in Texas. We also observe the institution attended (including private law schools in Texas) 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

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{\mathcal{C}}(\alpha_0^c + b_{cg} + \alpha^c_{\text{age}_{it}} + \alpha^c_{gen_i exp_{it}})C_{c(i)} + \gamma^{gj}G_{gjt} + X_{it}\beta + \sum_{p\in\mathscr{P}^g}\eta^g_{p(i)}P^g_{ip} + \nu_i + \epsilon_{it}, \quad (10)$$

are needed to identify the counterfactual earnings profile for those who do attend graduate school. 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.

[15] Mountjoy and Hickman (2020) uses a similar approach and the Texas administrative data to study the returns to particular undergraduate institutions. There is an extensive literature measuring the effects of undergraduate programs on earnings, including recent work by Hoxby (2018) and Chetty et al (2020).

where G_{gjt} indicates having a degree from program g of institution j by time t. The dummy variableP^g_{ip} is an indicator for whether i has an application/admission portfolio $p \in \mathscr{P}^g$ and $\eta^g_{p(i)}$ is the corresponding fixed effect. To construct the set $\mathscr{P}^g$, we consider three potential outcomes for each graduate program in field g: did not apply, applied and rejected, and applied and admitted. The set$\mathscr{P}^g$ is the set of mutually exclusive portfolios of all possible outcomes from all graduate degree programs of type g.[16]

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. As we noted in section 2.1, this assumption has some support in the data. However, we will only be able to identify application sets for people who actually enroll in the specific program type (eg.., an MBA program), and we restrict the estimation sample accordingly.

5 Results

We now turn to the estimates of the returns to graduate school. Section 5.1 reports estimates pooling all institutions. Section 5.2 considers a number alternative specifications and sensitivity checks. Section 5.3 present estimates for full time and part-time attendance. Section 5.4 presents net present discounted value and internal rate of return estimates. Section 5.5 discusses estimates by demographic group and college GPA. Section 5.6 presents estimates of returns to graduate programs by undergraduate major. Finally, in section 5.7, we report estimates of returns by US News and World Report ranking for a subset of the fields that we consider.

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. Standard errors (in parentheses) are clustered at the individual level. The column headings list the estimation procedure and the sample used.[17] 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

[16]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.

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

we noted above, the additional observations in the full sample contribute to identification of the time trends and the experience and age profiles. Keep in mind that both FEcg and FE account for fixed unobserved student characteristics and that time invariant student characteristics such as parental education drop out of the FE models.[18] 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 19 that are reported in the tables. We present estimates for many additional 4 digit CIP graduate degrees in Figures 4 to 11.

We also report OLS-pw and FEcg-pw estimates using (5) and (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. [19]

Columns 6, 7, and 8 display OLS, FEcg and FE estimates of γ^g_{1-10}, where $\gamma^g_{1-10}=\sum_{x=1,..,10}\gamma^g_x/10$. It is the average return over the first 10 years after graduate school. 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 Section 5.3 we present internal rates of return estimates. These are 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 if full-time. The estimates for 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

[18] As we noted earlier, the OLS and FEcg estimates are not sensitive to interacting gender with the college major specific quadratics in age. Columns 3-5 of Appendix Table A2.1 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, $\hat{\gamma}^g$ is an estimate of the combined effect of the degree and the lost actual experience that obtaining the degree entails.

[19] 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).

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 displays the FEcg postgraduate school experience profiles (γ^g_x) for each of the STEM or Health related degrees.[20] 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 a set of degrees that are classified in the category Computer and Information Sciences and Support Services (CIP 11). 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 master's 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 engineering.

[20] Keep in mind that we imposed a quadratic functional form on the γ^g_x.

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.

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 (Appendix Table A2.1 columns 1 and 2).

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 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. We do not have occupation data, but Appendix Table A2.3 reports OLS and FEcg estimates of the effect of each graduate degree on the 4-digit industry premium. The OLS estimate for clinical psychology shows a substantial negative effect (-0.066 (0.002)), while FEcg is -0.018 (0.002). The values for social work are -0.016 and 0.029 respectively. OLS attributes the drop industry premiums to the degrees, while FEcg is consistent with the fact that those who obtain psychology and social work degrees were in a low paying industries before 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. 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 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 the change in the sample) reduces the OLS estimate to 0.545 and the FEcg estimate to 0.525. About 0.06 of the return operates through 4 digit industry (Appendix Table A2.3)

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 large 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_x^g 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_{1-10}^g 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.

The FEcg estimate is that 0.114 of the return to a JD operates through industry (Table A2.3). This is industry effect estimate is the largest among the 19 fields we focus on.

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 controls 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_{1-10}^g 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 modest 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 master's 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. The OLS and FEcg estimates of the effect of an MPA on the industry premium are -.038 (0.004) and 0.01 (0.005) respectively. This accounts for most of the difference in the two estimators in the estimates of the return. Overall, the estimate suggests a 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 master's 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 master's in Fine Arts, History, Music, Philosophy, and English. The FEcg estimates are clustered around 0. The OLS estimates are negative for all degrees except Music and average about -0.10. We think they misstate the counterfactual occupation for those who choose to get an advanced degree in arts and humanities.

5.2 Alternative Specifications and Sensitivity Checks

5.2.1 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.

5.2.2 Assessing Bias from Ashenfelter's Dip

Column (2) of Table A2.2 reports FEcg estimates of (3) modified to include interactions between each of the $G_{g(i)t}$ indicators and 2 dummies for whether date of the earnings observation is 4, 5, or 6 quarters before the start of the graduate program or 7, 8, or 9 quarters before. The dummy variable coefficients (columns 3 and 4) are usually negative, consistent with Ashenfelter's dip.[21] The estimates with the dummies are smaller than the estimates from our basic specification (reproduced in column (1) by between 0.0 and 0.01 for 11 of the 19 degrees, including an MBA. The largest differences are 0.036 for pharmacy and 0.038 mechanical engineer. Corresponding results for the FE estimator are reported in columns 5-8. They are also suggest a small negative bias from Ashenfelter's dip.

5.2.3 Replacing Actual Experience with Age

Column (4) of Table A2.1 reports FEcg estimates with the c x *gender* interactions with a cubic in actual experience in (3) replaced by interactions with age. The estimates of γ_g using only age profiles are below the FEcg estimates in Table 3 column (2) by a magnitude that increases with program length (in years) by 0.0165 on average.[22]

In a future draft we will FEcg estimates with the actual experience replaced by potential experience.[23]

5.3 Returns to Graduate Degrees by Part-Time Status (preliminary)

Table 3a reports OLS and FEcg separate estimates of the return to advanced degrees four full-time and part-time. In the case of OLS, we simply interact field of study with full-time and part-time status. For FEcg, we also include separate cg fixed effects for full-time and part-time programs. Thus we are allowing for

[21] Arcidiacono et al (2008) provide a useful discussion of the issue. They do not find much evidence that Ashenfelter's dip is a problem in their study of the return to an MBA.

[22] We regressed difference between the estimates of γ_g in Table 3, column (2) and Table A2.1 on the assumed values of length of a full-time program used in our internal rate of return calculations and obtain 0.0165 with an intercept close to 0 and an adjusted R^2 of 0.403.

[23] We will set potential experience to age_{it}-22 for years before graduate school and age_{it}-22-$duration_{g(i)}$ for years after graduate school. Here $duration_{g(i)}$ is the assumed length of program g.

permanent unobserved differences to depend on full-time attendance. We focus on the FEcg estimates. In most cases, returns are higher for full-time attendance. The part time estimate is usually closer to the pooled estimates reported in table 3 column 2, which reflects the fact that part time accounts for more than 60% of the observations for most degrees. In the case of clinical psychology, the returns are 0.042 for part time and 0.149 for full-time. Similarly, social work (0.088 versus 0.141), curriculum and instruction (0.017 versus 0.086) and psychology (0.083 versus 0.289) show substantial differences in returns in favor of full-time.

The part-time/full-time gap is massive for computer science (0.149 (0.039) vs 1.128 (0.194)), but the value for full-time programs should be taken with a grain of salt given that the OLS estimates are 0.140 for part-time but only 0.091 for full-time. We also find large returns to full time attendance in the engineering fields, especially computer engineering (0.583 (0.049)). It is possible that prior earnings understate counterfactual earnings in some fields for those who came graduate school full-time. One mechanism would be if people who pursue a full-time masters degree in engineering were working as research scientists in an academic setting before entering graduate school full-time. We are currently investigating differences by full-time status in pre-graduate school earnings levels and industry.

For an MBA, the returns are 0.140 for part time and 0.184 for full time, and the OLS estimate exceeds FEcg by a larger amount in the full-time case. AZ show using panel data that occupations before and after MBA attainment are similar, in which case earnings prior to graduate school are probably a good guide to counterfactual earnings.

For a JD, the return to full-time degree is modestly higher than the return to a part-time degree (0.576 versus 0.515), although the difference is not statistically significant. The gap is somewhat larger in the case of and MD, but OLS and FEcg show similar full-time premiums even though FEcg is above OLS in both the full-time and part-time cases.r Note that part-time attendance is unusual in both of these fields.

