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RETURNS TO SPECIFIC GRADUATE DEGREES:
ESTIMATES USING TEXAS ADMINISTRATIVE RECORDS

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Returns to Specific Graduate Degrees: Estimates Using Texas Administrative Records
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ABSTRACT

We estimate causal effects of 121 graduate degrees on log earnings. The returns average 0.159 but vary widely across fields, with a standard deviation of 0.176. Experience profiles of the returns also vary and are particularly steep for medicine. Internal rates of return, which account for program length, tuition, and in-school earnings, are sizable but vary less across fields. Earnings effects are higher for women, lower for part time students, and depend on undergraduate major. Students from lower-paying undergraduate majors benefit more from an MBA or JD. School specific returns are higher for higher ranked JD and MBA programs.

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1 Introduction

Graduate education has become an increasingly important part of higher education in the U.S. The percentage of college graduates aged 35-39 with a graduate degree was already 31.3% in 1993 and increased to 42.1% in 2022.[1] The rapid growth of graduate education reflects the economy's increasing demand for a highly skilled labor force, but is costly in terms of education inputs and foregone earnings. There is also growing concern about the debt burden incurred in graduate school (Black, Turner, and Denning, 2023).

Despite this rapid growth, there is very little research studying differences in earnings for *specific* graduate degrees. Students and policy makers rely on average earnings of graduates.[2] Such estimates, as well as simple regression estimates, have been shown to be misleading guides to the returns to graduate degrees (Altonji and Zhong, 2021). For example, using data spanning the early 1990s to 2018 we report below that on average, MBA degree holders earn $112,458, while graduates with a master's in education earn $59,083. 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 part to occupational preferences (business versus teaching) and prior education and work experiences.

A few studies have attempted to estimate the return to specific graduate degrees, such as an MBA (Arcidiacono et al, 2008) and or an MD (Chen and Chevalier, 2012; Ketel et al, 2016). Under some strong assumptions, Altonji and Zhong (2021) (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.[3] While these data have many advantages, they have only limited information on family background and lack information on test scores and on academic performance in high school and in college. Furthermore, they do not identify educational institutions, so AZ could not estimate returns for specific schools or relate returns to measures of program quality. In addition sample sizes are limited, so AZ aggregate graduate degrees into 19 categories.

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 121 specific 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 18 specific degrees defined at the 4-digit CIP level.

[1] Authors' calculations from US Census Bureau (2023), Table 1. Educational Attainment in the United States: 2022

[2] The US Department of Education's College Scorecard provide data on median earnings for some school/graduate program combinations. The data are restricted to students who received federal financial aid and for the first few years after leaving school.

[3] Altonji, Humphries and Zhong (2023) use these data and the FEcg approach to study degree effects by gender. In addition to earnings, they consider hourly wages, work hours, and job satisfaction.

These include the MBA, the JD, and master's degrees in computer science and in four sub-fields of engineering. We also consider master's in education, psychology, social work and a set of health-related professional degrees that include the MD, PharmD, and nursing. 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 attained by the time that she is last observed (FEcg). AZ provide a detailed discussion of the advantages and disadvantages of FEcg and the assumptions that it requires. 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 relies primarily on people with earnings observations both before and after graduate school to identify key return parameters and only uses within person variation to estimate age profiles. Both approaches require strong assumptions about experience profiles in the absence of a graduate degree, which we revisit below. The fourth and fifth approaches are to refine the comparison groups for the OLS and FEcg estimators by using the probability of attaining a specific degree ("propensity scores"), such as an MBA, to reweight the sample.

Because we consider a large number of fields, use multiple estimation methods, and examine heterogeneity in returns, we do not give a blow by blow account of the estimates here. But regardless of the estimation method, we find that returns are substantial on average but vary greatly across degree types. In the FEcg specification, the weighted average return across degrees is 0.159, with a sampling error-adjusted standard deviation of 0.176.[4] The results for a few of the degrees illustrate the range. We find large effects of a JD degree on log earnings regardless of estimation approach. The OLS and FEcg estimates are 0.445 and 0.453 respectively. The return rises with time since graduate school. Weighing the evidence from the different estimation procedures, we find that the return to an MD degree is around 0.60. The return to a PharmD degree is even larger. The OLS and FEcg estimates for an MBA are 0.218 and 0.125, showing a substantial difference. The FEcg estimate of the return to master's in civil engineering is 0.179. The FEcg estimates for master's in electrical, computer, and mechanical engineering are 0.083, 0.068, and 0.097 and returns differ substantially across the other engineering fields that we consider. For computer science, the return is 0.098. The FEcg estimates for the various master's degrees in education that we consider are small to moderate, with the returns to curriculum and instruction and educational administration estimated to be 0.035 and 0.089 respectively. The FEcg estimates of the returns to social work and

[4]These statistics and the statistics for internal rate of return in the next paragraph are based on the 51 graduate degrees whose estimated earnings effects have a standard error less than 0.03.

to clinical psychology are 0.063 and 0.033 respectively, well above the OLS estimates.

We present estimates of how the return varies over the first fifteen years of post-graduate school experience. We find largest growth for an MD degree, which likely reflects the fact that after medical school most doctors work as residents for three or four years at relatively low pay. We also find significant growth for a masters of public administration, an MBA, educational administration, architecture, and several engineering degrees, but little growth for nursing and computer science.

We also present estimates of the percentage gain in net present value of life time earnings and estimates of internal rates of return (IRR) for the 18 fields we focus on. The IRR estimates average 0.161 with a sampling error corrected standard deviation across fields of 0.131. The IRR values of 0.02 for social work, 0.18 for an MBA, 0.08 for electrical engineering, 0.22 for a JD (law), and 0.33 for an MD provide a sense of the range. The IRR estimates often diverge from effects on log earnings because the IRR accounts for program length, tuition, and earnings during enrollment. For example, education administration yields an IRR of 0.230—more than twice its effect on log earnings—due to relatively high earnings during enrollment. In contrast, an MD, which takes four years, has relatively high tuition costs and low earnings during enrollment, resulting in an internal rate of 0.330. This is about half the magnitude of log earnings effect of an MD.

Part-time enrollment (defined as taking an average of less than 9 credits per semester) is very common in most fields, with JD, MD, and PharmD as important exceptions. Both OLS and FEcg estimates of the return are higher for full-time attendance for most degrees, and the gap is large in some cases, especially for FEcg. For example, the simple average of the full-time FEcg estimates for clinical psychology, social work, and psychology is 0.066, while the part-time average is 0.031. For an MBA, the values are 0.134 and 0.119.

The return to most graduate degrees is higher for women than for men, with the exception of nursing and civil and mechanical engineering. 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 by field. A one-point increase in college GPA increases the return to a JD by 0.125 but by only 0.010 for an MBA. It has a negative influence for education, social work, and clinical psychology. Averaging across degrees, a one point increase in college GPA (on a 4 point scale) has a slight negative influence on returns to graduate degrees (-0.019). [5]

Table 5 reports returns by college major (aggregated into 11 categories) and shows substantial heterogeneity. For an MBA, the FEcg estimates are only 0.081, 0.071, and 0.066 respectively for business, engineering, and computer science majors but exceed 0.21 for humanities, education, social science, and fine arts majors, which are lower paying undergraduate fields.[6] We also find that the

[5] The average is weighted by number of holders of each degree. The calculation is restricted to the 74 degrees with a sufficiently small standard error on the interaction effect between graduate degree and college GPA.

[6] Black, Sanders, and Taylor (2002) are perhaps the first to investigate this issue. They report OLS estimates of the return to a few graduate degree types for different majors using the 1993 National Survey of College Graduates. AZ report FEcg and OLS estimates of the return to an MBA for 8 undergraduate majors and also present results for a small number of other graduate field/undergraduate major combinations, but their estimates are relatively imprecise.

return to 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 0.073 for an engineering major but 0.294 for a fine arts major. The average return to a graduate degree is above 0.20 for fine arts majors but around 0.05 for business and computer science majors and negative for engineering majors.[7] This implies a significant role of graduate degrees in making up for a low paying undergrad major.

Students also have to decide *where* to go to graduate school, not just what to study. To this end, we also estimate *school specific* returns to a JD, an MBA, and degrees in nursing, pharmacy, and social work. To do so, we modify FEcg by drawing on Dale and Krueger's (2002) approach to estimating the return to college quality. Consider a JD degree. Basically, we treat JDs from different schools as different degrees and in addition add controls for selection into different law schools based on students' application and admission records. 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. We then regress the school specific returns on a measure of program rank from U.S. News & World Reports. We find that the institution has a substantial effect on the return to an MBA. An increase of 20 places in rankings increases the return by 0.026 (0.014), which is economically significant relative to the average return of 0.125. The average of the returns to a set of unranked MBA programs is close to zero (0.034). An increase of 20 places in the law school rankings increases the return by 0.07 (0.014), compared to an average return of 0.453. In contrast, we do not find that the returns to nursing, social work, and PharmD programs depend on the ranking.

We contribute to the growing literature on the importance of field of study, surveyed in Altonji, Blum, and Meghir (2012), Altonji, Arcidiacono and Maurel (2016) (who present OLS estimates for a set of graduate degrees), and Lovenheim and Smith (2023). At the undergraduate level, contributions include Turner and Bowen (1999), Arcidiacono (2004), Hastings, Nielson, and Zimmerman (2013), Kirkeboen, Leuven, and Mogstad (2016), Bleemer and Mehta (2022) and Humphries, Joensen, and Veramendi (2023) among others. At the graduate level, the literature is thinner, but has been expanding rapidly, with several new papers since the first draft of our paper. In addition to the papers mentioned above, recent contributions include Gottlieb, Polyakova, Rinz, Shiplett, and Udalova (2023) who provide detailed evidence on earnings of doctors. Britton et al (2020) use UK administrative data to provide OLS estimates of the average earnings returns at age 35 for a variety of masters degrees, PhD degrees, and postgraduate certificates. Minaya, Scott-Clayton, and Zhou (2024). provide individual fixed effects estimates for several master's degree types using administrative records from Ohio.

Bennett (2023) and Britton et al (2020) are among a growing literature that examines returns to institution specific returns to field. Bennett (2023) uses a correspondence study to show that having a resume from less selective institutions (often for online programs) has no effect on call back probabilities. Britton et al (2020) provide OLS evidence. We provide institution specific casual estimates for a subset of degrees. We are the first to use the FEcg approach and Dale and

[7] This is calculated among the 60 graduate degrees with the lowest standard errors of estimates for the fine arts major subsample.

Krueger's method to examine the institution-specific returns to a set of graduate degrees.

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, including their strengths and weaknesses. In section 5, we present estimates of the return to graduate degrees. Section 6 concludes.

2 Data

We use administrative data from Texas for our empirical analysis. The TSP data follows students from high school 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 earnings data is provided by the Texas Workforce Commission (TWC).[8]

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 the earnings returns to undergraduate degrees from particular institutions 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. We suspect that our estimates of the return to law school and business school quality may be understated as a result. However, restricting our analysis to individuals who attended high school in Texas does not significantly impact our returns estimates, suggesting that the underestimation may not be severe.

Earnings observations are from UI records. They are quarterly and are deflated to 2019 dollars.[9] To account for sporadic unemployment episodes and to focus on returns for full-time work, we only keep earnings observations that are (1) part of a sequence of four consecutive quarterly earnings observations; (2) at least three quarters after college degree attainment; (3) not during enrollment in graduate school; (4) either before graduate school or at least three quarters after advanced degree attainment; and (5) below $250,000 and above $3,000 (quarterly earnings). Throughout, we restrict the sample to those with a bachelor's degree.

The earnings data is available since 1990, and therefore allows us to observe labor market outcomes for individuals many years after graduate school. Post-degree observations have a fairly

[8]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 paper, we do not use information from the NSC, due to the lack of detailed enrollment information for out-of-state enrollment.

[9]Business income is excluded. This may be more important for some degree types, such as law and medicine. AZ (Appendix Table B4) report return estimates using a measure the includes net income businesses and a measure that does not. They do not find much difference on average across the 20 graduate fields they consider, but the estimates are noisy. They obtain larger point estimates of the return to Medicine and to Law when they use the measure with business income, but the difference is not statistically significant.

wide distribution. For example, the data has substantial mass between 10 and 18 years after a JD and 10 and 15 years after an MBA (Figures A4.1 and A4.2). Comparing the sample distribution between the FEcg sample and the FE sample shows that restricting the analysis to individuals for whom we have earnings observations both before and after graduate school (FE sample) significantly reduces the observations beyond a few years after graduate school enrollment.

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 in mathematics, reading, and writing as our main standardized test scores. These exams are required for high school graduation and cover a wider population in our sample.[10] Students' performances on the standardized exams, are measured using their percentile ranking among their cohort peers. We devoted considerable time to assessing the importance of controlling for the high school variables. But in the end, we focus on estimates that control for college credits and grades but not high school courses and tests to reduce loss of sample from missing data. We show below that adding high school tests and courses does not change the estimates by very much. This finding may be helpful to other researchers who lack access to high school performance measures. We do not use the SAT and the ACT test scores because they are missing for many students.

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. We only consider the latest graduate degree for individuals with multiple graduate degrees. We drop all individuals who have enrolled in doctoral programs outside of medical fields (i.e., PhD programs).[11] We treat 6 common double majors as separate undergraduate majors: social sciences + business, foreign language and literature + business, liberal arts and sciences + business, engineering + mathematics, communication and journalism + social sciences, and communication and journalism + foreign language and literature. For individuals with other combinations of multiple undergraduate majors, we consider the most popular major as

[10] 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. 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.

[11] Less than 3% of graduate degree holders have more than one graduate degree. The number of multiple graduate degree holders is slightly higher but still small for MBA holders (4.6%), JD holders (5.3%) and MD holders (6.7%).

their main major.[12] 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.

Our school specific estimates make use of students' graduate admission records, which contain information on where students applied to and were admitted to for Texas public universities since 2000. We also 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. We discuss these data in section 5.7.1.

3 Summary Statistics for the Full 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 18 key graduate fields that we focus on below. These are social work, clinical psychology, curriculum and instruction (education), psychology, education administration, architecture, biology, public administration (MPA), nursing, computer sciences, civil engineering, MBA, computer engineering, mechanical engineering, electrical engineering, PharmD (pharmacy), JD (law), and MD (medical doctor). We present results for 121 graduate fields in the supplemental appendix. Throughout, the graduate fields are presented in the above order, which ranks the 18 graduate programs according to their post-graduate school earnings from low to high (column 3). 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. In general, post-graduate school earnings have a strong positive correlation with pre-graduate school earnings (column 1). But it is notable that graduates from MD programs have the sixth lowest pre-graduate program income average even though they earn the highest post-graduate program income (column 1). This probably reflects the fact that medical schools, which are highly competitive, favor pre-graduate school experience in medicine related jobs that tend to pay less. For example, some aspiring medical students will choose to work in Emergency Medical Services or in university science labs for relevant experiences.[13] This would violate Assumption 6 of the FEcg approach, which we discuss in section 4.4. The violation raises the possibility that for some fields, pre-graduate school earnings do not reflect the counterfactual incomes that an advanced degree holder would have earned if she did not pursue a graduate degree. 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

[12] College course-level schedule and performance information are available since 2011, but we do not use it because of the relatively short horizon.

[13] Appendix Table A3.2 reports the most common 2 digit industry before and after graduate school for each degree. The most common pre and post NAICS industries are the same or very similar for all degrees except MD. The most common 2 digit industry for future MDs is educational services, which includes research positions in higher education institutions.

school earnings as a guide to the counterfactual incomes of graduate degree holders. This issue is probably most acute for medical degrees.

Average annual earnings during graduate school also varies substantially across programs, from a low of $10,468 for MD to a high of $57,240 for nursing. The value is only $20,052 for a JD but $46,972 for an MBA. 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 in the student record data, we define part-time attendance based on whether the individual obtained an average of less than 9 credits per semester enrolled. One can see that the majority of students attend graduate school on a part-time basis. The fractions range from 0.88 and 0.93 for nursing and for education administration (respectively) to 0.02 for a JD and MD. Below, we compute one set of internal rate of return estimates and gain in net present discounted value (PDV) estimates including earnings while in school and using the median 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 are typically larger for full-time degrees.

Table 1 also shows the average college major premium and industry premium of graduates from different degree programs.[14] Column 5 shows 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 gap 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 0.09 and 0.07, and psychology, with a negative gain of -0.03.

The left panel of Table 2 presents facts about demographic representation in the 18 graduate fields we focus on. The bottom row reports the share of all college graduates from the demographic group indicated by the column heading. The other rows report the share of the demographic group among holders of each graduate degree *relative* to the group's share among all college graduates. Values above (below) 1 indicate overrepresentation (underrepresentation). Females are overrepresented in social work, psychology, education, and nursing by factors ranging from 1.2 to 1.6 when compared to their representation among college graduates (Column 1). In contrast, females are underpresented in engineering and computer science by factors ranging from 0.2 to 0.4. The relative share of female graduates is also low in MBA and JD programs. Racial compositions also vary

[14]To construct these, we first compute the earnings premium associated with each 4 digit North American Industry Classification System (NAICS) industry code using a log earnings regression that includes 2-digit college major, college major $\times$ gender specific cubic age profiles, 4-digit 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. The college major premiums are estimated using a similar regression but with the industry dummies excluded and with the college major $\times$ gender specific cubic age profiles replaced with college major specific cubic age profiles. The college major premiums refer to age 35. The reference category for college majors is curriculum and instruction. The reference category for industry is elementary and secondary education. We then compute the average college major premium and industry premium of individuals with a given advanced degree.

widely across graduate programs.[15] For example, African Americans are overrepresented in clinical psychology, social work and public administration and underrepresented in most STEM-related programs, relative to their share among college graduates. Asian students are underrepresented in psychology, social work, education and public policy related programs. They are overrepresented in computer science, engineering, pharmacy, and medicine. College graduates who qualified for reduced price or free meals in high school are underrepresented in some of the highest paying programs, including JD (0.38) and MD (0.63).

Table 2 also presents graduates' average percentile rankings in the standardized Texas high school assessment exams as well as 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 stems from the fact that people selectively choose whether to enroll in graduate school and the fact that 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 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 six 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 and graduate degree the individual has obtained by the time that she is last observed (FEcg). The fourth and fifth approaches are to refine the counterfactual groups for OLS and FEcg by using propensity scores for attainment of a specific degree to re-weight the regression sample and as an additional control variable. We refer to these approaches as OLS-ps and FEcg-ps. Sixth, when estimating school specific returns to particular graduate degrees, we draw upon Dale and Krueger's approach to modify FEcg, as we discuss in 5.7.

Before turning to the econometric specifications, we need to introduce some notation. Let i index an individual student, and t index a time period. 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 $g \in \{0, 1, ..\mathcal{G}\}$. The value $g = 0$ is the case of no graduate degree.

[15] In all analyses in the paper related to race/ethnicity, keep in mind that international students are treated 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.

Throughout, we restrict our attention to individuals who already hold a bachelor's degree. The dummy variable $C_{c(i)}$ equals 1 if individual i's college major is c, and 0 otherwise. Similarly, the dummy variable $G_{g(i)t}$ equals 1 if individual i holds a graduate degree in field g at time t. The dummy variable $G_{g(i)}$ 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 that varies across models. Our main outcome variable is the natural log of w_{it}, which is real quarterly earnings in 2019 dollars. Our goal is to estimate the causal effect of $G_{g(i)t}$ on $\ln w_{it}$.

4.2 The Earnings Model

Our baseline specification assumes the effects of undergraduate major and graduate degrees are additively separable. The model is

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{\mathcal{C}} (\alpha^c_{\mathrm{gen}_i 0} + \alpha^c_{\mathrm{gen}_i \mathrm{age}_{it}}) C_{c(i)} + \sum_{g=1}^{\mathcal{G}} \gamma^g_{x_{it}} G_{g(i)t} + X_{it}\beta + u_{it}, \tag{1}$$

The effect of college major depends upon a $c \times$ gender specific intercept ($\alpha^c_{gen_i 0}$) and a $c \times$ gender specific cubic function of age_{it} ($\alpha^c_{\mathrm{gen}_i \mathrm{age}_{it}}$). The key parameter $\gamma^g_{x_{it}}$ is the return to graduate degree g at x_{it} years after graduate degree completion. Variable $x_{it} = 0$ for those who do not go to graduate school. We focus on the baseline case in which we restrict graduate returns to be constant, with $\gamma^g_{x_{it}} = \gamma^g$. But we also estimate a version in which the return is a quadratic function of x_{it}, with $\gamma^g_{x_{it}} = \gamma^g_0 + \gamma^g_1 x_{it} + \gamma^g_2 x^2_{it}$.

The control vector X_{it} includes year dummies, race/ethnicity, college GPA, and college credits accumulated. We exclude the high school performance data from our main specification for two reasons. First, the OLS and FEcg estimates are not very sensitive to including the high school controls, provided one controls for college GPA and college credits. Second, restricting the analysis to individuals who went to high school in Texas reduces our sample size by more than a half.[16]

The error term u_{it} may be written as $u_{it} = e_i + \varepsilon_{it}$. We decompose the 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:

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

OLS applied to (1) treats the composite error term u_{it} as random. The FE estimator treats e_i as a fixed effect and treats ε_{it} as random. It involves comparing the average earnings of an individual before and after advanced degree attainment, accounting for age profiles and year effects. 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

[16] See Appendix Table A1.1a and A1.1b. Excluding college GPA and college credits as well as the high school controls leads to a substantial increase in the OLS estimates for higher paying graduate degrees, while FEcg is not very sensitive to the controls.

