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ABSTRACT

This paper uses a college-by-graduate degree fixed effects estimator to evaluate the returns to 19 different graduate degrees for men and women. We find substantial variation across degrees, and evidence that OLS overestimates the returns to degrees with high average earnings and underestimates the returns to degrees with low average earnings. Second, we decompose the impacts on earnings into effects on wage rates and effects on hours. For most degrees, the earnings gains come from increased wage rates, though hours play an important role in some degrees, such as medicine, especially for women. Third, we estimate the net present value and internal rate of return for each degree, which account for the time and monetary costs of degrees. We show annual earnings and hours worked while enrolled in graduate school vary a lot by gender and degree. Finally, we provide descriptive evidence that gains in overall job satisfaction and satisfaction with contribution to society vary substantially across degrees.

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1 Introduction

Graduate education has grown rapidly in the U.S. over the last several decades, with especially rapid growth among women. The share of female college graduates aged 35-39 with an advanced degree rose from 28.6% in 1993 to 40.4% in 2019. For men, the share rose from 33.5% to 36.3%. The increase for women is especially striking because the percentage of women with at least a four-year college degree increased from 24.6% to 48.8% over the same time period and age range.[1]

It is important to assess the value of graduate school given that such high attendance rates among college graduates. A number of papers study the impact of graduate and college education on earnings levels and distribution (Blanden and Machin, 2004; Lemieux, 2006), as well as the gender gap (Blau and Kahn, 2017). However, there is less research on the economic value of specific graduate degrees (such as an MBA or a master's in nursing) by gender. While Goldin and Katz (2011) and Goldin and Katz (2016) are important examples of research on the entry of women into male-dominated professions that require graduate degrees, little is known about the returns to specific graduate degrees for women and men separately. Table 1 presents the mean of full-time earnings by gender for 19 graduate degrees. There are large differences across degrees, and between women and men with the same degrees. At the top, women with medical degrees make $139,379 on average, while men with medical degrees make $192,402. At the low end, women with a master's in art make $58,176, while men with a master's in art make $71,681, both of which are below the means for BA holders without a graduate degree.

These large differences in earnings by graduate degree suggest three questions. First, to what extent do these differences represent the causal effects of the degrees? This question is hard to answer as people likely sort into specific graduate programs based on their occupational preferences and predetermined ability, making it difficult to separate out the differences in sorting from differences in returns.

Second, how much of the earnings effects from graduate degrees comes from increased hourly wage rates versus increased hours of work? For example, men and women with medical degrees have the highest average earnings, but also the highest average hours worked per year: 2,672 for men and 2,353 for women. In contrast, those with a master's in psychology and social work on average earn less but also work fewer hours: 2,121 for men and 1,876 for women. These differences in hours worked could be due to sorting based on labor supply preferences, the causal effects of the degrees on hours of work, or a combination of both.[2]

Third, are there systematic differences in the effect of graduate fields on the nonpecuniary benefits of work? This is a natural question given that individuals with similar ability and prior education choose graduate fields with different earnings potential. Recent research has established that nonpecuniary preferences play a critical role in determining choice of college major (Arcidiacono et al., 2012; Zafar, 2013; Wiswall and Zafar, 2017), and we suspect the same is true for graduate degrees.

In this paper, we estimate the effects of specific graduate fields on earnings, hourly wage, and hours worked, which under some strong assumptions can be interpreted as causal. We also provide suggestive evidence of the impacts on nonpecuniary benefits. To estimate causal effects, we must account for the fact that the decision to attend graduate school and the choice of the specific field is not random. Preferences and predetermined ability influence field of study, occupation, and earnings, as well as hours worked and

[1] Authors' calculations from US Census Bureau tables using CPS data (Kominski and Adams, 1994; Census, 2020).

[2] Causal effects could work through at least three mechanisms. First, higher wages may increase labor supply. This effect might be larger for women who, on average, have a somewhat higher wage elasticity (Bargain and Peichl, 2016). Second, some graduate degrees may lead to jobs which have high returns to working more hours. Third, in some fields, graduate degrees may improve employment prospects. Causal effects on the wage rate may reflect both a direct effect conditional on hours and the fact that in some high level jobs long hours are associated with higher wage rates. See Bertrand et al. (2010) and Gicheva (2013).

wage rates. An individual's education and ability shift what they could earn across a range of occupations. However, observed earnings reflect the occupation actually chosen, a choice based on both preferences and potential earnings. Because preferences and ability also influence field of study, earnings comparisons may be misleading as estimates of the causal effect of a degree for those who choose it. The same problem arises for the study of wage rates and hours of work.

Following Altonji and Zhong (2021) (hereafter, AZ), we address the selection problem by using pre-graduate school earnings of individuals who later obtain a graduate degree to approximate what they would have earned had they not gone to graduate school. Because most people work for a few years between college and graduate school, it is natural to consider controlling for person specific fixed effects (FE) in a regression model that includes dummy variables for graduate degrees in the current period and time varying controls. Under some strong assumptions discussed below, this approach identifies the return to graduate school for those who earn graduate degrees, using only people with earnings observations both before and after graduate school. However, due to the design of our data, we observe relatively few people in the labor market both before and after they obtain a graduate degree. Furthermore, the post graduate school observations of such individuals are limited to the first few years after graduate school. For these reasons, we follow AZ and rely primarily on a group fixed-effects estimator they call FEcg, where the groups are the combination of last observed college major c and graduate field g for each individual. In contrast to FE, FEcg makes full use of individuals with earnings observations only before the advanced degree and individuals with earnings observations only after the advanced degree, not just individuals who are observed both before and after.

We use data from multiple waves of the National Survey of College Graduates (NSCG, 1993 to 2019) and the National Survey of Recent College Graduates (NSRCG, 1993 to 2010). Some individuals are surveyed more than once and can be followed over time. The data sets contain basic controls, earnings, work hours, occupation, information about job satisfaction, and education histories that record undergraduate and graduate degrees by field of study.

The paper makes four contributions. First, we estimate the effects on log earnings of 19 specific graduate degrees for men and women who earn graduate degrees. We find that the returns to graduate degrees vary substantially across fields and across gender within a given field. For example, on the high end, using our main specification the return to medicine is 0.718 (0.077) for men and 0.527 (0.133) for women. The corresponding values for law are 0.492 (0.086) and 0.543 (0.068). In the intermediate range, the return to an MBA is 0.146 (0.022) for men and 0.176 (0.036) for women. On the low end, the returns are under 0.1 for women in engineering, and negative for both men and women in arts. In addition, for some specific degrees, there are notable differences in the estimated returns for men and women. For example, the returns to women are substantially higher for degrees in humanities, health-related degrees, education, and law, while the returns to medicine, engineering, and the life sciences are somewhat larger for men. We are among the first to provide treatment on the treated estimates of the returns to a broad set of graduate degrees for men and women, while also addressing selection bias.[3] The FEcg estimates often differ substantially from OLS.

Second, we also consider effects on log annual hours worked and log wage rates in addition to log earnings. Consequently, we can decompose the impacts on earnings into the impacts on hourly wage rates and the impacts on hours worked. Our results show that most of the gain in log earnings comes from an increase in the log hourly wage, although increased hours worked plays an important role in medicine, law, MBA, other business, and health administration master's degrees.

Third, we use the results above to provide degree specific estimates of the percentage increase in present

[3] AZ present one table with separate estimates for men and women, as do Altonji and Zhu (2021) in contemporaneous work.

discounted value of earnings net of tuition and the internal rate of return. Because program lengths vary, the percentage gain in present discounted value provides a better sense of the overall gain, while the internal rate of return provides a better sense of the return to a unit of investment. As our base case, we assume that people attend graduate school full-time, do not work, and pay public school tuition. However, many people work while in graduate school and take more years than they would need to complete the degree had they enrolled full-time. We show that annual earnings and hours worked while enrolled in graduate school varies substantially by gender and degree. For example, average earnings while enrolled is $7,751 for men pursuing a medical degree but $55,971 for men pursuing an MBA. To address this, we also estimate the gain in present discount value and the internal rates of return using average completion times and average annual earnings while enrolled.

We will not discuss the estimates in detail here, but instead characterize what drives them and give a few examples. The percentage gains in present discounted value (PDV) are strongly correlated with estimates of effects on log earnings and to a lesser extent with in-school earnings, while the internal rate of return estimates are also strongly influenced by both degree completion time and treatment of earnings while in school. For example, in the case of medicine the percentage gain in PDV for men is 66.2% (12.9), while the internal rate of return is 0.16 (0.02). In the MBA case, the values are only 8.1% (2.2) and 0.09 (0.01). However, when we use average program duration and earnings while enrolled, the values for medicine increase only slightly, while the values for an MBA rise to 13.8% (2.2) and 0.21 (0.04).[4]

Finally, we go beyond effects on earnings, wage rates and hours to examine effects on measures of overall job satisfaction as well as satisfaction with specific aspects of the job, such as contribution to society. We rely on least squares estimates of linear probability models of being "very satisfied" because we do not have enough cases in which individuals are observed prior to obtaining the graduate degree to use FEcg, and therefore the estimates should be considered only correlations. Nevertheless, the estimates provide an interesting set of facts about how graduate degrees in specific areas are related to the working lives of men and women. First, graduate degrees increase overall job satisfaction for men, with the exception of degrees in social science and business, for which the estimates are slightly negative but not statistically significant. Second, the effects are larger for men than women in all cases except engineering, although the differences are small in some cases. Third, the effect on overall satisfaction varies substantially across fields. For example, it is particularly large in medicine (about 0.2 for both men and women), but it is close to zero for an MBA. Fourth, the degree specific effects on overall satisfaction have a strong positive correlation with the earnings effects estimates for both genders, but the relationship is stronger for women. Finally, the effects on being very satisfied with contribution to society also vary substantially across degrees, but are negatively correlated with earnings.

Our paper is related to several literatures. First, this paper is related to a growing body of work on the returns to specific fields of study in higher education, as reviewed in Altonji et al. (2012) and Altonji et al. (2016). Several paper focus specifically on the returns to college major, such as Hamermesh and Donald (2008) studying the returns to college major in the US, Kirkeboen et al. (2016) in Norway and Hastings et al. (2013) in Chile, though none of these papers focuses on gender differences, or the returns to graduate degrees.

Research on the returns graduate degrees is much more limited than research on college majors. Using NLS72, Altonji (1993) reports regression estimates of the return to the highest degree, including some college, ten aggregated college major categories, and five aggregated graduate school categories, with controls for family background, test scores, high school grades, and other 12th grade aptitude measures. His analysis is

[4] An important caveat is that the estimates of the internal rate of return are imprecise for some degrees when assuming full-time enrollment and zero earnings, and imprecise for most degrees when using earnings while enrolled.

for a relatively young sample, and assumes that only the field of highest degree matters. Black et al. (2003) report OLS estimates of the return to a few graduate degree types for different majors using the 1993 NSCG. Altonji et al. (2016) report OLS estimates for a broader set of graduate and undergraduate degrees using the 1993, 2003, 2010, and 2013 NSCG.

A few papers study the returns to a specific type of graduate degree. Arcidiacono et al. (2008) estimate the return to an MBA using panel data on people who registered to take the GMAT exam, a test used in MBA admissions. Altonji et al. (2016) estimate that the return to an MBA for men is 0.094 with basic controls, 0.063 after controlling for undergraduate GPA and GMAT test scores, and 0.048 after controlling for individual fixed effects. Results for women are similar. Similarly, Bhattacharya (2005), Chen and Chevalier (2012) and Ketel et al. (2016) are a part of a small literature that studies the return to medical degrees.[5] Altonji and Zhu (2021) also present estimates for detailed graduate degrees using FEcg and other approaches using administrative data for the state of Texas. Our paper is most strongly related to AZ, who used the FEcg estimator with the NSCG and NSRCG data to produce estimates of the earnings returns for the 19 fields we consider. They also present evidence on selection into graduate school field and estimate college major specific returns to an MBA and an Education degree. We do not consider the latter issues, but we treat men and women separately, extend the sample to 2019, expand the outcomes considered to wage rates, hours, and job satisfaction. We also consider earnings while in school and use empirical estimates of duration of graduate school when computing gains in present discounted value and internal rates of returns.

Finally, this paper also contributes to a literature documenting the earnings gap between men and women. Goldin (2014) and Blau and Kahn (2017) provide economy-wide estimates and find a large and persistent gap in earnings between men and women. In particular Blau and Kahn (2017) find that, between 1980 and 2010, the gender gap declined the least at the top of the wage distribution. This paper provides additional details on gender differences in the returns to graduate degrees.

The paper proceeds as follows. Section 2 describes the data. Section 3 presents basic facts about labor market outcomes of men and women by graduate field, including earnings, wage rates, hours, employment rates, and overall job satisfaction. Section 4 discusses the problem of selection bias, the estimation strategies we use, and the econometric specifications. Section 5 presents estimates of the return to graduate degrees on earnings, including the relative importance of effects on hourly wage rates versus annual work hours, and effects operating through occupation. Section 6 presents estimates of the internal rate of return to the graduate degrees and the effects of the degrees on the present discounted value of lifetime income. Section 7 presents OLS estimates of effects on various aspects of job satisfaction for each degree. We conclude in section 8.

2 Data

The construction of our data closely follows the process described in AZ. As mentioned above, we made a number of changes and extended the data to include the 2017 and 2019 waves of the NSCG. We also incorporated information on employment, annual hours, hourly wage rates, and job satisfaction. The description below draws heavily on AZ, with parts of the discussion taken verbatim.

We combine data from two closely related surveys, the NSCG 1993-2019 and the NSRCG 1993-2010.[6]

[5] See also Goldin and Katz (2011) and Goldin and Katz (2016) that document the entry of women in to certain professions requiring graduate degrees previously dominated by men.

[6] The NSRCG samples are restricted to individuals who have obtained a BA or advanced degree in an S&E field within three years prior to the survey reference date. The NSCG samples covers individuals who obtained the degrees at least three

Among these surveys, the NSCG 1993, 2003, 2010, 2013, 2015, 2017, and 2019 are representative samples from the most recent census or American Community Survey (ACS). Respondents of NSCG or NSRCG become part of the Scientists and Engineers Statistical Data System (SESTAT) sponsored by the National Center for Science and Engineering Statistics (NCSES) within the National Science Foundation (NSF). Surveys in the 1990s and 2000s that are not nationally representative are follow-up surveys of the SESTAT participants. Surveys from 2010 on include new respondents from the most recent ACS and returning respondents from the previous NSCG. The NSCG 1993 is also available from the Inter-university Consortium for Political and Social Research (ICPSR) and includes variables such as earnings and occupation from the 1990 census.[7] Combining all waves of both the NSCG and NSRCG allows us to work with an unbalanced panel data set.

Finally, most of the surveys ask two questions about earnings. The first asks about annualized salary at the main employer in the survey reference week. The second asks about the sum of earnings from all jobs in the prior calendar year. This provides a source of additional panel observations on earnings for many individuals.[8]

Annual hours worked is the product of weeks worked per year and hours worked per week at the principal job. The information on hours worked, occupation, and job satisfaction is not available for the previous calendar year. We construct the hourly wage rate for the prior calendar year using earnings that year, while we construct the wage for the survey year using the annualized salary measure. In both cases we divide earnings by annual hours worked at the principal job in the survey reference week. This assumes hours are stable across years All monetary variables are in 2013 dollars. We describe the job satisfaction data in section 7.

The combined dataset also contains detailed information on postsecondary education history, current and past employment, and basic demographic variables. The latter include gender, race, ethnicity, and parents' education. We use 19 aggregated BA categories and 19 aggregated graduate categories in most of our analyses.[9] Tables A1 and A2 provide the shares of the disaggregated fields in the aggregated categories of the graduate degrees and BA degrees respectively for women. The tables also report the mean and standard deviation of earnings and the regression coefficients from OLS estimates of equation (1) using the disaggregated degree categories. Tables A3 and A4 provide the same information for men.

We use the occupational earnings premiums constructed by AZ using the 2009-2014 waves of the ACS.[10] The estimates are merged into the NSCG-NSRCG dataset by disaggregated occupation. The ACS based premiums are reported in Online Appendix Table B3 of AZ.

We use sample weights unless otherwise noted. We construct the weights to make the pooled sample

years prior to the survey reference date, without restrict sampling to S&E fields. S&E includes the social sciences but excludes Health-related fields and occupations from 1993 to 2001. From 2003 on, Health is included. Throughout the paper, we use "BA" to refer to both bachelor's of arts and bachelor's of science degrees and use "MA" in a similar fashion.

[7] The 1990 occupation uses the 1990 census classification and has 363 disaggregated fields. To merge it with the occupation defined in NSCG and NSRCG, we define a 66-categories occupation classification. See AZ (Online Appendix Table B3) for the share of the occupations. The values for our study are slightly different because we made minor changes in the occupation classification and because we incorporate the 2017 and 2019 NSCG.

[8] Minor differences in the means of the two measures are absorbed by year dummies in the regression analyses. Any correlation in measurement error between the two measures will contribute to correlation in the earnings regression error term but will not lead to bias if the measurement error is uncorrelated with the regressors. Standard errors are clustered at the individual level throughout the paper. AZ present separate FEcg estimates of returns for each of the two earnings measures for a specification similar to what we report in Appendix Table A8, but for a pooled sample of men and women who went to graduate school. They do not find systematic differences.

[9] The classifications are guided by the NSF classification and cover all BA fields of study and all master's and professional degree fields of studies, respectively. We exclude PhD degree holders from the analysis sample.

[10] They are based on an OLS regression using the sample of full-time workers with BA degrees who are between 23 and 59 years old and are relative to top level managers. The regressions control for a cubic in age interacted with gender, race/Hispanic interacted with gender, and dummies for whether or not the person has a master's degree, a professional degree, and PhD. Note that they are the same for men and women.

representative of the US population of college graduates over the years of our sample.

We restrict the analysis to individuals with BA degrees who are between 23 and 59 years old in the survey reference year and who have at most one advanced degree. We exclude individuals who ever obtain a PhD, who obtain a BA before age 20 or after age 55, or who obtain their advanced degree after age 49.[11] We additionally require individuals to earn at least $5,000 per year, though for most of the analyses we focus on full-time workers.[12]

We also wish to exclude observations for individuals enrolled in school during the year of the earnings observation. To achieve this, we need information on when an individual earned a graduate degree and when they started. Unfortunately, the data does not include the start date. To address this data limitation, we estimate the start date by subtracting the typical number of years required to obtain the degree for a full-time student from the year the degree was earned. We classify observations as prior to graduate school if they are prior to the estimated start date.[13]

Our main earnings regression sample, which we call the "full sample," contains 378,090 person-year observations for 128,740 women, 99,210 of whom are observed more than once. Of these, 155,580 observations on 50,940 women are post graduate school. The sample also contains 4,370 pre advanced degree observations on 2,560 women. Sample sizes are about 70% larger for men.[14] Definitions and descriptive statistics for the dependent variables and the key control variables that appear in our regression models are in Tables 1 and A5.

3 Facts about labor market outcomes across graduate fields

Figure 1 presents descriptive facts about log earnings ($ln\ e$), log hours ($ln\ h$), and log hourly wage ($ln\ w$) across graduate degrees. All estimates are for the sample of individuals who work full-time, hold a graduate degree, and meet the other criteria for inclusion in our main regression sample for each of the three variables. Because our focus is on the effects of graduate education, all values are relative to the gender specific means of those who do not have a graduate degree. Table 1 reports actual means for each graduate degree and for those with only a BA.[15] Triangles denote the mean values for women and crosses for men. Red refers to earnings, blue refers to the log wage, and green refers to log hours. The fields of the degrees are listed along

[11] We code BA based on the primary field of the first BA obtained. Thus, we do not account for a second major, or a minor. We drop individuals who obtain multiple BA degrees in different years. Because of concerns about bias from choice based sampling, we also exclude the follow up observations for a small number of individuals who do not have degrees in S&E fields but are SESTAT-eligible only because of their S&E occupation choices in their first observation.

[12] We report estimates of degree effects on earnings for all workers in Appendix Figure A10 and effects on employment in Appendix Figure A11. We code an individual as full-time if she reported working full-time or if she worked at least 41 weeks per year and at least 35 hours per week. We used 41 weeks to accommodate the employment arrangements of many teachers. With the exception of the 1989 annual earnings measure, we assume that full-time status in the prior year is the same as the survey year when the earnings measure refers to the year before the survey, as we lack data on full-time status in the prior year.

[13] We assume 4 years for Medicine, 3 for Law, 2 for an MBA, master's degrees in business-related fields, health services administration, nursing, public administration, health-related fields, arts, and psychology and social work, and 1 for all other master's degrees. We chose the number of years conservatively to preserve as many pre advanced degree observations as possible. Using this criterion together with full-time employment requirement ensure the earnings measures of pre advanced degree observations in the regression samples are comparable with other full-time workers. Imposing the additional restriction that individuals are not enrolled in school in the survey reference week made little difference. See Online Appendix 9 for data on the timing of the earnings observations before and after graduate school.

[14] We round all observation counts to the nearest 10. The mean, 1st percentile, median, and 99th percentile of the number of observations per person in the full sample for earnings are 3.23, 1, 4, and 8.

[15] The earnings and to a lesser extent the log wage regression samples include observations based on income in the prior years, while the log hours sample does not. Consequently, the premiums do not add up to the $ln\ e$ premium. The results are very similar if we classify people based upon their degree when we last observe them rather than the current value of the degree. In large part this is because only 2.47% of observations on people who obtain graduate degrees refer to the period before graduate school. The values for the BA only category increase somewhat if we re-weight the BA only sample to have the same age distribution as the observations on graduate degree holders.

the horizontal axis. The degrees are arranged in increasing order of mean earnings for women, ranging from arts and humanities on the left to law and medicine are on the right.

The red triangles are typically above the red crosses, indicating that the simple earnings premiums for most graduate degrees (relative to a BA degree) are larger for women than for men. The premiums also vary dramatically across graduate degrees. For women, the premium is slightly negative for arts, less than 0.08 for both humanities and psychology/social work, but above 0.6 for both law and medicine. The variation across degrees is similar for men, with some differences. Relative to the overall premium, the gender differences are particularly large for the lower paying graduate degrees in the left half of the figure. Nursing and medicine are the two fields in which men gain more than women, though the difference for medicine is small.

The $ln\ w$ premiums (blue triangles and crosses) also increase substantially from the lower paying degrees to the higher paying, but at a slower rate than log earnings. For women, the wage premium is about 0.04 above the earnings premium for arts, humanities, psychology, and education, between 0.02 and 0.11 below the earnings premium for nursing, an MBA, business and law, and 0.20 below for medicine. The same pattern is present for men, with the wage premiums rising more slowly than the earnings premiums. The log wage premiums are typically larger for women than men, with nursing and medicine as the only exceptions.

The green triangles show that the variation in the graduate hours premium also plays an important role in variation in the earnings premiums for women. Women with master's degrees in the arts, humanities, and education work fewer hours than women with just a bachelor's degree. Women with an engineering degree, an MBA, a JD, or a medical degree work between 0.05 and 0.20 log points more. The pattern is similar for men, but the association between the hours premium and the earnings rate of the program is weaker than for women. Men with an engineering master's work slightly fewer hours than those who do not attend graduate school. Men with an MBA, business, or law degree work between 0.05 and 0.07 more hours (in logs), and those with a medical degree work 0.17 more hours.

The broad conclusion is that differences across graduate degrees in earnings premiums relative to a BA are a combination of both increased work hours and higher hourly wages, with higher hourly wages contributing the majority of the gains in most cases. The simple averages across all 19 graduate degrees of the log earnings, wage, and hours premiums are 0.304, 0.278, and 0.049 for women and 0.194, 0.194, and 0.00 for men. The share of the gain contributed by the wage rate is negatively related to the earnings premium.[16]

These findings are comparisons of means, no more and no less. However, we find a very similar pattern in the OLS estimates of the effects on earnings, wage and hours premiums, and a similar pattern in the FEcg estimates, for which sampling error is larger. Larger wage elasticities for women may partially explain why a larger portion of their earnings gains from graduate school come from increased hours. The labor supply response may feed back into higher earnings premiums. For example, Goldin and Katz (2011), Bertrand et al. (2010), and Gicheva (2013) provide evidence of a substantial wage premium for professionals who work long hours.

4 Econometric Models and Estimation Methods

Estimating the returns to graduate education is difficult because individuals choose which program to apply to, and graduate programs decide whom to admit based in part on student characteristics that matter for earnings. Altonji et al. (2016), AZ and Altonji and Zhu (2021) provide summary statistics showing that

[16]The role of work hours in the relationship between years of education and earnings has been discussed in a number of papers but in our view has not received the attention that it deserves in the context of postsecondary education. See Ashenfelter and Ham (1979) for an early study.

people who enroll in particular graduate programs differ in ways that also affect labor market outcomes. These include ability, prior academic preparation and performance in high school, college GPA, college major and occupational preferences. One can go part way toward addressing this problem by controlling for college major and parental education. However, these controls probably do not fully address bias from unobserved variables that influence both degree attainment and labor market outcomes, particularly occupational preferences.