5.4 Internal Rate of Return Estimates

Table 4 reports the net present discounted value (PDV) of income net of tuition between age 27 and 59 for each advanced degree (column 3), the counterfactual net PDV if the person had not attended graduate school (column 4), the percentage increase in PDV (column 5), and the internal rate of return (IRR) (column 6). The calculations are based on the assumed value for program duration in column 1 and the values of average tuition of public institutions in 2012 in column 2. The tuitions are adjusted for inflation to 2019 dollars. The results in Table 4 also assume earnings are zero while students are enrolled.

In computing PDVs, we evaluate the earnings setting the year to 2019 and the error term to 0. We set the race/ethnicity variables to non-Hispanic white but evaluate average earnings at each age over the g specific distribution of all of the other control variables, such as gender, GPA, C_i, and $C_iG_{g(i)}$. The Texas data does not have enough support after the mid-40s for some graduate degrees for us to be able to use it to predict earnings through age 59 without relying heavily on extrapolation. To address this, we use c x gender specific age profiles estimated by AZ after age 40. Because AZ lack information on actual experience, we reestimated the FEcg specification (3) after substituting age for actual experience. The estimates of γ^g are in Table A2.1 column 4. They tend to be smaller than the FEcg estimates using actual experience (Table 3 column 2). After age 40, we replace our estimates of the values of the age polynomials at each age with values based on AZ's c x gender specific polynomials plus constant terms that equate AZ's c x gender estimates with our estimates at age 40.[24]

The counterfactual PDVs vary from a low of $446,567 for those who obtain a master's in social work to a maximum of $1,423,989 for electrical engineering. The actual net PDVs also vary a great deal. The lowest value is social work, and highest value, perhaps surprisingly, is pharmacy (2,247,271). The percentage gains (based on a discount rate of 0.05) are negative for the six lowest paying degrees.

The percentage gains in net PDV are of course strongly related to the estimates γ^g. The gain for an MBA is only 0.59% over the counterfactual PDV of $1,168,751. Not surprisingly, the internal rates of return are also strongly negatively related to the ratio of $\hat{\gamma}^g$ to program length. The IRR for an MBA is 0.06 under the assumption that it takes two years full-time. The IRR for computer science and for the engineering degrees range from 0.13 to 0.22, with exception of computer engineering, for which the value is 0.07. We assume these degrees take 1 year full-time. The internal rates of return to a JD, pharmacy, and an MD are 0.17, 0.25, and 0.20 respectively. These values are much smaller than the estimates of γ^g because they account for program length.

Appendix Table A1.2 reports alternative estimates of the IRR and the gain in PDV using empirical estimates of program duration and of earnings while in graduate school. The mean durations for a JD, PharmD, and an MD are very close to the assumed values of 3, 4, and 4. However, the values for the other degrees are concentrated around 2.75. This is longer than our assumptions of 1 or 2 years for full-time attendance, which tends to produce lower values of the gain in PDV and of the IRR. However, average annuual earnings while enrolled in school are substantial for some degree types, as Table 1 documents.[25] This raises the PDV and IRR.

The alternative IRR estimates differ quite a bit from the estimates assuming full-time enrollment, no earnings during graduate school and the durations in Table 4. In the case of education administration, the

[24] We obtain very similar results using ratio links rather than additive constants to equate AZ's age profile to our estimates at age 40. See Table A1.1.

[25] We assume total tution is the product of annual full-time tuition and the durations given in table 4, column one. We set tuition per year to total tuition divided by average actual duration as reported in Table A1.2, column 1.

estimate rises from zero to 0.15. The other big increases are for nursing (0.11 to 0.46) and for an MBA (0.05 to 0.18). In all three cases, earnings during graduate school are large. On the other hand, the estimates decline substantially for three of the four engineering degrees, reflecting the fact that earnings while in graduate school is not enough to offset the increased estimate of the duration of the program. For example, the estimated IRR for civil engineering declines from 0.17 to 0.04, and the value for electrical engineering declines from 0.13 to 0.06.

In deciding how to treat those earnings in evaluating the return to graduate school, it is important to consider the total time devoted to work and study. For example, suppose that graduate school requires 40 hours a week and the student spends an additional 20 hours per week on a job. Suppose that the individual would have worked 40 hours a week had they not attended school. Then the total time commitment while in graduate school would exceed the counterfactual value by 20 hours. The person who did not attend graduate school may have had the opportunity to work additional hours on her main job or take a second job. In this case, the opportunity cost of graduate school evaluated when evaluated at the level of leisure during graduate school would be substantially larger than our estimate of counterfactual earnings. In the absence of good data on time use, we do not have a way to address these issues. Individuals might get more (or less) utility from time spent on school versus time at work. The issues point to the limitations of purely financial return measures in evaluating education decisions.

It is also important to keep in mind that the IRR is independent of the scale of the investment. This means that IRR rankings can be misleading as indicators of the impact of the degrees on the net PDV of earnings. An extreme case is education administration. It has a very health IRR of 0.15 but boosts net PDV by only 1.5% (Table A1.2). This is because earnings losses while in school are low for this program, so the size of the investment is small.

In a future draft, we hope to replace the public tuition measures based on national data with institution-program level data for Texas. This may make a substantial difference for some programs. For example, in 2021-2022, estimated one year tuition and fees for the University of Texas at Austin's MBA program will be $52,550. Thethe corresponding figure is $ 32,010 for the JD program and $20,673 for the MD program. It is $9,274 for the graduate school of education, assuming 9 credits per semester.

5.5 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.

5.5.1 Results for Males and Females

Table 5 presents OLS and FEcg estimates of γ^g for males and females separately. The OLS estimates show very large differences in favor of women, especially for degrees in lower paying fields. For men the OLS estimates of γ^g are -0.116 for social work, -.049 for clinical psychology, and -0.077 for curriculum and instruction. We suspect that differences between occupational preferences of those who seek degrees associated with the "helping professions" and those who do not (conditional on the controls) is greater on average for men than for women. As a result, the OLS estimates for these degrees suffer from a largere negative bias than the estimates for women. [26]

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 female-male difference in the returns to a JD, MD and an MBA are 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 to graduate school based on the FEcg estimates for all graduate degrees (not just the 19 reported in Table 5), the value is 0.202 for females and 0.167 for males. The FE estimates also show gaps in favor of females for most degrees.

In future work, we will 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.

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

Table 6 reports estimates of (1) and (3) by race/ethnicity. Column 1 and 2 contain the OLS and FEcg estimates of returns for African Americans. We focus on the FEcg estimates, although the 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 quite large for African Americans for the engineering degrees and computer science and for Asians in psychology and mechanical engineering, which should be kept in mind.

The FEcg estimates indicate that African Americans receive lower returns than non-Hispanic whites for 14 of the 19 degrees shown, and the gaps are large in some cases. The values are 0.097 (0.022) versus 0.256 (0.011) for nursing, 0.140 (0.012) versus 0.160 (0.006) for an MBA, 0.397 (0.037) versus 0.593 (0.015) for a

[26] Unfortunately, we do not have data on occupational preference measures. Nor do we have data on occupation that could be used to compare jobs before and after graduate school.

JD, and 0.678 (0.062) versus 0.824 (0.027) for an MD.

Hispanics receive substantially larger returns than non-Hispanic whites to engineering degrees. They receive a lower return to a JD (0.502 versus 0.593).

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, nursing, pharmacy, and a JD. We are puzzled by these results and will investigate further in a future draft.

5.5.3 The effect of GPA on returns

Table 7 estimates of the coefficientγ_1^g on the interaction between $G_{g(i)t}$ and college GPA_i. (We lack 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 on the return 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. Negative coefficients might be expected if GPA raises returns business more than in the helping professions. 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 is probably 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.

5.6 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. The point estimates of the returns for each program are reported in the panels of figure 14. The x-axis indicates the ranking. The orange dot refers to the average of the returns for the unranked programs. For each field the estimates of the regression of the school specific return on the program rank are also reported.

Returns to MBA and JD degrees are larger for higher ranking programs. In the MBA case, the return increases by 0.021 for a 10-position 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 but not 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.

5.7 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 11 broad categories of college majors..

The results are in Table 8. Each row refers to a graduate degree and each column refers to a broad major category. From left to right, the columns are in ascending order of average income. reports the FEcg estimates by college major categories. There is a tendency for the return to degrees that have high average earnings, such as MBA, a JD, and MD degree, to be larger for lower paying college majors. For example, the return to MBA is 0.242 (0.053) for fine arts, 0.213 (0.024) for humanities, and 0.234 (0.017) for social sciences but is below 0.12 for business, computer science, and engineering. This pattern can be seen in Figure 15, which graphs the estimates of $\gamma_{cg}$for a JD and and MBA by undergraduate field.