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{\mathcal{C}} (\alpha^c_{gen_i 0} + \alpha^c_{\text{gen}_i \text{age}_{it}}) C_{c(i)} + \sum_{g=1}^{\mathcal{G}} \gamma^g_{x_{it}} G_{g(i)t} + X_{it}\beta + \sum_{c=1}^{\mathcal{C}} \sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)} + \nu_i + \epsilon_{it}, \quad (3)$$

treating $v_i + \varepsilon_{it}$ as random.

4.3 Choice of Sample

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 field g consists of individuals who never obtain an advanced degree as well as observations on individuals who eventually obtain an advanced degree but do not have the degree by time t. We provide FEcg and FE estimates using both the full sample and the sample that excludes "college only" individuals who are not observed to go to graduate school. In both cases, the estimate of γ^g is based primarily on comparing the average earnings before and after obtaining advanced degree among students who are in the same bachelor's degree major $\times$ advanced-degree type group. We focus on the FEcg and FE results using the full sample to simplify comparisons to OLS and because the college only observations are critical for specifications that allow graduate school returns to depend on x_{it}.[17]

A second issue is whether or not to include those who go to graduate school directly out of college. Because FEcg and FE identify γ^g primarily from a comparison of earnings before the graduate school with earnings after graduate school, the case for interpreting them as treatment on the treated estimates is stronger if one excludes those who go to graduate school directly. However, to simplify comparisons among the estimators, we work primarily with the full sample and include these cases. They contribute to estimation of the age profiles as well as the effects of time invariant controls in the OLS and FEcg cases. In appendix Table A1.4, we report FEcg estimates in which we allow γ^g to depend on whether the individual delayed graduate school under the assumption that degree combination fixed effects b_{cg} are the same for the two groups.[18]

4.4 Assumptions of the FEcg Approach

AZ provide a detailed discussion of the assumptions under which FE and FEcg will identify treatment on the treated effects of graduate degrees. We briefly summarize the discussion here, drawing also on Altonji et al (2023). The first two assumptions relate to the intercept of counterfactual earnings. Assumption 1 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 underestimate what future earnings would have been in the absence of graduate school. This "Ashenfelter's dip" behavior would lead to upward bias in FEcg and FE (Ashenfelter, 1978). In Section 5.2 we ex-

[17] When we restrict $\gamma^g_{xt_i}$ to be constant, inclusion of the college 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.

[18] In the FE case, γ^g is not separately identified for those who go direct.

plore the issue and conclude that transitory variation probably leads to a small upward bias in the estimates. AZ reach a similar conclusion.

Assumption 2 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. Otherwise, pre-graduate school earning may not be a reliable guide to counterfactual earnings in the absence of graduate school. To see how this assumption 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 related occupation before starting an MBA. In this case FEcg and FE would make use of 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).

OLS is likely to be less sensitive to these two assumptions because it relies primarily on cross-sectional comparisons of individuals with graduate degrees at a point in time to individuals without graduate degrees at a point in time. In the full sample, only 4% of the observations on individuals without graduate degrees are pre-graduate school observations on individuals who obtain degrees. However, OLS will be biased to the extent that graduate degrees are associated with permanent differences in ability and preferences, conditional on the controls.

The next three assumptions are required to guarantee that for a given college major, the experience profiles of college graduates and those who obtain an advanced degree are parallel except for the causal effect of graduate school on the slope of postgraduate earnings. We need parallel profiles because we do not observe counterfactual earnings for years after graduate school. Assumption 3 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 $G_{g(i)}$ (conditional on college major), except for the effect of $G_{g(i)t}$. Assumption 4 is that earnings growth within an 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. Assumption 5 is that conditional on college major, the contribution of occupational progression to earnings growth would have been the same if the person did not go to graduate school. The three parallel experience profile assumptions are strong. In section 5.1 we add g specific experience profiles to the model.

Finally, assumption 6 is that the choice of one's early occupation neither has field-specific impacts on subsequent earnings nor affects the likelihood of graduate school admission. If this assumption does not hold, individuals who anticipate pursuing graduate school may select initial jobs they would otherwise avoid, potentially accepting lower pre-graduate earnings than they could have obtained without such plans. In that scenario, using pre-graduate earnings as a benchmark would understate the relevant counterfactual earnings and thus cause FEcg to overstate the true returns. We already alluded to this issue in the case of an MD in section 3. This issue may be especially pertinent for medicine, law, and certain PhD programs (excluded from our study), though it is likely less significant for most other degrees we consider, such as MBAs or master's degrees in engineering.

4.5 Propensity Score Weighting

When using OLS we are assuming that earnings of those without a graduate degree are good proxies for the counterfactual earnings of those with a degree, conditional on the other controls. In both FE and FEcg specifications, the gist of Assumptions 1-6 is that (1) the earnings of a person prior to graduate school enrollment is a good proxy for the counterfactual earnings of that person had she not gone to graduate school, and (2) 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 modify the OLS approach to place 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. We use a logit model to estimate the probability p_{ig} that i will eventually attain an advanced degree in g versus not get a graduate degree in any field:

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

Here C_i is the vector of college major dummies and X_i includes all time invariant elements of X_{it}. For each g, p_{ig} is the probability that $g(i) = g$ given C_i, X_i for the population of individuals who either obtain 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

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

For each degree, we estimate (4) to obtain p_{ig} and estimate (5) using the relative values of p_{ig} as the weight.[19] Note that the sample and the parameters differ across g. This is a way to address differences by graduate degree attainment in the effects of the control variables and age profiles. 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. However, unlike FE and FEcg, propensity score weighting does not address selection on unobservables.

5 Results

We now turn to the estimates of the return to graduate school. Section 5.1 reports our main estimates of average returns to specific graduate degrees. Section 5.2 considers alternative specifications and sensitivity checks. Section 5.3 presents estimates for full time and part-time attendance.

[19] We set p_{ig} to 1 for those who $g(i) = g$. 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.

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. Section 5.7 reports institution specific estimates of returns for a subset of the fields that we consider.

5.1 Estimates of returns to graduate degrees

5.1.1 Overview

Table 3 reports estimates of returns for 18 of the 124 degrees included in our regression models. We present estimates for many additional 4 digit CIP graduate degrees in Figure 1 and for all 121 degrees for which we observe more than 50 graduates in Table A1.5. In Table 3 columns 1-3, we report OLS, FEcg and FE estimates on the full sample of college graduates for the specification in which the return is constant.[20] 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.

Columns 4 and 5 report OLS-ps and FEcg-ps estimates using (5) with controls for $G_{g(i)}$ added. 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.[21]

Columns 6, 7, and 8 of Table 3 display OLS, FEcg and FE estimates of γ^g_{1-15}, where $\gamma^g_{1-15}=\sum_{x=1,..,15}\gamma^g_x/15$. It is the average return over the first 15 years after graduate school. Figures 2 and A1.1 display how the returns γ^g_x to specific graduate degrees change over years after graduation.[22]

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 master's programs to four years for an MD. In Section 5.4 we present internal rates of return (IRR) estimates. These estimates differ less across programs of different lengths than the effects on log earnings.

Before we dive into the results for the 18 main graduate degrees we focus on, some broader patterns are worth mentioning. First, we examine the relationship between the earnings effects and some observable characteristics by regressing the FEcg values of $\hat{\gamma}^g$ on g-specific averages of observable characteristics of those who obtain the 124 graduate degrees, one characteristic at a time. The regression coefficients are in Column 1 of Table A1.6. The results show that, generally speaking, returns are higher for graduate degrees that attract (1) individuals with higher-paying college majors, (2) individuals who work in higher-paying industries before and after graduate

[20]Table A1.2 presents estimates for the FEcg and FE models using only individuals who have attained a graduate degree. As we noted above, the additional observations in the full sample contribute to identification of the time trends and the experience and age profiles.

[21]We checked whether the difference between OLS and OLS-ps is due to weighting or to the change in samples by applying OLS using the same samples used for OLS-ps 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 FEcg-ps are less than |.003| in absolute value with the exceptions of MD (.018), PharmD (.030) and nursing (.006).

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

school, and (3) individuals who have higher college GPAs.

Second, we examine correlates of the difference between OLS and FEcg estimates of γ^g across all 124 graduate degrees. The results are presented in Column 2 of Table A1.6. Treating FEcg as the benchmark, we find that, as expected, OLS overestimates returns for graduate degrees that attract individuals with higher industry premiums before graduate school and individuals with higher industry premiums after graduate school (p-value=0.058), but the other variables are not statistically significant.

The third point is that FE estimates are typically lower. FE estimates are less than the FEcg estimates in 17 of 18 cases reported in Table 3. One would expect the FE estimates to differ from the FEcg estimates for three reasons (aside from sampling error). First, the FE specification does not use variation in $G_{g(i)t}$ associated with individuals who directly enroll in graduate programs after college. This is because these "go-direct" students do not have pre-graduate school earnings observations. FE estimates may be downward biased if "go-direct" students have higher returns. Second, for the FE model, identification of all parameters (not just γ^g) relies only on within-individual variations. This is likely to matter for the age and year profiles, which in turn influence the estimates of γ^g. Third, the variation in $G_{g(i)t}$ conditional on $G_{g(i)} = 1$ used by FEcg could be correlated with cohort differences in unobserved person characteristics, while the exclusively within person variation in $G_{g(i)t}$ used by FE is not.

To better understand how these factors affect FEcg and FE, we implement two alternative specifications. First, we estimate OLS and FEcg models allowing γ^g to differ for students who "go-direct" and do "not-go-direct". Second, we use a version of FEcg that estimates (3) by 2SLS using deviations from the individual means of the $G_{g(i)t}$ dummies as instruments for $G_{g(i)t}$ (FEcg-2SLS). Like FE, it only uses within person variation in $G_{g(i)t}$, but unlike FE, it uses both within and across person variation in the other variables. The results are reported in Table A1.4. Columns 3 and 4 show that the FEcg estimates are higher for those who go directly to graduate school in 12 of the 18 cases. Columns 4 and 5 show that the FEcg estimates for those who do not go directly to graduate school are similar to "FEcg-2SLS" estimates. This suggests that any cohort effects on earnings that are correlated with G_{it} are not the source of differences between FEcg and FE.

We prefer the FEcg estimates for three reasons. First, it incorporates returns for "go-direct" students and makes use of between-individual variation when appropriate. Second, 7 of the 18 FE estimates of γ^g are negative, which seems implausible. Finally, when we allow the returns to graduate degrees to vary with years since the degree, the experience profiles $\gamma^g_{x_{it}}$ of the returns are poorly identified using FE, which is not surprising.

5.1.2 Estimates of returns for a selection of degrees

Medicine, pharmacy, and nursing: We first consider three key health-related degrees, beginning with an MD. Not surprisingly, we find very large returns to an MD. The OLS estimate is 0.573 (0.007). The FEcg estimate is slightly higher at 0.614 (0.018). When we allow the returns to depend upon years of postgraduate school experience, we obtain estimates of γ^g_{1-15} that are a bit higher.

We graph the FEcg estimates of γ_x^g in Figure 2. The returns rise dramatically with experience, from a negative value in the first year to above 1.0 after ten years. This negative value reflects the fact that the vast majority of medical school graduates participate in relatively low-paying residency programs for several years after graduate school, so the initial earnings understate career earnings of MDs. Propensity score weighting (and the change in the sample) does not significantly impact the OLS estimate or the FEcg estimate. About 0.05-0.08 of the return operates through 4 digit industry (Appendix Table A3.1)

The return for PharmD is broadly similar to the results for an MD, but is even larger (in log points, not dollars). The OLS and FEcg estimates are 0.642 and 0.794. The return to a master's in nursing is more modest, but still quite large given that it requires less time and typically has lower tuition. The OLS and FEcg estimates are 0.380 and 0.232 respectively. Propensity score weighting does not make much difference. The estimates of γ_{1-15}^g are also similar.

Figure 1 displays estimates and 90% confidence intervals for a variety of degrees in the health professions (CIP 51). Keep in mind that they are arranged from left to right in increasing order of average earnings. Both OLS and FEcg estimates increase with average earnings. The FEcg estimates range from a low of 0.00 for chiropractic to a high of 0.794 for PharmD. The FEcg estimates are higher than the OLS estimates in all cases except nursing.

MBA and other Business Degrees: The OLS estimate of γ^g for an MBA degree is 0.218, which is well above the FEcg estimate of 0.125. For 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 the OLS estimate rises to 0.242 (0.004) (Table A1.1a). Propensity score weighting reduces the OLS estimates to 0.194 and leads to a similar reduction in FEcg. The estimates of γ_{1-15}^g are similar to the estimates of γ^g. Figure 2 shows that the return to an MBA rises from about 0.05 to about 0.20 fifteen years out of business school, displaying a substantial increase in the return over time.[23]

Figure 1 panel a displays OLS and FEcg estimates of γ^g for 13 different business related master's degrees. We find substantial differences across the degrees in returns, and these differences are positively related to average earnings. For example, the FEcg estimate of the return to hospitality management is only about -0.052, while the estimate for finance is 0.248. The FEcg estimates are below OLS for 10 of 13 degrees, although the confidence intervals overlap in most cases.

Law (JD): The OLS and FEcg estimates of the return to a JD degree are 0.445 and 0.453 respectively. Thus both estimators point to a substantial return to a JD, even accounting for the fact that it is a three year course of study. Propensity score weighting increases the OLS and FEcg estimates by about 0.1. The FEcg estimates of the experience profile of γ_x^g show an increase from 0.39 right after graduate school to 0.50 ten years out of law school (Figure 2). The FEcg estimate is that 0.083 of the return to a JD operates through industry (Table A3.1). This industry effect estimate

[23] Gicheva (2012) documents that employers often pay part of the costs of an MBA. The assistance often with the requirement that the individual remain with the firm for a period of time, perhaps delaying salary increases. We lack the data on tuition funding and job mobility that would be needed to investigate this.

is the largest among the 18 fields we focus on. The result makes sense, because a JD is required to practice as an attorney, and attorneys are the heart of the legal industry.

Psychology and Social Work: We report estimates for a master's in psychology, clinical psychology and social work. The OLS estimates are close to zero or negative for all three of these degrees. However, the FEcg estimates show a return of 0.063 (0.007) and 0.033 (0.006) respectively for social work and clinical psychology. Note that AZ find an even larger gap between the FEcg and OLS estimates for a combined social work and psychology category. The OLS-ps estimates are above the OLS estimates, ranging from 0.023 for psychology to 0.069 for social work. Propensity score weighting increases the FEcg estimate for clinical psychology from 0.033 to 0.104, for psychology from -0.032 to 0.038, and for social work from 0.063 to 0.102

The estimates point to a modest return to graduate degrees that are related to clinical psychology, counseling, and social work. AZ show that these degrees lead to relatively low earnings 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 A3.1 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 (-0.136 (0.002)), while FEcg is -0.016 (0.002). The OLS and FEcg estimates for social work are -0.082 and 0.064 respectively. OLS attributes the drop in industry premiums to the degrees, while the FEcg estimates indicate that those who obtain psychology and social work degrees were in low paying industries before graduate school.

Public Administration (MPA): The OLS estimate for an MPA is 0.099 (0.010), while the FEcg value is 0.155 (0.013). The corresponding estimates of γ^g_{1-15} are higher. Figure 2 shows a dramatic increase in returns from 0.05 to 0.35 from year one to year fifteen after graduate school. Propensity score weighting also increases the estimates. The OLS and FEcg estimates of the effect of an MPA on the industry premium are -0.076 (0.004) and 0.010 (0.006) respectively. This accounts for most of the difference in the two estimators in the estimates of the return. Overall, the estimates suggest a healthy return to an MPA, especially if one places more weight on FEcg. The OLS and FEcg estimates of γ^g for a master's in Public Policy Analysis are 0.122 (0.029) and 0.154 (0.034), respectively (Table A1.5).

Education and Education Administration: The OLS and FEcg estimates of the return to a masters in curriculum and instruction, the most popular of the education related masters degrees, are small. The OLS and FEcg estimates of 0.023 and 0.035 are below AZ's estimates of 0.102 using OLS and 0.188 using FEcg. Propensity score weighting partially closes the gap, increasing the OLS estimate to 0.086 and the FEcg estimate to 0.056. Table 3 also reports modest returns for education administration. The OLS estimates are around 0.082 (0.003) and the FEcg and FEcg-ps values and 0.089 (0.003) and 0.126 (0.003). Comparison of Table 1 Column 6 and Table 3 reveals that propensity score weighting increases estimates for graduate degrees that attract individuals with low paying college majors.

Figure 1 displays OLS and FEcg estimates for nine 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, 0.073, and education administration, 0.089.

Computer Science, Engineering, and Architecture: The estimates for a degree in computer and information sciences (CIP 1101) are 0.081 (0.015) using OLS and 0.098 (0.034) using FEcg. Overall, the estimates suggest a normal return to a master's in computer sciences, assuming that the degree takes one year if full-time. The estimates for civil engineering follow the same pattern across estimators, and suggest a sizable return. The FEcg estimate is 0.179 (0.019). The estimates for architecture and for the other engineering fields — computer engineering, mechanical engineering, and electrical engineering — also suggests moderate returns. The OLS estimates are 0.020 (0.008), 0.084 (0.016), 0.010 (0.014), and 0.091 (0.011) respectively, while the FEcg estimates are 0.076 (0.020), 0.068 (0.025), 0.097 (0.033), and 0.083 (0.016), respectively. Columns 4 and 5 report OLS-ps and FEcg-ps estimates. The OLS-ps estimates are smaller than the OLS estimates in three of the four cases. The FEcg estimates also drop by an average of about 0.05 for the engineering degrees.

Figure 1c displays the returns to a set of degrees in the computer and information sciences category (CIP 11) and Engineering category (CIP 14). The highest returns are for computer systems analysis (CIP 1105) and petroleum engineering (CIP 1425). Note that the 90% confidence intervals are fairly wide in a couple of cases, so the corresponding point estimates should be considered cautiously.

Arts and Humanities: Table A1.5 reports estimates for a number of masters degrees in the arts and humanities. The OLS and FEcg estimates are negative for a master's in fine arts (-0.210 (0.02) and -0.028 (0.03)), English (-0.154 (0.01) and -0.048 (0.02)), history (-0.185 (0.02) and -0.074 (0.03)), and music (0.00 (0.01) and -0.137 (0.07)). The simple average for the 4 degrees is -0.137 for OLS and -0.07 for FEcg. We think the very low OLS estimates are due to misrepresentation of the counterfactual occupations for those who choose to get an advanced degree in arts and humanities. Note, though, that a fine arts degree may provide an individual with the skill and network necessary for a career in the art world, which comes with lower earnings prospects.

5.2 Alternative Specifications and Sensitivity Checks

5.2.1 Sensitivity to Controls for High School and College Performances

We are not aware of any other large US data set that contains detailed information on performance in high school records, test scores, and college GPA, college credits, college major, graduate field, and earnings for many years. In Appendix Table A1.1a we use a common sample to explore the sensitivity of the estimates to choice of controls.

The results show that the OLS estimates are not very sensitive to the inclusion of the high school performance controls provided that one controls for college GPA and total college credits, which we do throughout. The estimates change by less than 0.01 in all cases except Pharmacy, a JD, and MD, which change by less than or equal to 0.03. Controlling for high school performance but not college GPA and total credits increases the estimates by around 0.02. The largest increase is 0.05 in the case of an MD.[24] Excluding college GPA and credits as well as high school performance leads to modest increases in the estimates relative to the model that includes both. However, failure to control for college major leads to large increases in the OLS estimates for engineering and computer science and large decreases for the lower paying degrees, such as social work. It is critical to control for college major when studying effects of graduate degrees.

The FEcg approach addresses selection on unobserved permanent characteristics. Consequently, it is not surprising that the FEcg estimates change very little when the high school controls are added or when the college GPA and credits controls are dropped (Table A1.1.b).

Finally, we follow Andrews et al's (2024) analysis of returns to college major and add fixed effects for high school by cohort and college by cohort to our baseline control set. Neither the OLS estimates nor the FEcg estimates are very sensitive to adding these controls (not reported).

5.2.2 Assessing Bias from Ashenfelter's Dip

Column 2 of Table A1.3 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.[25] The estimates of γ^G with the dummies are similar to those for our basic specification (reproduced in Column 1) for most of the 18 degrees, including an MBA. The largest differences are 0.031 for PharmD and 0.038 for MD but even these values are small relative to $\hat{\gamma}^G$ for these degrees. Corresponding results for the FE estimator are reported in Columns 5-8. They also suggest a small negative bias from Ashenfelter's dip. We conclude that Ashenfelter's dip is only a minor issue in our application.

5.3 Returns to Graduate Degrees by Part-Time Status

Table 3A reports OLS and FEcg estimates of the return to advanced degrees by full-time and part-time status. 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 permanent unobserved differences for a given *cg* combination 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 0.037 for part time and 0.045 for full-time. Similarly, social work (0.048 versus 0.085), biology (0.030 versus 0.176), and psychology (0.007 versus 0.067) show substantial differences in returns in favor of full-time.