We use two approaches to tackle endogenous selection into graduate programs. The first is simply OLS regression with controls for college major, parental education, and demographics. The second is OLS regression with controls for the combination of undergraduate degree and graduate degree the individual has obtained by the time that she is last observed (FEcg).

We need to introduce some notation before discussing the econometric specifications in more detail. Let i denote the person and t denote the year. Let e_{it} be real earnings of individual i at time t. Let w_{it} and h_{it} denote the real hourly wage and annual hours, respectively. The variable $c \in \{1, ..., \mathcal{C}\}$ is an index of the undergraduate major, and the variable $g \in \{0, ..., \mathcal{G}\}$ is an index of graduate degree type, with $g = 0$ for those with no graduate degree. Let $c(i)$ be the value of c for i and let $g(i)$ be the value of g for i when she was last observed. We often just use c or g without the person indicator.

We now turn to the econometric specifications and estimation methods. We work with a specification in which the effects of college and graduate school are additive. In the baseline version, the effect of the graduate degree does not depend upon years since graduate school and in the other specification it does. We leave implicit the fact that all model parameters are specific to gender and to the particular dependent variable.

4.1 Average Effects without Degree-Specific Experience Trends

Our baseline specification is

$$y_{it} = a_1 + \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{g=1}^{\mathcal{G}} \gamma_g G_{g(i)t} + X_{it}\beta + u_{it}. \tag{1}$$

Here y_{it} is the particular dependent variable, t denotes the year, $\alpha_0^c + \alpha_{age_{it}}^c$ is the return to c at age_{it} relative to the reference major (education), and $C_{c(i)}$ is a dummy variable for whether i majored in c. We specify $\alpha_{age_{it}}^c$ to be a major specific cubic polynomial in age_{it} and α_0^c to be a constant. Similarly, γ_g is the premium for graduate degree g relative to no graduate degree and $G_{g(i)t}$ is the associated indicator for whether i holds a g degree in t. The control vector X_{it} consists of race/Hispanic indicators, a cubic in age_{it} relative to age 35, and year dummies.

The error term u_{it} may be written as $u_{it} = \eta_i + \varepsilon_{it}$. We decompose the permanent component η_i into its mean b_{cg} for c majors who eventually get a graduate degree in g and an orthogonal component v_i. That is,

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

where $G_{g(i)}$ is an indicator for whether i eventually obtains a graduate degree in g, and $G_{0(i)}$ is 1 if i never obtains a graduate degree. The FEcg specification adds $\sum_{c=1}^{\mathcal{C}} \sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)}$ to equation (1) and applies OLS to

$$Y_{it} = a_1 + \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{g=1}^{\mathcal{G}} \gamma_g G_{g(i)t} + X_{it}\beta + \sum_{c=1}^{\mathcal{C}} \sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)} + v_i + \varepsilon_{it} \tag{3}$$

with v_i and ε_{it} treated as random. The $C_{c(i)}$ indicators are collinear with the set of $C_{c(i)}G_{g(i)}$ indicators, so α_0^c is not separately identified from the b_{cg} heterogeneity parameters. One can see that the FEcg approach controls for permanent differences in the earnings capacity of people who make different c, g choices.[17]

AZ motivate the use of FEcg in part by examining the pre- and post-graduate school occupations for a few specific undergraduate and graduate degree combinations, such as bachelor's in education paired with a master's in education or with an MBA. They find that the distribution of pre-graduate school occupations is shifted toward the occupations that are more common for the particular advanced degree. This suggests that the counterfactual occupations for those who get an MBA are different from the occupations of those do not attend graduate school, even after conditioning on college major. The *cg* fixed effects control for these differences.

4.2 Allowing Experience Profiles to Depend on Graduate Field

We also estimate models in which the potential experience profile of log earnings, the log wage rate, or log hours depends on g. In the additive case, the FEcg specification is

$$\begin{aligned} y_{it} = a_1 &+ \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{g=1}^{\mathcal{G}} \gamma_{gx_{it}} G_{g(i)t} \\ &+ X_{it}\beta + \sum_{c=1}^{\mathcal{C}} \sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)} + v_i + \varepsilon_{it}, \end{aligned} \tag{4}$$

where x_{it} is years since i obtained the advanced degree. It equals 0 for those without an advanced degree at time t. We assume the return to graduate degree g at x years after earning the degree is given by the polynomial $\gamma_{gx} = \gamma_{g0} + \gamma_{g1}x + \gamma_{g2}x^2$. In the OLS case, we exclude the term $\sum_{c=1}^{\mathcal{C}} \sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)}$.

If the return to g varies with time since graduate school, then the estimates of γ_g based on equations (1) and (3) identify a weighted average of the experience specific effects γ_{gx}. The weights are the sample distribution of x_{it} for those who chose g. In Table 2, we report γ_g based on equations (1) and (3). We also report the average return measure

$$\gamma_{g1\_28} = \frac{1}{28} \sum_{x=1}^{28} \left[\gamma_{g0} + \gamma_{g1}x + \gamma_{g2}x^2\right]$$

based on equation (4) with or without the $C_{c(i)}G_{g(i)}$ controls.[18] As we discuss below, the FEcg value of $\hat{\gamma}_{g1\_28}$

[17] A numerical example (borrowed from AZ Table 4) clarifies how observations contribute to FEcg estimates and the distinction between FEcg and estimation with individual fixed effects. For the example, we abstract from age and time effects and other covariates. Consider 3 women who obtained a BA in economics and are known to have obtained an MBA. Sara earned \$55,000 before getting an MBA and \$90,000 after, a gain of \$35,000. Ebony earned \$80,000 after her MBA, but her pre MBA earnings are not observed. Mary earned \$65,000 before her MBA but her post MBA earnings are not observed. The individual fixed effect estimate of γ_{MBA} is the growth in Sara's earnings — \$35,000. The FEcg estimate is the difference between the averages of post MBA earnings and pre MBA earnings — \$25,000=\$85,000-\$60,000. It makes use of all 4 of the earnings observations, not just Sara's.

[18] We stop at 28 because it is less than or equal to the 90th quantile of x_{it} for each of the 19 graduate degrees.

exceeds $\hat{\gamma}_g$ by an average, over the 19 degrees, of 0.061 for women and 0.041 for men. The corresponding OLS values are 0.028 for women and 0.016 for men.

4.3 Assumptions of the FEcg Approach

We refer readers to AZ for a detailed discussion of the challenges of estimating causal effect of graduate degrees on earnings, as well as the specific assumptions required for FEcg to identify treatment on the treated effects (ToT) of earning a graduate degree. Here we briefly list the main assumptions for FEcg and contrast them with the assumptions required for OLS.

The first two assumptions relate primarily to estimation of the intercept of the earnings model. Assumption 1 is that transitory declines in earnings do not drive the decision to attend graduate school. If such declines are an important influence on whether and when to attend graduate school, then earnings just prior to graduate school will underestimate what the individual would have earned in the future in the absence of graduate school. This "Ashenfelter's dip" phenomena (Ashenfelter, 1978) would probably lead to upward bias in FEcg. We would expect this bias to also apply to the analysis of wage rates and hours. Altonji and Zhu (2021) investigate the issue and find that it leads to a small upward bias in FEcg estimates that is between 0.0 and 0.01 for 11 of the 19 degrees they consider, including an MBA. The largest bias is for mechanical engineering (0.038). Arcidiacono et al. (2008) find no evidence of bias from Ashenfelter's dip in their FE estimates of the return to an MBA.

Assumption 2 is that occupational preferences and ability are stable between the pre-graduate school periods in which earnings are observed and the time when the decision to attend graduate school is made. FEcg uses pre-graduate school earnings to form the counterfactual for the future earnings of individuals, had they not attended graduate school. A change in occupational preferences or ability will induce individuals to seek occupations with earnings distributions that may differ from earnings in the prior job. If the preference or ability change drives the decision to attend graduate school, then pre-graduate school earnings would not be representative of what the individual would have earned with her new preferences in the absence of graduate school. We think that this issue is more of a concern when estimating return to a graduate degree by undergraduate major, which we do not do.[19]

What about OLS? The OLS estimates rely primarily on cross-sectional comparisons of earnings of individuals with graduate degrees to earnings of individuals without bachelors, rather than comparisons of earnings before and after the graduate degree. Among those who go to graduate school, only 2.47 percent of the observations are for the period before graduate school. For this reason, OLS is likely to be less affected by Ashenfelter's dip than FEcg and less affected by changes in preferences between when pre-graduate school earnings are observed and when the decision is made to go to graduate school. On the other hand, the OLS estimates are more likely to be affected by persistent differences in ability or preferences between those who go to graduate school and those who do not.

The next set of assumptions are needed to support the higher-level assumption that, absent any causal effects of the graduate degree, age profiles of college graduates and advanced degrees are parallel. One needs parallel trends because we do not observe counterfactual earnings for the post graduate school period. It is useful to first consider what one must assume if one were to apply FEcg to the sample who are observed to

[19] Consider, for example, an individual who majors in art in college and obtains a job as an art teacher. A few years later, she discovers that she does not like teaching, switches to a higher paying job in marketing, and goes on to obtain an MBA. Her earnings as a teacher would probably underestimate her earnings in the absence of graduate school, biasing upward estimates of the return to an MBA. Her job in marketing would provide a better guide. A bias in the opposite direction could arise in studying the return to a master's in education for individuals who major in business and initially pursue a business career.

obtain g, allowing all parameters, including the age profiles, to be g specific. Assumption 3 concerns growth in earnings arising from job changes in response to the arrival of new information about ability or preferences. Such information induces people to re-optimize job choice. Assumption 3 is that, conditional on $g(i) = g$ and $c(i) = c$, the effect of information on growth in ln e_{it} and the other labor market outcomes would have been the same if the individuals had not gone to graduate school.

Assumption 4 is that earnings and wage growth within an occupation is the same for all occupations conditional on c and ability. It is needed because the counterfactual sequence of occupations of those who choose $g(i) = g$ would differ from the actual sequence. Assumption 4a states the associated growth in earnings is the same.

Assumption 5 is that conditional on c, earnings growth from predictable shifts in occupation for those who choose g would be the same in the absence of graduate school.

In practice, we pool observations across graduate degrees, which means that we are imposing parallel age profiles conditional on c across different graduate degrees. Furthermore, to identify interactions between years of post graduate school experience and the return to graduate school using (4), we have to rely on observations of students who do not attend graduate school to identify the counterfactual earnings profile, not just observations of those who ultimately go to graduate school. The degree combination fixed effects address differences in the intercept of the earnings model across $g = 0, ..., G$, but not the possibility that age and experience profiles are different. Consequently, assumptions 3, 4, and 5 must hold conditional on $c(i) = c$, not just conditional on $c(i) = c, g(i) = g$.

What would happen if the assumptions fail? We suspect that if counterfactual earnings growth is flatter (steeper) for those who obtain a particular graduate degree than for those who do not, then FEcg we understate (overstate) the effect of that degree on earnings. We do not have evidence for or against these assumptions, or about how departures from them are likely to differ by gender or across degrees. But suppose that, conditional on $c(i)$, women who obtain certain graduate degrees are more committed to the labor market and are more likely to enter high paying, traditionally male, occupations. Then one would expect the counterfactual earnings slope to be steeper for women who obtain such degrees. This line of reasoning leads us to suspect the FEcg estimates may understate male-female differences in the return to degrees such as law, business, and medicine.

Finally, equation (3) implicitly assumes that early occupation does not have g-specific effects on later earnings or influence the probability of admission to graduate school. If this is not the case, then early job choices made with graduate school in mind may differ from what the individual would have pursued if graduate school were not a possibility. If the optimal job choice given the plan to attend graduate school pays significantly less, then earnings before graduate school might understate counterfactual earnings, leading FEcg to overstate returns.[20] We think this issue may be important for medical degrees and law degrees (and PhD degrees), but is likely less important for most of the other degrees we consider, such as an MBA or a master's in engineering. We do not think that the issue is likely to cause differential biases in the estimated returns for males and females.

4.4 The Estimation Method, the Parameter of Interest, and Choice of Sample

The choice of whether to include people who never attend graduate school influences the implicit control group and the nature of the variation that identifies the age profile parameters. In the case of OLS, one is

[20] For example, a prospective law student may choose to work as a legal assistant, or a prospective medical student may choose to work as lab assistant, but both may have taken higher paying jobs if they had not intended to go to grad school.

assuming that college graduates without advanced degrees are an appropriate control group (conditional on observables, including college major). Consequently, both AZ and this paper include those without graduate degrees in the OLS regressions. When using FEcg without the x_{it} interactions (i.e., equation (3)), AZ use the graduate degree sample, which excludes college-only individuals who do not have a graduate degree when last observed. They do so because the parameter of interest is treatment on the treated. However, when they allow for x_{it} interactions using equation (4), they use the full sample and assume that the age-earnings profile (but not the intercepts) for c majors who never go to graduate school is the counterfactual profile for c majors who do. As we just mentioned above, those who do not go to graduate school are needed to provide information about counterfactual age-earnings profiles for the ages after most people attend graduate school. Including them could lead to upward bias if those who do not go to graduate school have flatter age profiles than the counterfactual profiles of those who do. On the other hand, constraining graduate returns to be constant if they in fact rise with x_{it} might lead to upward bias in the age profiles, because age_{it} and x_{it} are correlated. This would lead to downward bias in γ_g as an estimate of the average return to g when equation (3) is used.

In part to facilitate comparison between OLS and FEcg, we use the full sample for both approaches. We report FEcg estimates using the graduate degree sample in the Appendix table A8. Using the full sample instead of the graduate degree sample usually leads to larger FEcg estimates of γ_g that are closer to the OLS estimates.[21]

As was already mentioned, the samples for $\ln h_{it}$ and the occupational wage component differ from the samples for $\ln e_{it}$ and (to a lessor extent) $\ln w_{it}$because information about hours and occupation in the prior year is not available.

5 Estimates of the Effects of Graduate Degrees on Earnings, Wage Rates, and Hours Worked

In this section we report estimates of the labor market effects of graduate education. Section 5.1 provides a guide to the key tables and figures and provides an overview of the estimates of the effects on earnings, wage rates and hours. Section 5.2 then discusses the findings for a subset of the specific graduate degrees we study.

5.1 Estimates of effects on earnings, wage rates, and hours worked

Figure 2 provides a graphical overview of the FEcg and OLS estimates of the returns to log earnings, γ_g, for men and women. As we provide similar figures for log hourly wage, log hours, and log occupation premium, we will describe this figure in detail. In the top panel, the light and dark green bars show the FEcg and OLS estimates for women, while the light and dark blue bars show the OLS and FEcg estimates for men. The error bars show 90 percent confidence intervals. The graduate degrees are ordered along the horizontal axis by increasing average earnings for women. The bottom panel of Figure 2 shows the estimated difference

[21] Another issue is whether to include people who go directly to graduate school from college. AZ excluded them on the grounds that FEcg estimates of γ_g are driven by observations on individuals who work before graduate school. We decided to include them, but this decision has a relatively small effect on our estimates. See AZ, section VII.A.2 for more discussion and for estimates of a model that allows returns to differ depending upon whether or not one attends graduate school directly. As they point out, in the FEcg case the coefficients on the "go direct" interactions with the advanced degree dummies combine the difference in the return to a particular graduate degree for those who go direct and those who delay with differences between the two groups in the b_{cg} heterogeneity terms.

between the FEcg and OLS estimates for women (green circles) and men (blue triangles).

Figure 2 provides four important takeaways. First, for both men and women, the OLS estimates and the FEcg estimates are higher for degrees that have higher average earnings. Regressing the OLS estimate of γ_g on the mean of the log of earnings for women with a degree in g yields a coefficient of 0.740 (0.075). The corresponding coefficient for the FEcg estimates of γ_g is 0.412 (0.118). For men, the corresponding regression coefficients are 0.827 (0.051) for OLS and 0.512 (0.108) for FEcg.

Second, the 90% confidence intervals for the FEcg estimates are fairly wide for some graduate fields. This reflects the fact that for some degrees, such as medicine, we have relatively few observations on earnings prior to graduate school. The confidence intervals of the FEcg estimates tend to be wider for women, for whom sample sizes are smaller. While the OLS and FEcg estimates differ and the FEcg estimates are somewhat imprecise, the correlation between the two estimates is positive and fairly strong.

Third, for both women and men, the FEcg estimates tend to be above OLS estimates for lower paying graduate fields and below OLS for the high paying fields. Regressing the FEcg estimates for the 19 graduate categories for men and for women on the corresponding OLS estimates for men and for women (38 cases altogether) yields a slope of 0.646 (0.083) and a constant of 0.085 (0.024). Thus the FEcg estimate tends to be small relative to the OLS estimate when OLS is large, and vice versa. These results suggest that OLS tends to overstate returns to advanced degrees that attract students from high paying majors and understate returns to degrees that attract students from low paying majors.

Fourth, the top panel of Figure 2 and Appendix Figure A13 show that the female-male difference in the estimates varies across degree. For the FEcg estimates, this difference varies from positive and statistically significant (education, health related fields), to insignificant (psychology, biology, business, and others), to negative and statistically significant (engineering and nursing). The point estimates for the difference are approximately equally split between positive and negative. The OLS estimates have a more systematic pattern, with positive female-male differences for 16 of the graduate fields.

Figures 3 and 4 provide estimates parallel to Figure 2, but for log hourly wage and log hours worked. Using these two outcomes, we can evaluate what proportion of the log earnings impacts comes from increased wage rates and what proportion comes from increased hours. One can see that hourly wage gains account for almost all of the earnings gains for most graduate fields and follow the same patterns across fields as the earnings effects. The exceptions are the fields with the highest earnings, such as medicine, law, and business. For these fields, we find that increased hours can count for as much as 25 percent of the increase in log earnings. The FEcg and OLS estimates for log hours are similar, with significant differences (pval$<$ 0.10) between FEcg and OLS estimates in only 3 cases for men and 5 cases for women. The log hours estimates are also broadly similar for women and men once sampling error is taken into account. For FEcg, the difference between women and men are insignificant at the 0.10 level for all degrees except Nursing, while the OLS estimates tend to be somewhat larger for women.

We also consider how much of the log earnings gain comes from the occupational component of earnings. This is of particular interest for the FEcg estimate, as it allows us to better understand how much of the return to a given degree is associated with switching occupations after the receipt of the degree. Figure 5 graphs the FEcg and OLS estimates of γ_g^{occ}, the occupational component of earnings. The OLS estimates tend to be negative and substantial for lower paying fields, especially for men. They also tend to be below the FEcg estimates for lower paying fields such as psychology, the humanities, and education and above the FEcg estimates for higher-paying degrees such as engineering, nursing, and business. The gaps are larger for men. We believe that the OLS estimates of earnings effects for degrees like psychology and social work are biased downward because those who choose to get a graduate degree in these fields have different occupational preferences than those who do not go to graduate school, conditional on college major. The opposite is true for fields such as an MBA. In contrast, the FEcg estimator primarily estimates γ_g^{occ} from before and after graduate school comparisons of the set of people who eventually get the graduate degree.

While Figures 2 - 5 provide useful overviews of the results, we also include Tables 2 - 5 in order to clearly report point estimates and standard errors as well as to compare the main estimates with estimates that allow for graduate degree-specific experience profiles. Columns 1-4 of Table 2 report the estimated effects of various graduate degrees on log earnings for women. Columns 1 and 2 of the table report FEcg and OLS estimates of γ_g for the specification where age profiles depend only on college major. These estimates are based on equation (3).[22] Columns 3 and 4 present FEcg and OLS estimates of γ_{g1_28}, where age profiles depend on both college major and graduate degrees (based on equation (4)). We call this the g-specific experience profile specification. Recall that γ_{g1_28} is the average of the return over the first 28 years after the graduate degree.[23] Columns 5-8 report the corresponding set of estimates for men. All estimates are for full-time workers. Tables 3, 4 and 5 report corresponding estimates with the same layout, but for log hourly wage, log hours worked, and log occupational earnings respectively.

5.2 Results by Graduate Degree

We now discuss the results for some of the specific graduate degrees. We continue the discussion in Appendix section 10.

5.2.1 Medicine

Medicine has the highest average earnings and the highest estimated earnings impact for both women and men. For women, the FEcg estimate on earnings, γ_g, is 0.527 (0.133) (Table 2, row 1, column 1). This is well below the OLS estimate of 0.717 (0.019), though sampling error is substantial. The FEcg and OLS values for men are 0.718 (0.077) and 0.775 (0.012). The majority of the increase in log earnings comes from the increase in log hourly wage. Table 3 reports estimates of γ_g^{lnw} for the hourly wage rates of full-time workers. For women, the FEcg and OLS estimates are 0.355 (0.097) and 0.528 (0.019) respectively (row 1, columns 1 and 2). For men, the FEcg and OLS estimates of γ_g^{lnw} are 0.543 (0.068) and 0.645 (0.011) respectively (columns 5 and 6). The differences between the earning and hourly wage effects are explained by the impacts on hours worked. For women the estimates of γ_g^{lnh} are 0.214 (0.023) for FEcg and 0.183 (0.007) for OLS. The estimates are very similar for men. Medicine is an outlier in that hours increases explain a substantial fraction of the increase in earnings and has the overall largest estimated effects on log hours. Part of the effect is probably a labor supply response to the higher wage rate.

Table 2 reports estimates of γ_{g1-28}, the average of log earnings returns when experience profiles are allowed to vary by graduate degree. The FEcg estimate of γ_{g1-28} is 0.13 larger than $\hat{\gamma}_g$ for women and

[22]Table A1 and A2 report OLS estimates of γ_g and α_c for 168 advanced fields and 144 BA fields, respectively, for women. These tables also report the composition of each of the 19 aggregated BA and graduate categories. Tables A3 and A4 report the corresponding estimates for men. The estimates should be regarded as descriptive, but they do show substantial differences in α_c and γ_g within the aggregated categories that we use. Altonji and Zhu (2021) also report OLS and FEcg estimates of γ_g for a large number of advanced fields using administrative data from Texas. Their FEcg estimates also show substantial differences in the returns to degrees within the same broad category. We do not have enough observations on earnings prior to graduate school to disaggregate the FEcg estimates much further.

[23]Estimates of the average of $\gamma_{gx_{it}}$ over the sample distribution of x_{it} for each graduate degree are typically close to but a bit below the estimates of γ_{g1_28}, especially for the FEcg estimates for women (not reported). The sample distribution of x_{it} is skewed somewhat to the left. Thus $\widehat{\gamma}_g$ places more weight on lower values, although it also places some weight on post graduate experience values above 28, while $\widehat{\gamma}_{g1\_28}$ does not.

0.035 larger for men, while the difference between OLS estimates are smaller and vary in sign. Figure A1 (k) graphs the FEcg estimates of γ_{gx} for women and the associated 90% confidence intervals. One can see that the returns rise steeply from a low base in the first few years after graduate school. The pattern is similar for men, but the estimates are higher throughout. The OLS estimates of the experience profiles of γ_{gx} for women are about 0.2 above the FEcg estimate, but follow the same experience pattern (Figure A2 (k)). They are very similar to both the FEcg and OLS experience profiles for men (Figure A1 (l) and Figure A2 (l)).[24]

Finally, the estimates of γ_g^{occ} in Table 5 show that occupation plays a key role in the return to a medical degree. The FEcg and OLS estimates are 0.504 (0.098) and 0.513 (0.007) for women, and 0.475 (0.051) and 0.474 (0.004) for men. Appendix Figures A7 and A8 show that the occupation effects are fairly constant over a career, in contrast to the upward sloping experience profile for earnings. The patterns for earnings and occupation effects align with careers in medicine where medical school graduates work as doctors, but start out in relatively low paying residency programs for the first few years after graduate school.

5.2.2 Law

For women, the FEcg and OLS estimates of γ_g for a law degree are both around 0.55. The values for men are 0.492 (0.086) and 0.469 (0.014). Part of the effect comes from increased hours, though most of the increase comes from increased hourly wage rates. For women, the FEcg and OLS estimates for log hourly wage are about 0.47, about 0.09 below the total effect on earnings (Table 3). For women, the FEcg and OLS estimates for log hours are 0.079 (0.021) and 0.091 (0.005), less than half of the value for medicine but still sizable (Table 4). The estimates for men are similar. Estimates are slightly larger for women, and similar for men, when allowing for g-specific potential experience profiles

The FEcg and OLS estimates in Table 5 indicate that γ_g^{occ} is about 0.33 for both men and women. The large occupational component of a return to a law degree is not surprising given that a JD degree is generally required to practice law. Most of the experience gradient in the return to law is within occupation rather than across occupations. Overall, the evidence indicates that the effect of a law degree is large for both men and women, though these estimates do not account for tuition costs, or that it is a 3-year degree.[25]

5.2.3 MBA degrees

Next we consider MBAs. We find that the OLS estimates are systematically higher than the FEcg estimates, though both sets of estimates report moderate returns. For both genders, most of the increase in log earnings comes from increased wage rates, though 10-20% of the increase comes from growth in log hours. The returns to an MBA degree are reported in Row 4 of Table 2. The FEcg estimates of γ_g are 0.176 (0.036) for women and 0.146 (0.022) for men. These values are well below the corresponding OLS estimates of 0.332 (0.014) for women and 0.248 (0.009) for men. We think that the OLS estimates overstate the treatment effect of an MBA. Part of the OLS estimate is due to better pre-MBA labor market opportunities and to business-related ability and preferences of many who pursue the degree. AZ show that individuals who pursue an MBA after having previously chosen a college major that is not closely tied to a business career often were working in business-related occupations prior to graduate school.