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 explore the structure of the relationship among the alternative estimators of γ^g and γ_c^g that we use. Fourth, we will expand on the analysis of 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	Average Earnings			Share	Log Earnings Premium		High School Test Score		College
	Pre Grad	During Grad	Post Grad	Enrolled Part-Time	College	Industry	Math	Reading	GPA
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Clinical Psychology	46373	26812	54308	0.83	0.00	-0.01	75.99	76.11	3.11
Social Work	41468	18676	55304	0.43	-0.04	0.01	74.46	74.83	3.14
Curriculum and Instruction	47764	40528	58579	0.91	0.02	-0.01	78.28	77.55	3.14
Psychology	42487	15932	60967	0.77	-0.03	-0.01	79.34	79.15	3.15
Edu Admin	49390	55228	68711	0.93	0.02	-0.01	78.68	76.57	3.02
Mathematics	50314	20044	68906	0.74	0.11	-0.01	88.56	82.23	3.32
Biology	41103	12964	70324	0.66	0.13	0.03	82.47	81.58	3.16
Architecture	46184	6472	70373	0.23	0.05	0.10	83.12	79.19	3.20
MPA	52132	32456	77286	0.79	0.05	0.04	76.91	77.89	3.02
Nursing	70140	59324	105347	0.92	0.21	0.15	81.00	80.11	3.31
CS	69903	17032	108772	0.62	0.25	0.18	89.47	85.36	3.37
MBA	71815	49492	109903	0.76	0.16	0.17	82.61	79.90	3.07
Civil	63717	16980	110127	0.62	0.43	0.18	89.12	83.91	3.27
Computer Engineer	80264	22520	111739	0.65	0.35	0.22	89.17	84.44	3.33
Mech	70183	15984	116762	0.64	0.44	0.23	89.06	83.41	3.32
Elec	82841	20788	129746	0.61	0.43	0.25	89.13	83.42	3.35
JD	55439	8420	129818	0.08	0.08	0.23	86.93	87.80	3.38
PharmD	50041	7304	129885	0.11	0.14	0.08	88.00	82.83	3.33
MD	46967	1628	178924	0.10	0.14	0.15	91.87	89.25	3.69
All College Grad	77450		-		0.10	0.09	79.26	77.38	2.98

Notes: This table reports the summary statistics related to students' annualized earnings in 2019 dollars, part-time enrollment, and academic performances by the type of graduate degrees attained. Students are defined as enrolling part-time if they average less than 9 credits per semester while in graduate school. Average college and industry premiums are calculated by taking the sample average for each graduate degree of the college and industry premiums. Industries are defined based on the four digit NAICS codes. 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' 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 return 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, and college credits accumulated. 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. Columns 1-5 report estimates of γ^g. Columns 6-8 report estimates γ^g_{1-10}. 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 based on (5), 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 3A: Returns to Graduate Degrees by Part-Time Status

Dependent Variable	Share Enrolled Part-Time	Log Quarterly Wage			
Specification		OLS		FEcg	
Coefficient		Full-Time	Part-Time	Full-Time	Part-Time
		(1)	(2)	(3)	(4)
Clinical Psychology	0.83	0.041	0.017	0.149	0.042
		(0.015)	-0.006	(0.019)	(0.007)
Social Work	0.43	0.052	0.031	0.141	0.088
		(0.007)	(0.009)	(0.011)	(0.011)
Curriculum Instruction	0.91	0.040	0.035	0.086	0.017
		(0.014)	(0.005)	(0.028)	(0.006)
Psychology	0.77	-0.010	-0.008	0.289	0.083
		(0.038)	(0.019)	(0.053)	(0.029)
Edu Admin	0.93	0.091	0.074	0.071	0.056
		(0.010)	(0.003)	(0.011)	(0.003)
Mathematics	0.74	-0.091	-0.081	0.003	0.028
		(0.048)	(0.021)	(0.091)	(0.024)
Biology	0.66	0.107	-0.045	0.299	0.101
		(0.032)	(0.019)	(0.045)	(0.032)
Architecture	0.23	0.081	0.049	0.19	0.13
		(0.010)	(0.019)	(0.021)	(0.042)
MPA	0.79	0.129	0.102	0.199	0.166
		(0.023)	(0.012)	(0.032)	(0.014)
Nursing	0.92	0.411	0.328	0.293	0.169
		(0.016)	(0.008)	(0.018)	(0.009)
CS	0.62	0.091	0.140	1.128	0.149
		(0.054)	(0.025)	(0.194)	(0.039)
MBA	0.76	0.272	0.197	0.184	0.140
		(0.006)	(0.005)	(0.008)	(0.005)
Civil Engineering	0.62	0.008	-0.020	0.341	0.115
		(0.022)	(0.018)	(0.085)	(0.028)
Computer Engineering	0.65	0.256	0.099	0.583	0.058
		(0.038)	(0.029)	(0.049)	(0.044)
Mechanical Engineering	0.64	0.117	0.013	0.346	0.245
		(0.036)	(0.020)	(0.060)	(0.048)
Electrical Engineering	0.61	0.150	0.121	0.472	0.173
		(0.020)	(0.018)	(0.030)	(0.029)
JD	0.08	0.517	0.533	0.576	0.515
		(0.008)	(0.040)	(0.012)	(0.051)
PharmD	0.11	0.741	0.757	0.947	1.129
		(0.010)	(0.108)	(0.020)	(0.261)
MD	0.10	0.686	0.502	0.870	0.737
		(0.009)	(0.044)	(0.021)	(0.064)
Sample Size		15181871	15181871	15181871	15181871

Note: This table reports the returns to graduate degrees ($\hat{\gamma}^g$) by students' part-time status, using OLS and FEcg. Columns (1) and (2) report the returns to graduate degrees for full-time and part-time programs in each majors estimated using an OLS specification that include separate indicators for full-time and part-time graduate programs. Columns (3) and (4) report the returns to graduate degrees for full-time and part-time programs in each majors estimated using an FEcg specification that include separate indicators for full-time and part-time graduate programs. In addition, the cg fixed effects are full-time status specific. A student is defined as being enrolled part-time if she averages less than 9 credits per semester enrolled. 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, and college credits accumulated. 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. Credit accumulations are not observable in private universities, and so the samples of the regressions reported here do not include students who earn graduate degrees from private universities.

Table 4: Net PDV and Internal Rate of Returns Estimates

Graduate Program	Duration (Yrs) (1)	Annual Tuition (2)	Net PDV Actual (3)	Net PDV Counterfactual (4)	Percentage Gain of PDV (5)	Internal Rate of Return (6)
Clinical Psychology	2	6736	778918	879340	-11.42	Negative
Social Work	2	6736	434079	446567	-2.80	0.03
Curriculum & Instruction	1	6736	595628	631545	-5.69	Negative
Psychology	2	6736	1046500	1099894	-4.85	0.01
Edu Admin	1	6736	714032	733575	-2.66	0.00
Mathematics	1	8131	1145609	1247799	-8.19	Negative
Biology	1	8131	1211777	1162646	4.23	0.11
Architecture	1	8131	1355365	1256176	7.90	0.15
MPA	2	6736	1025193	993451	3.20	0.07
Nursing	2	8131	1260537	1152551	9.37	0.11
CS	1	8131	1594747	1416959	12.55	0.20
MBA	2	9311	1177192	1168751	0.72	0.06
Civil Engineering	1	8131	1512560	1376434	9.89	0.17
Computer Engineering	1	8131	1411648	1392799	1.35	0.07
Mechanical Engineering	1	8131	1615196	1410523	14.51	0.22
Electrical Engineering	1	8131	1510954	1423989	6.11	0.13
JD	3	16697	1729197	1266309	36.55	0.17
PharmD	4	13317	2247271	1161764	93.44	0.25
MD	4	13317	2097582	1303166	60.96	0.20

Notes: This table reports net PDV and IRRestimates. All calculations are based on an FEcg specification that controls for a cubic in age, gender, ethnicity, a vector of high school standardized test scores, high school curriculum, high school attendance rate, college GPA, and college credits accumulated. In all specifications, the effect of age is college major and gender specific. We do not control for the actual labor market experience in the regressions underlying the internal rate of returns calculations. See Table A2.1 column 4. We extrapolate age profiles beyond age 40 using age profiles estimated by AZ (2020), as discussed in the text. We assume graduate programs are full-time, and students have zero earnings when they are enrolled. The assumed duration of the degrees is in Column 1. The annual tuitions reported in column (2) are the average tuition at public institutions in 2012 from the National Center for Education Statistics in 2019 dollars. The PDVs presented in Columns (3) and (4) are calculated assuming a 0.05 interest rate. Column (3) reports the actual PDVs with the corresponding graduate degrees, and column (4) reports the counterfactual PDVs if people with corresponding degrees did not earn the degrees. Column (5) presents the % gain in PDVs. Column (6) reports the estimates of the IRR of each advanced degree. The IRR is the discount factor that equates actual and counterfactual lifetime net income.

Table 5: Gender Heterogeneity in Returns to 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 return estimates ($\hat{\gamma}^g$) 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, and college credits accumulated. In all specifications, the effect of age is college major specific. The labor market experience profile is also college major specific.

Table 6: 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 OLS and FEcg average return estimates ($\hat{\gamma}^g$) using the sample for each race/ethnicity group. International students are not included in any of the ethnicities. Robust standard errors are clustered at the individual level, and are reported in parentheses. The controls include a cubic in age, gender, a vector of high school standardized test scores, high school curriculum, high school attendance rate, college GPA, and college credits accumulated. 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 7: The Effect of GPA on the Returns to Graduate Degrees

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 (5). 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, and college credits accumulated. 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. International students are excluded.