[24]The OLS estimates are not very sensitive to controlling for measures of parental income, but doing so leads to a large loss of sample (not reported).

[25]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.

The part-time/full-time gap is massive for computer science (0.051 (0.035) vs 0.172 (0.070)). We also find large returns to full time attendance in the engineering fields, especially mechanical engineering (0.084 (0.039) versus 0.232 (0.079)). It is possible that prior earnings understate counterfactual earnings in some fields for those who attend 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.

For an MBA, the returns are 0.119 for part time and 0.134 for full time, and the OLS estimate exceeds FEcg by a larger amount in the full-time case. For a JD, the FEcg estimate of the return to full-time degree is modestly higher than the return to a part-time degree (0.415 versus 0.467), although the difference is not statistically significant. The gap is much larger in the case of an MD. Note, though, that part-time attendance accounts for only 2% of JD and MD in our sample.[26]

5.4 Net PDV and 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 2) and the counterfactual net PDV if the person had not attended graduate school (Column 1). For both calculations, we assume a discount rate of 5%. The table also reports the percentage increase in PDV (Column 3), and the internal rate of return (IRR) (Column 4). The internal rate of return is the discount rate at which the counterfactual net PDV equals the actual net PDV given the predicted income flow. It takes into account tuition and forgone earnings while enrolled, not just the effect of a degree on the future path of log earnings ($\gamma^{g}_{x_{it}}$). The calculations are based on the values of average tuition of public institutions in 2012 in Column 1 and the median value for program duration in Column 2 of Appendix Table A2.1.[27] The tuitions are adjusted for inflation to 2019 dollars. The results in Table 4 are also based on the average earnings per year while enrolled in graduate school in Column 4 of Appendix Table A2.1. Note that average annual earnings during graduate school enrollment differ substantially across programs, from $10,469 for MD to $57,239 for Nursing. Standard errors of the PDVs and IRR estimates are calculated using a block bootstrap procedure, as explained in the note to Table 4.

In computing PDVs, we evaluate log earnings setting the year to 2019 and the race/ethnicity variables to non-Hispanic white. We evaluate average earnings for each gender at each age over the g specific distribution of all of the other control variables, such as GPA, C_i, and $C_i G_{g(i)}$. The Texas data does not have enough support after the mid-40s for some graduate degrees for us to

[26] The 2% value for JD programs struck us as low. A report based on the Law School Survey of Student Engagement estimates that 12% of currently enrolled students are part-time (Petzold, 2023). However, the percentage of enrolled part-time students will overstate the percentage of degrees that are obtained part-time, because part-time student are enrolled longer. Furthermore, credit load requirements of some part-time programs at Texas institutions may be high. For example, the credit load for the part-time program at South Texas College of Law is 9 or 10 courses in 4 of 6 semesters.

[27] The tuition figures are from the National Center of Education Statistics (2019). We assume total tuition is the product of annual full-time tuition and the assumed duration for a full time degree given in Appendix Table A2.1. We set tuition per year to total tuition divided by average actual duration as reported in Table A2.1.

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. 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.[28] In going from the log earnings model to the level of earnings, we calculate expected earnings under the assumption that the distribution of the earnings error $v_i + \varepsilon_{it}$ is log normal.[29]

The counterfactual PDVs vary from a low of \$1.05 million for a master's in social work to a maximum of \$2.26 million for electrical engineering. The actual net PDVs also vary a great deal. The lowest value is social work. The highest value, by a large margin, is MD, at \$3.70 million. The percentage gains (based on a discount rate of 0.05) are negative for the four lowest paying degrees.

The gain in PDV for an MBA is 12.5% over the counterfactual PDV of \$1.72 million, and the IRR is 0.18. The IRR for computer science and the engineering degrees range from 0.07 for computer engineering to 0.21 (civil engineering). The IRR to a JD, PharmD, and an MD are 0.22, 0.26, and 0.33, respectively.

The percentage gain in net PDV and the IRR estimates are of course strongly positively related to the estimates of γ^g and γ^g_{1-15}. However, the IRR are also strongly negatively related to the investment required for different degrees, which depends on the tuition rate, length of program, and counterfactual income relative to earnings while enrolled. In Appendix Table A.2.1, we calculate the annual investment required for different degrees. Education administration has the lowest investment required at just \$13,251 per year. The low value reflects the fact that students in this program have relatively high earnings during enrollment and have a relatively low counterfactual earning level. As a result, although the estimate of γ^g_{1-15} is only 0.106 for this program, it has the third highest IRR at 0.230.

Appendix Table A2.2 reports alternative estimates of the IRR and the gain in PDV when assuming full-time enrollment and no earnings during graduate school. The alternative IRR estimates differ quite a bit from the estimates using empirical durations and earnings during enrollment. In the case of education administration, the estimate drops from 0.23 to 0.10. Other big drops are for nursing (0.19 to 0.11) and for an MBA (0.18 to 0.10). In all three cases, earnings during graduate school are large, and the net annual investment is much less than tuition plus counterfactual

[28]The earnings estimates are based on (3) with $\gamma^g_x = \gamma^g_0 + \gamma^g_1 x_{it} + \gamma^g_2 x^2_{it}$, where x is years since graduate school. To avoid extrapolating the quadratic too far out of sample, we set $\hat{\gamma}^g_x = \hat{\gamma}^g_{15}$ when $x > 15$. The IRR estimates are nearly identical when we move the limit to $x > 20$. The only substantial change (>0.03) is curriculum and instruction (0.00 to 0.06), which is not surprising given the accelerating trend after year 15 in Figure 11. We obtain almost identical results using ratio links rather than additive constants to equate AZ's age profile to our estimates at age 40 (not reported). We mapped the 47 2-digit CIP codes that we use to AZ's 19 college major categories.

[29]That is, we evaluate the expected earnings level using the formula for the conditional mean of a log normal distribution. We use the mean squared error of our regression as a common variance estimate rather than use college major and graduate degree-specific estimates. We set earnings while in school to its mean value for each graduate program. As expected, the procedure yields larger PDVs than when setting the error term in the model to 0, but the percent gains in PDV and the IRRs are similar. An exception is education administration, for which the IRR estimate is 0.52 when setting the error term in the model to 0. This is because education administration has one of the highest average earnings during graduate enrollment. As a result, underestimating counterfactual earnings during enrollment by failing to account for the error variance when going from logs to levels pushes the net investment to close to zero.

earnings when enrolled.

In deciding how to treat earnings while enrolled when 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 at 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 might have had been able to work additional hours on her main job or take a second job. In this case, the opportunity cost of graduate school evaluated at the level of leisure during graduate school would be substantially larger than our estimate of counterfactual earnings. In the absence of good time use data, we do not have a way to address these issues.[30] Furthermore, individuals might get more (or less) utility from time spent on school versus time at work. These issues point to the limitations of purely financial return measures in evaluating education decisions.

Note 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 large IRR of 0.23 but boosts net PDV by only about \$95,000, which is 7.9%. This is because earnings losses while in school are low for this program, so the size of the investment is small (ignoring the time costs of school). In contrast, an MPA has a slightly lower IRR but boosts net PDV by 25.8%.

5.5 Differences in Returns by Demographic Group and College GPA

In this section we present estimates of the returns to advanced degrees by gender and by race/ethnic group. We estimate separate models for each gender category and the main race/ethnic categories. We also examine how the estimates vary with college GPA.

5.5.1 Results for Males and Females

Table A1.7 presents OLS and FEcg estimates of γ^g for males and females. The OLS estimates show very large differences in favor of women, especially for degrees in lower paying fields. For example, for men the OLS estimates of γ^g are -0.159 for social work, -0.111 for clinical psychology, and -0.099 for curriculum and instruction. In comparison, the OLS estimates for women are 0.030 for social work, 0.009 for clinical psychology, and 0.047 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 larger negative bias than the estimates for women.[31] Altonji et al (2023) also obtain substantially larger OLS

[30] Using the NSCG, Altonji et al (2023) provide estimates of annual hours worked while enrolled for 19 aggregated graduate degree fields. The simple average of the means for males and females exceeds 1100 for 16 of the 19 fields. The averages range from 159 hours for medicine to 1,903 for an MBA. We do not know of data by graduate field on time devoted to schooling.

[31] Unfortunately, we do not have data on occupational preference measures. Nor do we have data on occupation

estimates for women.

The FEcg estimates of the returns are higher for females in 14 of 18 fields. The exceptions are civil, mechanical, and computer engineering (heavily male fields) and nursing (a heavily female field). The female-male difference in the returns to a JD, MD and an MBA are 0.055, 0.092, and 0.034 respectively. The gap is also large for social work, clinical psychology, curriculum and instruction and educational administration. 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 18 reported in Table A1.7), the value is 0.202 for females and 0.167 for males. Altonji et al (2023) find larger estimates for women in 11 of 19 cases, but their estimates are less precise and are for much more aggregated degree categories.

We also find some important gender differences in the effects of obtaining a graduate degree on the industry component of earnings by gender. The most striking case is psychology, for which both the OLS and FEcg estimates of earnings effects reported in Table A1.7 are small and positive for women and large and negative for men. The FEcg estimate of the effect on the industry premiums are -0.050 (0.015) for women and -0.139 (0.033) for men. Thus gender differences in the effect of psychology on industry plays an important role in the gender difference in earnings effects. The difference in industry effects may be due to opportunities and/or preferences,

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

Table A1.8 reports OLS and FEcg estimates by race/ethnicity. We focus on the FEcg estimates, although the sign of the difference across groups depends on the estimator to some extent. Standard errors are quite large for African Americans for 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 higher returns than non-Hispanic whites for 10 of the 18 degrees shown and lower returns in 8, and the gaps are large in some cases. The values are 0.149 (0.020) versus 0.272 (0.010) for nursing, 0.288 (0.036) versus 0.487 (0.012) for a JD, and 0.578 (0.081) versus 0.658 (0.022) for an MD.

We do not find strong evidence of systematic differences between Hispanics and non-Hispanic whites relative to sampling error.

Asians receive substantially lower returns than non-Hispanic whites for most degrees. The Asian-White difference in the FEcg estimates is negative for 16 of the 18 degrees. The gaps in the OLS estimates are negative for 13 of the 18. The gap in the FEcg estimates are particularly wide for the highest paying degrees such as PharmD (0.671 (0.036) versus 0.789 (0.027)), JD (0.288 (0.043) versus 0.487 (0.012)), and MD (0.461 (0.045) versus 0.658 (0.022)). The gap is also wide for nursing. The pattern is mixed for the engineering degrees and computer science. Asians also receive substantially lower returns to some of the lower paying degrees, including clinical psychology, and educational administration although the estimates for Asians are noisy in some cases. We were

that could be used to compare jobs before and after graduate school.

surprised by these results and do not have an explanation for them.[32]

5.5.3 The effect of GPA on returns

We estimated versions of (1) and (3) with interactions between $G_{g(i)t}$ and college GPA_i added for each g. Table A1.9 presents estimates of γ^g_{GPA}, the coefficients on the interactions for the various degrees. The interactions represent the effect of a one-point increase in GPA on the return to degree. The standard deviation of GPA varies by graduate field but a typical value is about 0.5. The average of the estimates weighted by the degree shares in the sample is -0.019, indicating a slightly negative impact of college GPA on returns to advanced degrees on average.[33]

The effect of GPA on the return varies quite a bit across graduate fields. The FEcg coefficient estimates are -0.070 (0.009) for curriculum and instruction, -0.058 (0.005) for education administration, -0.052 (0.008) for clinical psychology, and about -0.05 for the health-related degrees. Negative coefficients might be expected if GPA raises returns in private sector business jobs more than in the helping professions. The interaction is large and positive for a JD degree: 0.125 (0.014). Part of the interaction effect for a JD degree is probably the return to attending a higher quality law school, which we document in Section 5.6. The interaction is only 0.010 (0.006) for an MBA.

5.6 Returns to Graduate Degrees by Undergraduate Major

We separately estimate the FEcg model for students who obtain college degrees in 11 broad categories of college majors. That is, we estimate separate returns to each 4 digit graduate degree for each of the 11 college major categories.[34]

The results are in Table 5. 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 and report the FEcg estimates by college major categories. There is a clear tendency for the return to degrees that have high average earnings, such as an MBA, a JD, and an MD degree, to be larger for lower paying college majors. For example, the return to MBA is 0.256 (0.043) for fine arts, 0.219 (0.021) for humanities, and 0.214 (0.016) for social sciences but is below 0.081 for business, computer science, and engineering. This pattern can be seen in Figure A1.2, which graphs the estimates of γ^{cg} for MBA, JD, MD, and PharmD by undergraduate field. The results confirm that returns to graduate degree are larger for lower paying college majors, and the pattern is mostly driven by graduate degrees that have higher average earnings.

[32]The difference between the groups in mean college GPA is small for most graduate degrees, and in any case we control for GPA in our analysis. For the degrees for which we have US News and World Report rankings, if anything Asians attended somewhat higher ranked schools on average than non-Hispanic whites. For each graduate degree, we examined whether the difference between Asians and non-Hispanic white differences in the FEcg estimates are primarily driven by differences in pre-graduate school earnings or post-graduate school earnings (conditional on the controls) and found that it is a mix. OLS and FEcg estimates of γ^g_{1-15} exhibit the same gaps between Asian and non-Hispanic whites, suggesting that differences in the experience distributions do not explain the results.

[33]The value is based on the 74 advanced degrees for which the standard error of the estimate of γ^g_{GPA} is less than 0.05. In the FEcg case the main effect of GPA on earnings is 0.072 (0.001), so there is a substantial positive relationship between GPA and earnings.

[34]The c,g fixed effects are based on the 47 2-digit CIP codes for college major, as in the specifications in Table 3.

5.7 Estimates by School and School Program Rank

In this section, we explore the effects of program rank on returns for a subset of fields — MBA, JD, nursing, PharmD, and social work. These are the graduate degrees for which there are significant numbers of Texas programs that have been ranked by US News and World Report. Our school specific estimates make use of Dale and Krueger's (2002) idea of addressing selection into specific institutions by controlling for the programs to which a student applied and was admitted.[35] We begin with a discussion of the data and our approach and then turn to the estimates.

5.7.1 Applications, Admissions and Program Quality Data

Students' admission records, which contain information on where students applied to and were admitted to, are available for Texas public universities since 2000 for both undergraduate and graduate programs. The application records are available even if students are rejected by a program or are accepted but do not eventually enroll. We lack application and admission data for out-of-state graduate programs and for private institutions in Texas. For public institutions, we observe whether the student applied to an associate, bachelor's, master's, doctoral, JD, DDS, OD (similar to an MD), or DVM (doctor of veterinary medicine) degree program. However, we do not observe what particular fields(s) the student applied to or was admitted to, which is ambiguous in the case of masters degrees. For example, we cannot distinguish an application for a master's in electrical engineering from an application for an MBA. Given the data limitations, using application and admission sets as an additional control is best suited to study the return to JD, 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 available application data. 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.[36]

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. 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.[37] When estimating the relationship between rank and return, we exclude programs that are unranked

[35] Dale and Krueger consider undergraduate degrees but do 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, although we do so in conjunction with the FEcg approach.

[36] 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.

[37] We do not use the years in which a program is not ranked when constructing its average rank because the number of programs ranked by US News changes over time. This means that being unranked conveys different information for different years. An alternative would be to estimate average rank using a limited dependent variables model that accounts variation in the number of ranked programs, but we prefer the simpler approach in an initial study.

in US News rankings in all years. We do, however, report the average of the returns to unranked programs along with the returns to the ranked programs.

5.7.2 Program Specific Returns: Controlling for Application and Admissions

To study returns to specific programs, we supplement the FEcg approach by using applications and admissions data to address selection bias into particular programs and particular institutions (Dale and Krueger, 2002).[38] We use the information in two ways, depending on data availability. First consider the return to JD programs, 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.[39] In our main specification we restrict the sample to people who either eventually go to law school or do not go to graduate school but have applied to JD programs. The regression model becomes

$$\ln w_{it} = \alpha_1 + \sum_{c=2}^{\mathcal{C}} (\alpha_0^c + \alpha^c_{gen_i age_{it}}) C_{c(i)} + \sum_{c=1}^{\mathcal{C}} b_{cg} C_{c(i)} G_i^g + \delta G^g_{j(i)} + \gamma^{gj} G_{gjt} + X_{it}\beta + \eta^g P_i^g + u_{it} \quad (6)$$

where G_{gjt} indicates having a degree from program g of institution j by time t. In the law school case g is the value of g for a JD and γ^{gj} is the return to a JD from j. $\eta^g P_i^g$ is calculated as $\sum_{p \in \mathscr{P}^g} \eta_p^g P_{ip}^g$. The dummy variable P_{ip}^g is an indicator for whether i has an application/admission portfolio $p \in \mathscr{P}^g$ and η_p^g 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 programs of type g. We also include school fixed effects, $G^g_{j(i)}$, and FEcg fixed effects $C_{c(i)} G_i^g$.

Our options are more limited for the other degree types we consider because we can only identify application sets for people who actually enroll in the specific program type (e.g., an MBA program).

[38]Mountjoy and Hickman (2021) use a similar approach and the Texas administrative data to study the returns to particular undergraduate institutions but do not consider field of study. Kirkeboen et al (2016) use a fuzzy RD approach to estimate school specific returns by field of study. They exploit application data with ranked lists of school-field combinations submitted by students, test score date, school-field specific admissions cutoffs, and the fact that Norway determines admissions using a deferred acceptance algorithm. There is an extensive literature measuring the effects of undergraduate schools on earnings, including recent work by Hoxby (2018) and Chetty et al (2020). Chetty et al (2023) use variation in who is admitted off of wait lists to estimate the effects of attending an Ivy-Plus college instead of a flagship public university on the probability of reaching the top 1% of the income distribution. They also consider average earnings. Given space limitations we focus on effects on the mean of log earnings, but our approach and data could easily be used to study other features of the earnings distribution. See Lovenheim and Smith (2023) for a recent survey of the literature on differences across undergraduate institutions in earnings effects.

[39]For students who attend private law schools, such as Southern Methodist University's law school, we control for in-state public university application and admissions profiles and treat the school they attend as part of the profile. For such schools, we are basically comparing earnings before and after graduate school for groups of people who attended the school and had the same application and admissions set.

For such programs, we restrict the sample to people who either eventually obtain a degree of that type (e.g., an MBA) or do not go to graduate school. We then estimate program-specific returns following equation (6), where the dummy variables P_{ip}^{g} are created assuming all applications were for the program type under study.[40]

With the program specific return estimates in hand, we study how they are related to the US News and World Report rankings. To do so, we regress the school-specific return estimates $\hat{\gamma}^{gj}$ on the average rankings. The values of $\hat{\gamma}^{gj}$ are reported in the panels of figure 3 (We have chosen not to to name the schools). The x-axis indicates the US News ranking of each program. 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 0.026 (0.014) for a 20-position increase in program ranking. In comparison the average return to an MBA is 0.125. Thus, a 20-spot increase in program ranking increases returns to an MBA by around 21%. The coefficient is significant at the 10% level. The estimate of the return to an unranked MBA program is 0.034.. The return to a JD increases by 0.07 (0.014) for a 20-spot increase in program ranking. In comparison the average return to JD is 0.453. The coefficient is significant at the 1% level.

In contrast, the returns to nursing are not significantly related to program ranking, even though the point estimate suggests a positive effect of rank. The return to PharmD and social work is in fact higher for lower ranking programs, although the pattern is not statistically significant.

One 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.

6 Conclusion and Research Agenda

Money is not everything. But with so many people investing in graduate education, there is a critical need for credible information about the economic value of specific graduate degrees. In this paper, we examine the causal returns to a large number of graduate programs using multiple estimation methods. Our preferred approach is FEcg, which accounts for selection into graduate programs by conditioning on fixed effects for undergraduate major–graduate field combinations. Under strong assumptions, it provides treatment-on-the-treated estimates of earnings effects. While we focus our discussion on 18 popular fields, we provide estimates for 121 fields in total.

Regardless of the estimation method, we find that returns are substantial on average but vary greatly across degree types. In the FEcg specification, the weighted average return across degrees is 0.159, with a sampling error-adjusted standard deviation of 0.176. We find large positive effects on log earnings for JD, MD, and PharmD degrees, and to a lesser extent, nursing. Estimated returns range from 0.125 to 0.179 for an MBA, civil engineering, and public administration, and from

[40] As a robustness check, we also used this specification to estimate program-specific JD returns. The estimates closely resemble those obtained with our preferred approach for JD degrees described in the previous paragraph.

0.068 to 0.098 for architecture, computer science, and the other highlighted engineering degrees. In contrast, estimates are lower for social work, clinical psychology, and psychology, and are negative for the humanities and arts degrees we examine.

Cross-field differences in internal rates of return are also substantial. These differences often diverge from earnings effects because internal rates of return account for program length, tuition, and earnings during enrollment. For example, education administration yields an internal rate of return of 0.230—more than twice its log earnings effect—because relatively high earnings during enrollment reduce the cost of the degree. In contrast, an MD program, which takes four years, has relatively high tuition costs and low earnings during enrollment, resulting in an internal rate of 0.330, about half the magnitude of its log earnings effect.