[24]For the degrees we consider the profiles of the OLS and FEcg estimates of γ_{gx} have similar shapes even though the levels differ and the confidence intervals are wider in the FEcg case. The two estimators use similar variation in the data to estimate the shapes of the profiles, which is why they are approximately parallel. The wider confidence intervals in the FEcg case reflects lower precision in return to graduate school at all experience levels.

[25]We do not know the institution or whether the graduate institution is public, private not-for-profit, or private for-profit, and so cannot estimate returns by institution or by type of institution. Altonji and Zhu (2021) present evidence that the returns are higher for law degrees from higher ranking institutions.

The estimates that allow for graduate-specific experience profiles are larger. For women, the FEcg and OLS estimates ofγ_{g1_28} are 0.256 (0.037) and 0.391 (0.017). For men, the estimates are 0.187 (0.022) and 0.266 (0.010). Figures A1 (k) and A2 (l) display the FEcg and OLS estimates of the experience profiles of the return to an MBA. The value of $\widehat{\gamma}_{gx}$ for women show a steady increase with experience, increasing from about 0.15 to 0.38 over 30 years. For men the increase is from about 0.02 to about 0.30.

The FEcg estimates show that an MBA improves occupational earnings by an average of 0.037 (0.015) for women over the first 28 years. The corresponding OLS estimate is much larger: 0.131 (0.007). The FEcg and OLS estimates for men are 0.01 (0.008) and 0.084 (0.004). The large disparity between the FEcg and OLS estimates of occupational returns, especially for women, suggests that the OLS estimates of the return to an MBA are upward biased.

5.2.4 MA in Nursing

For women, the FEcg and estimates OLS of γ_g are 0.154 (0.034) and 0.279 (0.013) respectively. This is a large difference. For men, the returns are much larger, but they should be treated with caution. The FEcg for men relies on observations from only 13 individuals who are observed prior to obtaining a nursing degree, and from only 215 individuals who are observed after they have a nursing degree. For men and women, the estimates of γ_{g1-28} are similar to the estimates of γ_g. For women, the experience-specific returns are relatively flat for the first 14 years, and then decline. Men follow a similar pattern, but with steeper growth over the first 14 years. For both groups the confidence intervals are fairly wide.

The FEcg estimate indicates that occupation accounts for 0.016 (0.009) of the return to a master's in nursing. The OLS estimate is approximately twice as large.[26] In our sample, 90.97% percent of the women and 86.40% percent of the men who obtain a master's in nursing majored in nursing as an undergraduate. Presumably most were working in nursing prior to getting the degree. Our occupation categories are not fine enough to distinguish between a registered nurse and more advanced nursing occupations, such as a nurse midwife or a nurse practitioner.[27] For men the FEcg and OLS estimates of γ_g^{occ} are larger: 0.058 (0.028) and 0.083 (0.017) respectively, but so are the estimates of γ_g

The FEcg and OLS estimates of effects on wage rates are similar to the effects on earnings (Figure 3) and thus account for most of the return. The FEcg and OLS estimates of γ_g^{lnh} for women are 0.014 (0.022) and 0.033 (.006). The OLS estimate for men is small and positive but the FEcg estimate is -0.171 (0.065). We discount the large negative value, because it is based upon only 9 men each of whom contributed 1 observation on hours for the pre-graduate school period.

5.2.5 MA in Health-related Fields

For men and women combined, the health-related category includes physical therapy (27.9%), audiology and speech pathology (19.3%), other health/medical sciences (19.2%), public health (16.7%), pharmacy (9.9%), and health/medical assistant (4.1%). For women, the FEcg and OLS estimates are 0.344 (0.056) and 0.227 (0.013) respectively. For men the OLS estimate is similar but the FEcg estimate is only 0.132 (0.069). The estimates are similar when allowing degree-specific returns to experience. Occupation specific training and

[26]AZ discuss estimates for the full sample of men and women and point out that the substantial difference between FEcg and OLS for earnings and the small difference for occupation suggest substantial earnings related selection among nurses who obtain a master's degree.

[27]Among those observed working while attending nursing school, 86.6% of women and 85.7% of men were in the combined occupation category consisting of registered nurses, pharmacists, dietitians, therapists, physician assistants, and nurse practitioners.

license requirements are important for most of the subfields in the category, which suggests that a substantial part of the return to a master's in health-related fields is through occupational upgrading. For women the FEcg and OLS estimates of γ_g^{occ} are 0.092 (0.21) and 0.079 (0.05), and the estimates for men are 0.131 (0.046) and 0.100 (0.010). As expected, occupational upgrading explains a large proportion of the gain in log earnings.

5.2.6 Engineering and Computer Science/Math

The FEcg and OLS estimates of γ_g for a master's in engineering are 0.081 (0.039) and 0.192 (0.013) for women. However, engineering is one of the cases with a large disparity between the estimates of γ_g and γ_{g1-28}. The disparity appears to be due in part to the fact that g_{gx} are initially negative for women but eventually rise to 0.3 (Figure A1 (i) and (j)). The OLS estimates also rise from near 0 to about 0.4 (Figure A2 (i) and (j)). For men, the FEcg and OLS estimates are close (0.164 versus 0.151), and the estimates of γ_{g1-28} are about 0.04 larger. The returns to an engineering degree also start low and increase with experience for men, but less dramatically than for women. We speculate that quite a few individuals obtain engineering master's while continuing to work full-time, given that the means of annual work hours while enrolled (including part-time workers and those who are not working) are 1,536 for women and 1,609 for men (Table 6). Also, recipients may not reap the full rewards from the master's degree unless they switch employers, which takes time.[28]

For women, much of the difference between FEcg and OLS stems from the fact that the OLS estimate of the occupational return exceeds the FEcg estimate by 0.084, with the FEcg estimate being close to zero. For men, FEcg and OLS estimates of γ_g^{occ} are 0.033 (0.012) and 0.051 (0.002).

In the case of computer science and math, the FEcg and OLS estimates are both about 0.23 for women, which is well above the values for engineering. For men the estimates are 0.167 (0.036) and 0.197 (0.009). For both men and women, the returns rise with experience but start to decline about 20 years after graduate school. (Figure A1 and A2, (g) and (h)). The pattern is more pronounced for women than for men. As with engineering, we find that for women the OLS estimate of the occupational return is well above the FEcg estimate: 0.079 (.006) versus 0.024 (0.018). OLS may miss the fact that people who obtain graduate degrees in these fields were typically in well-paying occupations before returning to school. For men, FEcg shows a small, statistically insignificant gain in the occupational premium, while the OLS estimate is 0.055 (0.004).

Overall, engineering and computer science and math offer healthy returns to both men and women. For women, the computer science and math estimates of γ_g and γ_{g1-28} are somewhat larger than the estimates for engineering, while for men they are similar.

5.2.7 Education

Next we turn to a master's in education, which is a common degree in the data, especially for women. Teacher contracts often mandate higher salaries for teachers with master's degrees, so a positive ToT effect is present for the population who chooses to remain teachers. However, the overall effects are more complicated, because the degree would also affect occupational choice and hours worked.

For women, the FEcg estimate is 0.219 (0.020) and the OLS estimate is 0.150 (0.007). The FEcg estimate is lower for men but still substantial, 0.146 (0.030), while the OLS estimate is essentially zero. The gap between FEcg and OLS is driven in part by a gap between the FEcg and OLS estimates of γ_g^{occ}, equal to 0.067 for women and 0.135 for men. Conditional on staying in the education sector, a small positive effect

[28] For currently enrolled students, the NSCG and NSRCG provides information about whether tuition is paid for by the employer. We do not use this information because we do not have it for degrees completed prior to the survey.

on the occupational premium is plausible, because more specialized master's degrees, such as a master's in educational administration, may open up higher paying positions. The negative OLS estimates probably reflects selection bias related to job preferences of those who pursue a master's in education.

The FEcg estimates of γ_{gx} show an increase from 0.138 (0.021) one year after the degree to about 0.326 (0.026) at 28 years for women. The profile for men starts from a lower base and is steeper. For men, the FEcg estimates indicate that growth in the occupation premium contributes about 0.09 to total growth. Interestingly, the OLS estimates of γ_{gx}^{occ} start at -0.132 (0.009) one year after graduate school and rise to -0.041 (0.011) 28 years after graduate school. The corresponding values for women are -0.019 (0.009) and 0.026 (0.011). This result seems consistent the view that pursuing a master's in education is an indication that the individual has decided to continue to work as a teacher or to switch into education from a higher-paying field. That is, it suggests that the counterfactual profiles of those who choose a master's in education are quite different from the profiles of those who do not go to graduate school, particularly in the case of men. However, the FEcg estimates seem high, at least for women.[29]

5.2.8 Psychology/Social Work, the Humanities, and the Arts

The FEcg and OLS estimates of γ_g for a master's in psychology and social work follow the same qualitative pattern as education but are quantitatively more extreme. FEcg shows a substantial positive return of 0.194 (0.030) for women and 0.201 (0.059) for men. The OLS estimates are lower: 0.099 (0.009) for women and actually negative for men. The estimates of γ_{g1-28} tell the same story but are somewhat larger. The discrepancy between the FEcg and OLS estimates is mirrored in the estimates of γ_g^{occ}. The OLS estimates are -0.054 (0.005) for women and -0.070 (0.010) for men, while the FEcg estimates are essentially zero. Comparing Figures 2 and 3, wage gains account for most of the FEcg estimates of earnings gains. The effect on hours is 0.026 (0.012) for women and essentially zero for men.

Next we consider a humanities master's. For women, the FEcg and OLS estimates are 0.138 (0.067) and 0.009 (0.019). For men the estimates are 0.010 (0.090) and -0.218 (0.019). When considering γ_{x1-28}, the results are qualitatively similar, including the large gap between estimates for women and men. For both men and women, the effects on the occupation premium are negative, though they are particularly large and negative in the OLS case for men.

Finally, the estimates of the return to a master's in the arts are small for FEcg and OLS. The FEcg estimates are negative for both genders, although they are not statistically significant.

6 Present Discounted Value and Internal Rates of Return Estimates

The estimates of γ_g, the effect of the various graduate degrees on log earnings, do not account for the differences in the tuition and time costs of graduate education. In particular, some degrees, such as medical degrees, have large earnings effects but also involve substantial time and monetary commitments. In this section we consider the net present discounted value and internal rate of return to degrees, which directly account for the time and monetary costs. We report the present discounted values (PDV) of lifetime income net of tuition for each advanced degree for those who pursued the degree, the counterfactual net PDV if they had not gone to graduate school, and percentage gain in net PDV from gradual school (%ΔPDV). We also estimate the internal rate of return (IRR, ρ_g) for each advanced field. Because graduate programs differ in

[29] Using Saenz-Armstrong (2021)'s estimates of lifetime earnings for a teacher with a BA and a teacher with an MA based on teacher contracts for 90 school districts, we computed a mean MA premium of 12.0%.

duration (e.g., Medicine versus a master's in education), the size of the investment may differ substantially. The %ΔPDV provides a better sense of the overall gain, while ρ_g provides a better sense of the return to a unit of investment.

6.1 Background to Estimation of %ΔPDV and ρ_g

We report estimates under two assumptions about earnings while enrolled and the duration of the program. The first is full-time attendance with zero earnings and the assumed program duration for full-time students listed in column 3 of Table 6. The duration values are our educated guesses about typical program length for full-time enrollees. The second case is based on empirical estimates of average program duration and earnings while enrolled (column 4). These estimates are from Altonji and Zhu (2021), who use administrative records for people who attended Texas institutions. They find that many students take longer to complete graduate degrees than the values that we have assumed for full-time enrollment. See Appendix section 9 for additional details and summary statistics on the timing of degrees. Table 6 columns 5 and 6 report the gender-specific estimates of average annual earnings while enrolled by graduate degree program. The estimates include those enrolled either full-time or part-time.[30]

Columns (1) and (2) of the table report average tuition in 2012 in 2013 dollars for full-time students at public institutions and private institutions, respectively. They are taken from National Center for Education Statistics (2019). These values are used for annual tuition in the case in which students attend school full-time and have zero earnings while enrolled. When using the average duration estimates, we adjust the annual tuition flow so that total tuition expenditures is the same regardless of how long one takes to complete the degree.[31]

In all cases, we assume people start graduate school in the indicated field at age 27 and retire at age 59. We set the earnings error term to 0 and the calendar year to 2012.[32] We estimate the incomes and calculate the internal rate of returns separately by gender. We set the race/Hispanic indicators to non-Hispanic white and parental education to the sample means for the full sample. We take a population weighted average over the gender specific distribution of undergraduate majors for each advanced degree. The PDV calculation

[30]To increase precision, we make use of observations on individuals who are currently enrolled even if we do not observe whether they completed the program. We recoded zero earnings as $1,000 because the earnings question is only asked of those who are currently employed. The regressions include quadratics in age and calendar time to allow us to produce age and year specific estimates. The values in the table are averages of the predictions over the estimated program duration in column 4 for someone who enters graduate school in 2012 at age 27. For men in nursing programs and women in arts or in health administration, we have less than 200 observations on people currently enrolled. In these cases, we use predicted earnings from a graduate degree specific regression that pools men and women but includes a gender dummy.

[31]We set the tuition flow to the product of annual tuition for full-time students and the ratio of duration for full-time students (Table 6, column 3) to the empirical mean of duration from Altonji and Zhu (2021) (column 4). We do not have data to identify people who started but did not complete a graduate program. They are treated as BA only observations in the regression analysis. We do not consider tuition and lost earnings of noncompleters in the IRR and PDV calculations. Consequently, the ex ante IRR to pursuing a graduate degree may be lower than our estimates, which assume that those who choose to start graduate school finish.

[32]Setting the log earnings error term to 0 is not innocuous, because we are going from a log earnings model to earnings levels when computing net present discounted values and internal rates of return. If the variance of the earnings residual does not depend upon degree status or age, then accounting for the variance would rescale the actual earnings stream and the counterfactual earnings stream in the absence of graduate school by the same amount. Because of tuition, this would still affect ratio of the actual and counterfactual PDVs and the internal rate of return, but the effect would probably be minor at public school tuition levels. However, if the variance grows with age or if it differs by graduate degree status, then an adjustment would matter more. One could address the issue using a suitably smooth regression model to estimate the residual variance of earnings by age and degree status, though selection bias would be a concern and would be hard to address. A second issue stems from the fact that the person specific error component v_i will be part of the estimated variance. This component affects log earnings with a graduate degree and counterfactual log earnings by the same amount. Differences in the variance of v_i by graduate degree status would lead to bias in the estimates of the PDVs. We conjecture that one would underestimate the IRR for graduate degrees that attract a population with a high variance in v_i relative to the unconditional variance for those with a bachelor's degree or higher.

assumes that the interest rate is 0.05.[33]

As our base case, we use FEcg estimates of the model (4), which features experience-specific returns. We assume public tuition, full-time attendance, and zero earnings while enrolled. The experience-dependent returns seem more appropriate given that the timing of earnings gains are important for both the PDV and the IRR.[34] We choose the case of full-time attendance with zero earnings for two reasons. First, it is simplest to interpret as a financial investment. If full-time school requires about the same number of hours as full-time work, one does not have to consider how to "price" time devoted to school versus time devoted to work, assuming that nonpecuniary differences in how the time is valued relative to leisure are small. The second and more pragmatic reason is that, for most degrees, the estimates of $\hat{\rho_g}$ are much less precise when we use mean earnings while enrolled. This is because of noise in earnings while enrolled and because the size of the investment in terms of tuition and foregone earnings is relatively small in some cases. The small sizes make the estimates of $\hat{\rho_g}$ sensitive to sampling error in earnings while enrolled and to the actual and counterfactual earnings streams. The standard errors of the estimates of $\%\Delta PDV$ are much less sensitive to treatment of earnings while enrolled.

6.2 Estimates of the Internal Rate of Return and Gain in PDV

Table 7 displays the results for the base case. Table 8 presents a corresponding set of results based on the OLS estimates of γ_{gx}.[35] In the tables we use a † to indicate that the standard error is affected by the floor of -0.4 or the ceiling of 1.0 that we used for $\hat{\rho}_g$. Appendix figure A21 graphs the FEcg and OLS estimates and 90% confidence intervals.

The counterfactual PDVs (no graduate school) for women and for men are in columns 2 and 6 of Table 7. These values do not depend upon assumed duration of the program, tuition, or earnings while enrolled. We

[33]The formula for the actual PDV calculation is

$$PDV_{c(i)g}^{\text{actual}}(r) = \Sigma_{age=27}^{59} \frac{net\ income_{c(i)g}(age)}{(1+r)^{age-27}},$$

where

$$net\ income_{c(i)g}(age) = \begin{cases} -tuition_g + Enrolled\_earnings_{age,g} & \text{if } age-27 \leq \text{duration of } g \\ exp\left(\hat{a_1} + \bar{X}_{t2012}\hat{\beta} + \left(\hat{\alpha_0^c} + \hat{\alpha_{age}^c}\right) + \hat{\gamma}_g + \hat{b_{cg}}\right) & otherwise \end{cases}.$$

and $\bar{X}_{t2012}$ is X_{it} evaluated at the mean of parental education for a non-Hispanic white with $t = 2012$.The interest rate is denoted by r. Enrolled_earnings$_{age,g}$ is set to zero in case one, which assumes full-time attendance and zero earnings while enrolled. The formula for counterfactual PDV is

$$PDV_{cg}^{\text{counterfactual}}(r) = \Sigma_{age=27}^{59} \frac{exp\left(\hat{a_1} + \left(\hat{\alpha_0^c} + \hat{\alpha_{age}^c}\right) + 0 + \bar{X}_{t2012}\hat{\beta} + \hat{b_{cg}}\right)}{(1+r)^{age-27}}.$$

The internal rate of return ρ_g of advanced field g is the solution to

$$\sum_c weight_{c|g} \times \left[PDV_{cg}^{\text{actual}}(\rho_g) - PDV_{cg}^{\text{counterfactual}}(\rho_g)\right] = 0 \tag{5}$$

where $weight_{c|g}$ is the gender specific probability that $c(i) = c$ given $g(i) = g$. All parameters and the values of $Enrolled\_Earnings_{age,g}$ are gender specific. We perform a fine grid search using values of ρ_g between -0.4 and 1.0, setting $\hat{\rho_g}$ to -.4 for negative returns or to 1.0 for positive returns if equation (5) does not have a solution. In the rare case of multiple positive roots, we chose the value nearest to 0.05.

[34]Appendix Table A9 and A10 present FEcg and OLS based estimates of $\%\Delta PDV$ and ρ_g for the case in which the return to graduate school does not depend on experience and in school earnings are 0. For women in the FEcg case, the value of $\hat{\rho}_g$ rises for 11 of 19 degrees and $\%\Delta PDV$ (evaluated at an interest rate of 0.05) falls for 18 of 19 degrees. For men, $\hat{\rho}_g$ rises for 13 of 19 degrees and $\%\Delta PDV$ falls for 15 of 19 degrees.

[35]Standard errors are estimated via a block bootstrap procedure. We divided the sample of individuals into 34 strata. We sampled with replacement in each strata to preserve the sample distribution of person counts across strata. The strata are defined by gender by number of appearances in the earnings regression sample used to estimate returns (0, 1, 2, 3, 5-9 appearances) by number of appearances in the enrolled earnings sample (0, 1, 2-4). We do not include people if they are absent from both earnings samples.

start with the case of full-time attendance and zero earnings while enrolled. The gender specific actual PDVs for each graduate degree are reported in columns 1 and 5. Both the counterfactual PDVs and the actual PDVs vary substantially across graduate degrees. For example, in the case of men, the counterfactual PDV is 1.51 million for those who get an MBA but only 0.89 million for psychology and social work. The variation across graduate degrees in the counterfactual PDVs is driven primarily by two factors. The first is the mix of undergraduate majors. The second is the variation in the mix of estimates of the degree combination fixed effects b_{cg} associated with the different graduate degrees. The b_{cg} parameters captures differences in the mean (in log units) of unobserved characteristics of the individuals with specific college and graduate degree pairs that influence earnings. The variation across degrees in actual PDVs is driven by variation in program length, in the level and experience profile of the return parameters γ_{gx}, as well as in the factors that drive the variation in the counterfactual PDVs.

Note that counterfactual earnings are substantially higher for men than women in all fields. This reflects the existence of a substantial gender gap among college graduates conditional on the final degree combination, as well as a tendency for women to obtain a bachelor's degrees in lower paying majors. The unweighted mean across all programs is 1.29 million for men and 0.93 million for women (not shown).

We now turn to the percentage gains in PDV in columns 3 and 7 and the internal rates of return in columns 4 and 8. For medicine, the estimate of $\%\Delta PDV$ (with tuition accounted for) is 39.9 (18.8) for women and 66.2 (12.9) for men. These are very big percentage gains, but medicine is a 4 year degree, and $\hat{\rho}_g$ is a more modest 0.12 (0.02) for women and 0.16 (0.02) for men. For law, the values of $\%\Delta PDV$ and $\hat{\rho}_g$ for women are 46.9 (6.7) and 0.16 (0.01), which are somewhat above the values for men. In the MBA case, the estimates of $\%\Delta PDV$ and ρ_g are 11.9 (3.7) and 0.10 (0.01) for women, and 8.1 (2.2) and 0.09 (0.01) for men.

In the cases of education and computer science and math, women receive an internal rate of return of 0.20 (0.02) and 0.21 (0.06) respectively. These are among the degrees that we assume take only one year to obtain when enrolled full-time, and the estimate of ρ_g would be lower if we were to assume a longer duration. For education the $\%\Delta PDV$ is 20%. The value for computer science and math is close (22%), but the similarity in $\%\Delta PDV$ for these two degrees hides the fact that both counterfactual earnings and actual earnings are about 1/3 higher for women who pursue computer science/math rather than education. For men, $\hat{\rho}_g$ is 0.19 (0.03) for computer science and math and 0.14 (0.02) for education.

Turning to the other degrees, the value of $\hat{\rho}_g$ for women is between 0.15 and 0.20 for a master's in the life sciences, health administration, physical and related sciences, health-related degrees, other social and related sciences, and other non-science and engineering degrees. The $\%\Delta PDV$ exceeds 15% in all of these cases. Again for women, $\hat{\rho}_g$ is between 0.10 and 0.14 for other business-related master's degrees, engineering, public administration, the humanities, and psychology. The $\%\Delta PDV$ is between 10.34 and 12.75 for all of these cases except for business-related degrees (20.6). The value of $\hat{\rho}_g$ is only 0.08 (0.02) for nursing and 0.09 for other science and engineering-related fields. For the arts, the estimate of ρ_g is negative and $\%\Delta PDV$ is -10.3 (9.59).

For men, $\hat{\rho}_g$ exceeds 0.23 in biology/agricultural and environmental sciences, nursing, and the physical sciences. It is between 0.11 and 0.18 in business-related, engineering, health administration, other non-science and engineering degrees, and other social and related sciences. It is between 0 and 0.10 for other science and engineering related fields, health-related fields, psychology and humanities. It is negative for the arts.

The correlation between the values of $\hat{\rho}_g$ for men and women is only 0.47. The modest value is due in part to the fact that, for some degrees, the estimates of γ_{gx} are noisy for men, for women, or for both. This is reflected in the substantial standard errors in some cases.

Table 8 presents estimates of $\%\Delta PDV$ and ρ_g when we use the OLS estimates of the earnings model with experience specific returns rather than the FEcg estimates. Like Table 7, they are for the case of full-time attendance and zero earnings while in school. Appendix figure A21 graphs the OLS and FEcg based estimates of ρ_g for men and women. For many graduate fields, the OLS and FEcg estimates differ substantially. For example, the OLS estimates of ρ_g for an MBA degree are 0.13 for men and 0.16 for women, about 0.06 above the corresponding FEcg estimates. The relative values are strongly related to relative values of the OLS and FEcg estimates of γ_{g1-28}. For example, in the case of psychology and social work, the FEcg estimate of ρ_g is 0.10 for both men and women, while the OLS value is 0.05 for women and -0.03 for men. The FEcg estimates of γ_{g1-28} are well above the OLS estimates, especially for men (2).[36]

6.3 Internal Rate of Return Estimates Based on Average Program Duration and Average Earning While Enrolled

Many people work at least part-time while in graduate school even when enrolled on a full-time basis. Many others enroll part-time and continue to work while pursuing their degrees. Table A11 report FEcg based estimates of the percentage gain in PDV and of $\hat{\rho}_g$ using estimates of mean duration of graduate school and mean annual earnings. The estimated duration values are the same as our assumed value for full-time enrollment in the case of law and medicine but are higher for most other fields (Table 6).