Table 8: Returns to Graduate Degrees by College Major Category

	College Major Area										
Grad Program	Fine Arts	Edu	Humanities	Social Sciences	Comm	Health	Life Sciences	Natural Sciences	Business	CS	Engineer
Clinical Psych	-0.058	0.078	0.009	0.090	-0.017	0.147	-0.068	-0.036	-0.027	-0.135	-0.323
	(0.039)	(0.039)	(0.020)	(0.013)	(0.032)	(0.035)	(0.035)	(0.042)	(0.026)	(0.164)	(0.103)
Social Work	0.225	0.000	0.129	0.108	0.038	0.302	0.089	-0.286	-0.031	-	-
	(0.085)	(0.122)	(0.036)	(0.008)	(0.061)	(0.056)	(0.091)	(0.010)	(0.084)		
Education	0.088	0.117	0.012	0.036	0.115	0.081	-0.028	-0.067	0.010	0.032	0.210
(Curriculum)	(0.037)	(0.029)	(0.017)	(0.021)	(0.041)	(0.088)	(0.026)	(0.035)	(0.029)	(0.051)	(0.117)
Psychology	0.092	-	-0.030	0.108	0.082	0.135	-0.094	0.068	-0.301	-	-
	(0.090)		(0.127)	(0.029)	(0.089)	(0.114)	(0.134)	(0.012)	(0.158)		
Edu Admin	0.026	0.095	0.055	0.050	0.029	0.122	-0.029	0.059	0.022	0.024	0.016
	(0.017)	(0.016)	(0.009)	(0.012)	(0.017)	(0.027)	(0.014)	(0.018)	(0.012)	(0.110)	(0.039)
Mathematics	0.159	-0.121	0.616	0.148	-0.012	-	-	0.015	0.243	-0.174	-0.082
	(0.005)	(0.041)	(0.102)	(0.114)	(0.035)			(0.027)	(0.146)	(0.109)	(0.089)
Biology	0.068	-	-0.065	-0.010	-0.100	0.007	0.119	0.530	0.005	-	0.858
	(0.217)		(0.153)	(0.126)	(0.087)	(0.154)	(0.029)	(0.093)	(0.426)		(0.015)
Architecture	0.474	-	0.215	0.187	-	-	0.353	-	0.072	-0.178	0.151
	(0.077)		(0.153)	(0.062)			(0.160)		(0.069)	(0.011)	(0.021)
MPA	0.268	-	0.163	0.214	0.124	0.064	0.232	0.167	0.106	-0.149	0.171
	(0.096)		(0.040)	(0.021)	(0.032)	(0.085)	(0.064)	(0.114)	(0.037)	(0.011)	(0.094)
Nursing	-0.222	0.626	0.272	0.413	0.431	0.224	0.218	0.679	0.327	-	0.411
	(0.165)	(0.094)	(0.080)	(0.064)	(0.130)	(0.009)	(0.043)	(0.233)	(0.096)		(0.263)
Computer	0.287	-	0.509	0.041	0.746	-	0.390	0.632	0.302	0.125	-0.059
Sciences	(0.141)		(0.031)	(0.185)	(0.133)		(0.195)	(0.164)	(0.134)	(0.044)	(0.089)
MBA	0.242	0.277	0.213	0.234	0.201	0.167	0.183	0.231	0.119	0.071	0.100
	(0.053)	(0.079)	(0.024)	(0.017)	(0.024)	(0.024)	(0.023)	(0.032)	(0.006)	(0.029)	(0.013)
Civil	-	-	-	-	-	-	0.440	0.345	0.685	-	0.099
Engineering							(0.426)	(0.120)	(0.231)		(0.028)
Computer	0.667	-	-	0.470	-	-	-	0.098	0.393	-0.014	0.110
Engineering	(0.080)			(0.007)				(0.120)	(0.203)	(0.045)	(0.044)
Mechanical	0.686	-	0.205	-	-	-	1.204	0.260	-	-	0.190
Engineering	(0.006)		-0.005				(0.007)	(0.172)			(0.046)
Electrical	-	-	0.651	-	-	-	-	0.255	0.415	0.063	0.113
Engineering			(0.296)					(0.083)	(0.005)	(0.062)	(0.023)
JD	0.684	0.74	0.633	0.585	0.667	0.445	0.57	0.63	0.512	0.488	0.399
	(0.088)	(0.213)	(0.031)	(0.021)	(0.040)	(0.118)	(0.068)	(0.127)	(0.025)	(0.112)	(0.046)
PharmD	0.795	-	0.999	1.216	1.174	0.818	0.948	0.982	0.846	0.737	0.749
	(0.358)		(0.099)	(0.112)	(0.193)	(0.085)	(0.025)	(0.062)	(0.085)	(0.228)	(0.105)
MD	0.817	-	0.733	0.945	1.211	0.721	0.798	0.788	0.666	0.71	0.494
	(0.131)		(0.105)	(0.088)	(0.199)	(0.090)	(0.022)	(0.072)	(0.084)	(0.195)	(0.081)

Note: This table reports estimates of 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. The college majors are ranked from left to right in ascending order of average income. 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 beside economics; Natural Sciences include chemistry, mathematics, and physics majors; Life Sciences include biology, environmental and agricultural sciences 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 including economics. 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, and college credits accumulated. 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.

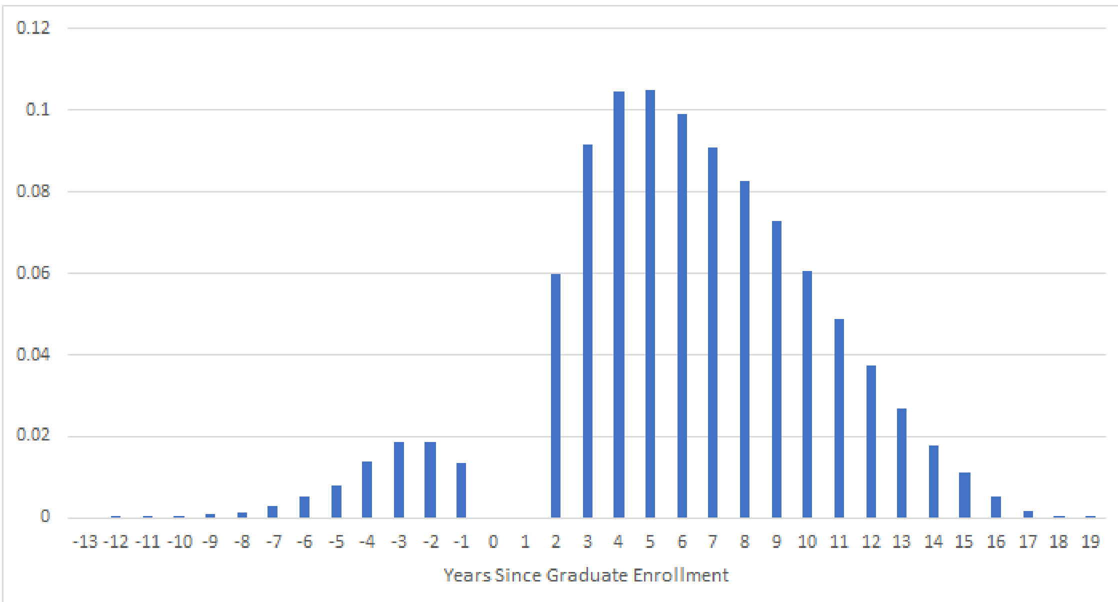

Figure 1: Distribution of Year Minus Graduate Enrollment in the Regression Sample — JD Degree Holders

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

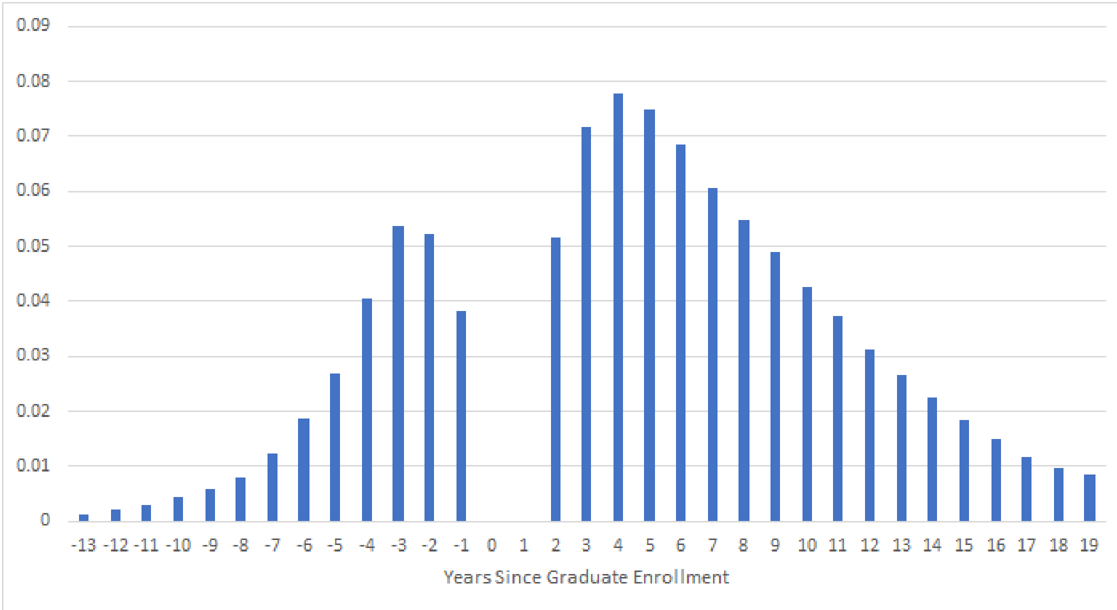

Figure 2: Distribution of Year Minus Graduate Enrollment in the FE Sample — JD Degree Holders