Program characteristics also shape returns. Earnings effects tend to be lower for part-time students. By supplementing the FEcg approach with controls for the schools where students apply and the admissions decisions made, we estimate school-specific returns. We find that MBA and JD programs with higher U.S. News & World Report rankings have higher returns.

Student characteristics matter as well. Returns are higher for women in most fields and vary across racial and ethnic groups. The effect of GPA differs by field but is slightly negative, on average, across degrees. Further, returns to degrees with high average earnings, such as JD and MBA programs, are larger for those whose college major typically leads to lower-paying jobs. These findings underscore the importance of individual circumstances, particularly one's undergraduate major, when considering graduate school.

Much work remains. While FEcg handles fixed unobserved heterogeneity affecting the earnings intercept, it assumes that conditional on observables, the slope of the counterfactual age profile for those who pursue a particular graduate degree is the same as for those who do not. We currently allow these counterfactual profiles to depend on college major interacted with gender, but it would be desirable to explore a richer set of conditioning variables. Second, it may be possible to produce school-specific return estimates for more institutions and more fields by imposing additional structure on how returns depend on school-specific characteristics. Finally, with some modifications to the econometric approach, future work could explore how graduate degrees affect the entire distribution of earnings, not just the mean. Such an extension would help address the question of risk associated with investing in graduate degrees in specific fields.

References

Altonji, Joseph G. 1993. "The Demand for and Return to Education When Education Outcomes Are Uncertainty." *Journal of Labor Economics*, 11 (1):48-83.

Altonji, Joseph G, Erica Blum and Costas Meghir. 2012. "Heterogeneity in Human Capital Investments: High School Curriculum, College Major, and Careers", Annual Reviews of Economics , Volume 4, pages 185-223.

Altonji, Joseph G, Peter Arcidiacono, and Arnaud Maurel. 2016. "The Analysis of Field Choice in College and Graduate School: Determinants and Wage Effects," in Handbook of the Economics of

Education. Vol. 5, Elsevier: 305-396.

Altonji, Joseph G, and Ling Zhong. 2021. "The Labor Market Returns to Advanced Degrees," *Journal of Labor Economics*, 39(2): 303-595.

Altonji, Joseph G, John Eric Humphries, and Ling Zhong. 2023. "The Effects of Advanced Degrees on the Wage Rates, Hours, Earnings, and Job Satisfaction of Women and Men," in Polacheck, S.W., and Tatsiramos, K. (Ed.) *50th Celebratory Volume Research in Labor Economics*, 50: 25-81.

Andrews, Rodney J, Scott A Imberman, Michael F Lovenheim, and Kevin M Stange. 2024. "The Returns to College Major Choice: Average and Distributional Effects, Career Trajectories, and Earnings Variability," *The Review of Economics and Statistics*, forthcoming.

Arcidiacono, Peter. 2004. "Ability Sorting and the Returns to College Major." *Journal of Econometrics*, 121(1-2): 345-375.

Arcidiacono, Peter, Jane Cooley, and Andrew Hussey. 2008. "The Economic Returns to an MBA." *International Economic Review*, 49(3): 873-899.

Ashenfelter, Orley. 1978. "Estimating the Effects of Training Programs on Earnings." *The Review of Economics and Statistics*, 60(1): 47-57.

Bennett, Christopher T. 2023. "Labor Market Returns to MBAs from Less-Selective Universities: Evidence from a Field Experiment During COVID-19." *Journal of Policy Analysis and Management*, 42(2): 525-551.

Bhattacharya, Jayanta. 2005. "Specialty Selection and Lifetime Returns to Specialization within Medicine." *Journal of Human Resources*, 40(1): 115-143.

Black, Dan, Seth Sanders, and Lowell Taylor. 2003. "The Economic Reward to Studying Economics." *Economic Inquiry*, 41(3): 365-77

Black, Sandra E., Lesley J. Turner, and Jeffrey T. Denning. 2023. "PLUS or Minus? The Effect of Graduate School Loans on Access, Attainment, and Prices." NBER Working Paper: 31291.

Bleemer, Zachary, and Aashish Mehta. 2022. "Will Studying Economics Make You Rich? A Regression Discontinuity Analysis of the Returns to College Major." *American Economic Journal: Applied Economics*, 14(2): 1-22.

Britton, Jack, Franz Buscha, Matt Dickson, Anna Vignoles, Ian Walker, Ben Waltmann, Yu Zhu, and Laura van der Erve. 2020. "The Earnings Returns to Postgraduate Degrees in the UK." London: Department for Education.

Chen, M Keith, and Judith A. Chevalier. 2012. "Are Women Overinvesting in Education? Evidence from the Medical Profession." *Journal of Human Capital*, 6(2): 124-149.

Chetty, Raj, John N. Friedman, Emmanuel Saez, Nicholas Turner, and Danny Yagan. 2020. "Income segregation and intergenerational mobility across colleges in the United States." *The Quarterly Journal of Economics* 135, no. 3, 1567-1633.

Chetty, Raj, David J. Deming and John N. Friedman. 2023. "Diversifying Society's Leaders? The Determinants and Causal Effects of Admission to Highly Selective Private Colleges". October 2023.

Dale, Stacy Berg, and Alan B. Krueger. 2002. "Estimating the payoff to attending a more selective college: An application of selection on observables and unobservables." *The Quarterly Journal of Economics* 117(4): 1491-1527.

Foote, Andrew and Kevin Stange 2019 "Attrition from Administrative Data: Problems and Solutions with an Application to Higher Education", unpublished paper.

Gicheva, Dora. 2012. "Worker Mobility, Employer-Provided General Training, and the Choice of Graduate Education," *Labour Economics* 19 (2): 232-240.

Gottlieb, Joshua D., Maria Polyakova, Kevin Rinz, Hugh Shiplett, and Victoria Udalova. 2023. "Who Values Human Capitalists' Human Capital? The Earnings and Labor Supply of US Physicians." NBER Working Paper: 31469.

Hastings, Justine S., Christopher A. Neilson, and Seth D. Zimmerman. 2014. "Are Some Degrees Worth More than Others? Evidence from College Admission Cutoffs in Chile." NBER Working Paper: 19241.

Hoxby, Caroline M. 2018. "The productivity of US postsecondary institutions." in Hoxby, Caroline M., and Kevin Stange (eds), *Productivity in Higher Education* (Chicago, IL): 1-60.

Ketel, Nadine, Edwin Leuven, Hessel Oosterbeek, and Bas van der Klaauw. 2016. "The Returns to Medical School: Evidence from Admission Lotteries." *American Economic Journal: Applied Economics*, 8(2): 223-254.

Kirkeboen, Lars J., Edwin Leuven, and Magne Mogstad. 2016. "Field of Study, Earnings, and Self-Selection." *The Quarterly Journal of Economics*, 131(3): 1057-1111.

Lovenheim Michael and Jonathan Smith. 2023. "Returns to different postsecondary investments: Institution type, academic programs, and credentials", in Eric A. Hanushek, Stephen Machin, Ludger Woessmann (Eds), *Handbook of the Economics of Education*, Volume 6: 87-318.

Minaya, Veronica, Judith Scott-Clayton, and Rachel Yang Zhou. 2024. "Heterogeneity in Labor Market Returns to Master's Degrees: Evidence from Ohio." *Research in Higher Education*, forthcoming.

Mountjoy, Jack, and Brent R. Hickman. 2021. "The Returns to College(s): Estimating Value-Added and Match Effects in Higher Education," BFI Working Paper, University of Chicago.

Jak Petzold. 2023 "Part 1: Part-Time Students and the Law School Experience" LSSSE, Indiana University Center for Postsecondary Research.

Turner, Sarah E., and William G. Bowen. 1999. “Choice of Major: The Changing (Unchanging) Gender Gap.” *ILR Review*, 52(2): 289-313.

US Census Bureau. 2017. Educational Attainment in the United States: 2016.

Tables and Figures

Table 1: Summary Statistics — Earnings by Graduate Field

Grad Program	Average Earnings			Share Enrolled Part-Time	Log Earnings Premium		
	Pre Grad	During Grad	Post Grad		College	Industry Pre	Industry Post
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Social Work	41166	21396	55590	0.34	0.09	-0.02	0.03
Clinical Psychology	45577	29328	57894	0.86	0.14	0.01	0.00
Curriculum and Instruction	47899	40000	59083	0.91	0.14	0.01	0.00
Psychology	43537	20344	61445	0.76	0.14	0.05	0.02
Edu Admin	48712	50848	68682	0.93	0.14	0.01	0.00
Architecture	47691	19284	72354	0.20	0.24	0.16	0.18
Biology	41155	19522	74382	0.64	0.37	0.05	0.07
MPA	52519	36680	79246	0.79	0.21	0.05	0.06
Nursing	70215	57240	108370	0.88	0.32	0.14	0.19
Computer Science	69419	42444	110106	0.82	0.47	0.22	0.24
Civil Engineering	61483	34756	111784	0.67	0.65	0.15	0.20
MBA	72248	46972	112458	0.74	0.36	0.20	0.21
Computer Engineering	82261	39240	113554	0.84	0.57	0.26	0.27
Mechanical Engineering	73429	33016	119551	0.78	0.66	0.24	0.27
Electrical Engineering	83092	39240	130953	0.76	0.65	0.28	0.30
PharmD	49892	21316	132460	0.03	0.36	0.10	0.10
JD	55521	20052	132520	0.02	0.26	0.16	0.25
MD	48650	10468	181691	0.02	0.36	0.10	0.17

Notes: This table reports the graduate field specific means of annualized earnings in 2019 dollars before, during, and after graduate school, the share enrolled part-time, and the average earnings premiums associated with college major and industry. Students are defined as enrolling part-time if they average less than 9 credits per semester while in graduate school. Average college major and industry premiums are calculated by taking the sample average for each graduate degree of the college major and industry premiums. Footnote 14 describes the regression procedure used to estimate the premiums. The reference category for college majors is 13 of the 2-digit CIP codes, which represents education majors. Industries are defined based on the four digit NAICS codes. The reference category of industry is 6111, which represents elementary and secondary education.

Table 2: Summary Statistics — Demographics and Academic Performance by Graduate Field

Grad Program	Relative Share of the Group						Academic Performance		
	Female	Asian	African American	Hispanic	Non-Hispanic White	Free/ Reduced Meal	HS Math	HS Reading	College GPA
Social Work	1.57	0.50	1.89	1.04	0.90	1.38	74.3	74.7	3.14
Clinical Psychology	1.50	0.33	2.67	0.70	0.94	1.06	76.9	76.4	3.07
Curriculum and Instruction	1.48	0.33	1.11	1.39	0.90	1.19	78.0	76.9	3.07
Psychology	1.33	0.67	1.33	1.09	0.95	1.19	77.9	77.8	3.12
Edu Admin	1.19	0.17	1.44	1.17	0.95	1.13	78.4	76.4	3.02
Architecture	0.57	0.83	0.67	0.96	1.05	0.81	83.0	79.1	3.20
Biology	1.00	1.67	0.56	0.91	1.00	1.00	81.2	80.7	3.16
MPA	0.95	0.33	1.78	1.30	0.81	1.38	76.8	77.5	3.00
Nursing	1.48	1.17	1.33	0.83	1.00	1.00	80.9	80.0	3.31
Computer Science	0.34	2.83	0.22	0.52	0.89	0.81	89.1	85.1	3.36
Civil Engineering	0.40	1.00	0.22	0.78	1.10	0.94	89.2	84.0	3.26
MBA	0.78	1.33	1.33	0.78	0.95	0.81	82.5	79.8	3.06
Computer Engineering	0.29	3.83	0.44	0.61	0.79	0.81	88.8	83.1	3.32
Mechanical Engineering	0.22	1.00	0.22	0.87	1.03	1.06	89.2	83.5	3.29
Electrical Engineering	0.24	3.50	0.33	0.65	0.81	0.88	89.1	83.1	3.33
PharmD	1.07	5.33	0.78	0.78	0.66	1.06	87.5	82.8	3.32
JD	0.78	1.00	0.67	0.70	1.16	0.38	86.8	87.8	3.37
MD	0.81	3.67	0.56	0.74	0.90	0.63	91.6	89.0	3.69
All College Grad	0.58	0.06	0.09	0.23	0.62	0.16	77.9	76.4	2.98

Notes: The left panel of this table presents statistics summarizing the representation of various demographic groups in the main graduate programs of interest. The share of each demographic group among all college graduates is listed in the last row of the left panel. The cells in the other rows are shares of the demographic groups relative to their shares among all college graduates. For example, the value 1.57 in the first row, first column indicates that the share of females among social work graduate degree holders is 1.57 times their share among all college graduates. The share of each ethnicity group is the share out of the four main race/ethnicity groups — African American, Non-Hispanic White, Asian, Hispanic. International students are not included in any of these categories. Statistics for free/reduced meal status are calculated using students' high school records. The right panel reports the means of high school math and reading scores and of college GPA by field of graduate degree. High school math and reading scores are measured by students' percentile rankings in Texas' senior year standardized exams.

Table 3: Average Returns to Selected Graduate Degrees

Dependent Variable	Log Quarterly earnings							
	Additive Model					With Post-Adv Exp Interaction		
Specification	OLS	FEcg	FE	OLS-ps	FEcg-ps	OLS 1-15 Yrs	FEcg 1-15 Yrs	FE 1-15 Yrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Social Work	0.006	0.063	0.001	0.069	0.102	0.010	0.069	-0.002
	(0.005)	(0.007)	(0.008)	(0.005)	(0.008)	(0.005)	(0.008)	(0.009)
Clinical Psychology	-0.011	0.033	-0.030	0.054	0.104	-0.006	0.040	-0.038
	(0.004)	(0.006)	(0.005)	(0.006)	(0.009)	(0.005)	(0.007)	(0.006)
Curriculum & Instruction	0.023	0.035	-0.036	0.086	0.056	0.021	0.035	-0.060
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Psychology	-0.027	-0.032	-0.092	0.023	0.038	-0.021	-0.021	-0.084
	(0.013)	(0.028)	(0.032)	(0.014)	(0.032)	(0.014)	(0.028)	(0.032)
Edu Admin	0.082	0.089	0.011	0.140	0.126	0.098	0.106	0.019
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Architecture	0.020	0.076	-0.021	0.041	0.101	0.030	0.091	0.002
	(0.008)	(0.020)	(0.023)	(0.008)	(0.018)	(0.009)	(0.020)	(0.024)
Biology	-0.070	0.079	-0.060	-0.052	0.079	-0.051	0.114	-0.011
	(0.013)	(0.023)	(0.028)	(0.014)	(0.025)	(0.014)	(0.024)	(0.029)
MPA	0.099	0.155	0.078	0.161	0.208	0.130	0.190	0.126
	(0.010)	(0.013)	(0.012)	(0.012)	(0.018)	(0.011)	(0.014)	(0.013)
Nursing	0.380	0.232	0.226	0.377	0.262	0.365	0.219	0.221
	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.0010)	(0.011)	(0.010)
Computer Science	0.081	0.098	0.011	0.049	0.052	0.087	0.105	0.021
	(0.015)	(0.034)	(0.038)	(0.016)	(0.036)	(0.015)	(0.035)	(0.039)
Civil Engineering	-0.028	0.179	0.069	-0.043	0.117	-0.021	0.190	0.080
	(0.010)	(0.019)	(0.029)	(0.011)	(0.020)	(0.011)	(0.020)	(0.029)
MBA	0.218	0.125	0.128	0.194	0.103	0.234	0.146	0.157
	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Computer Engineering	0.084	0.068	-0.024	0.069	0.027	0.091	0.081	-0.016
	(0.016)	(0.025)	(0.024)	(0.018)	(0.029)	(0.018)	(0.026)	(0.026)
Mechanical Engineering	0.010	0.097	-0.041	0.009	0.059	0.017	0.107	-0.056
	(0.014)	(0.033)	(0.029)	(0.014)	(0.036)	(0.015)	(0.033)	(0.030)
Electrical Engineering	0.091	0.083	0.000	0.063	0.033	0.097	0.093	-0.006
	(0.011)	(0.016)	(0.017)	(0.011)	(0.018)	(0.012)	(0.016)	(0.018)
PharmD	0.642	0.794	0.730	0.677	0.864	0.607	0.763	0.681
	(0.008)	(0.018)	(0.021)	(0.009)	(0.018)	(0.009)	(0.018)	(0.022)
JD	0.445	0.453	0.274	0.548	0.585	0.453	0.465	0.289
	(0.006)	(0.010)	(0.012)	(0.008)	(0.016)	(0.007)	(0.010)	(0.013)
MD	0.573	0.614	0.441	0.600	0.612	0.677	0.740	0.645
	(0.007)	(0.018)	(0.029)	(0.09)	(0.020)	(0.007)	(0.017)	(0.024)
Sample Size	31522717	31522717	31522717	*	*	31522717	31522717	31522717

Notes: This table reports return estimates based on various estimation strategies. Standard errors (in parentheses) are clustered at the individual level. The controls include ethnicity dummies, college GPA, college credits accumulated, and year dummies. Gender × college major specific intercepts and cubic age profiles are included. Degree combination dummies are included in the case of FEcg. Person fixed effects are included in the case of FE. Columns 1-5 report estimates of γ^g. Columns 6-8 report estimates γ^g_{1-15}. Regressions reported in Columns 1-3 and Columns 6-8 use the full sample of individuals who have a college degree. Columns 6-8 specify that the returns are a g specific quadratic function of years since graduate degree completion. Columns 4 and 5 present propensity score weighted regression results based on (5) (with $\sum_{c=1}^{\mathcal{C}} b_{cg} C_{c(i)} G_{g(i)}$ added in the FEcg case). For Columns 4 and 5, each estimate comes from a separate regression that uses the sample of holders of that particular degree and individuals with no graduate degree.

Table 3A: Returns to Graduate Degrees by Part-Time Status

Dependent Variable	Share Enrolled Part-Time	Log Quarterly Earnings			
Specification		OLS		FEcg	
Coefficient		Full-Time	Part-Time	Full-Time	Part-Time
		(1)	(2)	(3)	(4)
Social Work	0.34	0.010	0.007	0.085	0.048
		(0.006)	(0.008)	(0.011)	(0.010)
Clinical Psychology	0.86	0.012	-0.007	0.045	0.037
		(0.014)	(-0.005)	(0.021)	(0.006)
Curriculum Instruction	0.91	0.027	0.026	0.029	0.034
		(0.013)	(0.004)	(0.023)	(0.006)
Psychology	0.76	0.010	-0.036	0.067	0.007
		(0.030)	(0.017)	(0.086)	(0.034)
Edu Admin	0.93	0.087	0.085	0.071	0.090
		(0.010)	(0.003)	(0.011)	(0.003)
Architecture	0.20	0.023	0.007	0.076	0.063
		(0.008)	(0.017)	(0.024)	(0.038)
Biology	0.64	0.043	-0.110	0.176	0.030
		(0.024)	(0.015)	(0.042)	(0.028)
MPA	0.79	0.111	0.098	0.160	0.150
		(0.023)	(0.011)	(0.034)	(0.014)
Nursing	0.88	0.384	0.331	0.287	0.176
		(0.019)	(0.007)	(0.022)	(0.008)
Computer Science	0.82	0.096	0.080	0.172	0.051
		(0.036)	(0.016)	(0.070)	(0.035)
Civil Engineering	0.67	0.016	-0.054	0.277	0.144
		(0.017)	(0.013)	(0.051)	(0.021)
MBA	0.74	0.265	0.173	0.134	0.119
		(0.007)	(0.004)	(0.010)	(0.005)
Computer Engineering	0.84	0.086	0.062	0.134	0.086
		(0.047)	(0.021)	(0.138)	(0.038)
Mechanical Engineering	0.78	0.094	-0.013	0.232	0.084
		(0.034)	(0.016)	(0.079)	(0.039)
Electrical Engineering	0.76	0.075	0.068	0.184	0.126
		(0.020)	(0.014)	(0.069)	(0.026)
PharmD	0.03	0.637	0.351	0.790	-0.090
		(0.008)	(0.088)	(0.019)	(0.093)
JD	0.02	0.460	0.476	0.467	0.415
		(0.007)	(0.047)	(0.013)	(0.055)
MD	0.02	0.576	0.374	0.614	0.397
		(0.007)	(0.057)	(0.018)	(0.091)
Sample Size		30891652	30891652	30891652	30891652

Notes: This table reports separate estimates of the returns to graduate degrees by full-time/part-time status. Columns (1) and (2) report the OLS estimates. They are based on the model used in Table 3 Column 1, except that we add separate graduate degree indicators for full-time and part-time graduate students. Columns (3) and (4) report FEcg estimates. They are based on the model used for Table 3 Column 2, except that we include separate indicators for full-time and part-time graduate programs as well as cg fixed effects that are part-time status specific. A student is enrolled part-time if she averages less than 9 credits per semester. See the note to Table 3 for the control variables. We do not observe the credit accumulation data needed to construct the part-time status indicator for students with graduate degrees from private universities, so they are excluded. Standard errors (in parentheses) are clustered at the individual level.