Before turning to the estimates of the gain in PDV and of $\hat{\rho}_g$, we discuss the estimates of earnings and work hours while enrolled, which have received little attention in the economics literature on graduate education. The average across all graduate programs of annual earnings while enrolled is \$28,973 for women and \$37,174 for men. The averages vary substantially across degrees (columns 5 and 6). For men, earnings while enrolled in medicine (\$7,751) and law (\$13,319) programs are far below earnings while enrolled in most other fields. For example, average earnings while enrolled exceeds \$50,000 for MBA, business-related programs, and engineering and computer science/math programs. Men earn more on average, but the correlation across fields between male and female earnings while enrolled is 0.93.

Columns 7 and 8 of Table 6 report the mean of annual hours worked during graduate school for women and men respectively, including those who do not work. One can see that the averages vary across programs but are typically substantial. For example, the values for women range from a low 152 hours for medicine to 1,872 for an MBA. The fraction of individuals who were enrolled part-time at the time of the survey also varies substantially across programs. They are relatively low for medical degrees and health-related degrees and relatively high for business-related degrees, MBA programs, and education (not reported).

We now turn to estimates of $\%\Delta PDV_g$ and ρ_g in Appendix Table A11. When using average program duration and allowing for work while enrolled, the FEcg based estimate of $\hat{\rho}_g$ for law increases from 0.15 (0.02) to 0.18 (0.03) for men and from 0.16 (0.01) to 0.18 (0.02) for women.[37] The value of $\hat{\rho}_g$ for medical

[36] Appendix Table A13 presents FEcg estimates of $\hat{\rho}_g$ when tuition is set to the average of private school tuition in 2012 rather than public school tution for the full-time attendance with 0 earnings while enrolled. The values of private tuition exceed the public school values, and the tution gap is substantial for law and for medical degrees (Table 6). A comparison to public tuition results indicates that the higher tuition values lead to a drop in $\hat{\rho}_g$ of 0.01 and 0.02 with the exception of Medicine and Law, for which the declines are larger.

[37] A comparison of columns 4 and 8 in Table A11 with the corresponding columns in Table 7 backs up a point we made earlier, which is that in most cases the standard errors for ρ_g are substantially larger than in the case of fulltime enrollment with 0 earnings. The increase is larger for fields for which enrolled earnings are high. In these cases the size of the investment, which is the difference between earnings while enrolled net of tuition and counterfactual earning, is relatively small. The value of $\hat{\rho}_g$ becomes sensitive to modest changes in the estimate earnings streams. In contrast, the standard errors of the confidence intervals for $\%\Delta PDV$ are similar to values for the fulltime enrollment, 0 earnings case.

degrees increases by about 0.01 for men and is unchanged for women. For these degrees, the slight change in $\hat{\rho}_g$ is due to allowing for earnings while enrolled, because assumed duration is the same as the full-time case. In the MBA case, assumed enrollment duration increases from 2 to 2.75 years, but the effect of this increase on $\hat{\rho}_g$ is more than offset by the substantial earnings of both men and women while in business school. The estimate of ρ_g rises from 0.10 (0.01) to 0.20 (0.06) for women but $\%\Delta PDV$ increases by a smaller percentage—from 11.9 (3.67) to 18.1 (3.72). The reason the internal rate of return doubles is that the earnings of women enrolled in business school are relatively high compared to counterfactual earnings, so the size of the net financial investment of going to business school at public tuition rates is relatively small. It is important to keep in mind that $\%\Delta PDV$ and ρ_g do not take account of the value of the difference between counterfactual work hours and the sum of hours devoted to school and work while in school.

Overall, the estimates of ρ_g based on empirical duration and the mean of earnings while enrolled are typically substantially higher than the values based on our assumed values for duration of a full-time program with zero earnings while enrolled. The values of $\hat{\rho}_g$ rise for men in 13 of the 18 cases in which $\hat{\rho}_g$ is positive and fall in only 2 cases. The pattern is similar for women. For education, health administration, nursing, MBA, and other business-related master's degrees, the internal rate of return is much larger for both men and women when using the empirical duration and accounting for earnings while enrolled.

The OLS based estimates of ρ_g also typically increase for both men and women when use empirical duration and account for earnings while in school (Appendix Table A12). An extreme case is the MBA. For this degree, the value of $\hat{\rho}_g$ for women rises from 0.16 to 0.5, although the latter value is imprecisely estimated.

7 Graduate Degrees and Job Satisfaction

We now turn to estimates of the effects of graduate degrees on overall job satisfaction and with particular aspects of the job. The possible responses for each item are "very satisfied", "somewhat satisfied", "somewhat dissatisfied" and "very dissatisfied". We focus on indicators for whether the individual is very satisfied in a particular dimension.[38]

For each satisfaction measure, we produce OLS estimates of the coefficients γ_g^{sat} from a linear probability regression of an indicator for whether the respondent is "very satisfied" on the 19 graduate degree dummies and the controls. The reference category is BA only. The specification is equation (1) and the controls include undergraduate major along with the other controls mentioned earlier. The estimates are reported in Figure 6. The red and blue triangles are the coefficients on the graduate degree for women and men respectively. The light red and light blue crosses are the raw differences between the mean response of those with the particular graduate degree and the mean response of individuals with only a BA. The regression coefficients have a strong positive correlation with the simple differences in means, but they differ substantially in a few cases. Given the limited control set, the OLS estimates should be regarded as descriptive rather than causal. Here we only discuss results for overall job satisfaction and satisfaction with contribution to society, though results for additional sub-measures of satisfaction are included in the appendix.

Figure 6 (A) reports OLS estimates of the overall satisfaction with the job. First, the OLS estimates suggest that men with graduate degrees are overall more satisfied with their jobs, except for social sciences and business, for which the estimates are slightly negative but not statistically significant. Second, graduate

[38]Appendix Tables A14 to A15 report coefficients from an ordered probit regression of the four category satisfaction variables with the same control set used to estimate the linear probability models for "very satisfied". They follow the same pattern as the linear probability coefficients for "very satisfied". We focus on the latter because they are easier to interpret.

degrees raise overall satisfaction more for men than for women. One can see this both in the regression estimates and in the simple difference between the means for those with a graduate degree in those who did not go to graduate school. For women, the point estimates of γ_g^{sat} are essentially 0 or negative in 5 of 19 cases. They are also below the value for men in all cases except engineering, although the differences are small in some instances. The correlation between the male and female coefficients is 0.677. The third point is that the relationship between $\hat{\gamma}_g^{sat}$ for a degree and its salary is weak for men but positive for women. For men, the coefficient of a regression of the satisfaction coefficients (γ_g^{sat}) on salary rank is 0.0005 (0.0024). For women, the coefficient is 0.004 (0.002), implying a substantial difference in satisfaction with the lower-paying graduate degrees and the higher-paying degrees. The simple correlations are 0.056 for men and 0.461 for women. The satisfaction coefficients are also correlated with the OLS and FEcg estimates of γ_g for earnings.[39] These results suggest, not surprisingly, that salary matters but is not the sole driver of satisfaction. The correlations also suggest a weaker relationship between pay and satisfaction for men than for women.[40] These results are consistent with the notion that individuals are heterogeneous and choose graduate school and jobs based on a variety of factors, not just earnings potential The overall job satisfaction captures those factors. The finding that the link between overall satisfaction and salary is stronger for women runs counter to the popular notion that women may place a greater weight on non-pecuniary aspects of a job.

The fourth point is that there are substantial differences across fields in effects of a graduate degree on overall satisfaction. Both men and women with a medical degree are about 0.2 more likely to report that they are very satisfied with their job, relative to a mean of 0.443 for men with only a BA. For men, the coefficient for law is 0.074, near the average across graduate degrees (0.067), and it is close to the value for women. In contrast, the estimates of γ_g^{sat} for an MBA and for a business degree are close to zero for both men and women.

Figure 6 (B) displays OLS estimates of the effects of the graduate degrees on the probability of being very satisfied with the contribution of the job to society. The estimates vary considerably across degrees. Interestingly, they are negatively correlated with salary rank for both men and women. The correlation between the coefficients for societal contribution and overall satisfaction is 0.608 for women and 0.752 for men. For men, the coefficients are above 0.20 for humanities, psychology, education, health, and medicine. For women, the largest coefficients are for psychology, education, health, and medicine. For both men and women, the estimates are near zero or negative for computer science and math, engineering, an MBA, and other business-related master's degrees. The effects of the degrees on satisfaction with societal contribution for women and men are highly correlated (0.921).[41]

8 Conclusion

Over the last several decades the share of individuals who pursue graduate degrees has grown rapidly, especially among women. Yet, there is little evidence about the returns to graduate degrees for men and women, and how this varies by type of graduate degree. Even less is known about how graduate degrees affect other aspects of work life, such as hour worked and job satisfaction. Such evidence is important for individuals

[39]For women, the correlation is 0.686 (pval = 0.001) for OLS and 0.700 (pval = 0.001) for FEcg. For men, correlations are 0.451 (pval = 0.053) for OLS and 0.548 (pval = 0.0152) for FEcg. When considering rank correlations, the relationship is weaker: 0.316 (pval = 0.188) and 0.418 (pval = 0.075) for women and -0.046 (pval = 0.853) and 0.090 (pval = 0.716) for men.

[40]Figure A18 shows satisfaction with salary for women and men. The gap in salary satisfaction is smaller than the gap in overall satisfaction. Both groups are more satisfied with salaries in higher-paying degrees.

[41]Appendix Figures A17-A20 provide additional results for satisfaction with other specific aspects of the job: challenge, responsibility, salary, career advancement, benefits, independence, and job security.

thinking about graduate school and for policy makers who wish to understand how these returns differ for women and men. Unfortunately, estimating the effects of graduate education is complicated by that fact that the choice to obtain to attend graduate school in a particular field is not random and depends on preferences and abilities, which are typically not observed. This creates a challenging selection problem and suggests that simple earnings comparisons across graduate degrees may be misleading.

In this paper, we estimate the causal effects of specific graduate fields on earnings, the occupational component of earnings, the hourly wage, and hours worked. Using data from the National Survey of College Graduates and the National Survey of Recent College Graduates, we address the selection problem using the methodology developed in Altonji and Zhong (2021). This methodology uses pre-graduate school earnings of individuals who later obtain graduate degrees to approximate what they would have earned if they had not gone to graduate school

The paper makes three contributions. First, we estimate the labor market effects for 19 specific graduate degrees for men and women. There are far too many estimates to review here but, averaging across gender, the earnings effects are highest for medicine and law, and lowest for the humanities, the arts, and other sciences. For some degrees, there are notable differences in the estimated returns for men and women. For example, the returns to women are notably higher for humanities, and—to a lesser degree—law, while the returns to medical degrees are somewhat larger for men. Second, we expand the set of outcomes considered to additionally include log annual hours worked and log wage rates. While most of the gains come from increased wage rates, we find that increased hours play an important role in some degrees, such as law and especially medicine. Third, we use the results above to estimate the percentage gain in present discounted value of earnings net of tuition and the internal rate of return to the various graduate degrees under alternative assumptions about program duration and earnings while enrolled. Along the way, we provide gender and degree specific estimates of annual earnings and hours worked while enrolled, which vary considerably across degrees. Overall, the field differences in the IRR estimates tend to be smaller than field differences in the log earnings estimates, as some programs with the highest returns, such as law and medicine, take longer and are most expensive.

Finally, we provide descriptive evidence (based on OLS regressions) on how the various graduate degrees affect overall job satisfaction, as well as several specific dimensions of job satisfaction. Overall, job satisfaction tends to increase with the acquisition of a graduate degree, including in degrees that have limited economic returns. The gains in satisfaction are also somewhat higher for men for many degrees. An MBA and other business related degrees have little effect on overall satisfaction and negative effects on satisfaction with contribution to society.

There are several limitations to our approach that bear repeating. First, and foremost, the FEcg approach relies on using experience adjusted earnings observed prior to the advanced degree as the estimate of what people would have earned had they not gone to graduate school As we explained above and AZ discuss in more detail, this will only be true under some strong assumptions. Relaxing this assumption would likely require quasi-experimental variation that induces some individuals to switch from not going to graduate school to obtaining a specific graduate degree, or a combination of quasi-experimental variation and restrictions from a more structured model. Second, the FEcg estimates reported for men and women are for the treatment on the treated parameter of completing a degree. They may not represent the returns for marginal students, which may be the relevant parameter for certain policy decisions. Third, our estimates do not account for institutional quality, which may matter, especially for some degrees where quality may greatly affect job prospects, such as law. Fourth, our estimates fundamentally rely on individuals who work between college and graduate school. The returns for those who go directly to graduate school after enrolling may differ.

While our estimation strategy requires many strong assumptions, we believe this paper provides important new evidence on the returns to graduate degrees for men and women, and what drives those returns.

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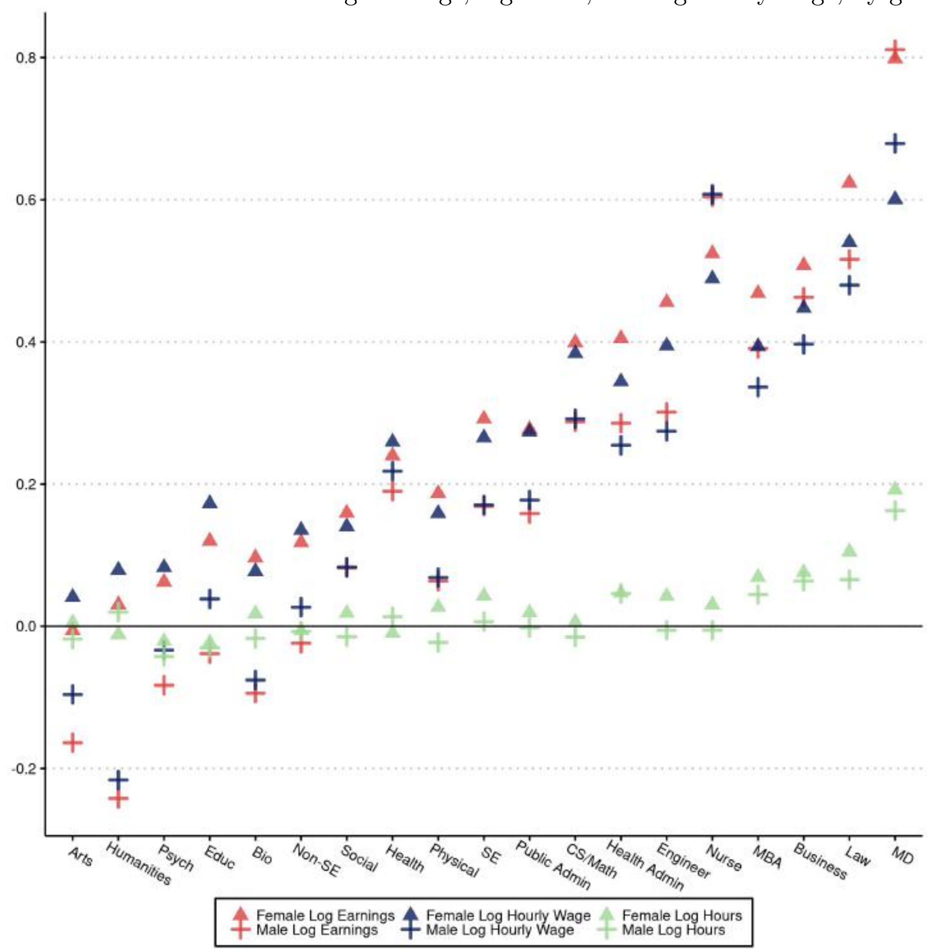
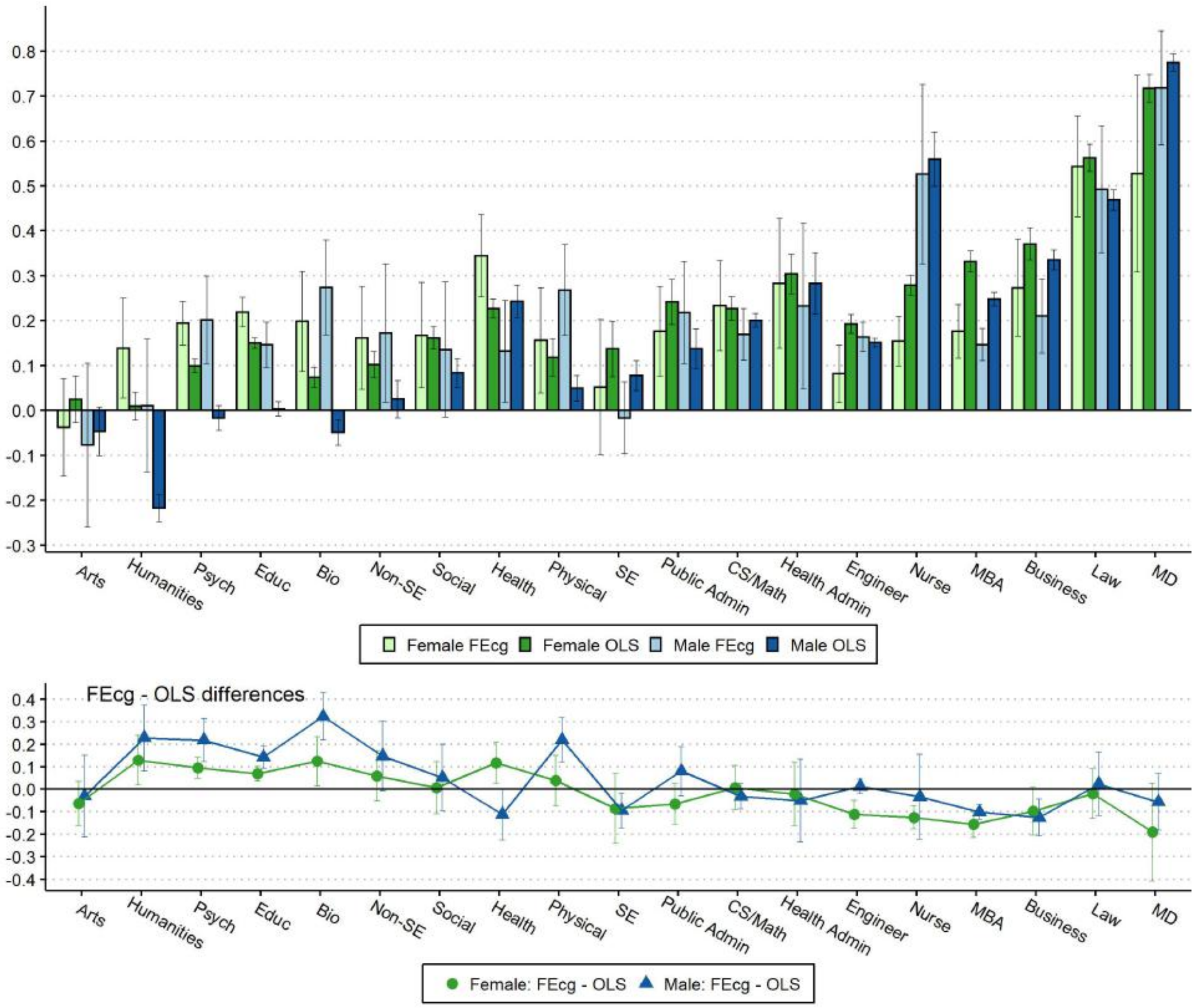
Figure 1: Graduate - BA differences in log earnings, log hours, and log hourly wage, by graduate field



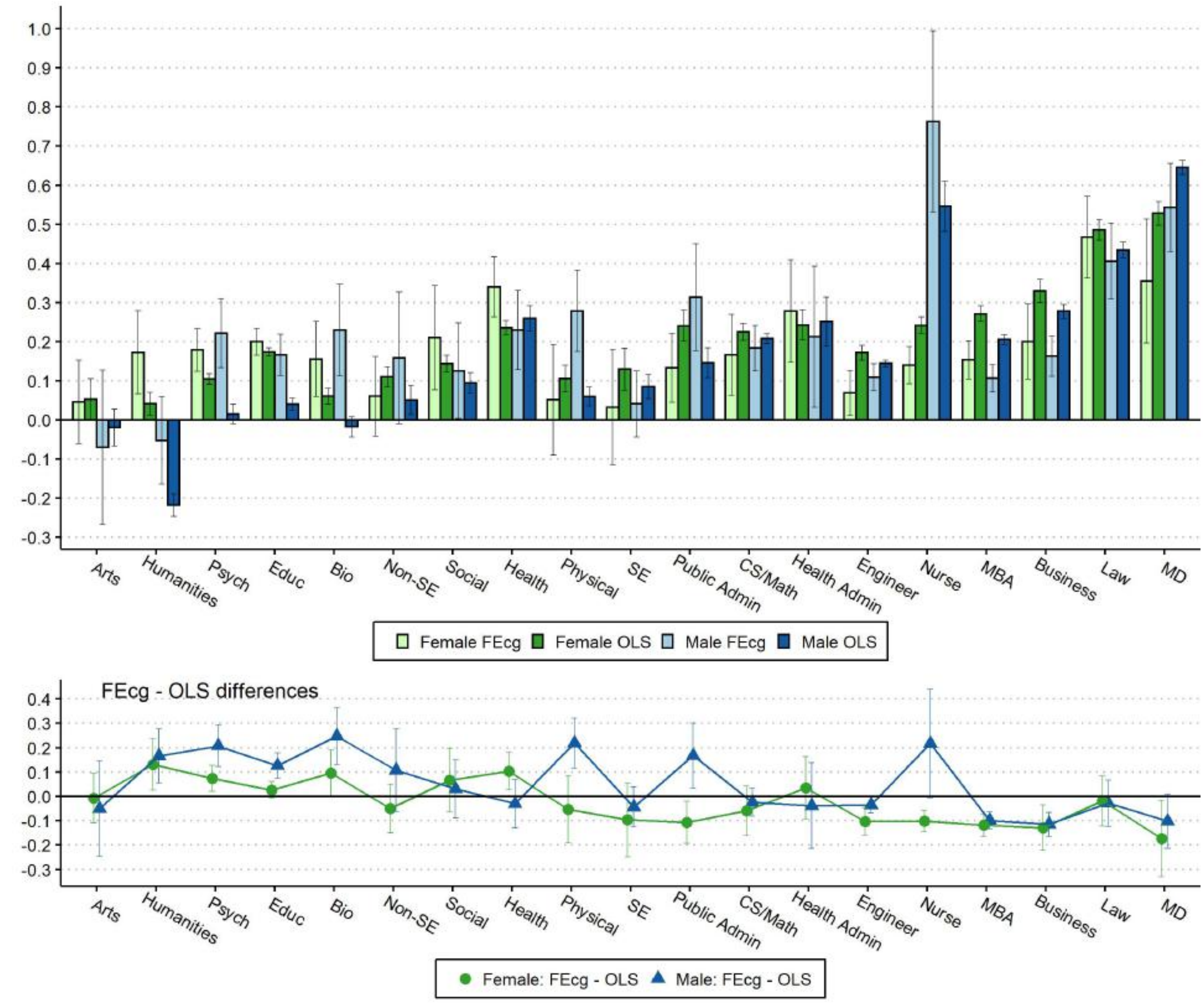
Notes: The figure shows the average difference in various outcomes between graduate degree holders and college graduates for 19 different graduate degrees. The red triangles and crosses show the average difference in log earnings for females and males. The blue triangle and crosses show the average difference in log hourly wage for females and males. The green triangles and crosses show the average difference in log hours worked for females and males. All estimates are for full-time workers.