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

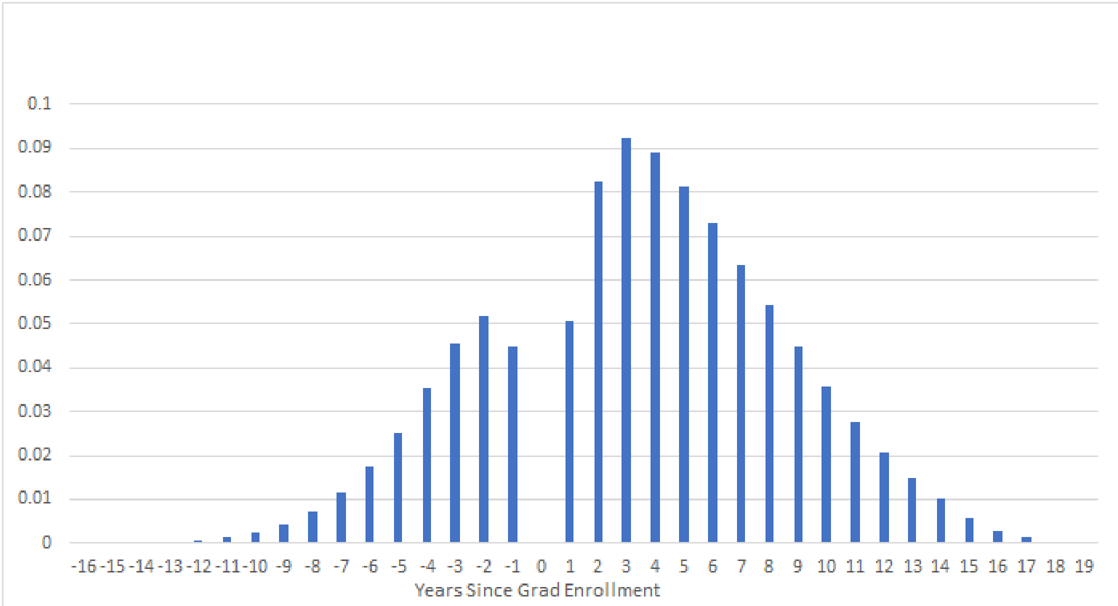

Figure 3: Distribution of Year Minus Graduate Enrollment in the Regression Sample — MBA Degree Holders

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

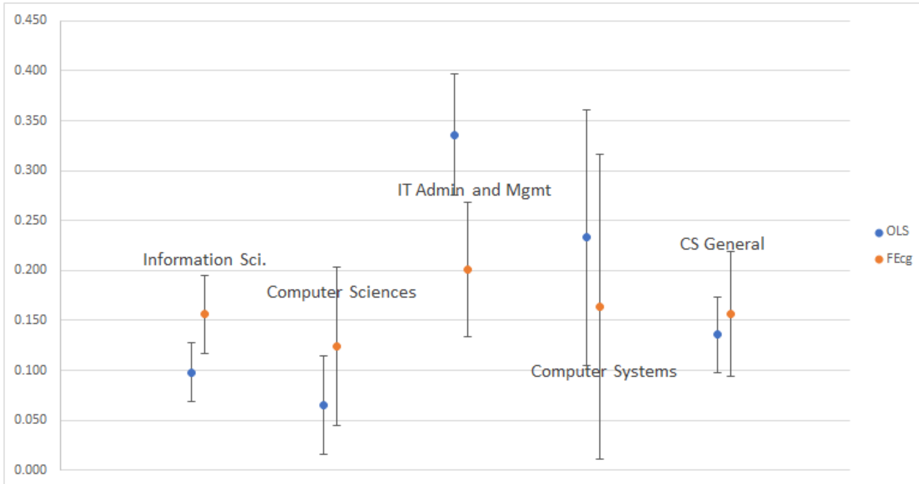

Figure 4: Additional Average Returns Estimates — Computer Sciences

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.

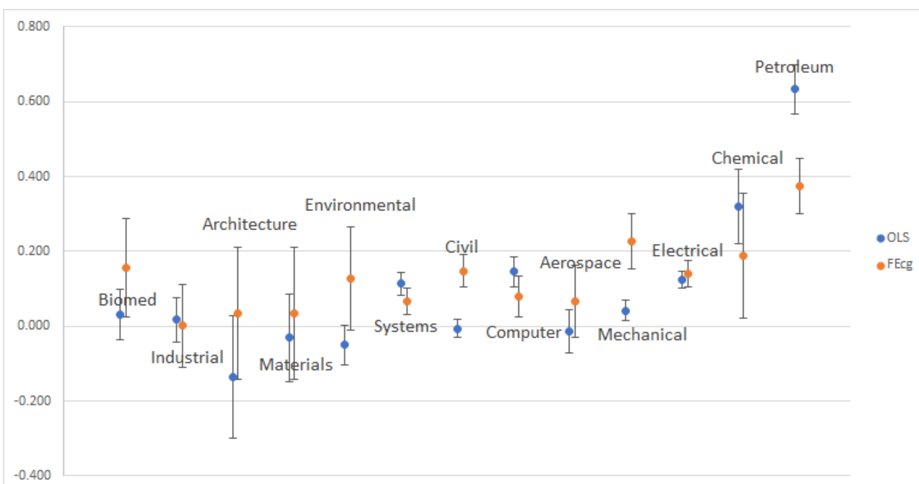

Figure 5: Additional Average Returns Estimates — Engineering

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.

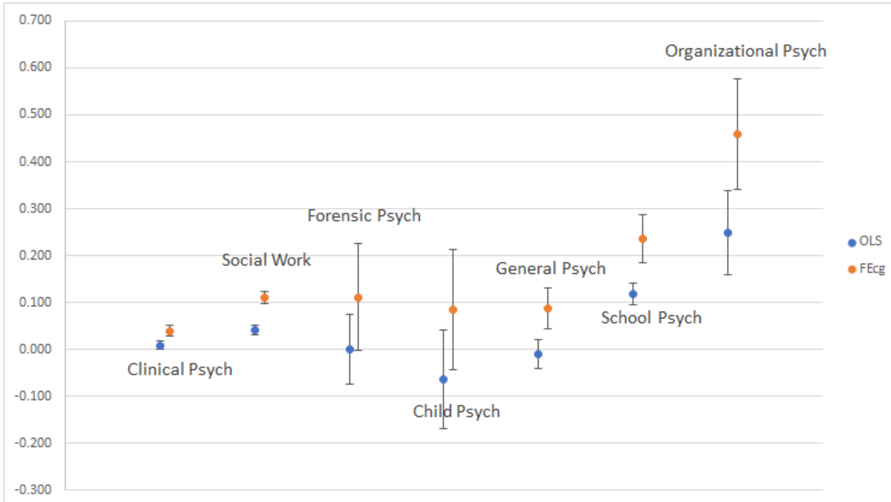

Figure 6: Additional Average Returns Estimates — Psychology

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.

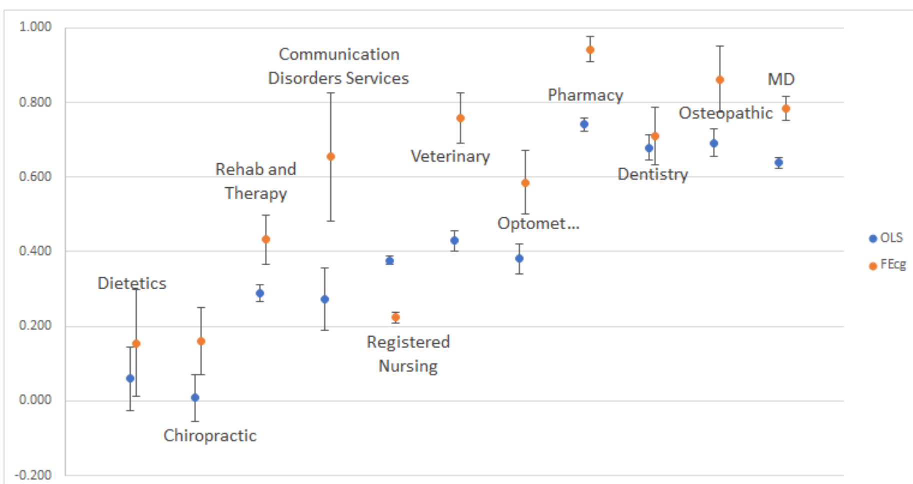

Figure 7: Additional Average Returns Estimates — Health

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.