Table 4: Net PDV and Internal Rate of Returns Estimates

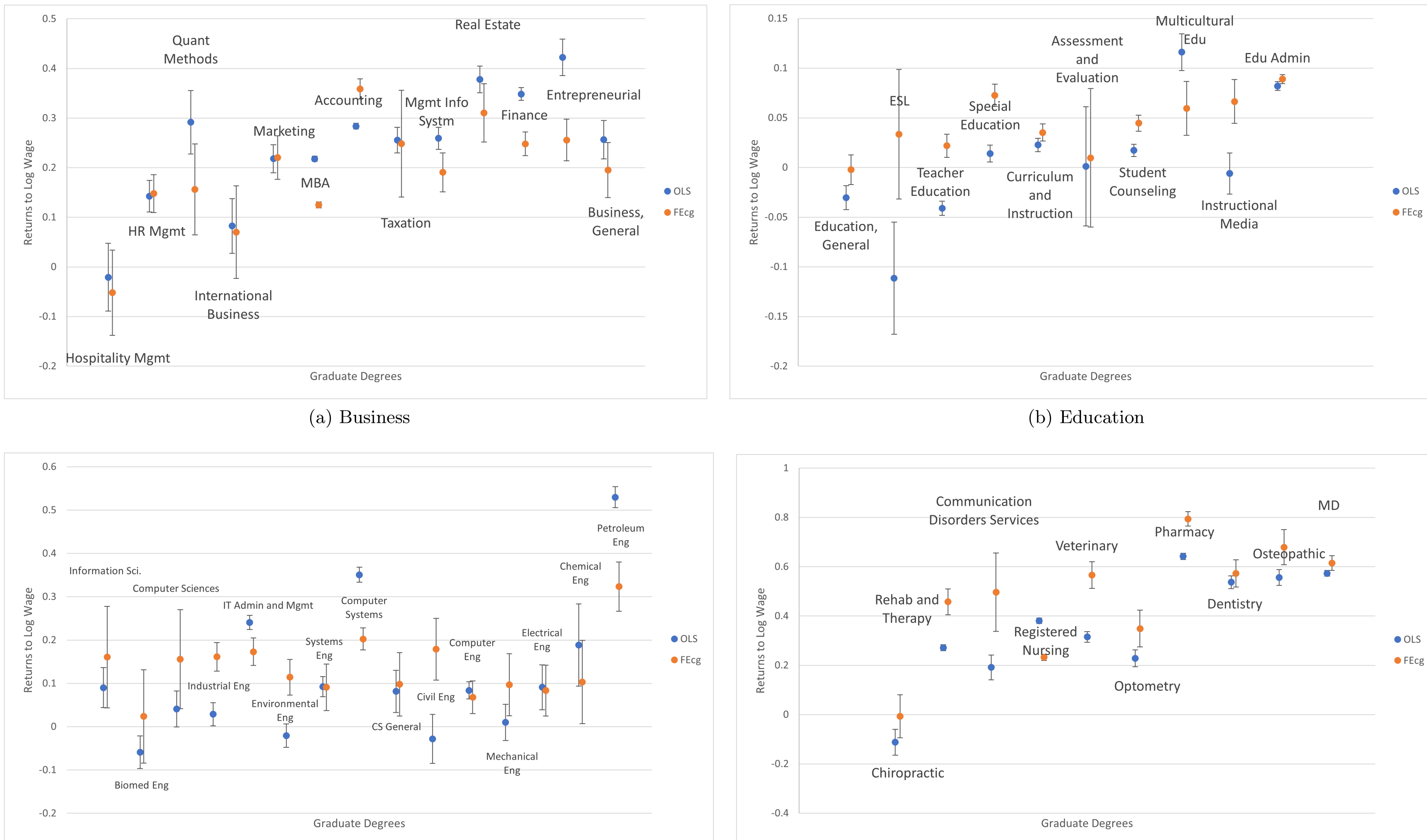
	Net PDV Counterfactual	Net PDV Actual	% Gain of PDV	Internal Rate of Returns
	(1)	(2)	(3)	(4)
Social Work	1,045,884	1,020,845	-2.4	0.020
	(11,900)	(12,630)	(1.5)	(0.023)
Clinical Psychology	1,094,789	1,040,889	-4.9	-0.020
	(9,205)	(10,128)	(1.2)	(0.033)
Curriculum Instruction	1,135,585	1,113,297	-2.0	0.000
	(9,338)	(15,532)	(1.6)	(0.058)
Psychology	1,154,257	1,060,595	-8.1	-0.020
	(27,545)	(20,621)	(2.2)	(0.044)
Edu Admin	1,206,579	1,301,778	7.9	0.230
	(3,820)	(8,595)	(0.8)	(0.015)
Architecture	1,342,216	1,389,545	3.5	0.080
	(27,352)	(22,178)	(2.2)	(0.017)
Biology	1,153,974	1,311,234	13.6	0.130
	(27,295)	(32,064)	(3.2)	(0.015)
MPA	1,198,480	1,508,025	25.8	0.210
	(12,891)	(34,445)	(3.0)	(0.014)
Nursing	1,541,135	1,726,278	12.0	0.190
	(9,528)	(29,422)	(1.8)	(0.012)
Computer Science	1,885,524	1,995,574	5.8	0.120
	(61,561)	(37,103)	(3.4)	(0.033)
Civil Engineering	1,803,380	2,146,418	19.0	0.210
	(35,559)	(32,907)	(2.4)	(0.017)
MBA	1,715,486	1,930,462	12.5	0.180
	(5,275)	(11,929)	(0.6)	(0.006)
Computer Engineering	2,115,246	2,158,402	2.0	0.070
	(55,891)	(65,508)	(4.1)	(0.043)
Mechanical Engineering	2,056,675	2,127,855	3.5	0.090
	(68,378)	(60,917)	(4.6)	(0.044)
Electrical Engineering	2,256,768	2,337,338	3.6	0.080
	(29,128)	(51,749)	(2.7)	(0.026)
PharmD	1,140,782	1,911,816	67.6	0.260
	(18,443)	(35,399)	(4.3)	(0.009)
JD	1,445,734	2,043,092	41.3	0.220
	(13,202)	(23,758)	(2.0)	(0.007)
MD	1,357,542	3,700,572	172.6	0.330
	(23,902)	(53,374)	(5.8)	(0.006)

Notes: This table reports net PDV and IRR estimates, based on the FEcg specification underlying Table 3, Column 7. The note to Table 3 provides details about the controls. To avoid extrapolating the quadratic too far out of sample when predicting earnings, we set $\hat{\gamma}_x^g = \hat{\gamma}_{15}^g$ when $x > 15$, where x is years after graduate school. We extrapolate age profiles beyond age 40 using estimates from AZ (2020), as discussed in the text. When calculating PDV, we assume a 0.05 interest rate and use the median duration of enrollment observed in the data for each graduate degree, reported in Table A2.1. We assume that total tuition equals the annual tuitions for full-time students reported in Table A2.1 multiplied by assumed duration of full-time students reported in Table A2.1. During enrollment, we assume earnings equal the average income during enrollment observed in the data for each graduate degree. Column (2) reports the PDVs with the corresponding graduate degrees. Column (1) reports the counterfactual PDV if people with corresponding degree did not enroll in graduate school. Column (3) presents the % gain in PDV. Column (4) reports the estimates of the IRR. The IRR is the discount factor that equates actual and counterfactual PDV. We use a block bootstrap procedure to calculate standard errors (in parentheses). We sampled with replacement in 46 strata to preserve the sample distribution of person counts across strata. The strata are defined by gender (2 blocks), number of appearances in the earnings regression sample (6 blocks), and number of appearances in the enrolled earnings sample (4 blocks). We exclude people who are absent from both earnings samples. The reported standard errors are standard deviations of the PDV and IRR estimates over 200 bootstrap samples.

Table 5: 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	Computer Science	Engineer
Social Work	0.159	-	0.061	0.091	-0.107	0.184	-	-	-0.268	-	-
	(0.065)	(0.131)	(0.036)	(0.008)	(0.064)	(0.046)			(0.064)		
Clinical Psych	-0.065	0.063	0.019	0.057	0.015	0.079	-0.065	-0.045	-0.026	-	-
	(0.054)	(0.036)	(0.019)	(0.013)	(0.036)	(0.030)	(0.036)	(0.051)	(0.031)		
Education (Curriculum)	0.055	0.017	0.056	0.055	0.070	0.062	-0.010	0.022	0.000	-	0.031
	(0.032)	(0.023)	(0.014)	(0.022)	(0.034)	(0.067)	(0.026)	(0.031)	(0.026)		(0.086)
Psychology	-	-	0.097	0.006	-	-	-0.448	-	-0.163	-	-
			(0.159)	(0.030)			(0.117)		(0.127)		
Edu Admin	0.031	0.073	0.095	0.089	0.041	0.140	-0.036	0.068	0.036	-	0.000
	(0.013)	(0.016)	(0.008)	(0.010)	(0.018)	(0.022)	(0.014)	(0.020)	(0.012)		(0.053)
Architecture	0.294	-	-	0.088	-	-	-	-	-	-	0.073
	(0.079)			(0.089)							(0.019)
Biology	-	-	-	-	-	-	0.058	0.134	-	-	-
							(0.024)	(0.128)			
MPA	-	-	0.193	0.216	0.133	-0.036	0.071	-	0.129	-	0.112
			(0.044)	(0.021)	(0.039)	(0.090)	(0.070)		(0.036)		(0.066)
Nursing	-	-	0.447	0.412	-	0.257	0.165	-	0.090	-	-
			(0.103)	(0.058)		(0.008)	(0.054)		(0.092)		
Computer Sciences	-	-	-	0.167	-	-	0.370	-	0.289	0.056	-0.092
				(0.229)			(0.076)		(0.210)	(0.039)	(0.061)
Civil Engineering	-	-	-	-	-	-	-	-	-	-	0.113
											(0.020)
MBA	0.256	0.326	0.219	0.214	0.140	0.182	0.150	0.137	0.081	0.066	0.071
	(0.043)	(0.094)	(0.021)	(0.016)	(0.020)	(0.020)	(0.019)	(0.027)	(0.005)	(0.022)	(0.010)
Computer Engineering	-	-	-	-	-	-	-	-	-	0.044	-0.005
										(0.045)	(0.032)
Mechanical Engineering	-	-	-	-	-	-	-	0.428	-	-	0.032
								(0.081)			(0.034)
Electrical Engineering	-	-	-	-	-	-	-	0.081	-	0.073	0.024
								(0.118)		(0.038)	(0.018)
PharmD	-	-	-	0.915	-	0.543	0.838	0.851	0.604	-	0.566
				(0.086)		(0.067)	(0.018)	(0.061)	(0.069)		(0.132)
JD	0.645	-	0.584	0.510	0.520	0.316	0.469	0.395	0.356	0.357	0.335
	(0.085)		(0.024)	(0.018)	(0.035)	(0.079)	(0.043)	(0.090)	(0.023)	(0.087)	(0.031)
MD	-	-	0.720	0.667	1.158	0.274	0.723	0.635	0.552	0.173	0.267
			(0.094)	(0.072)	(0.098)	(0.061)	(0.018)	(0.074)	(0.097)	(0.203)	(0.056)
Sample Size	1003607	195616	2167413	3228398	1587227	1878126	2232017	671974	8131432	602120	2191209

Notes: This table reports estimates of the returns to graduate degrees for separate college major categories, using the FEcg approach. 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. The c,g fixed effects are based on the 47 2-digit CIP codes for college major, not the 11 aggregated categories. We suppress estimates for degree combinations containing fewer than 20 people with earnings before graduate school and/or fewer than 20 people with earnings after graduate school. Standard errors (in parentheses) are clustered at the individual level. The note to Table 3 lists the other control variables.



(a) Business

(b) Education

(c) Engineering and CS

(d) Health

Figure 1: Additional Average Returns Estimates

Note: This figure reports the OLS estimates (blue dots) and FEcg estimates (orange dots) of average returns to sets of business, education, engineering and computer sciences, and health-related graduate degrees. Ninety percent confidence interval bands (based on standard errors clustered at the individual level) 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.

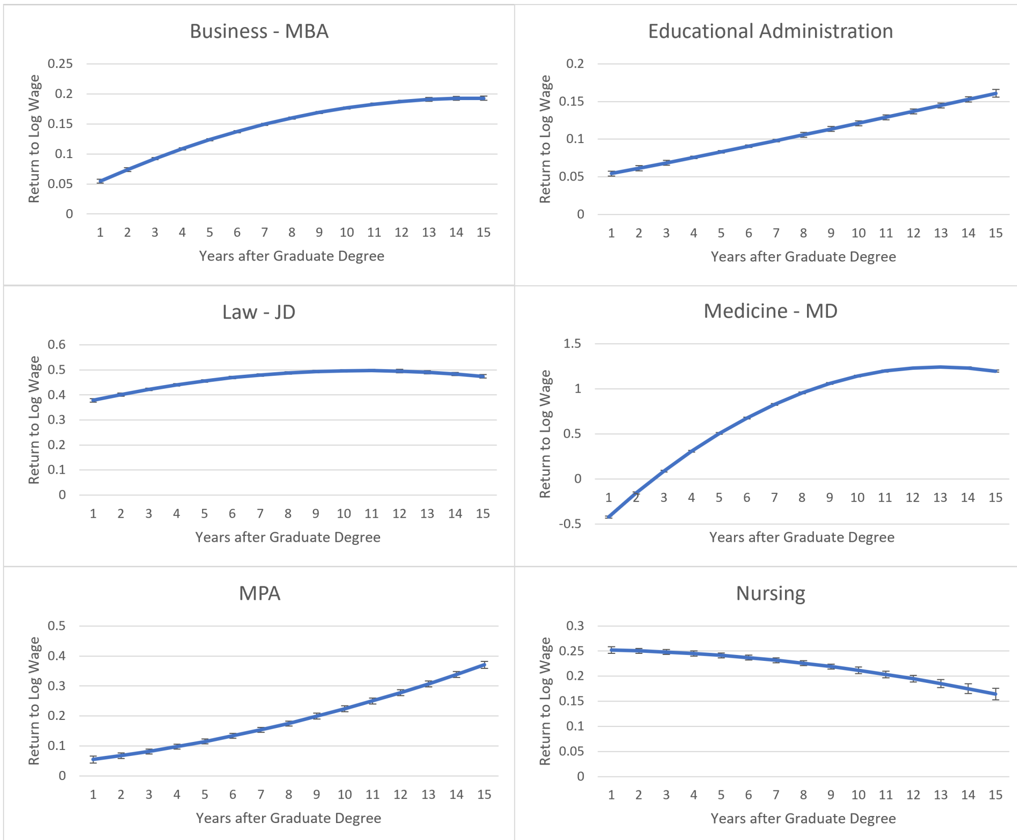


Figure 2: Graduate Degree Returns by Post Graduate School Experience

Notes: This figure reports estimates of $\gamma^g_{x_{it}}$, the return to the graduate degree at x years of post graduate school experience for 6 of the 18 main graduate degrees over the first 15 years after graduation. (The other 12 are in Appendix figure A1.1.) We estimate an FEcg model (3) with graduate degree specific experience trends following $\gamma^g_{x_{it}} = \gamma^g_0 + \gamma^g_1 x_{it} + \gamma^g_2 x^2_{it}$. The note to Table 3 lists the controls. The estimates of $\gamma^g_{x_{it}}$ for the first 15 years of experience after graduation are the values of $\hat{\gamma}^g_0 + \hat{\gamma}^g_1 x_{it} + \hat{\gamma}^g_2 x^2_{it}$ for the graduate degree of interest. 90% confidence intervals are reported as the wicks. They are based on standard errors clustered at the individual level.

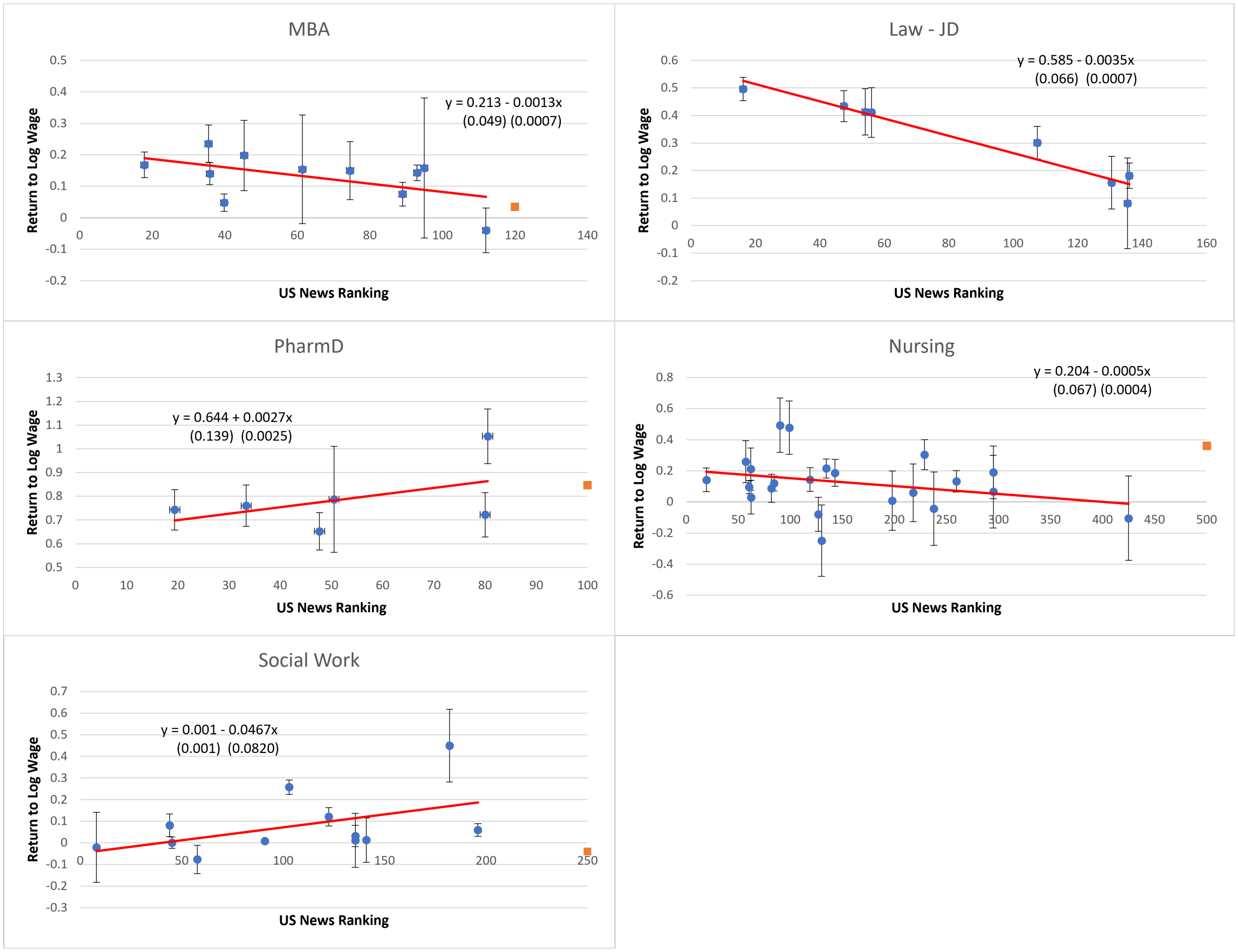


Figure 3: School Specific Returns to Graduate Degrees by US News Report Rank

Notes: This figure reports the relation between the return to individual graduate programs and the program rankings for MBA, JD, Social Work, PharmD, and Nursing. The vertical axis is effect of a degree from a particular school on ln earnings. The horizontal axis is the US News and World Report Rank of the school's program. Each blue point and associated 90% confidence interval in the figure corresponds to the return to one individual graduate program, which is estimated following the FEcg specification in (6). The specification includes controls for the application and admission portfolios of individuals. The orange dot is the average of the estimates for unranked programs in our sample. The regression line relating the earnings effect (y) to the US News ranking (x) is calculated using the estimated returns for ranked programs only. The regression coefficient estimates and the standard errors are reported in the panels.