Figure 2: Effects of graduate degrees on log earnings (full-time)



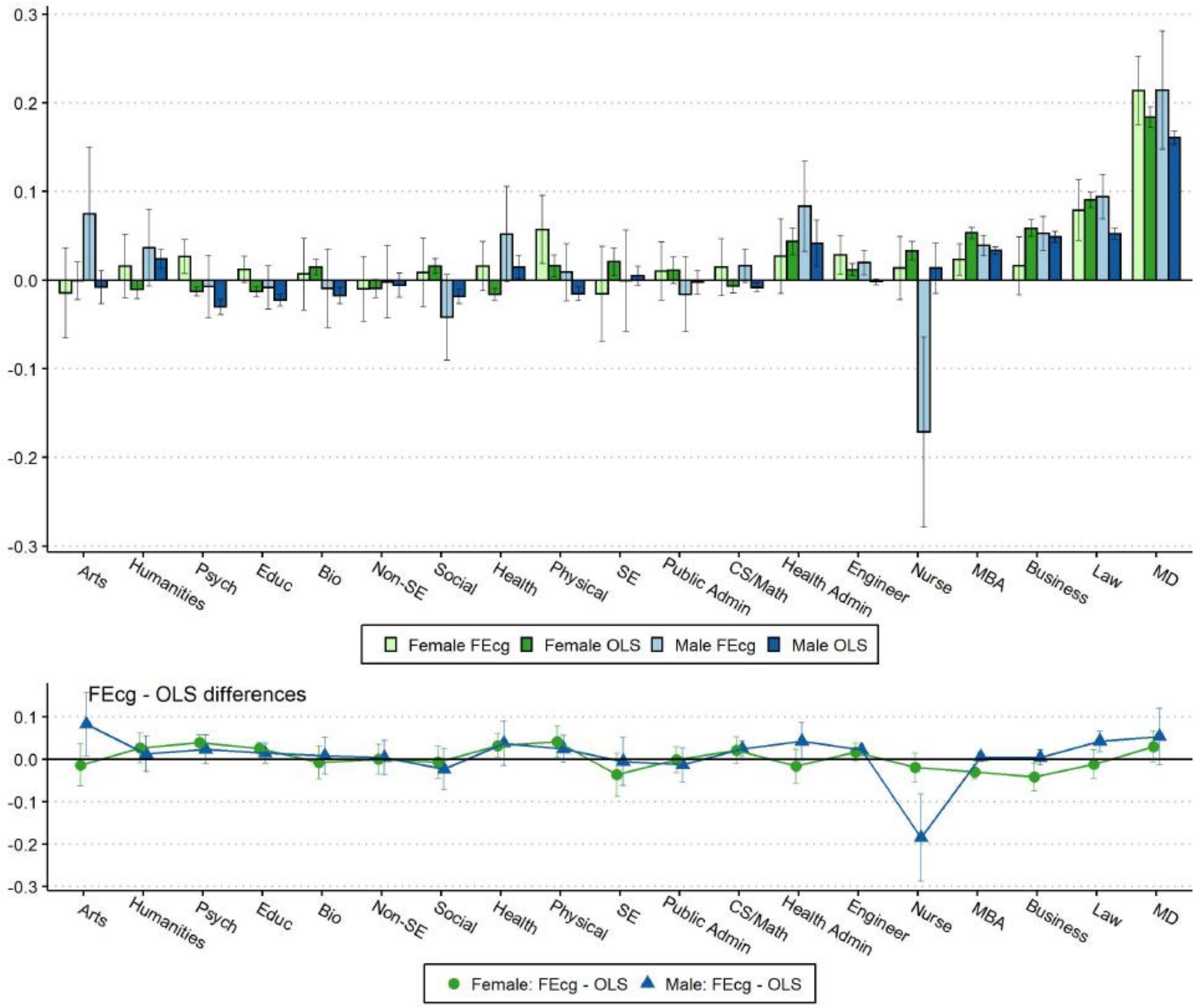
Notes: The figure shows OLS and FEcg estimates of the effects of 19 graduate degrees on log earnings of full-time workers. The top panel shows the point estimates with light green showing FEcg estimates for females, green showing OLS estimates for females, light blue showing FEcg estimates for males, and blue showing OLS estimates for males. The bottom panel shows the difference between the FEcg and OLS estimates for females (green) and males (blue). Error bars show 90 percent confidence intervals. Sample weights are used. The OLS estimates are based on equation (1), which includes include dummies $C_{c(i)}$for BA field and $G_{g(i)t}$ for each advanced degree at time t, race, Hispanic origin, parental education, calendar year, a cubic in age, and an interaction between a cubic in age and BA field. The FEcg estimates are based on equation (3), which adds the dummies for combinations of college major and graduate degree ($C_{c(i)}G_{g(i)}$).

Figure 3: Returns to graduate degrees on log hourly wage (full-time)



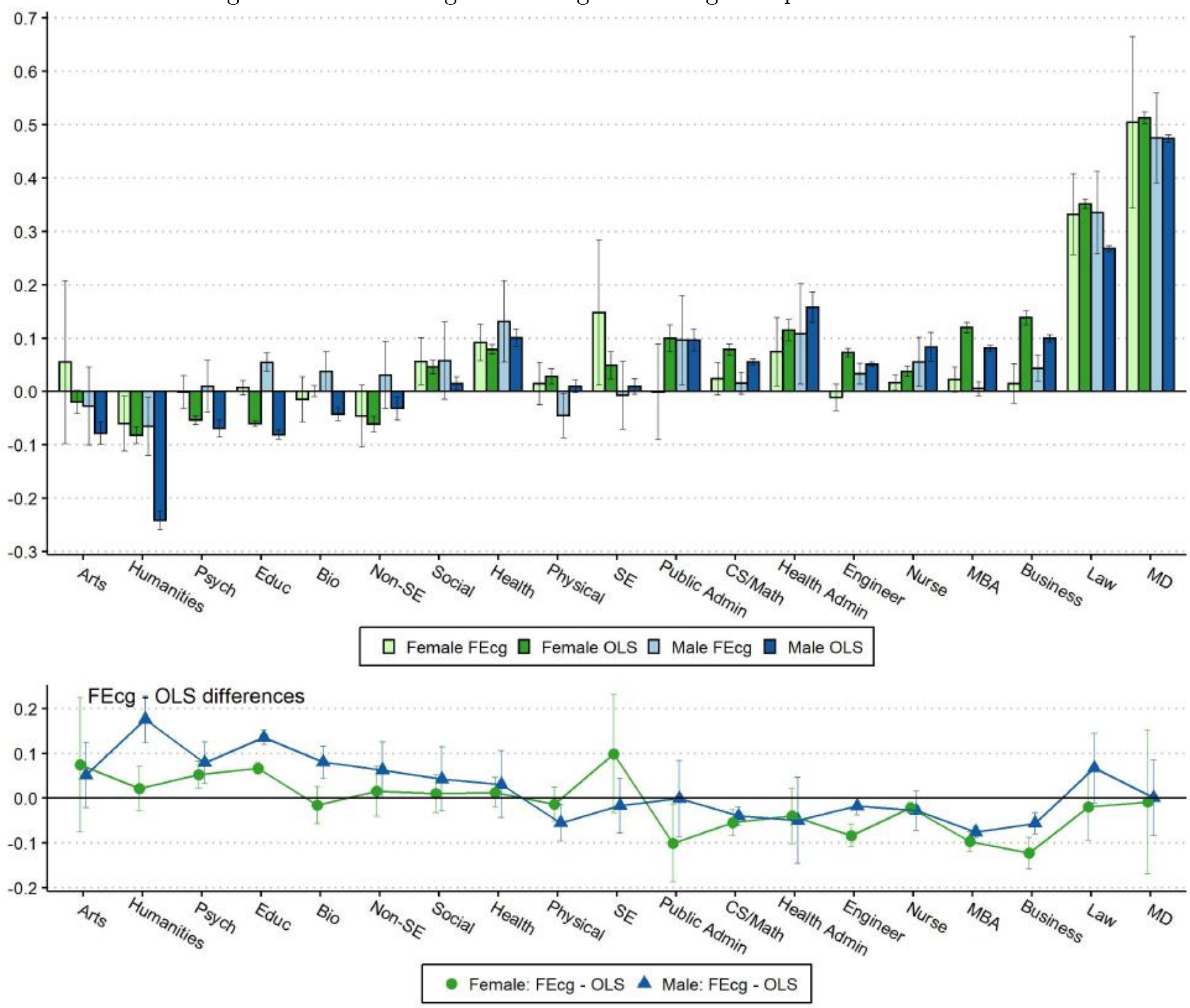
Notes: The figure shows OLS and FEcg estimates of the 19 graduate degrees for log hourly wage. The top panel shows the point estimates with light green showing FEcg estimates for females, green showing OLS estimates for females, light blue showing FEcg estimates for males, and blue showing OLS estimates for males. The bottom panel shows the difference between the FEcg and OLS estimates for females (green) and males (blue). Error bars show 90 percent confidence intervals. Sample weights are used. The OLS estimates are based on equation (1), which includes include dummies $C_{c(i)}$for BA field and $G_{g(i)t}$ for each advanced degree at time t, race, Hispanic origin, parental education, calendar year, a cubic in age, and an interaction between a cubic in age and BA field. The FEcg estimates are based on equation (3), which adds the dummies for combinations of college major and graduate degree ($C_{c(i)}G_{g(i)}$).

Figure 4: Returns to graduate degrees on log hours (full-time)



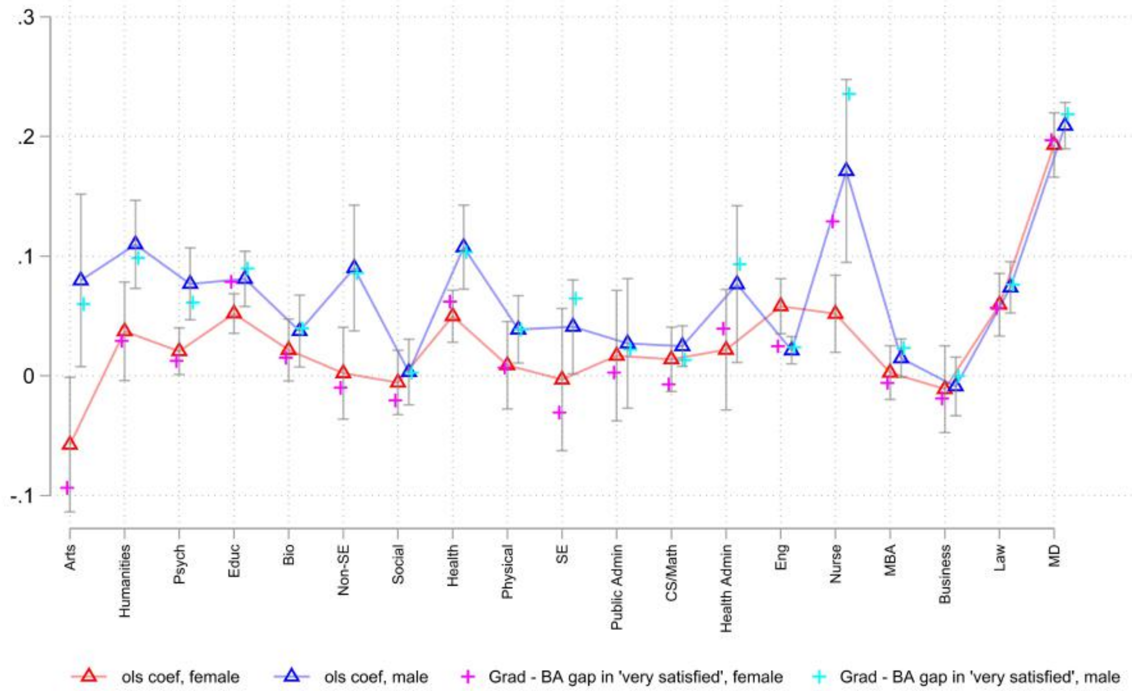
Notes: The figure shows OLS and FEcg estimates of the 19 graduate degrees for log hours of full-time workers. The top panel shows the point estimates with light green showing FEcg estimates for females, green showing OLS estimates for females, light blue showing FEcg estimates for males, and blue showing OLS estimates for males. The bottom panel shows the difference between the FEcg and OLS estimates for females (green) and males (blue). Error bars show 90 percent confidence intervals. Sample weights are used. The OLS estimates are based on equation (1), which includes include dummies $C_{c(i)}$for BA field and $G_{g(i)t}$ for each advanced degree at time t, race, Hispanic origin, parental education, calendar year, a cubic in age, and an interaction between a cubic in age and BA field. The FEcg estimates are based on equation (3), which adds the dummies for combinations of college major and graduate degree when last observed ($C_{c(i)}G_{g(i)}$).

Figure 5: Returns to graduate degrees on Log Occupation Premium

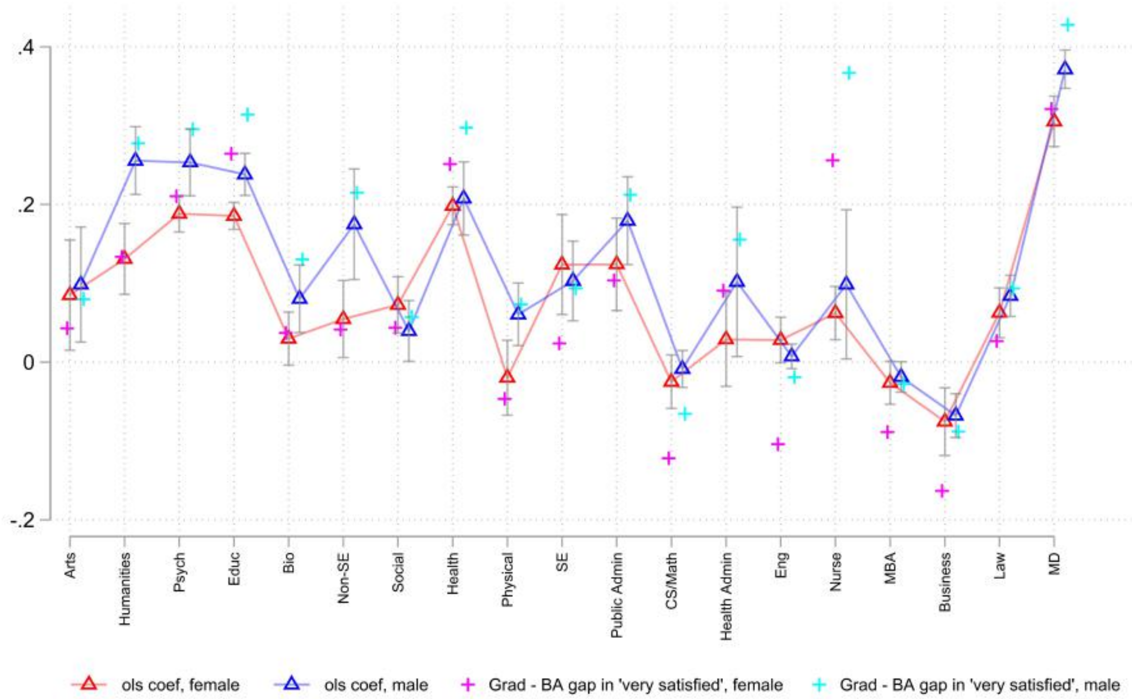


Notes: The figure shows OLS and FEcg estimates of the 19 graduate degrees for log occupational premium. The top panel shows the point estimates with light green showing FEcg estimates for females, green showing OLS estimates for females, light blue showing FEcg estimates for males, and blue showing OLS estimates for males. The bottom panel shows the difference between the FEcg and OLS estimates for females (green) and males (blue). The regressions include dummies for BA field and each advanced degree, race, Hispanic origin, parental education, calendar year, a cubic in age, and an interaction between a cubic in age and BA field.

Figure 6: OLS estimates of effects of graduate degrees on job satisfaction.
(A) Dep. variable: "very satisfied" overall.



(B) Dep variable: "very satisfied" with contribution to society.



Notes: The figure reports estimates of the effect of completing advanced degrees on overall job satisfaction (panel A) and satisfaction with contribution to society (panel B), by graduate degree field. The dependent variable is an indicator for whether the individual responded that they were "very satisfied". Sample weights are used. Standard errors are clustered by person. The red line and triangles report the OLS estimates for women and blue line with triangles report the OLS estimates for men. The pink crosses report the raw differences between the mean response of women with the particular graduate degree and women with only a BA. The light-blue crosses report the corresponding differences for men.

Table 1: Summary statistics of the key dependent variables

	Earnings		ln(Earnings)		ln(Hourly Wage)		ln(Annual Hours)		Occ Premium		Overall Job Satisfaction	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
No Advanced Degree	59,091	84,127	10.84	11.16	3.15	3.40	7.67	7.74	-0.67	-0.56	0.44	0.44
	[38,999]	[59,232]	[0.54]	[0.59]	[0.49]	[0.54]	[0.17]	[0.17]	[0.26]	[0.26]	[0.50]	[0.50]
Medicine	139,379	192,402	11.64	11.98	3.75	4.08	7.87	7.91	-0.15	-0.12	0.63	0.66
	[90,925]	[120,911]	[0.68]	[0.66]	[0.71]	[0.66]	[0.26]	[0.25]	[0.20]	[0.17]	[0.48]	[0.47]
Law	114,075	144,614	11.46	11.68	3.69	3.88	7.78	7.81	-0.32	-0.31	0.49	0.52
	[76,661]	[101,605]	[0.61]	[0.65]	[0.54]	[0.59]	[0.19]	[0.19]	[0.16]	[0.13]	[0.50]	[0.50]
Master's in business-related fields	98,342	134,352	11.34	11.63	3.59	3.79	7.75	7.81	-0.48	-0.43	0.42	0.44
	[63,747]	[98,433]	[0.55]	[0.60]	[0.48]	[0.51]	[0.16]	[0.18]	[0.20]	[0.19]	[0.49]	[0.50]
MBA	94,405	122,061	11.31	11.55	3.54	3.73	7.74	7.79	-0.51	-0.45	0.43	0.47
	[60,207]	[84,510]	[0.56]	[0.55]	[0.47]	[0.48]	[0.17]	[0.18]	[0.23]	[0.22]	[0.50]	[0.50]
Master's in nursing	92,275	139,404	11.36	11.77	3.64	4.00	7.71	7.74	-0.50	-0.45	0.56	0.68
	[40,682]	[58,734]	[0.38]	[0.40]	[0.35]	[0.43]	[0.17]	[0.17]	[0.17]	[0.15]	[0.50]	[0.47]
Master's in engineering	89,134	105,909	11.29	11.47	3.54	3.67	7.72	7.74	-0.45	-0.43	0.46	0.47
	[47,898]	[53,469]	[0.48]	[0.47]	[0.43]	[0.43]	[0.13]	[0.15]	[0.17]	[0.17]	[0.50]	[0.50]
Master's in health services	85,275	109,260	11.24	11.45	3.49	3.65	7.72	7.79	-0.53	-0.43	0.47	0.54
administration	[43,105]	[68,323]	[0.48]	[0.55]	[0.42]	[0.49]	[0.18]	[0.24]	[0.23]	[0.23]	[0.50]	[0.50]
Master's in computer and	85,304	105,467	11.24	11.45	3.53	3.69	7.68	7.73	-0.52	-0.46	0.43	0.46
mathematical sciences	[43,526]	[55,333]	[0.51]	[0.50]	[0.44]	[0.44]	[0.17]	[0.16]	[0.20]	[0.17]	[0.49]	[0.50]
Master's in public administration	76,142	92,965	11.11	11.32	3.42	3.57	7.69	7.74	-0.58	-0.49	0.44	0.47
	[44,647]	[46,477]	[0.52]	[0.50]	[0.43]	[0.45]	[0.17]	[0.17]	[0.27]	[0.26]	[0.50]	[0.50]
Master's in other science and	76,098	95,264	11.13	11.33	3.41	3.57	7.72	7.75	-0.57	-0.54	0.40	0.51
engineering-related fields	[35,904]	[57,365]	[0.50]	[0.51]	[0.43]	[0.47]	[0.14]	[0.18]	[0.23]	[0.22]	[0.49]	[0.50]
Master's in physical and	71,042	88,122	11.02	11.23	3.31	3.47	7.70	7.72	-0.63	-0.56	0.44	0.48
related sciences	[40,844]	[50,505]	[0.56]	[0.59]	[0.54]	[0.57]	[0.17]	[0.16]	[0.19]	[0.20]	[0.50]	[0.50]
Master's in health-related fields	70,926	99,509	11.08	11.35	3.41	3.61	7.67	7.76	-0.60	-0.51	0.50	0.55
	[34,352]	[62,247]	[0.44]	[0.57]	[0.40]	[0.52]	[0.17]	[0.21]	[0.20]	[0.25]	[0.50]	[0.50]
Master's in other social and	68,402	92,122	11.00	11.25	3.29	3.48	7.69	7.73	-0.65	-0.58	0.41	0.45
related sciences	[43,385]	[66,632]	[0.52]	[0.61]	[0.47]	[0.53]	[0.19]	[0.18]	[0.25]	[0.26]	[0.49]	[0.50]
Master's in other non-science and	63,509	79,485	10.95	11.14	3.28	3.42	7.67	7.74	-0.76	-0.65	0.43	0.53
engineering fields	[36,191]	[54,921]	[0.45]	[0.53]	[0.42]	[0.49]	[0.18]	[0.18]	[0.23]	[0.25]	[0.49]	[0.50]
Master's in biological/agricultural/	62,650	73,893	10.93	11.07	3.22	3.32	7.69	7.73	-0.68	-0.66	0.45	0.48
environmental/life sciences	[31,751]	[43,415]	[0.49]	[0.54]	[0.46]	[0.52]	[0.17]	[0.19]	[0.20]	[0.22]	[0.50]	[0.50]
Master's in education fields	61,826	74,095	10.96	11.13	3.32	3.43	7.65	7.71	-0.81	-0.72	0.51	0.53
	[26,516]	[36,032]	[0.40]	[0.42]	[0.42]	[0.42]	[0.22]	[0.21]	[0.18]	[0.23]	[0.50]	[0.50]
Master's in psychology and	59,711	73,729	10.90	11.08	3.23	3.36	7.65	7.70	-0.78	-0.70	0.45	0.51
social work	[33,905]	[40,316]	[0.44]	[0.51]	[0.41]	[0.49]	[0.17]	[0.19]	[0.22]	[0.28]	[0.50]	[0.50]
Master's in humanity fields	58,684	64,595	10.87	10.92	3.23	3.18	7.66	7.76	-0.79	-0.86	0.46	0.54
	[30,781]	[43,694]	[0.48]	[0.55]	[0.48]	[0.53]	[0.20]	[0.22]	[0.23]	[0.30]	[0.50]	[0.50]
Master's in arts	58,176	71,681	10.83	11.00	3.19	3.30	7.68	7.72	-0.74	-0.74	0.34	0.50
	[33,043]	[56,677]	[0.54]	[0.59]	[0.52]	[0.54]	[0.21]	[0.23]	[0.21]	[0.22]	[0.47]	[0.50]

Note: Weighted mean and standard deviations of key dependent variables by gender and advanced field. All statistics are measured on the OLS regression sample with corresponding gender and dependent variable. Columns 1-2 and 3-4 present the statistics on earnings levels and ln(earnings) for men and women. Columns 5-6 are for the ln(hourly wage rate). Columns 7-8 are for ln(annual hours at work) for full time workers. Columns 9-10 are for the occupational premium. Columns 11-12 are for the indicator for whether the interviewee's overall job satisfaction is "very satisfied".

Table 2: Return to advanced degrees by gender: log earnings

	Female				Male			
	FEcg	OLS	γ_{g1-28}^{FEcg}	γ_{g1-28}^{OLS}	FEcg	OLS	γ_{g1-28}^{FEcg}	γ_{g1-28}^{OLS}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	.527	.717	.630	.806	.718	.775	.753	.769
	(.133)	(.019)	(.144)	(.021)	(.077)	(.012)	(.077)	(.012)
Law	.543	.563	.606	.602	.492	.469	.509	.466
	(.068)	(.018)	(.070)	(.020)	(.086)	(.014)	(.086)	(.014)
Master's in business-related fields	.273	.371	.321	.409	.210	.335	.238	.345
	(.066)	(.022)	(.068)	(.025)	(.051)	(.013)	(.050)	(.013)
MBA	.176	.332	.256	.391	.146	.248	.187	.266
	(.036)	(.014)	(.037)	(.017)	(.022)	(.009)	(.022)	(.010)
Master's in nursing	.154	.279	.147	.271	.526	.559	.569	.596
	(.034)	(.013)	(.035)	(.016)	(.122)	(.037)	(.130)	(.063)
Master's in engineering	.081	.192	.205	.293	.164	.151	.209	.175
	(.039)	(.013)	(.042)	(.019)	(.020)	(.006)	(.021)	(.007)
Master's in health services administration	.283	.304	.354	.362	.232	.283	.288	.327
	(.088)	(.027)	(.091)	(.032)	(.112)	(.042)	(.115)	(.048)
Master's in computer and mathematical sciences	.233	.227	.275	.262	.169	.200	.207	.224
	(.061)	(.016)	(.061)	(.02)	(.035)	(.009)	(.036)	(.010)
Master's in public administration	.176	.242	.237	.280	.218	.137	.264	.162
	(.06)	(.031)	(.063)	(.036)	(.069)	(.027)	(.069)	(.027)
Master's in other science and engineering-related fields	.051	.137	.131	.179	-.017	.077	.004	.076
	(.092)	(.038)	(.094)	(.042)	(.049)	(.021)	(.049)	(.020)
Master's in physical and related sciences	.156	.118	.245	.187	.268	.049	.328	.072
	(.071)	(.025)	(.073)	(.030)	(.062)	(.017)	(.062)	(.018)
Master's in health-related fields	.344	.227	.341	.206	.132	.243	.186	.262
	(.056)	(.013)	(.057)	(.016)	(.069)	(.022)	(.069)	(.023)
Master's in other social and related sciences	.168	.161	.235	.207	.135	.084	.173	.095
	(.071)	(.015)	(.073)	(.020)	(.091)	(.019)	(.092)	(.022)
Master's in other non-science and engineering fields	.161	.102	.224	.134	.172	.025	.204	.036
	(.07)	(.018)	(.071)	(.018)	(.093)	(.025)	(.095)	(.026)
Master's in biological/agricultural/environmental/life sciences	.198	.074	.276	.121	.274	-.049	.348	-.021
	(.068)	(.014)	(.068)	(.016)	(.064)	(.017)	(.065)	(.018)
Master's in education fields	.219	.150	.260	.174	.146	.003	.179	.013
	(.02)	(.007)	(.02)	(.008)	(.030)	(.010)	(.031)	(.010)
Master's in psychology and social work	.194	.099	.262	.151	.201	-.017	.245	.007
	(.03)	(.009)	(.031)	(.011)	(.059)	(.017)	(.059)	(.017)
Master's in humanity fields	.138	.009	.188	.034	.010	-.218	.037	-.214
	(.067)	(.019)	(.069)	(.021)	(.09)	(.019)	(.091)	(.019)
Master's in arts	-.038	.025	.019	.059	-.078	-.047	-.026	-.036
	(.066)	(.031)	(.071)	(.033)	(.111)	(.033)	(.115)	(.032)

Note: The table reports estimates of returns to advanced degrees for a set of regression specifications, by gender. Sample weights are used. Standard errors are clustered by person. The dependent variable is log earnings in 2013 dollars. The 4 columns on the left are for women, and those on the right are for men. The regressions include dummies for each BA field (OLS only) and each advanced degree, as well as race/Hispanic, parental education, the year, a cubic in age, and interactions between a cubic in age and BA field. The age polynomials and the year dummies control for linear birth cohort trend and partially control for nonlinear birth cohort effects. The regression samples are restricted to full-time workers. For each gender, we present estimates of the return to each advanced field from four specifications: FEcg columns report FEcg estimates of γ_g using equation (3) on the full sample that includes people who never get an advanced degree. OLS columns report OLS estimates of γ_g using (1). γ_{g1-28}^{FEcg} and γ_{g1-28}^{OLS} report FEcg and OLS estimates of γ_{g1-28}, the simple average of the experience specific return γ_{gx} to each advanced degree from 1 to 28 years after degree attainment, using the full sample. They are based on equation (4), with degree combination fixed effects excluded in the OLS case. The samples have 377,835 and 641,263 observations for females and males, respectively.