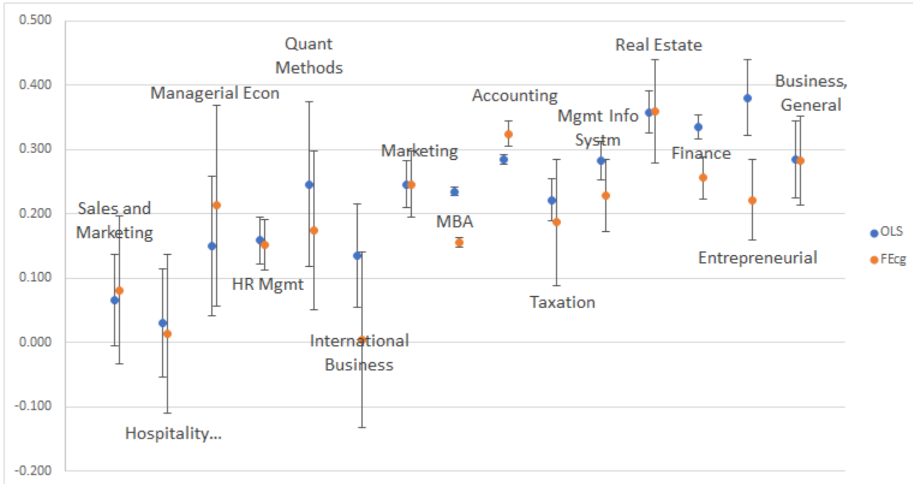

Figure 8: Additional Average Returns Estimates — Business

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.

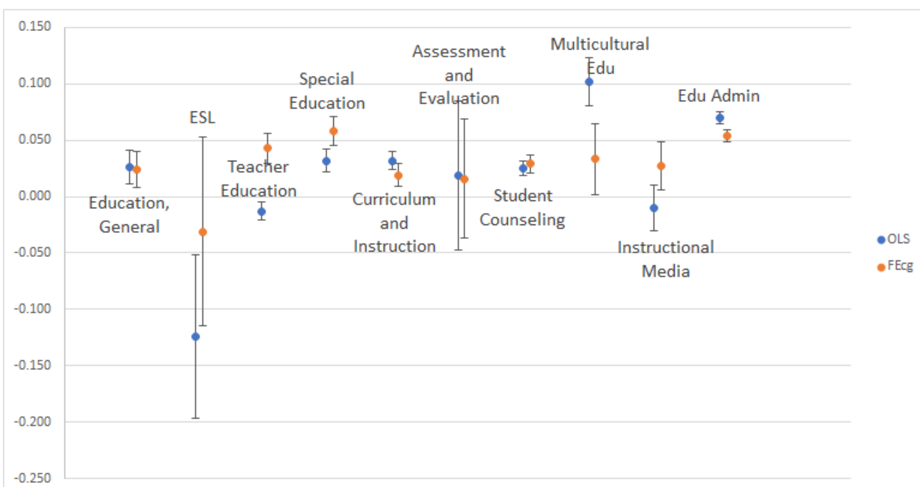

Figure 9: Additional Average Returns Estimates — Education

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.

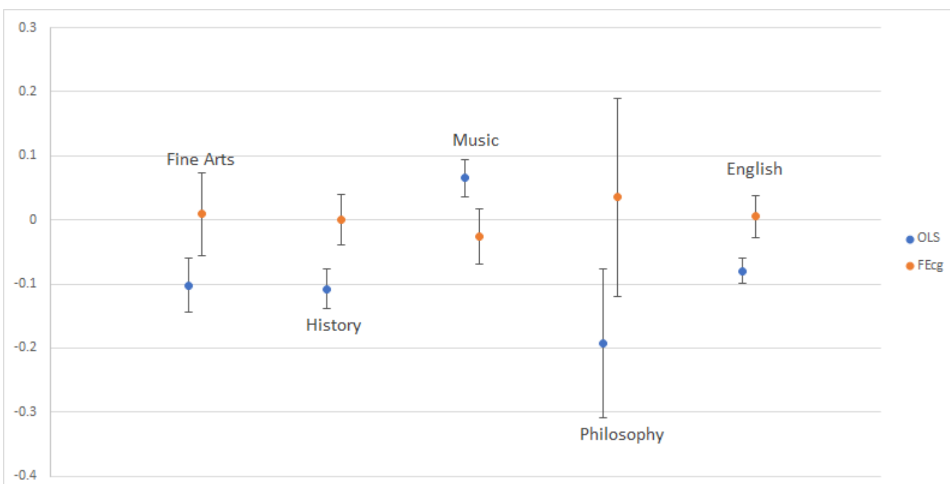

Figure 11: Additional Average Return Estimates — Arts and Humanities

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.

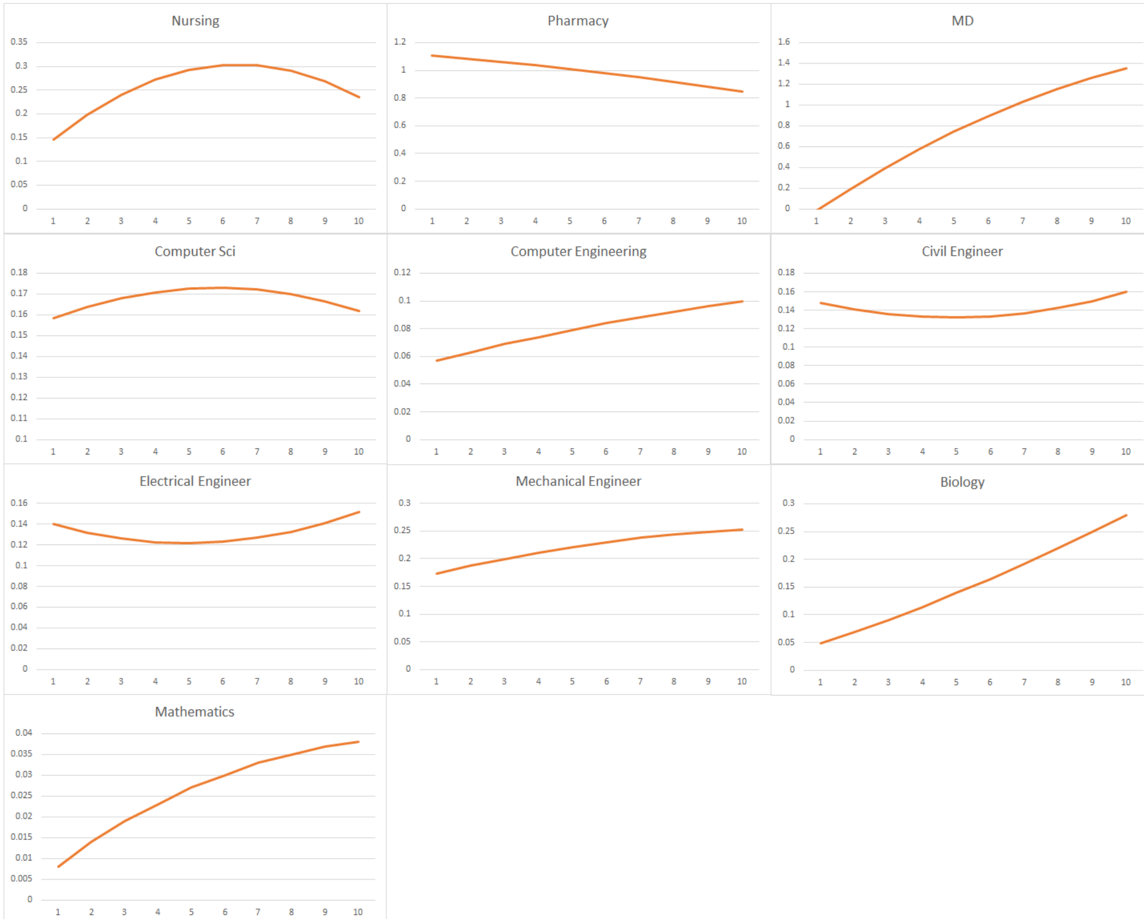

Figure 12: Graduate Degree Returns by Post Graduate School Experience — STEM Degree

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.