Returns to Specific Graduate Degrees: Estimates Using Texas Administrative Records

Online Appendix

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Supplemental Material for Online Publication Only

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Appendix A1: Alternative and Additional Estimates of the Average Returns

Table A1.1a: Sensitivity of OLS Estimates of Average Returns (γ_g) to Choice of Controls

Dependent Variable	Log Quarterly Earnings						
Specification	OLS						
Sample	Main	Sample with High School Variables					
Social Work	0.006 (0.005)	0.008 (0.006)	0.007 (0.006)	0.046 (0.006)	0.037 (0.006)	-0.073 (0.006)	-0.068 (0.006)
Clinical Psychology	-0.011 (0.004)	-0.011 (0.006)	-0.010 (0.006)	0.017 (0.006)	0.012 (0.006)	-0.069 (0.006)	-0.070 (0.006)
Curriculum & Instruction	0.023 (0.004)	0.018 (0.005)	0.013 (0.005)	0.040 (0.005)	0.028 (0.005)	-0.025 (0.005)	-0.038 (0.005)
Psychology	-0.027 (0.013)	-0.046 (0.018)	-0.045 (0.018)	-0.014 (0.019)	-0.019 (0.019)	-0.123 (0.019)	-0.125 (0.019)
Edu Admin	0.082 (0.003)	0.069 (0.003)	0.068 (0.003)	0.087 (0.003)	0.081 (0.003)	0.006 (0.003)	0.005 (0.003)
Architecture	0.020 (0.008)	0.015 (0.011)	0.012 (0.011)	0.049 (0.011)	0.038 (0.011)	-0.008 (0.009)	-0.029 (0.009)
Biology	-0.070 (0.013)	-0.074 (0.018)	-0.072 (0.018)	-0.039 (0.019)	-0.044 (0.018)	-0.047 (0.019)	-0.076 (0.018)
MPA	0.099 (0.010)	0.079 (0.012)	0.076 (0.012)	0.104 (0.012)	0.094 (0.012)	0.051 (0.012)	0.045 (0.012)
Nursing	0.380 (0.007)	0.400 (0.009)	0.392 (0.009)	0.428 (0.009)	0.412 (0.009)	0.500 (0.008)	0.473 ().008)
Computer Science	0.081 (0.015)	0.087 (0.026)	0.078 (0.027)	0.131 (0.027)	0.110 (0.028)	0.308 (0.025)	0.234 (0.027)
Civil Engineering	-0.028 (0.010)	-0.055 (0.015)	-0.057 (0.015)	-0.020 (0.015)	-0.030 (0.015)	0.371 (0.015)	0.285 (0.015)
MBA	0.218 (0.003)	0.210 (0.004)	0.202 (0.004)	0.242 (0.004)	0.226 (0.004)	0.311 (0.004)	0.279 (0.004)
Computer Engineering	0.084 (0.016)	0.102 (0.026)	0.091 (0.025)	0.152 (0.026)	0.130 (0.025)	0.428 (0.026)	0.333 (0.024)
Mechanical Engineering	0.010 (0.014)	-0.000 (0.019)	-0.005 (0.019)	0.041 (0.020)	0.026 (0.020)	0.418 (0.019)	0.326 (0.019)
Electrical Engineering	0.091 (0.011)	0.073 (0.016)	0.065 (0.016)	0.127 (0.016)	0.107 (0.016)	0.481 (0.015)	0.381 (0.015)
PharmD	0.642 (0.008)	0.655 (0.011)	0.639 (0.011)	0.709 (0.010)	0.676 (0.010)	0.703 (0.010)	0.633 (0.010)
JD	0.445 (0.006)	0.435 (0.009)	0.414 (0.009)	0.516 (0.009)	0.472 (0.009)	0.502 (0.009)	0.441 (0.009)
MD	0.573 (0.007)	0.531 (0.009)	0.501 (0.010)	0.643 (0.010)	0.582 (0.010)	0.631 (0.009)	0.521 (0.009)
Demographic	x	x	x	x	x	x	x
College Major	x	x	x	x	x		
College Major Specific Age Profile	x	x	x	x	x		
College GPA and Credits	x	x	x				
High School Performance			x		x		x
Sample Size	31,522,717	12,757,807	12,757,807	12,757,807	12,757,807	12,757,807	12,757,807

Notes: This table reports OLS estimates of the average return to graduate degree g, while controlling for and not controlling for high school performance variables, college performance variables, and college majors. Column 1 uses the full or "main" sample. It replicates Table 3 Column 1. Robust standard errors (in parentheses) are clustered at the individual level. All specifications control for age, gender, ethnicity, and year dummies. The age profile is a cubic for men and women. For specifications where college major is controlled for, the age profile is college major specific.

Table A1.1b: Sensitivity of FEcg Estimates of Average Returns (γ_g) to Choice of Controls

Dependent Variable	Log Quarterly Earnings				
Specification	FEcg				
Sample	Main	High School Sample			
Social Work	0.063 (0.007)	0.068 (0.009)	0.068 (0.009)	0.098 (0.009)	0.092 (0.009)
Clinical Psychology	0.033 (0.006)	0.016 (0.008)	0.014 (0.008)	0.035 (0.008)	0.027 (0.008)
Curriculum & Instruction	0.035 (0.005)	0.012 (0.007)	0.009 (0.007)	0.026 (0.007)	0.019 (0.007)
Psychology	-0.032 (0.028)	-0.040 (0.033)	-0.045 (0.033)	-0.030 (0.034)	-0.037 (0.034)
Edu Admin	0.089 (0.003)	0.041 (0.004)	0.039 (0.004)	0.054 (0.004)	0.049 (0.004)
Architecture	0.076 (0.020)	0.074 (0.023)	0.080 (0.023)	0.096 (0.023)	0.097 (0.023)
Biology	0.079 (0.023)	0.064 (0.036)	0.067 (0.035)	0.072 (0.035)	0.074 (0.035)
MPA	0.155 (0.013)	0.121 (0.016)	0.122 (0.016)	0.143 (0.016)	0.140 (0.016)
Nursing	0.232 (0.008)	0.242 (0.010)	0.242 (0.010)	0.255 (0.010)	0.252 (0.063)
Computer Science	0.098 (0.034)	0.099 (0.057)	0.103 (0.061)	0.128 (0.061)	0.132 (0.064)
Civil Engineering	0.179 (0.019)	0.155 (0.030)	0.158 (0.029)	0.188 (0.032)	0.186 (0.031)
MBA	0.125 (0.004)	0.109 (0.005)	0.108 (0.005)	0.129 (0.005)	0.122 (0.005)
Computer Engineering	0.068 (0.025)	0.072 (0.040)	0.066 (0.042)	0.097 (0.038)	0.086 (0.040)
Mechanical Engineering	0.097 (0.033)	0.114 (0.052)	0.110 (0.052)	0.151 (0.056)	0.139 (0.055)
Electrical Engineering	0.083 (0.016)	0.093 (0.024)	0.082 (0.024)	0.111 (0.025)	0.096 (0.025)
PharmD	0.794 (0.018)	0.856 (0.023)	0.851 (0.023)	0.890 (0.023)	0.877 (0.023)
JD	0.453 (0.010)	0.451 (0.014)	0.444 (0.014)	0.496 (0.014)	0.478 (0.014)
MD	0.614 (0.018)	0.646 (0.024)	0.636 (0.024)	0.690 (0.024)	0.668 (0.024)
Demographic	x	x	x	x	x
College Major	x	x	x	x	x
College Major Specific Age Profile	x	x	x	x	x
College GPA and Credits	x	x	x		
High School Performance			x		x
Sample Size	31,522,717	12,757,807	12,757,807	12,757,807	12,757,807

Notes: This table reports FEcg estimates of the average return to graduate degree g, while controlling for and not controlling for high school performance variables, college performance variables, and college majors. Column 1 uses the full or "main" sample. It replicates Table 3 Column 2. Robust standard errors (in parentheses) are clustered at the individual level. All specifications control for age, gender, ethnicity, and year dummies. The age profile is a cubic for men and women. For specifications where college major is controlled for, the age profile is college major specific.

Table A1.2: Average Returns with "Graduate School" Sample

Dependent Variable	Log Quarterly Earnings	
Specification	FEcg (1)	FE (2)
Social Work	0.068 (0.007)	0.037 (0.008)
Clinical Psychology	0.023 (0.006)	-0.026 (0.005)
Curriculum and Instruction	0.022 (0.005)	-0.050 (0.005)
Psychology	-0.019 (0.029)	-0.052 (0.032)
Edu Admin	0.072 (0.003)	0.000 (0.003)
Architecture	0.087 (0.022)	0.099 (0.025)
Biology	0.063 (0.023)	-0.060 (0.0230)
MPA	0.154 (0.013)	0.105 (0.011)
Nursing	0.216 (0.009)	0.194 (0.009)
Computer Sciences	0.119 (0.035)	0.054 (0.037)
Civil Engineering	0.187 (0.019)	0.121 (0.042)
MBA	0.114 (0.004)	0.163 (0.004)
Computer Engineering	0.078 (0.025)	0.010 (0.023)
Mechanical Engineering	0.111 (0.033)	0.035 (0.030)
Electrical Engineering	0.092 (0.016)	0.026 (0.017)
PharmD	0.781 (0.018)	0.814 (0.023)
JD	0.457 (0.010)	0.417 (0.013)
MD	0.650 (0.019)	0.599 (0.031)
Sample Size	5215342	5215342

Notes: This table reports the average return estimates using FEcg and FE on the sample of individuals who have earned a graduate degree. Robust standard errors are clustered at the individual level, and are reported in parentheses. The specification is the same as that for Table 3 Columns 2 and 3. See the note to Table 3 for more details.

Table A1.3: Return Estimates Allowing for Earnings Dips Before Graduate School

Dependent Variable	Log Quarterly Earnings							
Specification	FEcg				FE			
	Main	Ashenfelter			Main	Ashenfelter		
Coefficient	G_g (γ^g) (1)	G_g (γ^g) (2)	q456 (3)	q789 (4)	G_g (γ^g) (5)	G_g (γ^g) (6)	q456 (7)	q789 (8)
Social Work	0.063	0.057	-0.025	-0.008	0.001	-0.007	-0.030	-0.011
	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.009)	(0.006)	(0.006)
Clinical Psychology	0.033	0.036	0.009	0.015	-0.030	-0.035	-0.019	-0.009
	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
Curriculum Instruction	0.035	0.038	0.020	0.001	-0.036	-0.040	-0.007	-0.021
	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Psychology	-0.032	-0.046	-0.058	-0.016	-0.092	-0.104	-0.045	-0.005
	(0.029)	(0.030)	(0.026)	(0.032)	(0.032)	(0.031)	(0.025)	(0.030)
Edu Admin	0.089	0.095	0.028	0.017	0.011	0.008	-0.009	-0.013
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Architecture	0.076	0.060	-0.061	-0.008	-0.021	-0.043	-0.074	-0.013
	(0.020)	(0.023)	(0.021)	(0.023)	(0.023)	(0.026)	(0.018)	(0.022)
Biology	0.079	0.060	-0.059	-0.034	-0.060	-0.086	-0.075	-0.046
	(0.023)	(0.025)	(0.021)	(0.023)	(0.028)	(0.029)	(0.017)	(0.020)
MPA	0.155	0.146	-0.036	-0.021	0.078	0.068	-0.034	-0.017
	(0.013)	(0.015)	(0.012)	(0.013)	(0.012)	(0.012)	(0.010)	(0.011)
Nursing	0.232	0.236	0.004	0.019	0.226	0.224	-0.011	0.004
	(0.008)	(0.008)	(0.006)	(0.006)	(0.007)	(0.008)	(0.005)	(0.005)
Computer Science	0.098	0.101	0.021	-0.007	0.011	0.002	-0.037	-0.005
	(0.034)	(0.040)	(0.037)	(0.040)	(0.038)	(0.043)	(0.030)	(0.034)
Civil Engineering	0.179	0.173	-0.021	-0.012	0.069	0.065	-0.017	-0.004
	(0.019)	(0.022)	(0.023)	(0.025)	(0.029)	(0.032)	(0.023)	(0.024)
MBA	0.125	0.120	-0.024	-0.011	0.128	0.130	0.005	0.008
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Computer Engineering	0.068	0.070	-0.004	0.024	-0.024	-0.017	0.020	0.017
	(0.025)	(0.028)	(0.025)	(0.031)	(0.024)	(0.025)	(0.020)	(0.025)
Mechanical Engineering	0.097	0.082	-0.061	0.003	-0.041	-0.041	-0.017	0.034
	(0.033)	(0.034)	(0.029)	(0.030)	(0.029)	(0.030)	(0.024)	(0.025)
Electrical Engineering	0.083	0.072	-0.066	-0.070	0.000	-0.001	-0.012	0.013
	(0.016)	(0.016)	(0.024)	(0.028)	(0.017)	(0.017)	(0.025)	(0.028)
PharmD	0.794	0.763	-0.116	-0.034	0.730	0.701	-0.108	-0.020
	(0.020)	(0.021)	(0.038)	(0.029)	(0.021)	(0.023)	(0.025)	(0.038)
JD	0.453	0.439	-0.061	-0.010	0.274	0.255	-0.070	-0.009
	(0.012)	(0.013)	(0.017)	(0.015)	(0.012)	(0.015)	(0.015)	(0.017)
MD	0.614	0.576	-0.145	-0.028	0.441	0.415	-0.086	-0.029
	(0.019)	(0.021)	(0.032)	(0.030)	(0.029)	(0.033)	(0.034)	(0.040)
Sample Size	31522717	31522717	31522717	31522717	31522717	31522717	31522717	31522717

Notes: This table reports FEcg estimates of the average return γ^g when controlling for potential dips in earnings prior to graduate school enrollment. Robust standard errors (in parentheses) are clustered at the individual level. The estimates are based on the model used for Table 3 Column 2. See the note to Table 3 for the control variables. Columns (1) and (5) (labeled "main") reports the FEcg and FE estimates previously reported in Columns (2) and (3) of Table 3. Columns (2) and (6) report the FEcg and FE estimates of γ^g 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 particular 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 throughout the paper earnings observations 1-3 quarters prior to enrolling in graduate programs are dropped from the earnings regressions.

Table A1.4: Reconciling FEcg and FE Estimates

Dependent Variable	Log Quarterly Earnings				
Specification	OLS		FEcg		FEcg-2SLS
Coefficient	Go-Direct	Not-Go-Direct	Go-Direct	Not-Go-Direct	
	(1)	(2)	(3)	(4)	(5)
Social Work	0.028	-0.036	0.076	0.035	0.026
	(0.006)	(0.007)	(0.008)	(0.008)	(0.005)
Clinical Psychology	-0.005	-0.029	0.036	0.010	-0.001
	(0.005)	(0.007)	(0.008)	(0.007)	(0.004)
Curriculum Instruction	0.021	0.020	0.037	0.021	-0.007
	(0.006)	(0.006)	(0.007)	(0.006)	(0.004)
Psychology	-0.021	-0.064	-0.031	-0.068	-0.066
	(0.015)	(0.031)	(0.029)	(0.036)	(0.016)
Edu Admin	0.088	0.075	0.095	0.078	0.044
	(0.004)	(0.003)	(0.004)	(0.003)	(0.002)
Architecture	0.020	-0.020	0.082	0.043	0.043
	(0.009)	(0.015)	(0.021)	(0.022)	(0.013)
Biology	-0.001	-0.122	0.081	0.019	-0.039
	(0.015)	(0.028)	(0.024)	(0.032)	(0.014)
MPA	0.093	0.105	0.142	0.161	0.132
	(0.013)	(0.015)	(0.016)	(0.016)	(0.007)
Nursing	0.347	0.394	0.202	0.241	0.225
	(0.011)	(0.008)	(0.012)	(0.009)	(0.003)
Computer Science	0.085	0.055	0.087	0.075	0.077
	(0.016)	(0.035)	(0.054)	(0.044)	(0.017)
Civil Engineering	-0.030	-0.024	0.173	0.180	0.154
	(0.011)	(0.027)	(0.020)	(0.029)	(0.014)
MBA	0.154	0.277	0.061	0.178	0.197
	(0.005)	(0.004)	(0.005)	(0.004)	(0.002)
Computer Engineering	0.092	0.060	0.081	0.026	0.058
	(0.020)	(0.029)	(0.030)	(0.028)	(0.016)
Mechanical Engineering	0.018	-0.045	0.100	0.031	0.056
	(0.016)	(0.025)	(0.034)	(0.035)	(0.019)
Electrical Engineering	0.077	0.127	0.075	0.086	0.079
	(0.012)	(0.020)	(0.018)	(0.020)	(0.009)
PharmD	0.644	0.625	0.783	0.769	0.759
	(0.009)	(0.015)	(0.018)	(0.022)	(0.009)
JD	0.471	0.399	0.482	0.408	0.347
	(0.008)	(0.009)	(0.011)	(0.012)	(0.004)
MD	0.550	0.606	0.591	0.638	0.479
	(0.008)	(0.013)	(0.019)	(0.021)	(0.009)
Sample Size	31522727	31522727	31522727	31522727	31522727

Notes: Columns (1) and (2) report OLS estimates of the returns to graduate degrees (γ^g) for "go-direct" and "not-go-direct" students by field. We use a version of equation (1) that includes separate $G_{g(i)t}$ indicators for "go-direct" and "not-go-direct" students. Columns (3) and (4) report the corresponding set of FEcg estimates using a version of equation (3) that includes separate $G_{g(i)t}$ indicators for "go-direct" and "not-go-direct" students. A student is defined as "go-direct" if she enrolled in graduate school within one year of college graduation. Column (5) report the FEcg-2SLS estimates of γ^gusing equation (3). We instrument for the $G_{g(i)t}$ using within-individual deviation from the individual means of the $G_{g(i)t}$. The note to table 3 lists the controls. Standard errors (in parentheses) are clustered at the individual level.

Table A1.5: Summary Statistics and OLS and FEcg Return Estimates for All Graduate Degrees

Graduate Degree	Average College GPA	Pre-Grad Earnings	Post-Grad Earnings	OLS Return Estimate (γ^g)	FEcg Returns Estimate (γ^g)
Agriculture, General	2.99	$40,471	$67,038	0.12 (0.02)	0.12 (0.05)
Agricultural Business and Management	3.21	$46,354	$88,409	0.12 (0.03)	0.26 (0.10)
Animal Sciences	3.12	$39,125	$75,560	-0.07 (0.02)	0.26 (0.06)
Plant Sciences	3.11	$45,080	$82,840	-0.01 (0.03)	0.24 (0.08)
Natural Resources Conservation and Research	3.05	$47,226	$82,436	0.03 (0.02)	0.07 (0.03)
Environmental/Natural Resources Management and Policy	2.97	$45,543	$70,706	0.01 (0.04)	0.22 (0.05)
Architecture	3.21	$47,061	$72,427	0.02 (0.01)	0.08 (0.02)
City/Urban, Community, and Regional Planning	2.96	$45,986	$77,510	-0.00 (0.02)	0.04 (0.03)
Landscape Architecture	3.14	$41,973	$64,069	-0.15 (0.05)	0.05 (0.07)
Communication and Media Studies	3.09	$44,227	$58,846	-0.05 (0.01)	0.02 (0.02)
Journalism	3.16	$44,129	$73,746	-0.01 (0.02)	0.08 (0.04)
Radio, Television, and Digital Communication	3.35	$44,825	$68,579	-0.10 (0.05)	-0.06 (0.07)
Public Relations, Advertising, and Applied Communication	3.29	$47,993	$77,754	0.17 (0.03)	0.18 (0.06)
Communications Technologies/Technicians	3.12	$43,554	$54,554	-0.08 (0.05)	0.13 (0.06)
Computer and Information Sciences	3.35	$67,349	$112,050	0.08 (0.02)	0.10 (0.03)
Information Science/Studies	3.22	$53,490	$79,710	0.09 (0.01)	0.16 (0.02)
Computer Systems Analysis	3.26	$67,893	$112,828	0.35 (0.06)	0.20 (0.06)
Computer Science	3.27	$61,150	$97,673	0.04 (0.03)	0.15 (0.04)
Computer/Information Technology Administration and Management	3.01	$68,202	$109,510	0.24 (0.03)	0.17 (0.04)

Table A1.5: Summary Statistics and FEcg Returns Estimates for All Graduate Degrees (Continued)

Graduate Degree	Average College GPA	Pre-Grad Earnings	Post-Grad Earnings	OLS Return Estimate (γ^g)	FEcg Return Estimate (γ^g)
Education, General	3.02	$47,700	$57,134	-0.03 (0.01)	0.00 (0.01)
Bilingual, Multilingual, and Multicultural Education	2.97	$47,358	$61,855	0.12 (0.01)	0.06 (0.02)
Curriculum and Instruction	3.12	$47,562	$59,194	0.02 (0.00)	0.03 (0.01)
Educational Administration and Suprevision	3.01	$48,494	$68,974	0.08 (0.00)	0.09 (0.00)
Educational/Instructional Media Design	3.06	$47,837	$67,190	-0.01 (0.01)	0.07 (0.01)
Educational Assessment, Evaluation, and Research	3.06	$44,932	$62,933	0.00 (0.04)	0.01 (0.04)
Special Education and Teaching	3.04	$44,672	$59,535	0.01 (0.01)	0.07 (0.01)
Student Counseling and Personnel Services	3.04	$44,519	$59,755	0.02 (0.00)	0.04 (0.00)
Teacher Education and Professional Development, Specific Levels and Methods	3.08	$43,786	$57,009	-0.04 (0.00)	0.02 (0.01)
Teacher Education and Professional Development, Specific Subject Areas	3.10	$45,845	$62,769	-0.03 (0.01)	0.02 (0.01)
Teaching English or French as a Second or Foreign Language	3.16	$41,812	$58,501	-0.11 (0.03)	0.03 (0.04)
Education, Other	3.26	$49,314	$58,967	0.04 (0.02)	-0.02 (0.02)
Engineering, General	2.99	$73,681	$108,394	0.07 (0.04)	0.10 (0.07)
Biomedical/Medical Engineering	3.36	$56,769	$96,530	-0.06 (0.03)	0.03 (0.07)
Chemical Engineering	3.41	$85,781	$143,564	0.19 (0.03)	0.10 (0.04)
Civil Engineering	3.26	$61,453	$111,987	-0.03 (0.01)	0.18 (0.02)
Computer Engineering	3.31	$80,045	$113,837	0.08 (0.02)	0.07 (0.03)
Electrical Engineering	3.33	$81,600	$131,838	0.09 (0.01)	0.08 (0.02)
Environmental/Environmental Health Engineering	3.14	$60,968	$106,636	-0.02 (0.03)	0.11 (0.07)
Mechanical Engineering	3.30	$73,792	$120,126	0.01 (0.01)	0.10 (0.03)
Petroleum Engineering	3.24	$92,871	$200,539	0.53 (0.03)	0.32 (0.04)
Systems Engineering	3.07	$76,416	$107,404	0.09 (0.02)	0.09 (0.02)
Industrial Engineering	3.17	$66,287	$118,963	0.03 (0.02)	0.17 (0.07)