Table 3: Return to advanced degrees by gender: log of hourly wage rate

	Female				Male			
	FEcg	OLS	γ_{g1-28}^{FEcg}	γ_{g1-28}^{OLS}	FEcg	OLS	γ_{g1-28}^{FEcg}	γ_{g1-28}^{OLS}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	.355	.528	.495	.647	.543	.645	.581	.641
	(.097)	(.019)	(.108)	(.019)	(.068)	(.011)	(.068)	(.011)
Law	.467	.486	.53	.531	.406	.434	.424	.433
	(.064)	(.016)	(.063)	(.018)	(.059)	(.012)	(.060)	(.012)
Master's in business-related fields	.200	.329	.252	.372	.163	.278	.190	.289
	(.058)	(.018)	(.061)	(.022)	(.031)	(.011)	(.031)	(.011)
MBA	.153	.272	.221	.321	.106	.205	.143	.222
	(.030)	(.012)	(.031)	(.014)	(.021)	(.008)	(.022)	(.008)
Master's in nursing	.140	.242	.148	.246	.763	.546	.764	.535
	(.029)	(.013)	(.031)	(.016)	(.141)	(.039)	(.153)	(.070)
Master's in engineering	.069	.172	.190	.273	.109	.144	.157	.174
	(.035)	(.012)	(.038)	(.017)	(.021)	(.005)	(.021)	(.006)
Master's in health services administration	.278	.243	.337	.289	.213	.251	.274	.293
	(.079)	(.023)	(.082)	(.031)	(.110)	(.038)	(.112)	(.044)
Master's in computer and mathematical sciences	.167	.225	.207	.261	.183	.208	.223	.235
	(.063)	(.013)	(.063)	(.017)	(.035)	(.008)	(.036)	(.009)
Master's in public administration	.134	.241	.191	.276	.313	.146	.358	.172
	(.054)	(.024)	(.059)	(.032)	(.083)	(.023)	(.083)	(.023)
Master's in other science and engineering-related fields	.032	.129	.106	.176	.041	.085	.059	.086
	(.090)	(.033)	(.094)	(.037)	(.052)	(.019)	(.051)	(.018)
Master's in physical and related sciences	.052	.106	.161	.189	.278	.060	.357	.098
	(.086)	(.021)	(.089)	(.026)	(.063)	(.015)	(.064)	(.016)
Master's in health-related fields	.340	.236	.343	.219	.230	.260	.274	.271
	(.047)	(.011)	(.048)	(.014)	(.061)	(.020)	(.060)	(.020)
Master's in other social and related sciences	.210	.144	.279	.194	.125	.095	.164	.109
	(.081)	(.013)	(.081)	(.018)	(.074)	(.016)	(.075)	(.018)
Master's in other non-science and engineering fields	.061	.110	.116	.138	.158	.051	.189	.063
	(.062)	(.016)	(.063)	(.016)	(.103)	(.023)	(.103)	(.023)
Master's in biological/agricultural/environmental/life sciences	.156	.060	.235	.112	.230	-.018	.314	.021
	(.059)	(.012)	(.058)	(.015)	(.071)	(.016)	(.071)	(.017)
Master's in education fields	.200	.174	.243	.199	.166	.040	.197	.049
	(.021)	(.006)	(.021)	(.007)	(.032)	(.009)	(.032)	(.009)
Master's in psychology and social work	.179	.105	.247	.161	.222	.015	.262	.039
	(.033)	(.008)	(.034)	(.010)	(.054)	(.015)	(.052)	(.016)
Master's in humanity fields	.172	.041	.221	.066	-.052	-.218	-.029	-.213
	(.065)	(.017)	(.065)	(.019)	(.068)	(.018)	(.069)	(.018)
Master's in arts	.046	.053	.105	.086	-.070	-.019	-.025	-.008
	(.065)	(.032)	(.069)	(.033)	(.120)	(.029)	(.120)	(.028)

Note: See notes of Table 2 for detailed information on regression specifications and table layout. The samples have 226,258 and 384,030 observations for females and males, respectively.

Table 4: Return to advanced degrees by gender: log of annual hours

	Female				Male			
	FEcg	OLS	γ^{FEcg}_{g1-28}	γ^{OLS}_{g1-28}	FEcg	OLS	γ^{FEcg}_{g1-28}	γ^{OLS}_{g1-28}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	.214 (.023)	.184 (.007)	.179 (.022)	.154 (.007)	.214 (.041)	.161 (.005)	.208 (.041)	.161 (.005)
Law	.079 (.021)	.091 (.005)	.079 (.021)	.091 (.006)	.094 (.015)	.052 (.004)	.094 (.015)	.052 (.004)
Master's in business-related fields	.016 (.02)	.059 (.006)	.015 (.02)	.058 (.006)	.053 (.012)	.049 (.004)	.055 (.012)	.051 (.004)
MBA	.023 (.011)	.053 (.004)	.031 (.011)	.061 (.005)	.039 (.007)	.033 (.003)	.042 (.007)	.037 (.003)
Master's in nursing	.014 (.022)	.033 (.006)	.01 (.023)	.032 (.008)	-.171 (.065)	.013 (.017)	-.139 (.072)	.044 (.035)
Master's in engineering	.028 (.013)	.012 (.004)	.029 (.014)	.015 (.006)	.02 (.008)	-.002 (.002)	.021 (.008)	-.001 (.002)
Master's in health services administration	.027 (.025)	.043 (.009)	.039 (.027)	.053 (.011)	.083 (.031)	.042 (.016)	.088 (.034)	.043 (.018)
Master's in computer and mathematical sciences	.015 (.019)	-.007 (.005)	.021 (.02)	-.001 (.006)	.016 (.011)	-.008 (.003)	.019 (.011)	-.006 (.004)
Master's in public administration	.01 (.02)	.011 (.009)	.009 (.021)	.012 (.01)	-.016 (.026)	-.002 (.008)	-.011 (.026)	.001 (.008)
Master's in other science and engineering-related fields	-.015 (.033)	.021 (.01)	-.019 (.033)	.017 (.01)	-.001 (.035)	.005 (.006)	.001 (.035)	.006 (.007)
Master's in physical and related sciences	.057 (.023)	.016 (.008)	.056 (.024)	.017 (.009)	.009 (.02)	-.015 (.005)	.003 (.02)	-.017 (.005)
Master's in health-related fields	.016 (.017)	-.016 (.004)	.013 (.017)	-.017 (.005)	.052 (.033)	.015 (.008)	.054 (.033)	.019 (.008)
Master's in other social and related sciences	.009 (.024)	.016 (.005)	.015 (.024)	.022 (.006)	-.042 (.029)	-.018 (.005)	-.041 (.03)	-.017 (.005)
Master's in other non-science and engineering fields	-.01 (.022)	-.009 (.006)	-.011 (.022)	-.01 (.007)	-.002 (.025)	-.006 (.008)	-.004 (.025)	-.007 (.008)
Master's in biological/agricultural/environmental/life sciences	.007 (.024)	.015 (.005)	.002 (.025)	.012 (.006)	-.009 (.027)	-.017 (.006)	-.015 (.027)	-.017 (.006)
Master's in education fields	.012 (.009)	-.013 (.003)	.011 (.009)	-.014 (.003)	-.008 (.015)	-.022 (.004)	-.009 (.015)	-.023 (.004)
Master's in psychology and social work	.026 (.012)	-.013 (.003)	.026 (.012)	-.014 (.004)	-.007 (.021)	-.03 (.005)	-.006 (.022)	-.029 (.005)
Master's in humanity fields	.016 (.022)	-.01 (.007)	.016 (.022)	-.01 (.007)	.036 (.026)	.024 (.007)	.037 (.026)	.023 (.007)
Master's in arts	-.015 (.031)	-.001 (.013)	-.018 (.031)	-.003 (.014)	.075 (.046)	-.008 (.011)	.072 (.046)	-.010 (.012)

Note: See notes of Table 2 for detailed information on regression specifications and table layout. All regressions in this table are estimated on full-time workers' current year observations. The samples have 196,376 and 334,648 observations for females and males, respectively.

Table 5: Return to advanced degrees by gender: Occupational premium

	Female				Male			
	FEcg	OLS	γ_{g1-28}^{FEcg}	γ_{g1-28}^{OLS}	FEcg	OLS	γ_{g1-28}^{FEcg}	γ_{g1-28}^{OLS}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	.504	.513	.491	.505	.475	.474	.476	.476
	(.098)	(.007)	(.097)	(.007)	(.051)	(.004)	(.051)	(.004)
Law	.331	.351	.329	.349	.335	.268	.337	.269
	(.046)	(.005)	(.046)	(.007)	(.047)	(.003)	(.047)	(.003)
Master's in business-related fields	.015	.138	.024	.149	.043	.099	.047	.102
	(.023)	(.008)	(.024)	(.010)	(.015)	(.004)	(.015)	(.004)
MBA	.022	.119	.034	.131	.005	.081	.010	.084
	(.014)	(.006)	(.015)	(.007)	(.008)	(.003)	(.008)	(.004)
Master's in nursing	.016	.038	.013	.031	.055	.083	.074	.091
	(.009)	(.006)	(.010)	(.007)	(.028)	(.017)	(.034)	(.023)
Master's in engineering	-.011	.073	-.003	.086	.033	.051	.036	.054
	(.015)	(.005)	(.017)	(.008)	(.012)	(.002)	(.012)	(.003)
Master's in health services administration	.074	.115	.083	.129	.108	.158	.131	.177
	(.039)	(.012)	(.039)	(.014)	(.057)	(.017)	(.058)	(.020)
Master's in computer and mathematical sciences	.024	.079	.024	.079	.015	.055	.015	.056
	(.018)	(.006)	(.019)	(.008)	(.013)	(.004)	(.013)	(.004)
Master's in public administration	-.001	.100	.013	.110	.096	.097	.110	.107
	(.055)	(.015)	(.055)	(.020)	(.051)	(.013)	(.051)	(.013)
Master's in other science and engineering-related fields	.148	.049	.167	.068	-.007	.009	-.007	.008
	(.083)	(.016)	(.082)	(.018)	(.039)	(.009)	(.038)	(.009)
Master's in physical and related sciences	.015	.028	.013	.027	-.045	.010	-.050	.007
	(.024)	(.009)	(.025)	(.012)	(.025)	(.007)	(.026)	(.008)
Master's in health-related fields	.092	.079	.073	.062	.131	.100	.140	.107
	(.021)	(.005)	(.021)	(.007)	(.046)	(.01)	(.047)	(.012)
Master's in other social and related sciences	.056	.046	.066	.055	.058	.015	.063	.018
	(.027)	(.008)	(.027)	(.009)	(.044)	(.008)	(.045)	(.008)
Master's in other non-science and engineering fields	-.046	-.061	-.045	-.062	.031	-.032	.032	-.032
	(.035)	(.009)	(.036)	(.010)	(.038)	(.013)	(.039)	(.014)
Master's in biological/agricultural/environmental/life sciences	-.015	.001	-.003	.014	.038	-.043	.041	-.039
	(.026)	(.006)	(.026)	(.008)	(.022)	(.007)	(.023)	(.008)
Master's in education fields	.007	-.060	.013	-.055	.054	-.081	.060	-.080
	(.008)	(.003)	(.008)	(.003)	(.010)	(.005)	(.011)	(.005)
Master's in psychology and social work	-.001	-.054	.007	-.046	.01	-.070	.020	-.063
	(.019)	(.005)	(.019)	(.006)	(.030)	(.010)	(.030)	(.010)
Master's in humanity fields	-.060	-.082	-.050	-.074	-.066	-.242	-.062	-.242
	(.031)	(.010)	(.031)	(.010)	(.033)	(.010)	(.033)	(.011)
Master's in arts	.055	-.020	.051	-.020	-.028	-.079	-.021	-.077
	(.093)	(.013)	(.091)	(.014)	(.045)	(.013)	(.046)	(.013)

Note: See notes of Table 2 for detailed information on regression specifications and table layout. Occupational premium regression sample includes 1988 (from the SESTAT questionnaire in 1993), 1990 (from Census), and all survey years. The samples have 245,858 and 426,528 observations for females and males, respectively.

Table 6: Tuition, program duration, and earnings and work hours while enrolled in graduate school, by field

	Tuition		Duration of the degree		Annual earnings when enrolled		Fraction with earnings < \$1,000		Annual working hours when enrolled		Fraction with zero hours	
	Public	Private	Full-time	All	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Medicine	13,317	31,807	4	4.00	5,506 (1,141)	7,751 (1,636)	0.85	0.87	152 [553]	167 [594]	0.84	0.86
Law	16,697	28,555	3	3.00	11,599 (1,811)	13,319 (1,553)	0.65	0.68	376 [702]	373 [723]	0.63	0.66
MA in business-related fields	6,736	12,302	2	2.25	31,882 (5,029)	50,906 (6,406)	0.28	0.16	1,495 [1,077]	1,673 [1,003]	0.29	0.17
MBA	9,311	13,807	2	2.75	49,528 (2,507)	55,971 (2,037)	0.13	0.13	1,872 [897]	1,933 [912]	0.12	0.13
MA in nursing	8,131	14,058	2	3.25	48,597 (2,385)	44,872 (4,480)	0.12	0.24	1,652 [835]	1,582 [1,007]	0.13	0.23
MA in engineering	8,131	14,058	1	2.75	44,630 (2,871)	56,465 (1,893)	0.17	0.15	1,536 [935]	1,609 [949]	0.17	0.15
MA in health services administration	6,736	12,302	2	2.75	39,450 (4,829)	46,334 (5,601)	0.17	0.06	1,628 [902]	2,020 [816]	0.17	0.06
MA in computer and mathematical sciences	8,131	14,058	1	2.75	40,341 (3,537)	51,519 (3,159)	0.18	0.14	1,472 [921]	1,617 [915]	0.17	0.14
MA in public administration	6,736	12,302	2	2.75	33,550 (3,988)	41,408 (3,491)	0.15	0.10	1,511 [876]	1,769 [912]	0.16	0.11
MA in other science and engineering-related fields	8,131	14,058	1	2.75	15,472 (4,518)	32,669 (5,394)	0.30	0.31	927 [901]	1,222 [1,087]	0.30	0.30
MA in physical and related sciences	8,131	14,058	1	2.75	26,997 (3,006)	32,025 (2,544)	0.17	0.13	1,293 [947]	1,400 [952]	0.18	0.12
MA in health-related fields	8,131	14,058	2	2.75	18,853 (1,589)	18,045 (2,491)	0.44	0.42	752 [890]	771 [916]	0.43	0.43
MA in other social and related sciences	6,736	12,302	1	2.50	22,184 (2,550)	31,473 (3,031)	0.24	0.18	1,103 [885]	1,316 [953]	0.22	0.18
MA in other non-science and engineering fields	6,736	12,302	1	2.50	28,641 (2,990)	40,884 (4,009)	0.14	0.09	1,421 [879]	1,671 [800]	0.13	0.10
MA in biological/agricultural/ environmental/life sciences	8,131	14,058	1	2.75	26,384 (1,857)	20,812 (2,072)	0.21	0.23	1,250 [942]	1,298 [1,000]	0.20	0.22
MA in education fields	6,736	12,302	1	2.75	33,107 (984)	35,549 (1,527)	0.12	0.10	1,616 [869]	1,745 [927]	0.11	0.10
MA in psychology and social work	6,736	12,302	2	2.50	21,423 (1,361)	26,209 (2,506)	0.26	0.20	1,182 [912]	1,325 [914]	0.25	0.20
MA in humanity fields	6,736	12,302	1	2.50	23,534 (2,571)	23,822 (2,668)	0.17	0.17	1,192 [917]	1,462 [1,030]	0.18	0.16
MA in arts	6,736	12,302	2	2.50	15,939 (4,470)	21,352 (4,937)	0.32	0.20	959 [924]	1,219 [983]	0.30	0.22

Note: The table reports statistics for the IRR calculation. Columns 1 and 2 report the tuition rates at public and private institutions in 2012 from the National Center of Education Statistics. Column 3 reports the assumed duration of each degree if enrolled full-time. Column 4 reports the average years taken to complete each degree, from Altonji and Zhu (2021). Columns 5 and 6 are the estimates of the average annual earnings of men and women while enrolled in graduate school, constructed as follows. We estimate two regression specifications for each advanced field. The first is an OLS regression of the level of earnings when people are enrolled in the program on race, gender, and quadratics of age and the year (centered at 2012). The second set consists separate regressions for men and women. Each approach yields age and gender-specific estimates for earnings while enrolled in the advanced degree program, normalized for non-hispanic whites in 2012. When the regression sample of the second approach is at least 200, we use the estimate from the gender-specific regression. If not, we use the estimate from the pooled regression. Columns 7 and 8 are the fractions of observations with actual earnings less than \$1,000 among all observations in the regression samples for columns 5 and 6, respectively. Columns 9 and 10 are the averages of annual working hours of men and women who are enrolled in the degree. Columns 11 and 12 are the fraction of observations with zero working hours when enrolled.

Table 7: Internal Rate of Return to Advanced Degrees by Gender: public institution with zero earnings when enrolled, FEcg with post-adv experience

	Female				Male			
	PDV actual	PDV counter-factual	%Gain in PDV	IRR	PDV actual	PDV counter-factual	%Gain in PDV	IRR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	1.54 [0.03]	1.10 [0.13]	39.93 [18.84]	0.12 [0.02]	2.01 [0.03]	1.21 [0.10]	66.22 [12.88]	0.16 [0.02]
Law	1.35 [0.03]	0.92 [0.05]	46.85 [6.73]	0.16 [0.01]	1.65 [0.03]	1.19 [0.09]	38.59 [9.57]	0.15 [0.02]
Master's in business-related fields	1.32 [0.04]	1.09 [0.06]	20.56 [6.96]	0.14 [0.03]	1.72 [0.03]	1.51 [0.09]	13.89 [7.62]	0.11 [0.03]
MBA	1.28 [0.03]	1.14 [0.04]	11.86 [3.67]	0.10 [0.01]	1.60 [0.02]	1.48 [0.03]	8.12 [2.17]	0.09 [0.01]
Master's in nursing	1.26 [0.02]	1.21 [0.04]	3.64 [3.91]	0.08 [0.02]	1.94 [0.12]	1.24 [0.15]	57.11 [22.56]	0.30 [0.07]
Master's in engineering	1.45 [0.03]	1.29 [0.05]	12.54 [4.37]	0.12 [0.02]	1.68 [0.01]	1.45 [0.03]	15.47 [2.24]	0.17 [0.02]
Master's in health services administration	1.20 [0.04]	0.96 [0.12]	24.99 [13.67]	0.15 [0.05]	1.47 [0.07]	1.24 [0.12]	18.58 [12.25]	0.14 [0.06†]
Master's in computer and mathematical sciences	1.24 [0.02]	1.02 [0.07]	21.78 [8.74]	0.21 [0.06]	1.62 [0.02]	1.40 [0.05]	15.98 [4.23]	0.19 [0.03]
Master's in public administration	1.05 [0.04]	0.95 [0.05]	10.34 [6.64]	0.10 [0.04†]	1.27 [0.04]	1.11 [0.07]	14.68 [6.77]	0.11 [0.03]
Master's in other science and engineering-related fields	1.11 [0.04]	1.04 [0.09]	6.37 [9.13]	0.09 [0.06]	1.31 [0.03]	1.41 [0.08]	-6.74 [5.49]	0.01 [0.04]
Master's in physical and related sciences	1.05 [0.03]	0.90 [0.06]	17.03 [7.99]	0.15 [0.05]	1.26 [0.02]	0.97 [0.06]	29.07 [9.12]	0.21 [0.06]
Master's in health-related fields	1.03 [0.02]	0.81 [0.05]	26.57 [7.46]	0.20 [0.03]	1.40 [0.04]	1.29 [0.09]	8.29 [7.58]	0.09 [0.06†]
Master's in other social and related sciences	1.02 [0.02]	0.87 [0.06]	16.67 [8.08]	0.17 [0.06]	1.27 [0.03]	1.13 [0.09]	12.36 [9.80]	0.14 [0.08]
Master's in other non-science and engineering fields	0.93 [0.02]	0.81 [0.06]	15.36 [10.01]	0.15 [0.06]	1.13 [0.04]	0.98 [0.10]	15.69 [12.02]	0.18 [0.10]
Master's in biological/agricultural/ environmental/life sciences	0.95 [0.01]	0.78 [0.05]	21.86 [6.84]	0.20 [0.04]	1.06 [0.02]	0.81 [0.05]	31.27 [7.55]	0.24 [0.05]
Master's in education fields	0.92 [0.01]	0.76 [0.01]	20.36 [2.40]	0.20 [0.02]	1.07 [0.01]	0.95 [0.03]	12.28 [3.06]	0.14 [0.02]
Master's in psychology and social work	0.86 [0.01]	0.76 [0.02]	12.75 [3.78]	0.10 [0.01]	1.00 [0.02]	0.89 [0.05]	12.41 [6.42]	0.10 [0.02]
Master's in humanity fields	0.83 [0.02]	0.75 [0.05]	11.63 [7.20]	0.14 [0.07†]	0.87 [0.03]	0.89 [0.07]	-1.69 [8.09]	0.04 [0.10†]
Master's in arts	0.77 [0.04]	0.86 [0.08]	-10.34 [9.59]	-0.03 [0.21†]	0.92 [0.04]	1.08 [0.13]	-14.72 [12.19]	-0.04 [0.13†]

Note: The statistics are calculated from regression coefficients underlying equation (4). For each advanced degree, we calculate the predicted value of actual income in levels (with graduate education) and counterfactual income (without graduate education) from age 27 to 59. When evaluating the log earnings model we set the earnings error term to 0, the parental education variables to their weighted sample means and the calendar year to 2012. We also set the race/Hispanic indicators to non-Hispanic white. For each graduate degree we calculate the population weighted average of predicted earnings at each age over the distribution of gender and of undergraduate major for that graduate degree. We subtract the tuition of the graduate degree from actual income to obtain net income. In this table, we use tuition rates at public institutions in 2012 from the National Center of Education Statistics. We assume all graduate programs are full-time, and students have zero earnings when they are enrolled. The tuition rate and the duration of the programs when enrolled full-time are reported in Table 6. Then we calculate the present discounted value of the lifetime net income, assuming the interest rate is 0.05. The internal rate of return is the discount factor that equates actual and counterfactual lifetime net income. We search for the internal rate of return over the interval of [-0.4, 1] using a fine grid. If the actual lifetime net income is below (above) the counterfactual on the entire interval of [-0.4, 1], we report -0.4 (1) as the internal rate of return to that degree. Columns 1-4 are for females and columns 5-8 are for males. For each gender, the four columns report the PDV of actual income in millions of 2013 dollars, the PDV of counterfactual income, the percentage increase in net income, and the internal rate of return, respectively, for each advanced degree. For each statistic, we report standard errors based on a block bootstrap procedure with 200 replications. For each bootstrap sample, we use the same grid search procedure to find the internal rate of return. We place a † next to the standard deviation if the estimate from 1 or more of the 200 replications hit the -0.4 or 1.0 boundary, meaning that the standard deviation should be interpreted with caution.