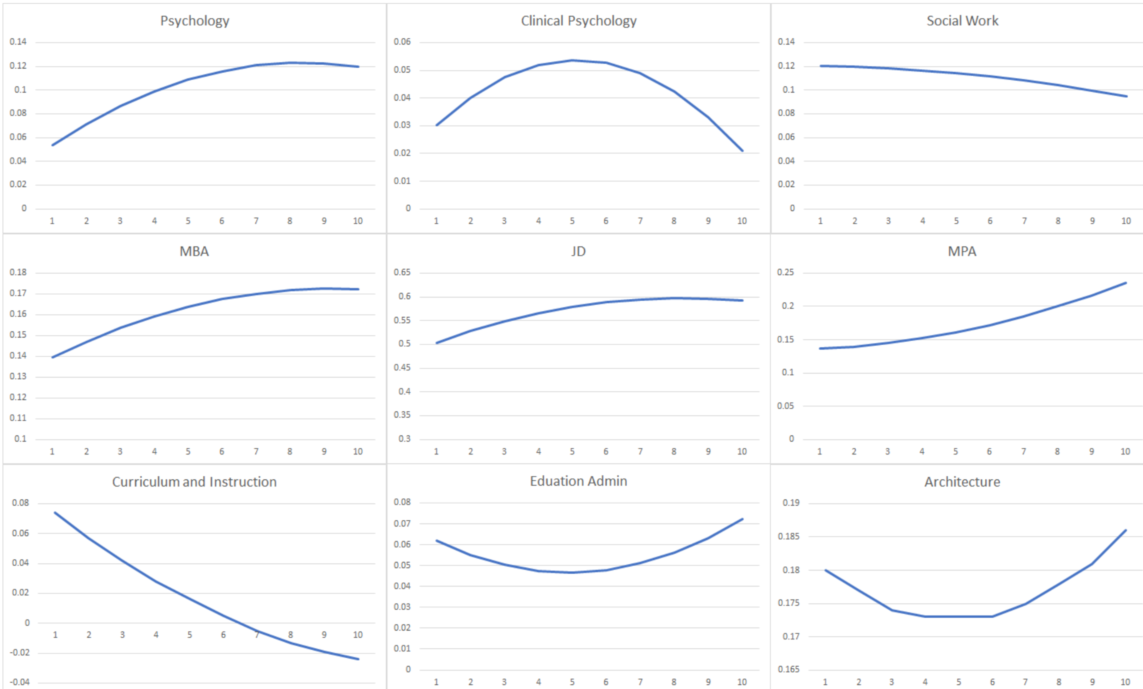

Figure 13: Graduate Degree Returns by Post Graduate School Experience — Non-STEM

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.

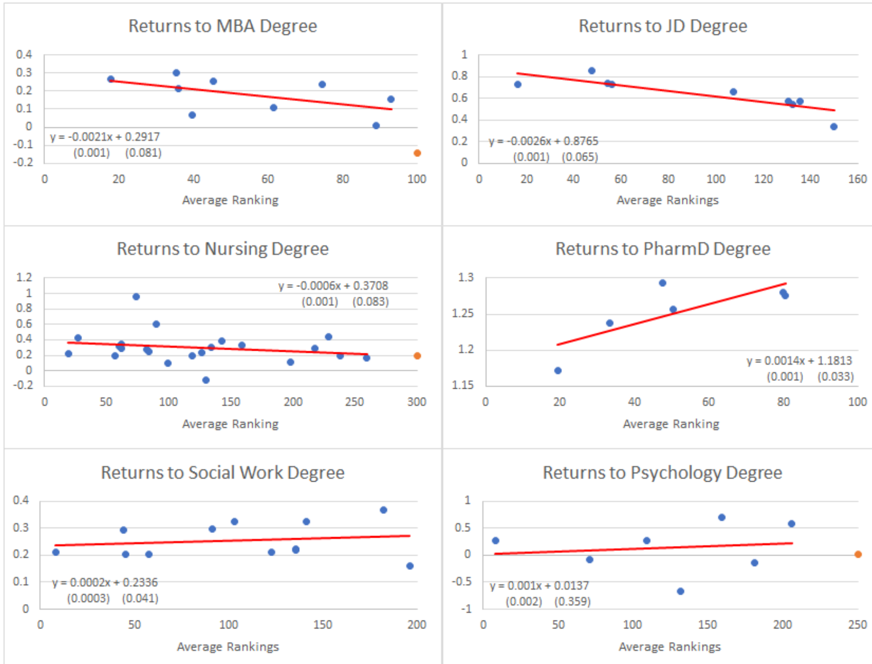

Figure 14: Returns by Program Ranking

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.

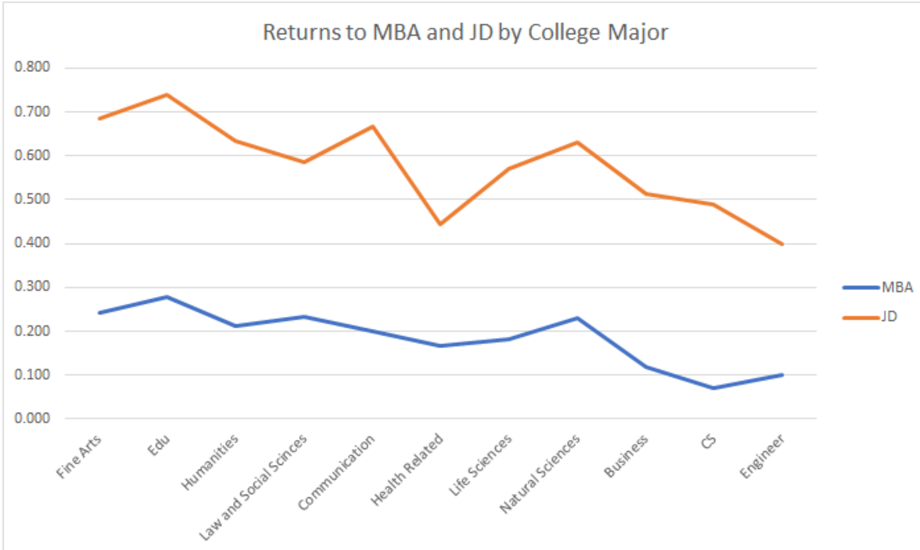

Figure 15: Major Heterogeneity: MBA and JD

Notes: This figure reports the returns to an MBA and a JD for students from each aggregated category of college majors. The returns reported here are estimated with the FEcg specification. The major categories are ordered in ascending order of their average income from left to right.

Appendix A:

Appendix A1: Alternative Estimates of the Internal Rate of Return

Table A1.1: Internal Rate of Returns Results with Scale Translation

Graduate Program	Duration (Yrs)	Annual Tuition	Net PDV Actual	Net PDV Counterfactual	Percentage Gain of PDV	Internal Rate of Return
	(1)	(2)	(3)	(4)	(5)	(6)
Clinical Psychology	2	6736	775148	875545	-11.47	Negative
Social Work	2	6736	432154	444800	-2.84	0.03
Curriculum & Instruction	1	6736	593201	629112	-5.71	Negative
Psychology	2	6736	1040918	1094645	-4.91	0.01
Edu Admin	1	6736	709843	729501	-2.69	0.00
Mathematics	1	8131	1144425	1246576	-8.19	Negative
Biology	1	8131	1205921	1157308	4.20	0.11
Architecture	1	8131	1348987	1250549	7.87	0.15
MPA	2	6736	1019406	988424	3.13	0.07
Nursing	2	8131	1256583	1149340	9.33	0.11
CS	1	8131	1591989	1414628	12.54	0.20
MBA	2	9311	1173291	1165281	0.69	0.06
Civil Engineering	1	8131	1507812	1372326	9.87	0.17
Computer Engineering	1	8131	1408437	1389788	1.34	0.07
Mechanical Engineering	1	8131	1609831	1406065	14.49	0.22
Electrical Engineering	1	8131	1506173	1419704	6.09	0.13
JD	3	16697	1720583	1261017	36.44	0.17
PharmD	4	13317	2235362	1156824	93.23	0.25
MD	4	13317	2085266	1297013	60.77	0.20

Notes: This table reports the internal rate of returns results when using a ratio link rather than a constant to equate college major x gender specific age profiles Altonji and Zhong (2020) to our estimates at age 40. See the text and the note for Table 4 for additional details. We assume graduate programs are full-time, and students have zero earnings when they are enrolled. The assumed duration of the degrees is in Column 1. The annual tuitions reported in column (2) are the average tuition at public institutions in 2012 from the National Center for Education Statistics. The PDVs presented in Columns (3) and (4) are calculated assuming a 0.05 interest rate. Column (3) reports the actual PDVs with the corresponding graduate degrees, and Column (4) reports the counterfactual PDVs if people with corresponding degrees did not earn the degrees. Column (5) presents the percentage increase in PDV . Coulmn (6) reports the estimates of the internal rate of return of each advanced degrees. The internal rate of return is the discount factor that equates PDV of the actual and counterfactual lifetime net income.