Table A1.5: Summary Statistics and FEcg Returns Estimates for All Graduate Degrees (Continued)

Graduate Degree	Average College GPA	Pre-Grad Earnings	Post-Grad Earnings	OLS Return Estimate (γ^g)	FEcg Return Estimate (γ^g)
Engineering, Other	3.12	$91,432	$129,246	0.12 (0.03)	0.04 (0.04)
Engineering Technologies/Technicians, General	3.01	$58,699	$88,698	-0.06 (0.05)	0.16 (0.06)
Industrial Production Technologies/Technicians	2.96	$58,772	$92,586	-0.02 (0.04)	0.04 (0.06)
Engineering-Related Fields	3.05	$79,372	$114,435	0.11 (0.02)	0.08 (0.03)
Linguistic, Comparative, and Related Language Studies and Services	3.22	$40,365	$58,170	-0.19 (0.04)	-0.01 (0.06)
Romance Languages, Literatures, and Linguistics	3.16	$44,409	$56,043	-0.10 (0.02)	-0.11 (0.03)
Family and Consumer Sciences/ Human Sciences, General	2.95	$42,175	$56,141	0.00 (0.02)	0.07 (0.04)
Human Development, Family Studies, and Related Services	3.17	$40,543	$53,872	-0.04 (0.02)	0.04 (0.04)
Law (JD)	3.37	$54,665	$133,817	0.45 (0.01)	0.45 (0.01)
Legal Research and Advanced Professional Studies	3.22	$65,682	$130,610	0.48 (0.05)	0.58 (0.09)
Legal Support Services	2.90	$39,586	$58,684	-0.04 (0.03)	0.20 (0.04)
English Language and Literature, General	3.26	$43,284	$59,291	-0.15 (0.01)	-0.05 (0.02)
Rhetoric and Composition / Writing Studies	3.25	$43,542	$62,480	-0.04 (0.02)	0.10 (0.04)
Liberal Arts and Sciences, General Studies and Humanities	3.02	$50,510	$71,089	0.01 (0.02)	0.04 (0.02)
Library Science and Administration	3.22	$44,715	$57,756	-0.07 (0.02)	0.02 (0.01)
Biology, General	3.16	$40,961	$76,020	-0.07 (0.01)	0.08 (0.02)
Biotechnology	3.20	$40,013	$76,573	0.07 (0.01)	0.21 (0.06)
Ecology, Evolution, Systematics, and Population Biology	3.18	$46,133	$65,179	-0.08 (0.03)	0.01 (0.05)
Mathematics	3.31	$50,764	$73,953	-0.14 (0.02)	0.02 (0.02)
Statistics	3.23	$56,356	$92,951	0.14 (0.03)	0.31 (0.08)
Biological and Physical Sciences	2.95	$47,264	$79,690	-0.07 (0.04)	-0.04 (0.04)

Table A1.5: Summary Statistics and FEcg Returns Estimates for All Graduate Degrees (Continued)

Graduate Degree	Average College GPA	Pre-Grad Earnings	Post-Grad Earnings	OLS Returns Estimate (γ^g)	FEcg Returns Estimate (γ^g)
Peace Studies and Conflict Resolution	2.92	\$50,989	\$68,582	0.06 (0.04)	0.06 (0.05)
Behavioral Sciences	2.94	\$57,600	\$73,012	0.17 (0.04)	0.13 (0.05)
Nutrition Sciences	3.32	\$39,558	\$68,565	0.07 (0.02)	0.15 (0.15)
Intercultural/Multicultural and Diversity Studies	3.08	\$48,078	\$56,022	-0.04 (0.04)	0.04 (0.05)
Multi/Interdisciplinary Studies, Other	3.01	\$47,749	\$72,022	-0.04 (0.02)	0.04 (0.03)
Parks, Recreation, and Leisure Facilities Management	2.97	\$40,322	\$63,377	-0.05 (0.03)	0.10 (0.04)
Sports, Kinesiology, and Physical Education/Fitness	3.01	\$46,279	\$63,417	-0.04 (0.01)	0.00 (0.02)
Religious Education	3.08	\$50,854	\$61,656	0.03 (0.03)	0.06 (0.03)
Theological and Ministerial Studies	3.14	\$54,057	\$55,010	-0.26 (0.04)	-0.14 (0.05)
Chemistry	3.10	\$47,891	\$79,798	-0.03 (0.03)	0.02 (0.06)
Geological and Earth Sciences/Geosciences	3.01	\$70,268	\$133,294	0.49 (0.02)	0.29 (0.05)
Physics	3.07	\$54,729	\$103,516	0.11 (0.05)	0.13 (0.07)
Psychology, General	3.11	\$41,893	\$61,433	-0.03 (0.01)	-0.03 (0.03)
Research and Experimental Psychology	3.20	\$39,830	\$55,570	-0.08 (0.03)	0.08 (0.05)
Clinical, Counseling, and Applied Psychology	3.06	\$44,908	\$57,966	-0.01 (0.00)	0.03 (0.01)
Criminal Justice and Corrections	2.99	\$53,279	\$65,985	0.02 (0.01)	-0.01 (0.02)
Public Administration (MPA)	2.98	\$49,145	\$78,733	0.10 (0.01)	0.16 (0.01)
Public Policy Analysis	3.44	\$51,429	\$86,281	0.12 (0.03)	0.15 (0.03)
Social Work	3.12	\$40,549	\$55,252	0.01 (0.01)	0.06 (0.01)
Anthropology	3.24	\$39,885	\$62,254	-0.19 (0.03)	0.03 (0.05)
Criminology	2.94	\$53,313	\$79,404	0.16 (0.03)	0.16 (0.03)

Table A1.5: Summary Statistics and FEcg Returns Estimates for All Graduate Degrees (Continued)

Graduate Degree	Average College GPA	Pre-Grad Earnings	Post-Grad Earnings	OLS Return Estimate (γ^g)	FEcg Returns Estimate (γ^g)
Economics	3.17	$51,500	$102,058	0.25 (0.03)	0.25 (0.05)
Geography and Cartography	3.18	$47,725	$74,904	0.01 (0.03)	0.11 (0.04)
International Relations and National Security Studies	3.34	$50,232	$81,953	0.10 (0.04)	0.18 (0.06)
Political Science and Government	3.14	$50,499	$68,192	-0.13 (0.02)	-0.01 (0.07)
Sociology	2.96	$42,559	$64,335	-0.03 (0.02)	0.06 (0.03)
Design and Applied Arts	3.25	$49,808	$64,531	0.09 (0.04)	0.08 (0.05)
Drama/Theatre Arts and Stagecraft	3.16	$42,617	$53,887	-0.07 (0.02)	-0.01 (0.04)
Fine and Studio Arts	3.24	$41,922	$50,565	-0.21 (0.02)	-0.03 (0.03)
Music	3.37	$49,658	$58,136	0.00 (0.01)	-0.14 (0.02)
Health Services/Allied Health/ Health Sciences, General	3.03	$51,899	$57,534	-0.06 (0.07)	-0.14 (0.07)
Chiropractic	3.00	$49,298	$70,043	-0.11 (0.03)	-0.01 (0.05)
Communication Disorders Sciences and Services	3.37	$43,271	$80,975	0.19 (0.03)	0.50 (0.10)
Dentistry	3.52	$52,617	$153,458	0.54 (0.02)	0.57 (0.03)
Health and Medical Administrative Services	3.03	$55,078	$96,815	0.23 (0.01)	0.22 (0.01)
Allied Health Diagnostic, Intervention, and Treatment Professions	3.47	$51,941	$103,929	0.48 (0.01)	0.48 (0.02)
Medicine (MD)	3.69	$48,767	$181,139	0.57 (0.01)	0.61 (0.02)
Mental and Social Health Services and Allied Professions	3.16	$45,692	$56,748	-0.10 (0.01)	-0.03 (0.02)
Optometry	3.40	$41,841	$103,839	0.23 (0.02)	0.35 (0.05)
Osteopathic Medicine	3.58	$45,296	$169,444	0.56 (0.02)	0.68 (0.04)
Pharmacy, Pharmaceutical Sciences, and Administration (PharmD)	3.33	$47,521	$132,537	0.64 (0.01)	0.79 (0.02)
Public Health	3.17	$47,931	$76,326	0.11 (0.01)	0.21 (0.02)
Rehabilitation and Therapeutic Professions	3.54	$42,237	$76,815	0.27 (0.01)	0.46 (0.03)
Medical Illustration and Informatics	3.26	$64,720	$87,148	0.17 (0.06)	0.25 (0.07)
Registered Nursing, Nursing Administration, Nursing Research and Clinical Nursing	3.29	$67,210	$107,856	0.38 (0.01)	0.23 (0.01)

Table A1.5: Summary Statistics and FEcg Returns Estimates for All Graduate Degrees (Continued)

Graduate Degree	Average College GPA	Pre-Grad Earnings	Post-Grad Earnings	OLS Return Estimate (γ^g)	FEcg Return Estimate (γ^g)
Business/Commerce, General	3.05	\$58,665	\$142,857	0.26 (0.02)	0.19 (0.03)
Business Administration, Management, and Operations (MBA)	3.06	\$70,589	\$114,150	0.22 (0.00)	0.12 (0.00)
Accounting and Related Services	3.42	\$51,650	\$104,480	0.28 (0.00)	0.36 (0.01)
Entrepreneurial and Small Business Operations	3.07	\$75,795	\$148,938	0.42 (0.02)	0.26 (0.03)
Finance and Financial Management Services	3.37	\$66,962	\$128,148	0.35 (0.01)	0.25 (0.01)
Hospitality Administration/Management	3.07	\$49,654	\$73,316	-0.02 (0.04)	-0.05 (0.05)
Human Resources Management and Services	3.00	\$52,030	\$89,429	0.14 (0.02)	0.15 (0.02)
International Business	3.00	\$60,606	\$95,972	0.08 (0.03)	0.07 (0.06)
Management Information Systems and Services	3.25	\$61,567	\$116,897	0.26 (0.01)	0.19 (0.02)
Management Sciences and Quantitative Methods	3.23	\$69,080	\$87,588	0.29 (0.04)	0.16 (0.06)
Marketing	3.29	\$53,005	\$100,200	0.22 (0.02)	0.22 (0.03)
Real Estate	3.20	\$64,523	\$123,065	0.38 (0.02)	0.31 (0.04)
Taxation	3.48	\$55,445	\$108,642	0.26 (0.02)	0.25 (0.07)
History	3.19	\$47,218	\$60,000	-0.19 (0.02)	-0.07 (0.03)

Note: This table reports the average college GPA, average pre-graduate school earnings, average post-graduate school earnings, OLS, and FEcg estimates of the returns to 121 graduate degrees. Standard errors are clustered at the individual level and reported in parentheses. The degrees are listed in the order of their 4-digit CIP codes, and include all degrees for which we observe more than 50 graduates. The return estimates are drawn from the OLS and FEcg regressions that are the basis of Table 3 Columns 1 and 2. See the note to Table 3 for details.

Table A1.6: Univariate Regressions of FEcg and OLS Estimates of $\gamma_g$on College and Industry Premiums and Academic Achievement

	FEcg Returns Estimate (1)	OLS Estimate - FEcg Estimate (2)
College Major Premium	0.646 (0.188)	0.112 (0.119)
Pre-Graduate Industry Premium	0.879 (0.379)	0.482 (0.172)
Post-Graduate Industry Premium	0.954 (0.238)	0.289 (0.151)
College GPA	0.794 (0.072)	-0.100 (0.067)
HS Math Score	0.029 (0.004)	-0.000 (0.002)
HS Reading Score	0.033 (0.004)	-0.002 (0.002)
HS Writing Score	0.037 (0.004)	-0.002 (0.002)
Sample Size	124	124

Note: This table explores patterns across FEcg and OLS estimates of γ^g for all 124 graduate degrees for which we have sufficient sample sizes. Column 1 reports the coefficient from the regression of the FEcg estimates of γ_g on the variable listed in the row. Column 2 reports coefficients from the corresponding regressions using the difference between the OLS estimates and FEcg estimates of γ^g as the dependent variable. The return estimates are drawn from the OLS and FEcg regressions that are the basis of Table 3 Columns 1 and 2. See the note to Table 3 for details. Each cell represents one simple linear regression. The graduate degrees are weighted by the inverse of the number of graduates we observe for the main regression sample.

Table A1.7: Gender Differences in Returns to Graduate Degrees

Dependent Variable	Log Quarterly Earnings			
Specification	OLS		FEcg	
Gender	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
Social Work	0.030	-0.159	0.081	0.020
	(0.005)	(0.016)	(0.007)	(0.023)
Clinical Psychology	0.009	-0.111	0.049	-0.014
	(0.004)	(0.015)	(0.006)	(0.024)
Curriculum & Instruction	0.047	-0.099	0.051	-0.007
	(0.004)	(0.014)	(0.005)	(0.020)
Psychology	0.007	-0.156	0.023	-0.113
	(0.015)	(0.028)	(0.027)	(0.068)
Edu Admin	0.130	-0.028	0.118	0.029
	(0.003)	(0.005)	(0.003)	(0.005)
Architecture	0.082	-0.022	0.101	0.055
	(0.012)	(0.010)	(0.030)	(0.026)
Biology	-0.037	-0.117	0.079	0.076
	(0.015)	(0.023)	(0.027)	(0.040)
MPA	0.131	0.057	0.161	0.133
	(0.013)	(0.015)	(0.016)	(0.021)
Nursing	0.378	0.425	0.236	0.276
	(0.007)	(0.020)	(0.008)	(0.024)
Computer Science	0.162	0.059	0.125	0.087
	(0.031)	(0.016)	(0.060)	(0.040)
Civil Engineering	-0.057	-0.028	0.143	0.167
	(0.022)	(0.011)	(0.039)	(0.022)
MBA	0.231	0.201	0.142	0.108
	(0.005)	(0.004)	(0.006)	(0.005)
Computer Engineering	0.046	0.090	0.042	0.056
	(0.050)	(0.017)	(0.081)	(0.027)
Mechanical Engineering	-0.006	0.005	0.036	0.084
	(0.036)	(0.015)	(0.089)	(0.035)
Electrical Engineering	0.130	0.082	0.096	0.066
	(0.030)	(0.011)	(0.045)	(0.017)
PharmD	0.671	0.596	0.820	0.767
	(0.010)	(0.012)	(0.022)	(0.027)
JD	0.507	0.387	0.479	0.424
	(0.009)	(0.008)	(0.013)	(0.014)
MD	0.627	0.515	0.664	0.572
	(0.009)	(0.011)	(0.024)	(0.026)

Notes: This table reports the estimates of γ^g for the female and male samples separately, using OLS and FEcg specifications that correspond to Columns 1 and 2 of Table 3 for the combined sample. Standard errors are clustered at the individual level, and are reported in parentheses. The note to Table 3 lists the controls, except that gender interaction terms are no longer relevant.

Table A1.8: Race and Ethnic Group Heterogeneity in Returns to Graduate Degrees

Dependent Variable	Log Quarterly Earnings							
Ethnicity	African American		Non-Hispanic White		Asian		Hispanic	
Specification	OLS	FEcg	OLS	FEcg	OLS	FEcg	OLS	FEcg
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Social Work	0.059	0.075	-0.029	0.057	-0.002	0.042	0.062	0.099
	(0.010)	(0.015)	(0.007)	(0.010)	(0.026)	(0.047)	(0.008)	(0.012)
Clinical Psychology	0.022	0.038	-0.046	0.022	-0.119	-0.118	0.050	0.030
	(0.008)	(0.011)	(0.006)	(0.008)	(0.036)	(0.061)	(0.009)	(0.012)
Curriculum & Instruction	0.070	0.068	-0.009	0.022	-0.068	-0.012	0.050	0.032
	(0.011)	(0.016)	(0.005)	(0.007)	(0.022)	(0.038)	(0.006)	(0.008)
Psychology	0.017	0.039	-0.051	0.007	-0.104	-0.104	0.001	-0.046
	(0.032)	(0.049)	(0.018)	(0.046)	(0.096)	(0.142)	(0.025)	(0.048)
Edu Admin	0.122	0.089	0.052	0.081	0.030	0.047	0.127	0.091
	(0.006)	(0.007)	(0.004)	(0.004)	(0.021)	(0.023)	(0.004)	(0.005)
Architecture	0.088	-0.082	0.009	0.066	-0.025	0.088	0.038	0.103
	(0.029)	(0.054)	(0.010)	(0.025)	(0.033)	(0.077)	(0.015)	(0.031)
Biology	-0.018	0.070	-0.084	0.077	-0.095	0.065	-0.019	0.094
	(0.064)	(0.088)	(0.017)	(0.029)	(0.043)	(0.102)	(0.023)	(0.042)
MPA	0.115	0.143	0.116	0.175	-0.083	0.001	0.093	0.157
	(0.025)	(0.036)	(0.014)	(0.020)	(0.048)	(0.054)	(0.016)	(0.020)
Nursing	0.383	0.149	0.395	0.272	0.289	0.185	0.390	0.214
	(0.018)	(0.020)	(0.009)	(0.010)	(0.022)	(0.025)	(0.014)	(0.016)
Computer Science	0.066	-0.034	0.057	0.100	0.100	0.038	0.183	-0.103
	(0.092)	(0.082)	(0.022)	(0.042)	(0.028)	(0.069)	(0.036)	(0.141)
Civil Engineering	0.166	0.414	-0.058	0.168	0.013	0.204	0.034	0.196
	(0.059)	(0.076)	(0.012)	(0.024)	(0.044)	(0.067)	(0.028)	(0.045)
MBA	0.237	0.131	0.219	0.129	0.216	0.115	0.198	0.113
	(0.009)	(0.011)	(0.004)	(0.005)	(0.010)	(0.012)	(0.007)	(0.009)
Computer Engineering	0.140	0.197	0.055	0.024	0.081	0.016	0.191	0.143
	(0.052)	(0.143)	(0.024)	(0.031)	(0.033)	(0.062)	(0.042)	(0.063)
Mechanical Engineering	0.043	0.701	-0.003	0.103	0.084	0.044	0.017	0.020
	(0.101)	(0.107)	(0.019)	(0.039)	(0.040)	(0.068)	(0.026)	(0.050)
Electrical Engineering	0.135	0.127	0.087	0.099	0.087	0.043	0.123	0.092
	(0.096)	(0.103)	(0.015)	(0.022)	(0.023)	(0.030)	(0.025)	(0.049)
PharmD	0.650	0.737	0.615	0.789	0.563	0.671	0.775	0.976
	(0.023)	(0.055)	(0.012)	(0.027)	(0.013)	(0.036)	(0.017)	(0.029)
JD	0.334	0.288	0.468	0.487	0.313	0.288	0.392	0.391
	(0.024)	(0.036)	(0.007)	(0.012)	(0.027)	(0.043)	(0.014)	(0.022)
MD	0.622	0.578	0.587	0.658	0.400	0.461	0.661	0.665
	(0.032)	(0.081)	(0.010)	(0.022)	(0.016)	(0.045)	(0.016)	(0.043)

Notes: This table reports the OLS and FEcg estimates of γ^g for the sample for each race/ethnicity group considered separately. We use OLS and FEcg specifications that correspond to Columns 1 and 2 of Table 3 for the combined sample. The note to Table 3 lists the controls, except that race/ethnicity dummies are excluded. International students are not included in any of the ethnicity groups. Standard errors are clustered at the individual level, and are reported in parentheses.

Table A1.9: The Effect of GPA on the Returns to Graduate Degrees

Dependent Variable	Log Quarterly Earnings	
Specification	OLS (1)	FEcg (2)
Social Work # GPA	-0.084 (0.009)	-0.076 (0.008)
Clinical Psychology # GPA	-0.039 (0.008)	-0.052 (0.008)
Curriculum and Instruction # GPA	-0.047 (0.009)	-0.070 (0.009)
Psychology # GPA	-0.016 (0.028)	-0.027 (0.029)
Edu Admin # GPA	-0.037 (0.005)	-0.058 (0.005)
Architecture # GPA	0.028 (0.025)	0.028 (0.024)
Biology # GPA	0.000 (0.028)	-0.007 (0.028)
MPA # GPA	-0.040 (0.021)	-0.048 (0.020)
Nursing # GPA	-0.057 (0.016)	-0.053 (0.016)
Computer Sciences # GPA	0.086 (0.030)	0.098 (0.029)
Civil Engineering # GPA	0.009 (0.021)	0.021 (0.021)
MBA # GPA	0.003 (0.006)	0.010 (0.006)
Computer Engineering # GPA	-0.061 (0.037)	-0.042 (0.035)
Mechanical Engineering # GPA	-0.017 (0.031)	-0.019 (0.030)
Electrical Engineering # GPA	-0.007 (0.023)	-0.001 (0.022)
PharmD # GPA	-0.053 (0.019)	-0.057 (0.018)
JD # GPA	0.132 (0.014)	0.125 (0.014)
MD # GPA	-0.082 (0.022)	-0.085 (0.021)

Notes: This table reports the estimates of γ^{g}_{GPA}, the effect of a one point increase in College GPA has on the return to graduate degree g, using OLS and FEcg. The estimates are based on (1) and (3) with the addition of interactions between $G_{g(i)t}$ and GPA_i for each g. Standard errors are clustered at the individual level, and are reported in parentheses. The note to Table 3 lists the other controls, which include GPA. 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.