Table 8: Internal Rate of Return to Advanced Degrees by Gender: public institution with zero earnings when enrolled, OLS with post-adv experience

	Female				Male			
	PDV actual	PDV counter-factual	%Gain in PDV	IRR	PDV actual	PDV counter-factual	%Gain in PDV	IRR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	1.53	0.92	65.64	0.15	2.02	1.20	68.38	0.16
	[0.03]	[0.01]	[3.61]	[0.00]	[0.03]	[0.01]	[2.61]	[0.00]
Law	1.34	0.92	46.47	0.16	1.66	1.25	32.49	0.14
	[0.03]	[0.01]	[3.30]	[0.01]	[0.03]	[0.01]	[2.43]	[0.01]
Master's in business-related fields	1.30	0.99	30.96	0.17	1.72	1.35	26.66	0.16
	[0.03]	[0.01]	[3.44]	[0.01]	[0.03]	[0.01]	[1.96]	[0.01]
MBA	1.26	0.99	28.07	0.16	1.59	1.37	16.64	0.13
	[0.03]	[0.01]	[2.49]	[0.01]	[0.02]	[0.01]	[1.30]	[0.01]
Master's in nursing	1.26	1.08	16.91	0.15	1.96	1.22	60.74	0.31
	[0.02]	[0.01]	[1.83]	[0.01]	[0.13]	[0.03]	[10.50]	[0.02]
Master's in engineering	1.45	1.19	22.32	0.17	1.68	1.51	11.28	0.14
	[0.03]	[0.02]	[2.28]	[0.01]	[0.01]	[0.01]	[0.69]	[0.00]
Master's in health services	1.20	0.95	25.66	0.15	1.48	1.21	22.23	0.14
administration	[0.04]	[0.01]	[4.11]	[0.01]	[0.07]	[0.02]	[6.25]	[0.02]
Master's in computer and	1.24	1.04	19.73	0.19	1.63	1.39	17.11	0.19
mathematical sciences	[0.02]	[0.01]	[2.09]	[0.01]	[0.02]	[0.01]	[1.30]	[0.01]
Master's in public administration	1.04	0.91	15.02	0.12	1.27	1.23	3.31	0.07
	[0.04]	[0.01]	[4.32]	[0.01]	[0.04]	[0.01]	[3.21]	[0.02]
Master's in other science and	1.09	0.99	10.50	0.11	1.31	1.31	0.00	0.05
engineering-related fields	[0.04]	[0.02]	[4.21]	[0.02]	[0.03]	[0.02]	[2.09]	[0.01]
Master's in physical and	1.05	0.96	10.20	0.11	1.26	1.26	-0.25	0.05
related sciences	[0.03]	[0.01]	[3.14]	[0.02]	[0.02]	[0.01]	[1.86]	[0.01]
Master's in health-related fields	1.02	0.92	10.72	0.12	1.39	1.20	16.17	0.13
	[0.02]	[0.01]	[1.92]	[0.01]	[0.04]	[0.01]	[2.94]	[0.01]
Master's in other social and	1.02	0.90	13.43	0.14	1.27	1.24	3.06	0.07
related sciences	[0.02]	[0.01]	[2.30]	[0.01]	[0.03]	[0.01]	[2.33]	[0.02]
Master's in other non-science and	0.93	0.89	5.06	0.08	1.14	1.17	-2.49	0.03
engineering fields	[0.02]	[0.01]	[2.31]	[0.02]	[0.04]	[0.01]	[3.08]	[0.05†]
Master's in biological/agricultural/	0.95	0.91	4.10	0.08	1.06	1.17	-9.22	-0.03
environmental/life sciences	[0.01]	[0.01]	[1.56]	[0.01]	[0.02]	[0.01]	[1.79]	[0.05†]
Master's in education fields	0.93	0.84	10.20	0.13	1.08	1.14	-5.26	0.01
	[0.01]	[0.01]	[1.08]	[0.01]	[0.01]	[0.01]	[1.15]	[0.02]
Master's in psychology and	0.86	0.85	0.83	0.05	1.00	1.13	-11.41	-0.03
social work	[0.01]	[0.01]	[1.15]	[0.01]	[0.02]	[0.01]	[1.56]	[0.06†]
Master's in humanity fields	0.84	0.88	-4.39	0.01	0.88	1.16	-23.91	-0.40
	[0.02]	[0.01]	[2.23]	[0.19†]	[0.02]	[0.01]	[1.96]	[0.10†]
Master's in arts	0.78	0.84	-7.77	0.00	0.91	1.08	-15.51	-0.05
	[0.03]	[0.01]	[4.17]	[0.16†]	[0.04]	[0.03]	[3.84]	[0.12†]

Note: This table reports the same statistics as Table 7 using the OLS regression coefficients.

WEB APPENDIX

9 Additional Details on the Timing of the Earnings Observations and Degree Completion

This section provides additional details on the timing of earnings observations and degree completions in the data. Column 1 of Table A6 panel B reports the unweighted mean and the 10th, 25th, 50th, 75th, and 90th quantiles of the number of years from BA completion for earnings observations that precede graduate school enrollment for men. The 10th, 50th, and 90th quantiles are 1 (the minimum), 5, and 12. More than 90% of pre-graduate school earnings observations occur between 1 and 5 years before completion of the advanced degree (column 2). Column 3 reports that the 10th, 50th, and 90th quantiles of time from advanced degree completion to post advanced degree earnings observations, which are 2, 11, and 26.[42] Thus, we have good coverage of the post graduate degree period. Finally, column 4 presents time from BA to advanced degree completion for those who obtained a graduate degree. This column does not condition on the availability of a pre-graduate degree earnings observation. The 10th, median and 90th quantiles are 2, 5, and 12. The values for women in panel C are very similar, except that the distribution of time since advanced degree is higher for men by 2.4 years on average (column 3).

Appendix Table A7 panels B and C present the unweighted age distribution of the earnings observations for men and for women. The first column refers to the full sample. For men, the 10th, 50th and 90th quantiles are 27, 39, and 54 (panel B). The 10th, median and 90th quantiles of the age distribution of the 5,450 pre-graduate degree observations of men with a graduate degree by the last interview are 24, 28, and 37 (column 3). The mean is 29.4. These individuals are younger and have a more condensed distribution than those who only have a BA when last observed (column 2). The fourth column reports the age distribution of the post advanced degree earnings observations. The 10th, 50th, and 90th percentiles are 28, 40, and 54. The values for women are similar, although they are about two years younger.

10 Additional Results by Graduate Degree

MA in Health Services Administration, and Public Administration

We next consider two other management and administration related degrees. In the case of health services administration, the FEcg and OLS estimates of γ_g for a master's in health administration are similar and large: 0.283 (0.088) and 0.304 (0.027). For men, the FEcg estimate is 0.232 (0.112) while the OLS value is 0.283 (0.042), which is close to the value for women. When we allow the returns to vary with experience, the returns grow over the first 15 years before leveling out (see Figure A2 (g)-(j)).

For women, the FEcg estimates of the wage and hours effects indicate that wages account for almost the entire increase in earnings. The OLS estimates suggest that the wage effect is about 5.5 times as large as the hours effect. Overall, the evidence suggests hours plays only a modest role in the earnings effect. Occupational changes play a larger role, with the occupational premium accounting for around 25 percent of the log earnings gain for women and 40% for men in the FEcg specification, with slightly higher estimates for OLS.

[42] Column 5 shows that the number of post-advanced degree earnings observations for individuals with both pre and post advanced degree observations is only 5,310 for men and 4,040 for women. This is a key reason why we do not present FE estimates.

Next, we consider public administration. For women, the FEcg and OLS estimates of γ_g for public administration are 0.176 (0.060) and 0.242 (0.031). For men, the corresponding estimates are 0.218 (0.069) and 0.137 (0.027). Given sampling error, we view the results for public administration and health services administration to be broadly similar, though the point estimates for health services administration are somewhat larger. The occupation returns are also similar, with the exception that the FEcg occupational premium for women is -0.001 (0.055). Both the FEcg and OLS estimates of the effects of public administration on the wage rate are close to the estimates of the effect on earnings, with little of the effect coming from changes in hours.[43]

Biology/Agriculture/Environmental Sciences and Physical Sciences

For women, the FEcg and OLS estimates of γ_g for master's degrees in biology, agricultural, environmental and life sciences are 0.198 (.068) and 0.074 (0.014). The gap between the FEcg and OLS estimates is even larger for γ_{x1-28}: 0.276 (0.068) versus 0.121 (0.016). These differences are even larger for men, where the FEcg and OLS estimates of γ_g are 0.274 (0.064) and -0.049 (0.017), and the estimates of γ_{x1-28} are 0.348 (0.065) and -0.021 (0.018). Almost all of the return is coming from increased wage rates, with small and largely statistically insignificant estimates on log hour and log occupational premium for both women and men.

The physical sciences also have a large gap between the FEcg and OLS estimates, especially for men. The FEcg and OLS estimates are 0.156 (0.071) and 0.118 (0.025) for women, and 0.268 (0.062) and 0.049 (0.017) for men. The γ_{g1-28} estimates are 0.03 to 0.09 larger and, as shown in Figure A2 (e) and (f), the returns are initially small, but grow rapidly with the first 14 years of experience, and then level off. For both the biology, agricultural, and environmental life sciences degree and the physical sciences degree, there are only small and largely statistically insignificant effects on both log hours and on occupational premiums.

Other Business Related Fields

The business-related master's degree category consists of financial management (54.1%), business marketing and business management (19.0%) and accounting (18.5%), with smaller shares for agricultural economics, marketing research, other agricultural business and production, and actuarial science (not reported).[44] Similar to the results for MBAs, we find that OLS estimates are systematically higher than the FEcg estimates. We also find that the estimates for other business related fields are somewhat larger than those for MBAs.

The return to a business-related master's degree are reported in Row 3 of Table 2. For women, the FEcg and OLS estimates are 0.273 (0.066) and 0.371 (0.022), and for men they are 0.210 (0.051) and 0.335 (0.013), which are 0.06 to 0.10 larger than the values for an MBA. For both women and men, the FEcg estimates of γ_{gx} rise steadily over the first 20 years after graduate school and then level off. The OLS estimates follow the same pattern (Figures A2 (k) and A2 (l)). The FEcg estimates of γ_g^{occ} suggest that only a small part of the return operates through the occupational premium. As is the case with an MBA, the OLS estimates of γ_g^{occ} are much higher, especially for women (0.138 (0.008)). For women, the FEcg estimates of the occupational premium rise from 0.005 (0.025) to 0.073 (0.050) after 28 years of post graduate school experience. The OLS

[43] For men the OLS estimate of the wage effect is 0.146 (0.023), slightly above the earnings effect estimate. The FEcg estimate of the wage effect is 0.313 (0.083), which is well above the earnings effect (0.218). Given that the hours effect estimates are near 0, we attribute the difference to sampling error, and again point out that the earnings estimates make use of data on both current earnings and annual earnings for the prior year, while observations for the prior year are not available for the other outcomes.

[44] See Online Appendix Tables A1 and A3 for the breakdown by gender.

estimates follow the same pattern, but the base is elevated by about 0.12. The profiles of γ_{gx}^{occ} for men are similar.

Other Science/Engineering Related Fields

We also present estimates for the "Other Science/Engineering Related Fields" category. It is dominated by architecture and environmental design (70.5%), though it also contains electrical and electronic technologies, engineering technologies, and industrial production technologies. For women, the FEcg estimate ofγ_g is only 0.051 (0.092) but is very noisy. The estimate of γ_{g1-28} is 0.131 (0.094). The corresponding FEcg estimates for men are near zero, with the standard error of about 0.049. The OLS estimate of γ_g is 0.137 (0.038) for women and 0.077 (0.021) for men. When we allow returns to vary with experience, we find relatively steep slopes for both men and women, with initial returns near zero for women and negative for men. Overall, the estimated return to other science and engineering related fields is modest. It ranks below high earnings degrees, such as law, business, or medicine, as well as degrees in the middle of the earnings distribution, such as public administration, social science, or education.

Not Science or Engineering Related

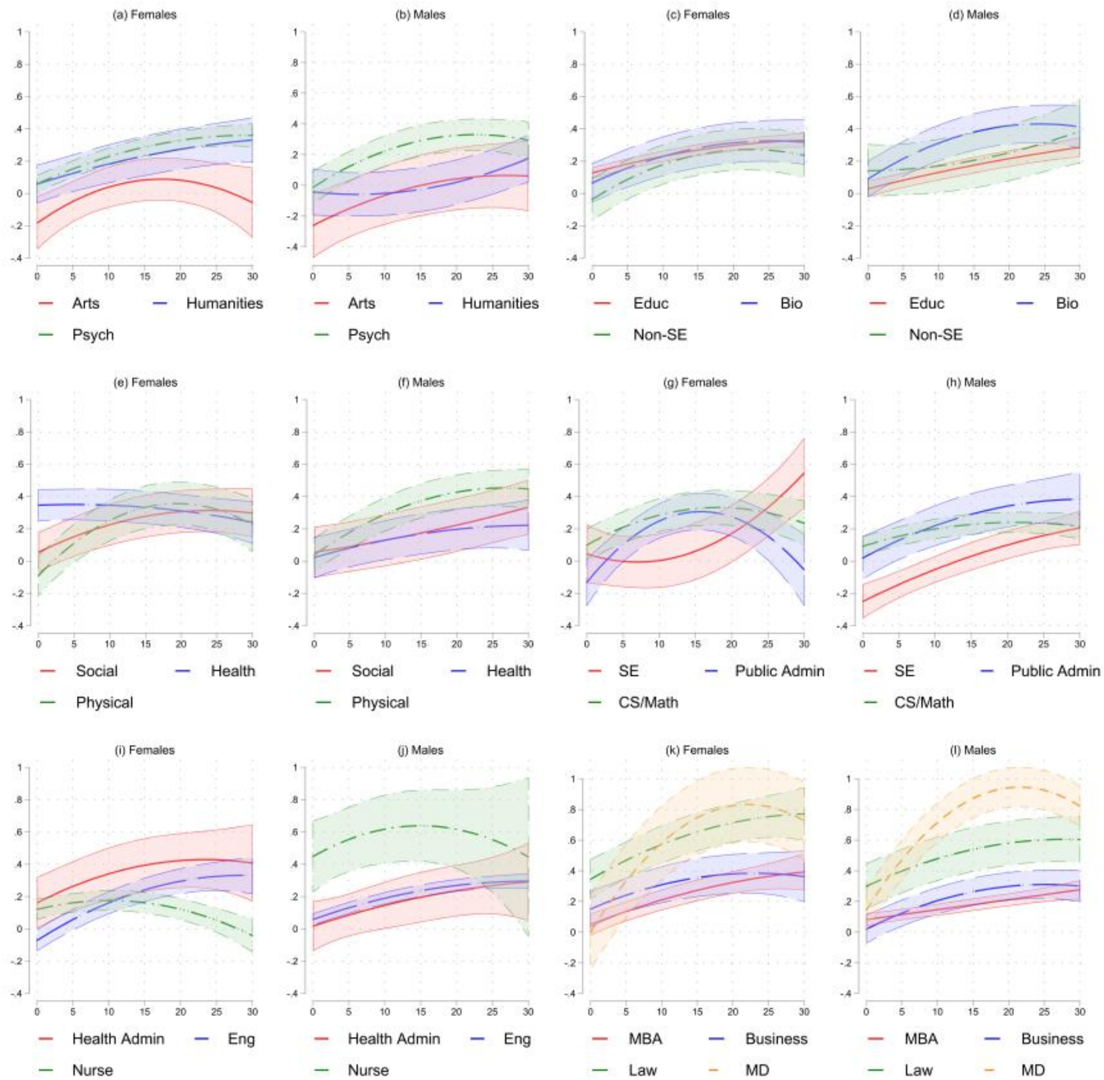
The "Not science or engineering related" group consists of communications (12.0%), library science (36.5%), criminal justice/protective services (16.5%), and journalism (9.4%). The results are qualitatively similar to the results for psychology and social work. The FEcg estimate is well above the OLS estimate, especially for men, though the standard errors on the FEcg estimate are large for this degree, especially for men.

Social Sciences

The FEcg estimate for a social science master's (excluding psychology) is 0.168 (0.071) for women and 0.135 (0.091) for men. The corresponding OLS estimates are 0.161 (0.015) and 0.084 (0.019) respectively. The γ_{g1-28} estimates are similar though somewhat larger for both men and women. The estimates of γ_{gx} increase with years since graduate school from a low base, with the convex shape for men and a concave shape for women. The FEcg estimates suggest that occupation contributes about 0.05 to the earnings effect, although the estimates are noisy.

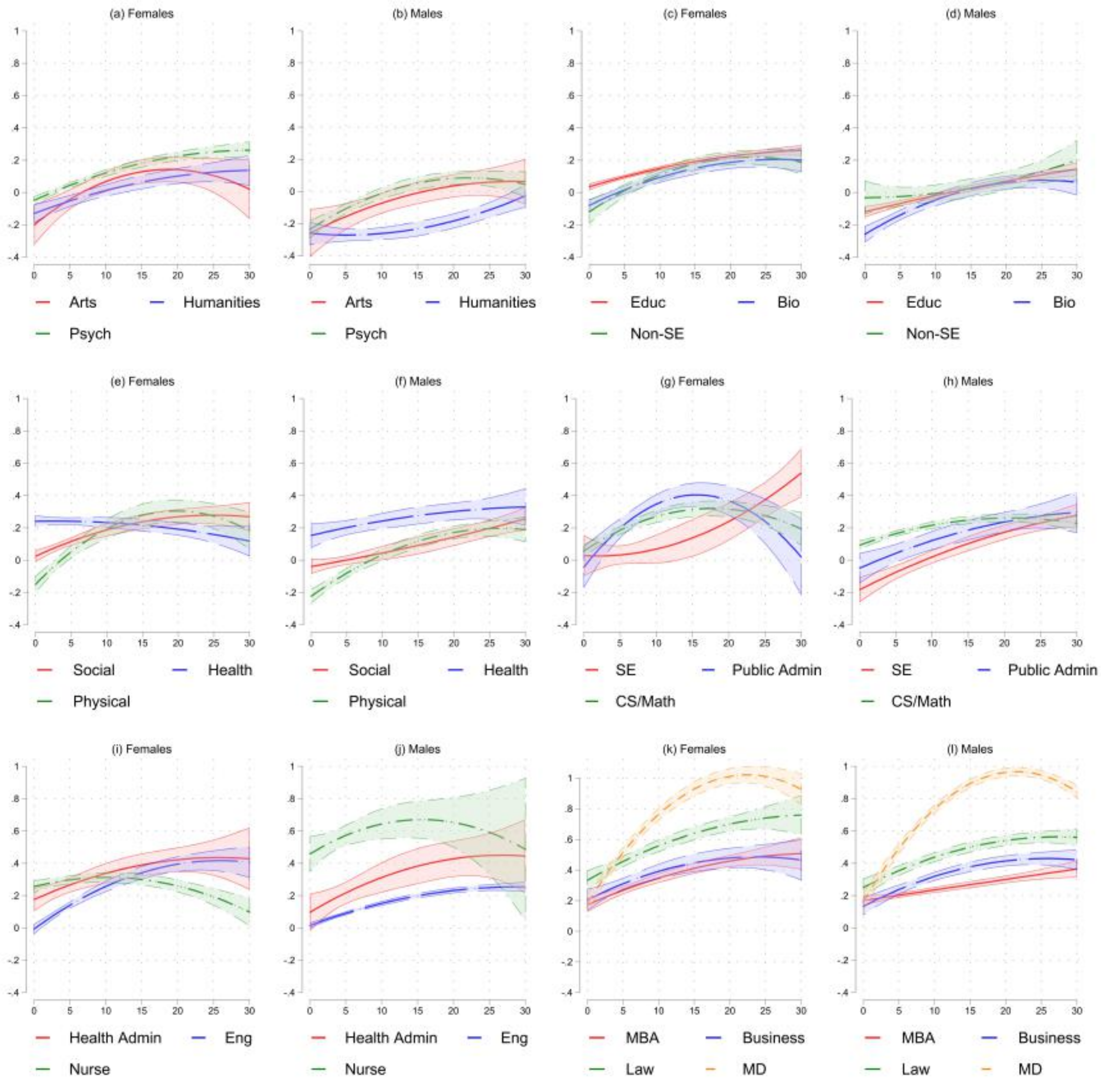
11 Additional Figures

Figure A1: FEcg Estimates of experience-specific returns to log earnings for graduates degrees.



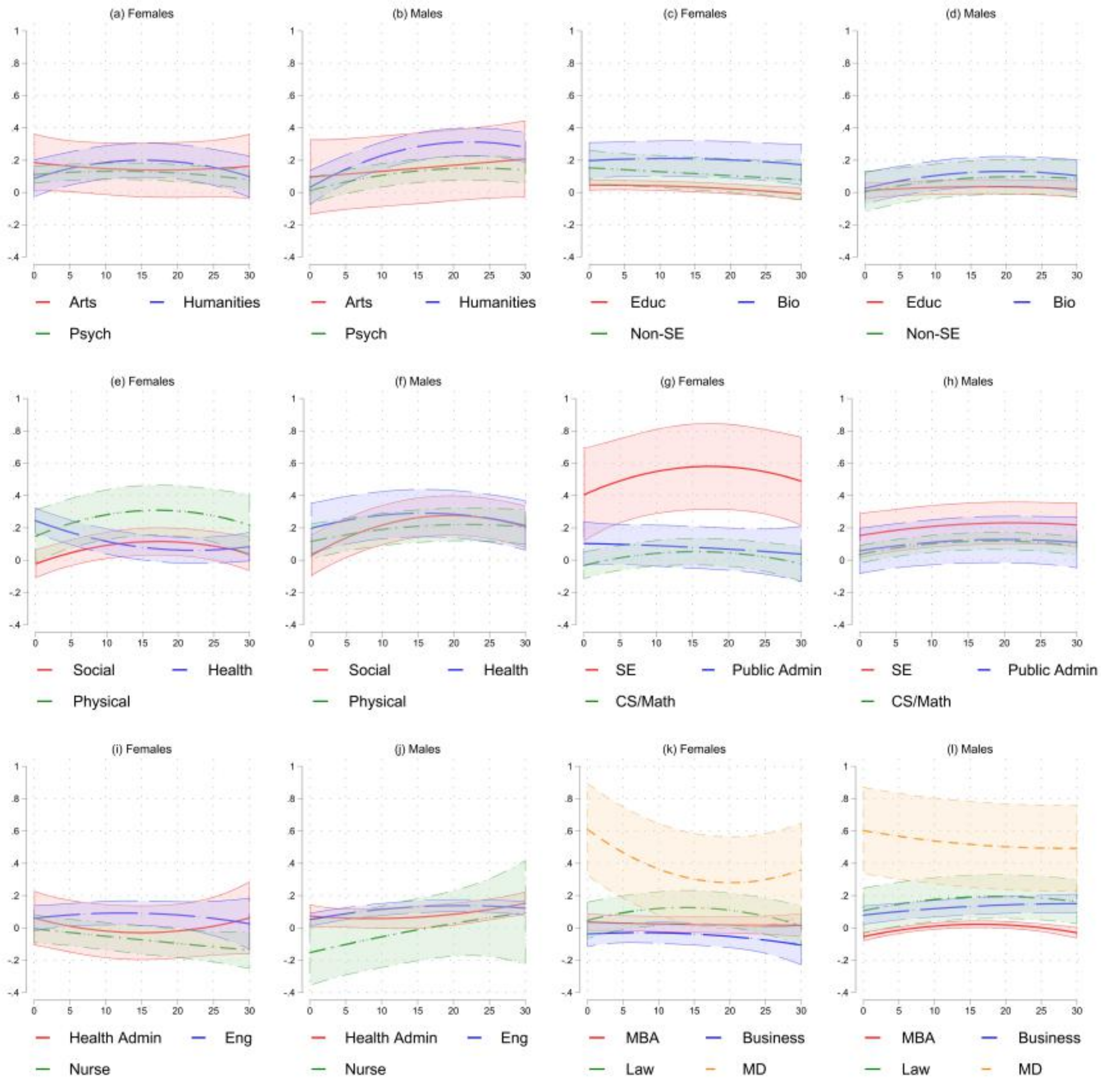
Notes: The figure reports the experience-specific FEcg returns to log earnings for each graduate degree for males and females. Sample weights are used. Standard errors are clustered by person. The regressions include dummies for each BA field (OLS only) and each advanced degree, as well as race/Hispanic, parental education, the year, a cubic in age, and interactions between a cubic in age and BA field. Estimates are based on equation (4). Each sub-panel shows estimates for three to four graduate degrees for either men or women. The confidence bands show 90 percent confidence intervals.

Figure A2: OLS Estimates of experience-specific returns to log earnings for graduates degrees.