Table A1.2: Internal Rate of Returns Estimates Using Empirical Durations and Earnings During Enrollment

Graduate Program	Duration (Yrs)	Annual Tuition	Net PDV Actual	Net PDV Counterfactual	Percentage Gain of PDV	Internal Rate of Return
	(1)	(2)	(3)	(4)	(5)	(6)
Clinical Psychology	2.5	5389	809690	879341	-7.92	Negative
Social Work	2.75	4899	440200	446568	-1.43	0.04
Curriculum Instruction	2.75	2449	603322	631546	-4.47	Negative
Psychology	2.75	4899	1045294	1099894	-4.96	0.01
Edu Admin	2.75	2449	744552	733576	1.50	0.15
Mathematics	2.75	2957	1100657	1247799	-11.79	Negative
Biology	2.75	2957	1145789	1162646	-1.45	0.04
Architecture	2.75	2957	1263741	1256177	0.60	0.05
MPA	2.75	4899	1058516	993452	6.55	0.12
Nursing	3.25	5004	1354934	1152551	17.56	0.46
CS	3	2710	1495342	1416960	5.53	0.09
MBA	2.75	6772	1256564	1168752	7.51	0.18
Civil Engineering	2.5	3252	1447027	1376434	5.13	0.09
Computer Engineering	3.25	2502	1332723	1392799	-4.31	0.01
Mechanical Engineering	2.75	2957	1525859	1410523	8.18	0.11
Electrical Engineering	2.75	2957	1442714	1423990	1.31	0.06
JD	3	16697	1748535	1266309	38.08	0.19
PharmD	3.75	14205	2299318	1161765	97.92	0.28
MD	3.75	14205	2127722	1303166	63.27	0.21

Notes: This table reports the net PDV and IRR results when using the average durations of programs from the Texas data and accounting for students' earnings during enrollment in different graduate programs. All calculations are based on an FEcg specification that controls for a cubic in age, gender, ethnicity, a vector of high school standardized test scores, high school curriculum, high school attendance rate, college GPA, and college credits accumulatedl. In all specifications, the effect of age is college major and gender specific. See Table A2.1 column 4. We do not control for the actual labor market experience in the regressions underlying the internal rate of returns calculations. We assume total tuition is the product of annual full-time tuition and the durations given in Table 4, column 1. We set tuition per year to total tuition divided by duration from column 1 of this table. The PDVs presented in Columns (3) and (4) are calculated assuming a 0.05 interest rate. Column (3) reports the actual PDVs with the corresponding graduate degrees, and Column (4) reports the counterfactual PDVs if people with corresponding degrees did not earn the degrees. Column (5) presents the % gain in PDVs for earning the degrees. Coulmn (6) reports the estimates of the IRR for each advanced degrees. The IRR is the discount factor that equates actual and counterfactual lifetime net income.

Appendix A2:Additional Tables and Figures

Table A2.1: Average Returns with Graduate School Sample or Replacing Actual Experience with Age

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, and college credits accumulated. In all specifications, the effect of age is college major specific. In columns (1) and (2) the labor market experience profile is a cubic and with separate major specific profiles for men and women, and the sample consists 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.

Table A2.2: Return Estimates Allowing for Earnings Dips Before Graduate School

Dependent Variable	Log Quarterly Wage							
Specification	FEcg				FE			
	Main	Ashenfelter			Main	Ashenfelter		
Coefficient	Main Effect	Main Effect	q456	q789	Main Effect	Main Effect	q456	q789
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Clinical Psychology	0.040	0.037	-0.005	-0.006	0.042	0.037	-0.018	-0.018
	(0.007)	(0.007)	(0.009)	(0.008)	(0.006)	(0.006)	(0.008)	(0.007)
Social Work	0.111	0.101	-0.036	-0.010	0.097	0.086	-0.051	-0.019
	(0.008)	(0.009)	(0.011)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)
Curriculum & Instruction	0.019	0.019	0.013	-0.007	-0.005	-0.010	-0.015	-0.025
	(0.006)	(0.007)	(0.008)	(0.008)	(0.005)	(0.006)	(0.007)	(0.007)
Psychology	0.087	0.073	-0.055	-0.014	0.060	0.052	-0.030	-0.023
	(0.026)	(0.028)	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)	(0.033)
Edu Admin	0.054	0.054	0.016	-0.008**	0.033	0.028	-0.007	-0.029
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Mathematics	0.023	-0.001	-0.104	-0.050	-0.061	-0.074	-0.059	-0.042
	(0.023)	(0.023)	(0.033)	(0.034)	(0.024)	(0.024)	(0.030)	(0.034)
Biology	0.130	0.107	-0.113	-0.041	0.112	0.090	-0.104	-0.053
	(0.026)	(0.027)	(0.033)	(0.029)	(0.031)	(0.032)	(0.030)	(0.028)
Architecture	0.177	0.17	-0.057	0.03	0.19	0.179	-0.065	0.000
	(0.019)	(0.021)	(0.028)	(0.030)	(0.023)	(0.025)	(0.029)	(0.029)
MPA	0.168	0.152	-0.044	-0.054	0.150	0.138	-0.038	-0.049
	(0.0127)	(0.013)	(0.015)	(0.015)	(0.012)	(0.013)	(0.013)	(0.013)
Nursing	0.223	0.218	-0.000	-0.005	0.260	0.258	-0.003	-0.011
	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)
CS	0.157	0.150	-0.074	0.013	0.103	0.080	-0.116	-0.045
	(0.038)	(0.040)	(0.057)	(0.044)	(0.034)	-0.034	(0.054)	(0.037)
MBA	0.156	0.149	-0.024	-0.019	0.194	0.193	-0.001	-0.005
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Civil Engineering	0.148	0.139	-0.062	-0.025	0.094	0.076	-0.086	-0.024
	(0.027)	(0.029)	(0.038)	(0.037)	(0.027)	(0.028)	(0.031)	(0.032)
Computer Engineering	0.079	0.078	0.020	-0.016	0.021	0.030	0.031	0.022
	(0.033)	(0.036)	(0.043)	(0.035)	(0.032)	(0.035)	(0.035)	(0.029)
Mechanical Engineering	0.227	0.189	-0.191	-0.084	0.125	0.093	-0.165	-0.069
	(0.044)	(0.046)	(0.058)	(0.063)	(0.039)	(0.039)	(0.049)	(0.038)
Electrical Engineering	0.141	0.134	-0.067	-0.046	0.072	0.064	-0.060	-0.020
	(0.021)	(0.022)	(0.039)	(0.035)	(0.023)	(0.023)	(0.029)	(0.031)
JD	0.565	0.548	-0.053	-0.056	0.453	0.434	-0.073	-0.060
	(0.012)	(0.013)	(0.017)	(0.015)	(0.015)	(0.015)	(0.017)	(0.015)
PharmD	0.943	0.907	-0.166	-0.082	0.896	0.868	-0.163	-0.091
	(0.020)	(0.021)	(0.038)	(0.029)	(0.023)	(0.025)	(0.038)	(0.031)
MD	0.784	0.753	-0.151	-0.090	0.594	0.575	-0.103	-0.062
	(0.019)	(0.021)	(0.032)	(0.030)	(0.033)	(0.034)	(0.040)	(0.037)
Sample Size	15664350	15664350	15664350	15664350	15664350	15664350	15664350	15664350

Notes: This table reports the average returns estimates when controlling for potential dips in earnings prior to graduate school enrollment. Robust standard errors are clustered at the individual level, and are reported in parentheses. All 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, and college credits accumulated. In all specifications, the effect of age is college major specific. The labor market experience profile is a gender specific cubic. Columns (1) and (5) reports the main FEcg and FE estimates previously reported in Columns (2) and (3) of Table 3. Columns (2) and (6) report the returns estimates using FEcg and FE when controlling for potential earnings dips prior to enrollment. Columns (3) and (7) report the coefficient estimates for a dummy indicating that the observation is 4-6 quarters prior to enrolling in the cular graduate program, and Columns (4) and (8) report the coefficient estimates for the corresponding dummy indicating the observation is 7-9 quarter prior to enrollment. Note that through out the paper earnings observations 1-3 quarters prior to enrolling in graduate programs are dropped from the earnings regressions.

Table A2.3: Returns to Industry Earnings Premium

Dependent Variable	Log Industry Earnings Premium	
Specification	OLS (1)	FEcg (2)
Clinical Psychology	-0.066 (0.002)	-0.018 (0.002)
Social Work	-0.016 (0.002)	0.029 (0.004)
Curriculum and Instruction	-0.055 (0.001)	-0.011 (0.002)
Psychology	-0.066 (0.006)	-0.022 (0.010)
Edu Admin	-0.061 (0.001)	-0.01 (0.001)
Mathematics	-0.109 (0.008)	-0.01 (0.008)
Biology	-0.043 (0.006)	0.007 (0.009)
Architecture	0.007 (0.003)	0.023 (0.006)
MPA	-0.038 (0.004)	0.01 (0.005)
Nursing	0.064 (0.002)	0.032 (0.002)
CS	0.022 (0.010)	0.031 (0.017)
MBA	0.045 (0.002)	0.011 (0.002)
Civil	-0.04 (0.005)	0.043 (0.011)
Computer Engineering	0.028 (0.010)	0.002 (0.015)
Mech	0.001 (0.008)	0.069 (0.017)
Elec	0.023 (0.006)	0.027 (0.009)
JD	0.144 (0.002)	0.114 (0.005)
PharmD	-0.013 (0.004)	0.003 (0.008)
MD	0.055 (0.002)	0.071 (0.007)
Sample Size	15664350	15664350

Notes: This table reports the average returns to log industry earnings premiums estimates using OLS and FEcg. Robust standard errors are clustered at the individual level, and are reported in parentheses. All 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, and college credits accumulated. 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. Industry premiums are the coefficient estimates of industry dummies in ln earnings regressions as specified in Section 3. Industries are defined based on the four digit NAICS codes.