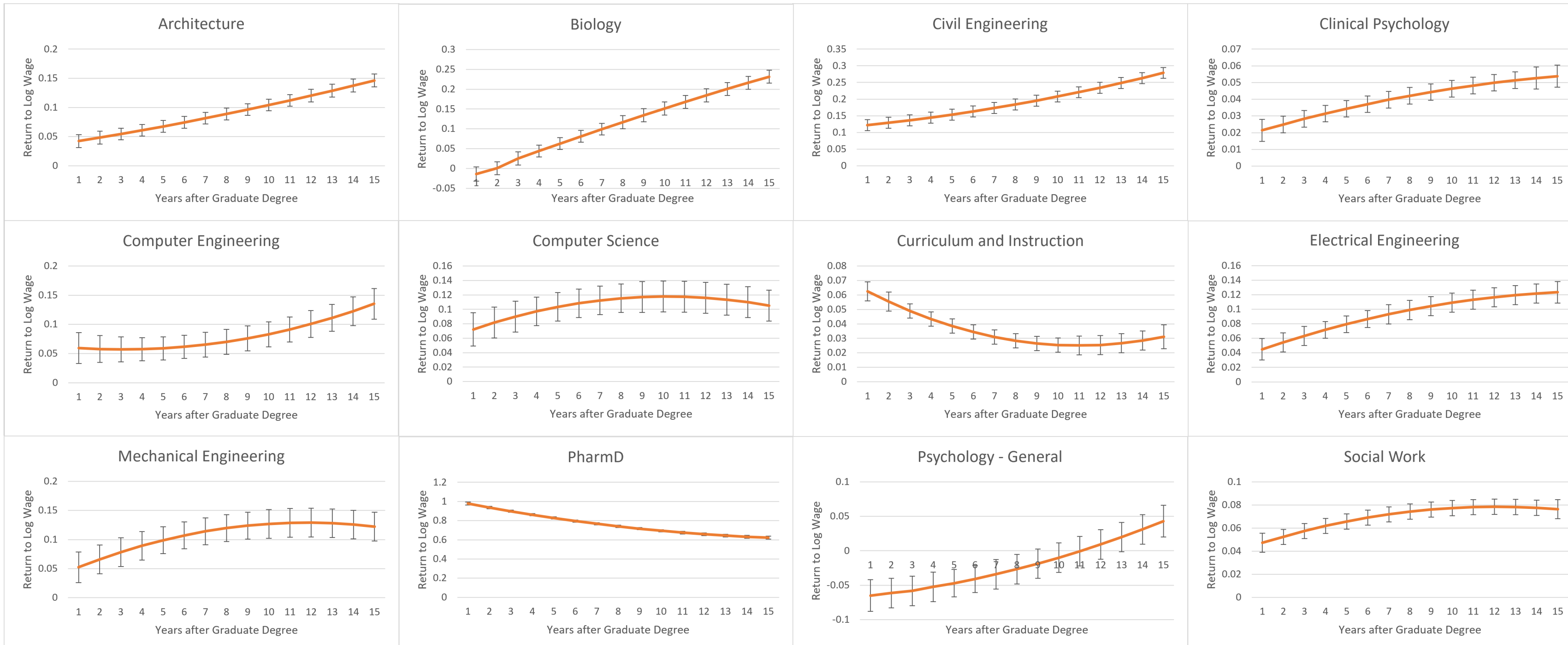

Figure A1.1: Returns by Post Graduate School Experience for Additional Degrees

Notes: This figure reports estimates of $\gamma^g_{x_{it}}$, the return to the graduate degree g at x years of post graduate school experience for 12 of the 18 main graduate degrees. The value of x is on the horizontal axis. (The graphs for the other 6 degrees are in Figure 2.) We estimate the FEcg specification (3) with graduate degree specific experience trends following $\gamma^g_{x_{it}} = \gamma^g_0 + \gamma^g_1 x_{it} + \gamma^g_2 x^2_{it}$. The note to Table 3 lists the controls. The estimates of $\gamma^g_{x_{it}}$ for the first 15 years of experience after graduation are the values of $\hat{\gamma}^g_0 + \hat{\gamma}^g_1 x_{it} + \hat{\gamma}^g_2 x^2_{it}$ for the graduate degree of interest. 90% confidence intervals are reported as the wicks. They are based on standard errors clustered at the individual level.

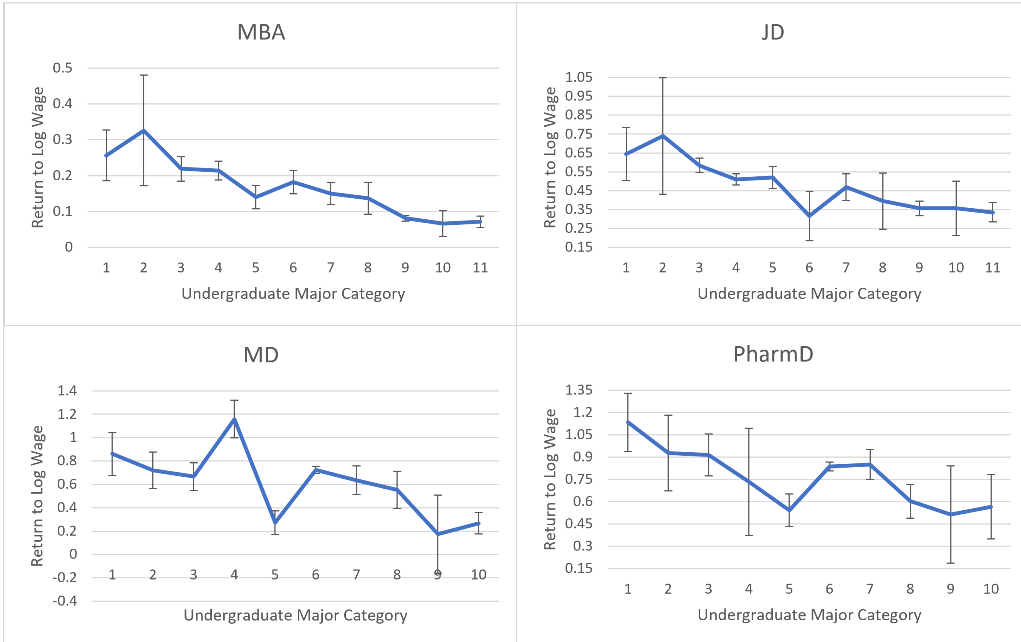

Figure A1.2: Major Heterogeneity

Notes: This figure graphs the returns to an MBA, JD, MD, and PharmD for students from each aggregated category of college majors. The returns reported here are estimated with the FEcg specification and are taken from Table 5. The major categories are ordered in ascending order of their average income from left to right. They are: fine arts, education, humanities, law and social sciences, communication, health-related, life sciences, natural sciences, business, computer sciences, and engineering. 90% confidence intervals are reported in the wicks. They are based on standard errors clustered at the individual level.

Appendix A2: Additional Tables on PDVs and Internal Rates of Returns

Table A2.1: Duration and Tuition of Programs, and Earnings and Investment while Enrolled

	Tuition (1)	Median Duration in Data (2)	Full-time Duration Assumed (3)	Average Annual Earnings while Enrolled (4)	Counterfactual Earnings while Enrolled (5)	Annual Investment (6)
Social Work	7344	2.0	2	21396	50542	36488
Clinical Psychology	7344	3.0	2	29327	52373	30388
Curriculum Instructions	7344	2.3	1	39998	54160	21504
Psychology	7344	3.0	2	20343	53895	40894
Edu Admin	7344	2.3	1	50847	56755	13251
Architecture	7344	2.0	1	19285	59790	47848
Biology	8864	3.0	1	19551	52882	42193
MPA	7344	2.0	2	36682	57574	28235
Nursing	8864	3.0	2	57239	78891	30516
Computer Science	8864	2.5	1	42443	84976	51396
Civil Engineering	8864	2.0	1	34756	80018	54125
MBA	10148	2.3	2	46971	76915	40093
Computer Engineering	8864	2.5	1	37824	94386	65425
Mechanical Engineering	8864	2.3	1	33014	90599	66447
Electrical Engineering	8864	2.3	1	39242	100963	70584
PharmD	14516	4.0	4	21318	55201	48398
JD	18200	3.0	3	20051	67448	65997
MD	14516	4.0	4	10469	64046	68092

Notes: This table reports the time and monetary investments for different graduate degrees. Column 1 reports the assumed tuition per year calculated from the average tuition at public institutions in 2012 from the National Center for Education Statistics, in 2019 dollars. Columns 2 and 3 reports the median duration of enrollment calculated from the TSP data set, and the assumed duration for full-time students, taken from Altonji and Zhong (2020). Average annual earnings while enrolled and estimated counterfactual earnings while enrolled are calculate from the TSP data set and reported in Columns 4 and 5. Column 6 reports the net annual investment of each graduate program, defined as Tuition + Counterfactual Earnings − Earnings During Enrollment.

Table A2.2: Internal Rate of Returns Estimates Assuming Full Time Enrollment and No Earnings During Enrollment

	Net PDV Counterfactual (1)	Net PDV Actual (2)	Gain of PDV (3)	Internal Rate of Returns (4)
Social Work	1,045,884	988,257	-5.5%	0.000
	(11,900)	(12,814)	(1.5%)	(0.022)
Clinical Psychology	1,094,789	1,006,057	-8.1%	-0.030
	(9,205)	(10,299)	(1.2%)	(0.030)
Curriculum Instructions	1,135,585	1,093,805	-3.7%	-0.020
	(9,938)	(15,789)	(1.6%)	(0.058)
Psychology	1,154,257	1,053,089	-8.8%	-0.030
	(27,545)	(20,753)	(2.2%)	(0.043)
Edu Admin	1,206,579	1,263,413	4.7%	0.100
	(3,820)	(8,755)	(0.8%)	(0.058)
Architecture	1,342,216	1,417,054	5.6%	0.110
	(27,352)	(22,156)	(2.3%)	(0.020)
Biology	1,153,974	1,358,007	17.7%	0.180
	(27,295)	(33,100)	(3.3%)	(0.021)
MPA	1,198,480	1,454,241	21.3%	0.140
	(12,891)	(34,055)	(3.0%)	(0.010)
Nursing	1,541,135	1,664,842	8.0%	0.110
	(9,528)	(29,301)	(1.9%)	(0.010)
Computer Science	1,885,524	2,027,381	7.5%	0.150
	(61,561)	(37,787)	(3.5%)	(0.040)
Civil Engineering	1,803,380	2,162,311	19.9%	0.230
	(35,559)	(32,311)	(2.4%)	(0.018)
MBA	1,715,486	1,848,716	7.8%	0.100
	(5,275)	(11,844)	(0.6%)	(0.004)
Computer Engineering	2,115,246	2,203,870	4.2%	0.100
	(55,891)	(65,044)	(4.1%)	(0.051)
Mechanical Engineering	2,056,675	2,183,407	6.2%	0.130
	(68,378)	(61,518)	(4.6%)	(0.048)
Electrical Engineering	2,256,768	2,390,733	5.9%	0.120
	(29,128)	(51,176)	(2.7%)	(0.027)
PharmD	1,140,782	1,834,962	60.9%	0.200
	(18,443)	(35,438)	(4.3%)	(0.007)
JD	1,445,734	1,986,150	37.4%	0.170
	(13,202)	(23,698)	(2.0%)	(0.006)
MD	1,357,542	3,661,869	169.7%	0.310
	(23,902)	(53,714)	(5.8%)	(0.005)

Notes: This table reports the net PDV and IRR results when using the assumed duration of programs for full-time students, and assuming that students do not earn income during graduate school. All calculations are based on the FEcg specification underlying Table 3, Column 7. The note to Table 3 lists the controls. To avoid extrapolating the quadratic too far out of sample when predicting earnings, we set $\hat{\gamma}_x^g = \hat{\gamma}_{15}^g$ when $x > 15$, where x is years after graduate school. We extrapolate age profiles beyond age 40 using age profiles estimated by AZ (2020), as discussed in the text. When calculating PDV, we use the assumed duration of full-time students reported in Column 3 of Appendix Table A2.1. We assume that total tuition equals the annual tuitions for full-time students reported in Column 1 of Appendix Table A2.1. The full-time annual tuitions are the average tuition at public institutions in 2012 from the National Center for Education Statistics, in 2019 dollars. During enrollment, we assume earnings equal 0. The PDVs presented in Columns 1 and 2 are calculated assuming a 0.05 interest rate. For each degree, Column 2 reports the PDV . Column 1 reports the counterfactual PDV if people with corresponding degree did not enroll in graduate school and did not earn the degree. Column 3 presents the % gain in PDV. Column 4 reports the estimates of the IRR of each advanced degree. The IRR is the discount factor that equates actual and counterfactual lifetime net income. We use a block bootstrap procedure to calculate standard errors (in parentheses). We divided the sample of individuals into 46 strata. We sampled with replacement in each strata to preserve the sample distribution of person counts across strata. The strata are defined by gender (2 blocks), by number of appearances in the earnings regression sample used to estimate returns (6 blocks), and by number of appearances in the enrolled earnings sample (4 blocks). We exclude people who are absent from both earnings samples. The reported standard errors are the standard deviations of the PDV and IRR estimates over 200 bootstrap samples.

Appendix A3: Additional Tables Concerning Industry Premiums and Industry Choice

Table A3.1: Returns to Industry Earnings Premium

Dependent Variable	Log Industry Earnings Premium	
Specification	OLS (1)	FEcg (2)
Social Work	-0.082 (0.002)	0.064 (0.004)
Clinical Psychology	-0.136 (0.002)	-0.016 (0.002)
Curriculum and Instruction	-0.136 (0.001)	-0.012 (0.002)
Psychology	-0.119 (0.006)	-0.060 (0.015)
Edu Admin	-0.153 (0.001)	-0.007 (0.001)
Architecture	0.092 (0.003)	0.020 (0.009)
Biology	-0.057 (0.006)	0.017 (0.013)
MPA	-0.076 (0.004)	0.010 (0.006)
Nursing	0.117 (0.002)	0.025 (0.003)
Computer Science	0.096 (0.008)	0.007 (0.022)
Civil Engineering	0.103 (0.004)	0.032 (0.009)
MBA	0.093 (0.001)	0.010 (0.002)
Computer Engineering	0.140 (0.007)	-0.011 (0.013)
Mechanical Engineering	0.170 (0.006)	0.033 (0.018)
Electrical Engineering	0.196 (0.005)	0.008 (0.009)
PharmD	-0.031 (0.003)	-0.002 (0.009)
JD	0.099 (0.002)	0.083 (0.005)
MD	0.047 (0.002)	0.080 (0.009)
Sample Size	31522717	31522717

Notes: This table reports OLS and FEcg estimates of the effect of the graduate degree on the log industry earnings premium. Robust standard errors are clustered at the individual level, and are reported in parentheses. The specification is the same as the specification for Columns 1 and 2 of Table 3, except that we use the industry premium rather than log earnings as the dependent variable. See the note to Table 3 for the controls. Footnote 14 describes the regression procedure used to estimate the industry premiums. Industries are defined based on the four digit NAICS codes. The reference category of industry is 6111, which represents elementary and secondary education.

Table A3.2: Most Common Industries Before and After Graduate School

	Most Common NAICS Industry - 2 Digit	
Time Period	Before Grad School	After Grad School
Social Work	Health Care and Social Assistance (62)	Health Care and Social Assistance (62)
Clinical Psychology	Educational Services (61)	Educational Services (61)
Curriculum and Instruction	Educational Services (61)	Educational Services (61)
Psychology	Educational Services (61)	Educational Services (61)
Edu Admin	Educational Services (61)	Educational Services (61)
Architecture	Professional, Scientific, and Technical Services (54)	Professional, Scientific, and Technical Services (54)
Biology	Educational Services (61)	Educational Services (61)
MPA	Public Administration (92)	Public Administration (92)
Nursing	Health Care and Social Assistance (62)	Health Care and Social Assistance (62)
Computer Science	Manufacturing (33)	Professional, Scientific, and Technical Services (54)
Civil Engineering	Professional, Scientific, and Technical Services (54)	Professional, Scientific, and Technical Services (54)
MBA	Finance and Insurance (52)	Finance and Insurance (52)
Computer Engineering	Manufacturing (33)	Manufacturing (33)
Mechanical Engineering	Professional, Scientific, and Technical Services (54)	Professional, Scientific, and Technical Services (54)
Electrical Engineering	Manufacturing (33)	Manufacturing (33)
PharmD	Retail Trade (44)	Retail Trade (44)
JD	Professional, Scientific, and Technical Services (54)	Professional, Scientific, and Technical Services (54)
MD	Educational Services (61)	Health Care and Social Assistance (62)

Notes: This table reports the most common industries for individuals with specific graduate degrees before and after graduate enrollment. Industries are defined based on the two-digit NAICS codes.

Appendix A4: The Distribution of the Time Between the Year of Earnings Observations and Graduate Enrollment: JD and MBA Graduates

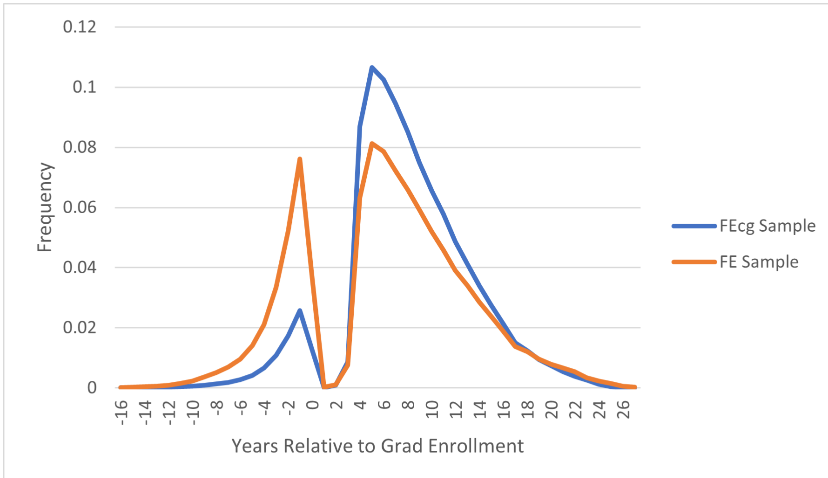

Figure A4.1: Distribution of Year of Earnings Minus Graduate Enrollment Year in the Regression Samples — JD Degree Holders

Notes: This figure shows the distribution of the time between each earnings observation and the year of graduate school enrollment for those who attain a JD degree. The FEcg sample includes everyone for whom we observe their college degree, and the FE sample includes everyone for whom we observe their college degree who have earnings both before and after graduate school.

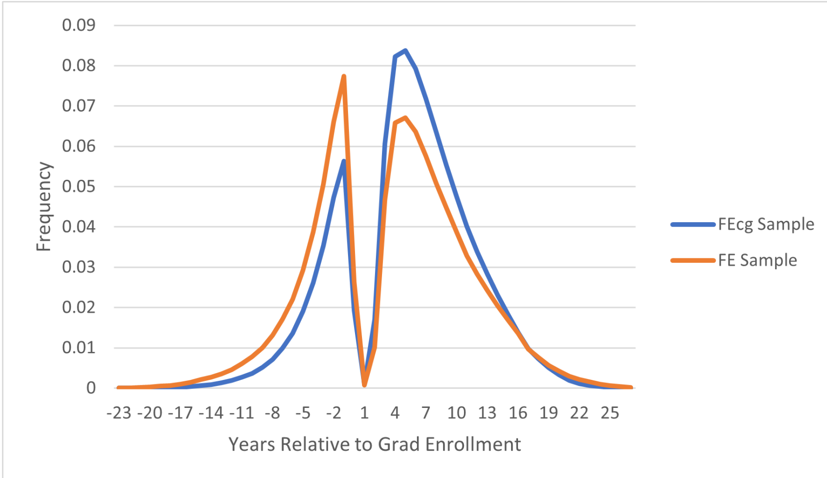

Figure A4.2: Distribution of Year Minus Graduate Enrollment in the Regression Samples — MBA Degree Holders

Notes: This figure shows the distribution of the time between each earnings observation and the year of graduate school enrollment for those who attain a MBA degree. The FEcg sample includes everyone for whom we observe their college degree, and the FE sample includes everyone for whom we observe their college degree, and who have earnings observations both before and after graduate school.