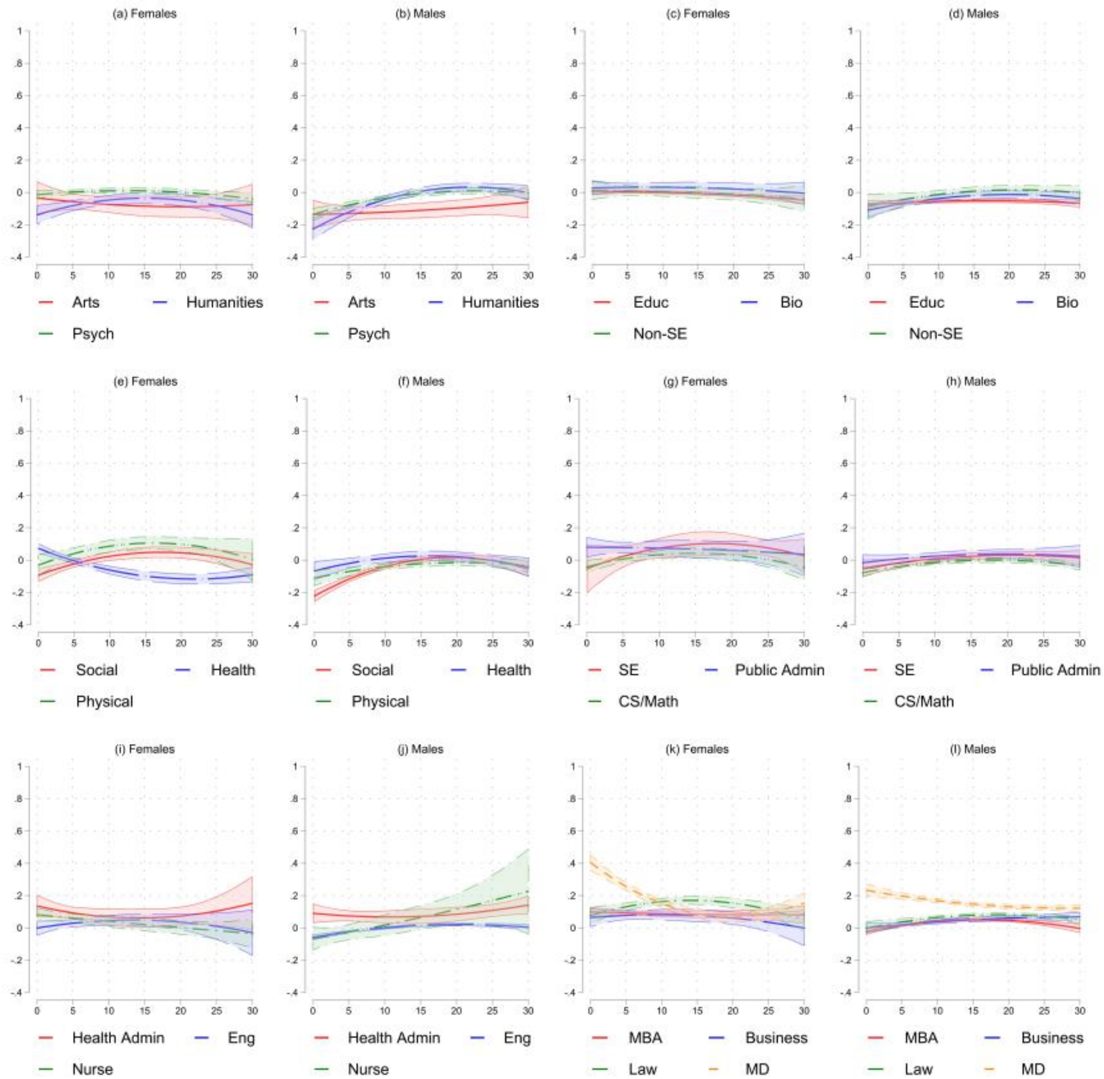
Notes: The figure reports the experience-specific OLS returns to log earnings for each graduate degree for males and females. Sample weights are used. Standard errors are clustered by person. The regressions include dummies for each BA field (OLS only) and each advanced degree, as well as race/Hispanic, parental education, the year, a cubic in age, and interactions between a cubic in age and BA field. . Estimates are based on equation (4) with degree combination fixed effects excluded. Each sub-panel shows estimates for three to four graduate degrees for either men or women. The confidence bands show 90 percent confidence intervals.

Figure A3: FEcg Estimates of experience-specific returns to log hours for graduates degrees.



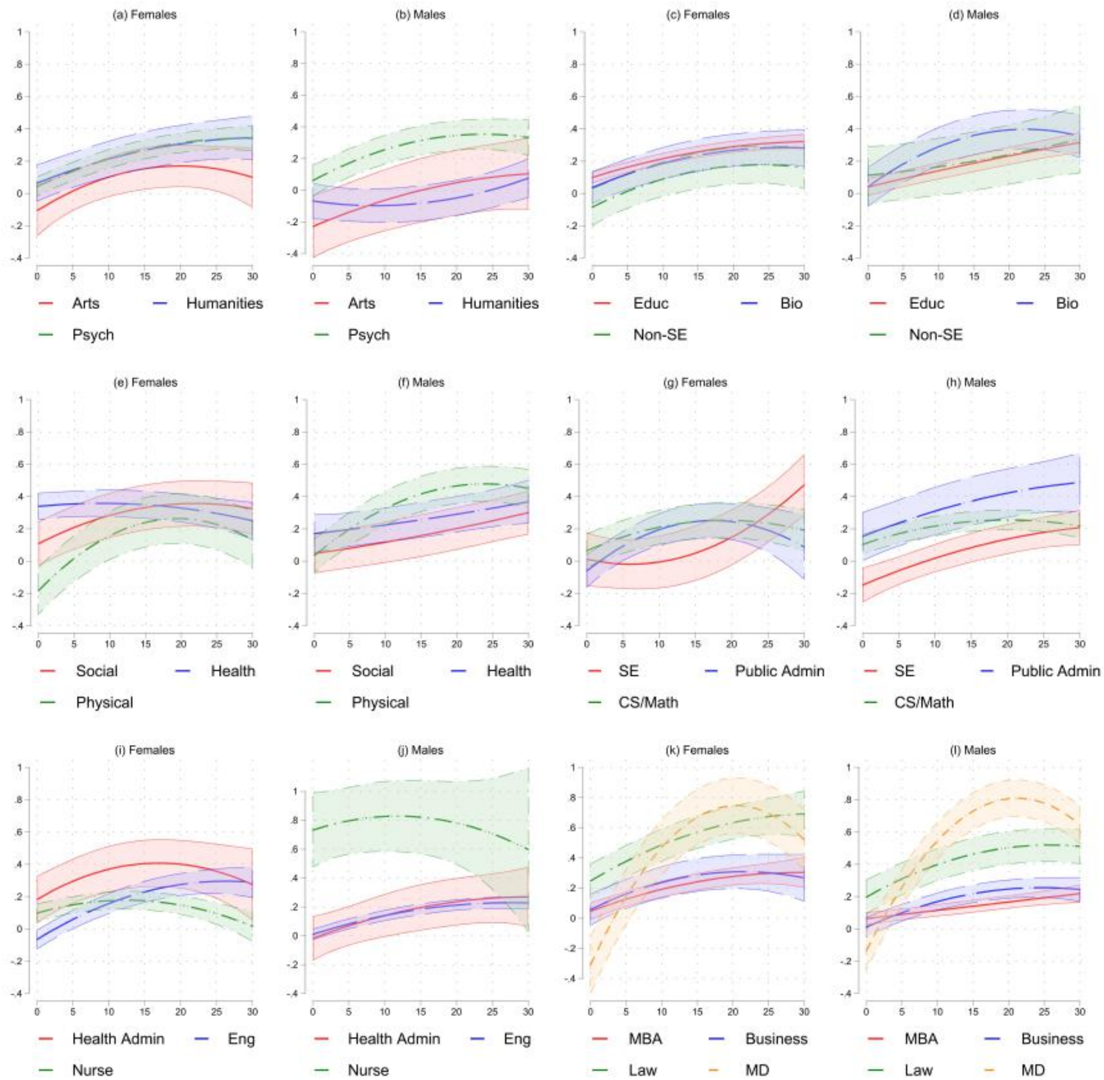
Notes: The figure reports the experience-specific FEcg returns to log hour for each graduate degree for males and females. Sample weights are used. Standard errors are clustered by person. The regressions include dummies for each BA field (OLS only) and each advanced degree, as well as race/Hispanic, parental education, the year, a cubic in age, and interactions between a cubic in age and BA field. Estimates are based on equation (4) with degree combination fixed effects excluded. Each sub-panel shows estimates for three to four graduate degrees for either men or women. The confidence bands show 90 percent confidence intervals.

Figure A4: OLS Estimates of experience-specific returns to log hours for graduates degrees.



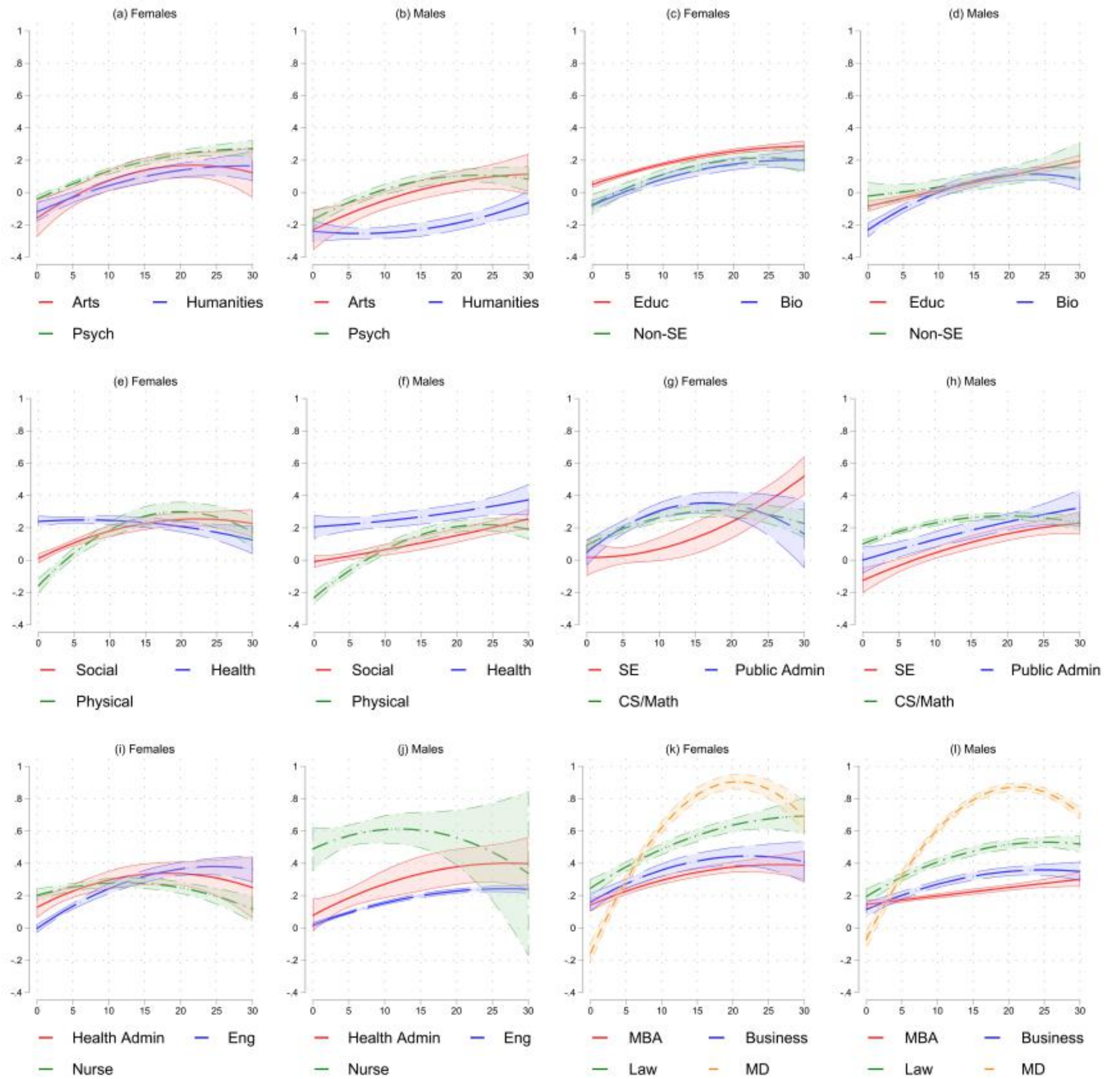
Notes: The figure reports the experience-specific OLS returns to log hour for each graduate degree for males and females. Sample weights are used. Standard errors are clustered by person. The regressions include dummies for each BA field (OLS only) and each advanced degree, as well as race/Hispanic, parental education, the year, a cubic in age, and interactions between a cubic in age and BA field. Estimates are based on equation (4) with degree combination fixed effects excluded. Each sub-panel shows estimates for three to four graduate degrees for either men or women. The confidence bands show 90 percent confidence intervals.

Figure A5: FEcg Estimates of experience-specific returns to hourly wage for graduates degrees.



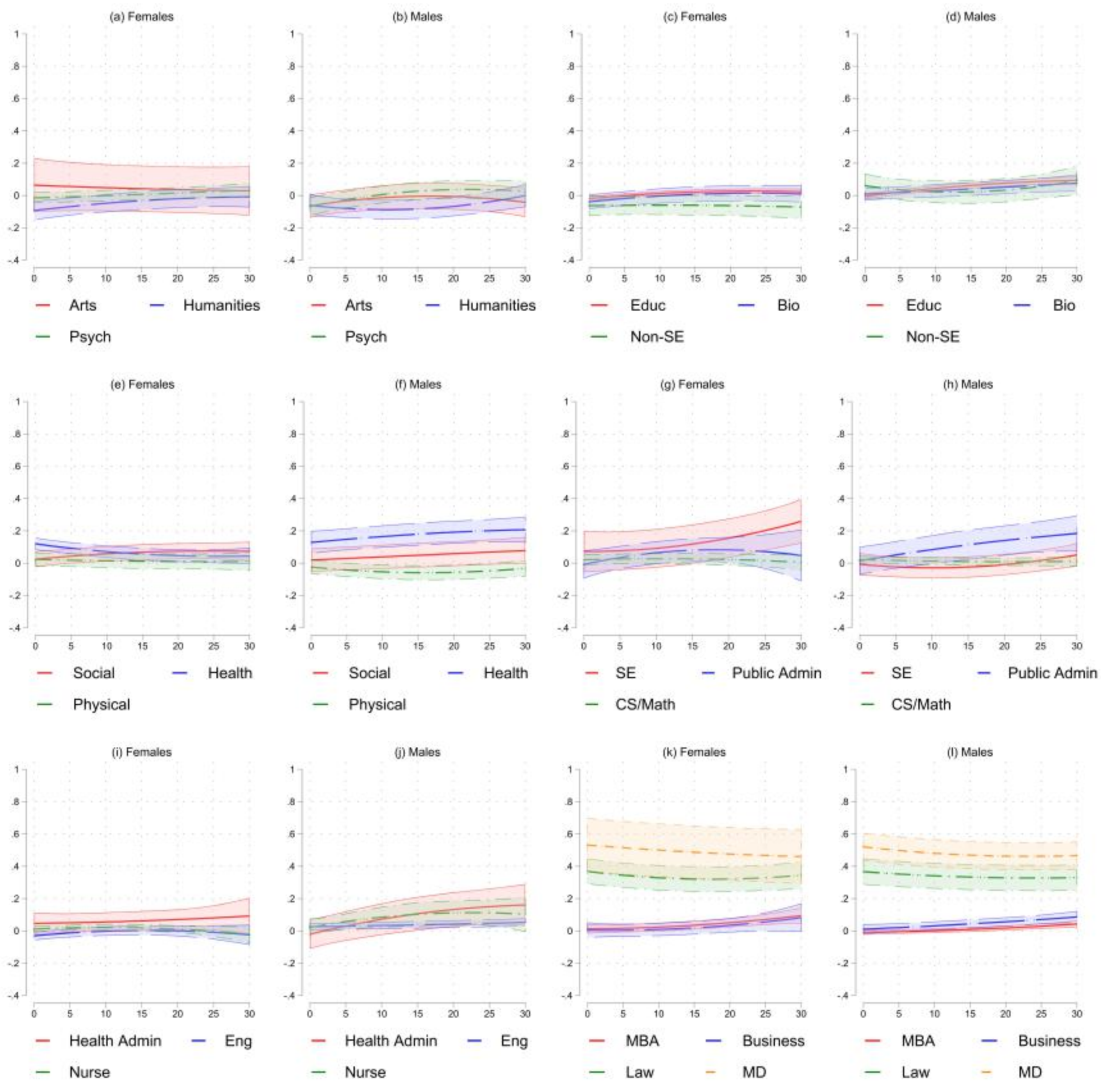
Notes: The figure reports the experience-specific FEcg returns to log hourly wage for each graduate degree for males and females. Sample weights are used. Standard errors are clustered by person. The regressions include dummies for each BA field (OLS only) and each advanced degree, as well as race/Hispanic, parental education, the year, a cubic in age, and interactions between a cubic in age and BA field. Estimates are based on equation (4). Each sub-panel shows estimates for three to four graduate degrees for either men or women. The confidence bands show 90 percent confidence intervals.

Figure A6: OLS Estimates of experience-specific returns to log hourly wage for graduates degrees.



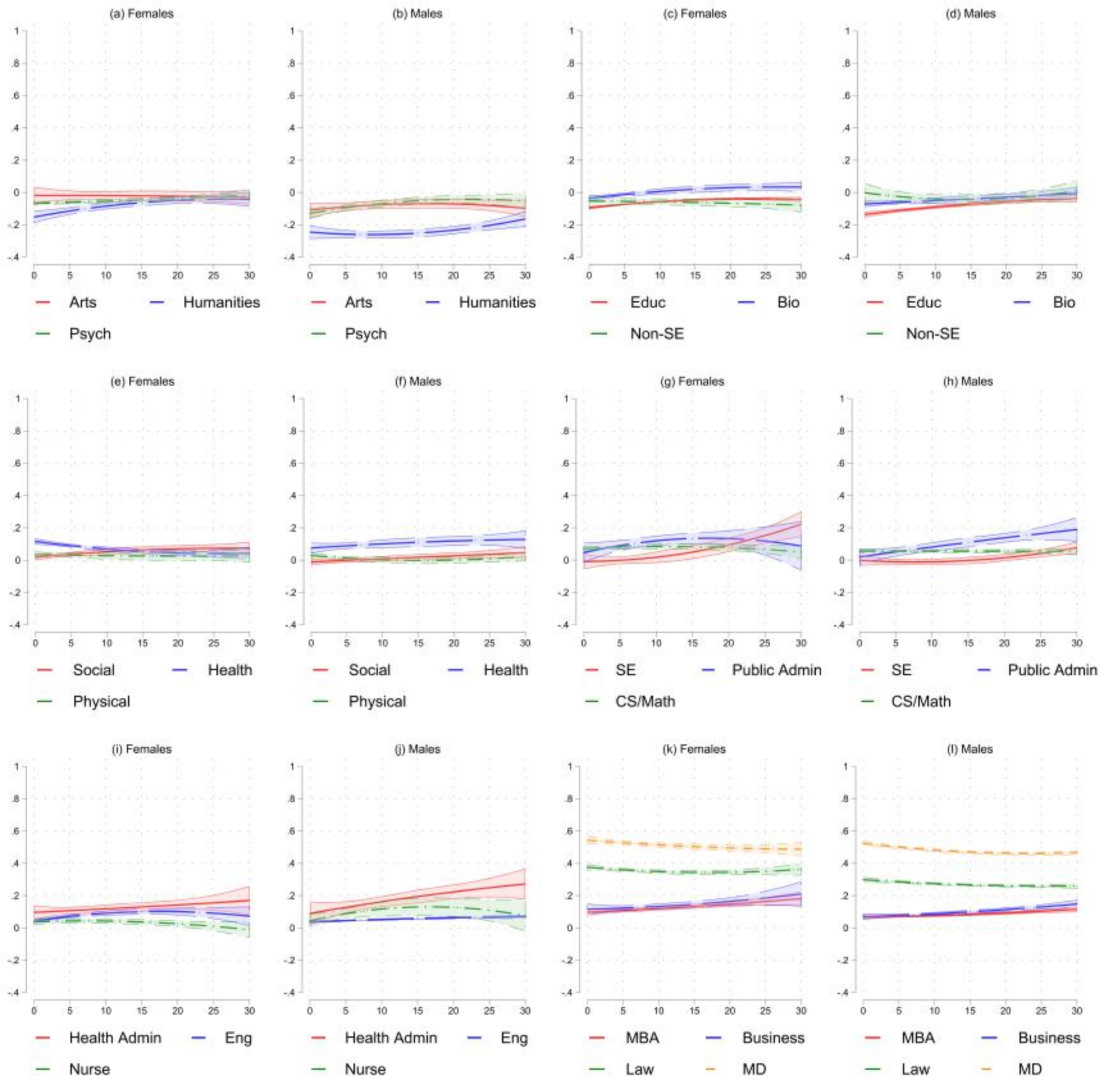
Notes: The figure reports the experience-specific OLS returns to log hourly wage for each graduate degree for males and females. Sample weights are used. Standard errors are clustered by person. The regressions include dummies for each BA field (OLS only) and each advanced degree, as well as race/Hispanic, parental education, the year, a cubic in age, and interactions between a cubic in age and BA field. Estimates are based on equation (4) with degree combination fixed effects excluded. Each sub-panel shows estimates for three to four graduate degrees for either men or women. The confidence bands show 90 percent confidence intervals.

Figure A7: FEcg Estimates of experience-specific returns to occupation premium for graduates degrees.



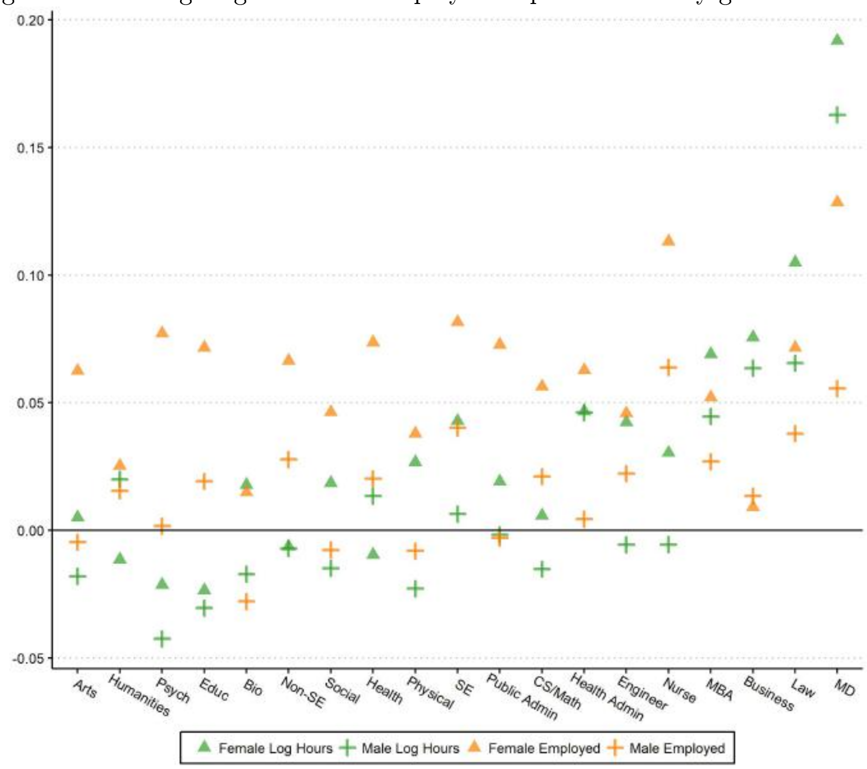
Notes: The figure reports the experience-specific FEcg returns to occupation premium for each graduate degree for males and females. Sample weights are used. Standard errors are clustered by person. The regressions include dummies for each BA field (OLS only) and each advanced degree, as well as race/Hispanic, parental education, the year, a cubic in age, and interactions between a cubic in age and BA field. Estimates are based on equation (4). Each sub-panel shows estimates for three to four graduate degrees for either men or women. The confidence bands show 90 percent confidence intervals.

Figure A8: OLS Estimates of experience-specific returns to occupation premium for graduates degrees.



The figure reports the experience-specific OLS returns to occupation premium for each graduate degree for males and females. Sample weights are used. Standard errors are clustered by person. The regressions include dummies for each BA field (OLS only) and each advanced degree, as well as race/Hispanic, parental education, the year, a cubic in age, and interactions between a cubic in age and BA field. Estimates are based on equation (4) with degree combination fixed effects excluded. Each sub-panel shows estimates for three to four graduate degrees for either men or women. The confidence bands show 90 percent confidence intervals.

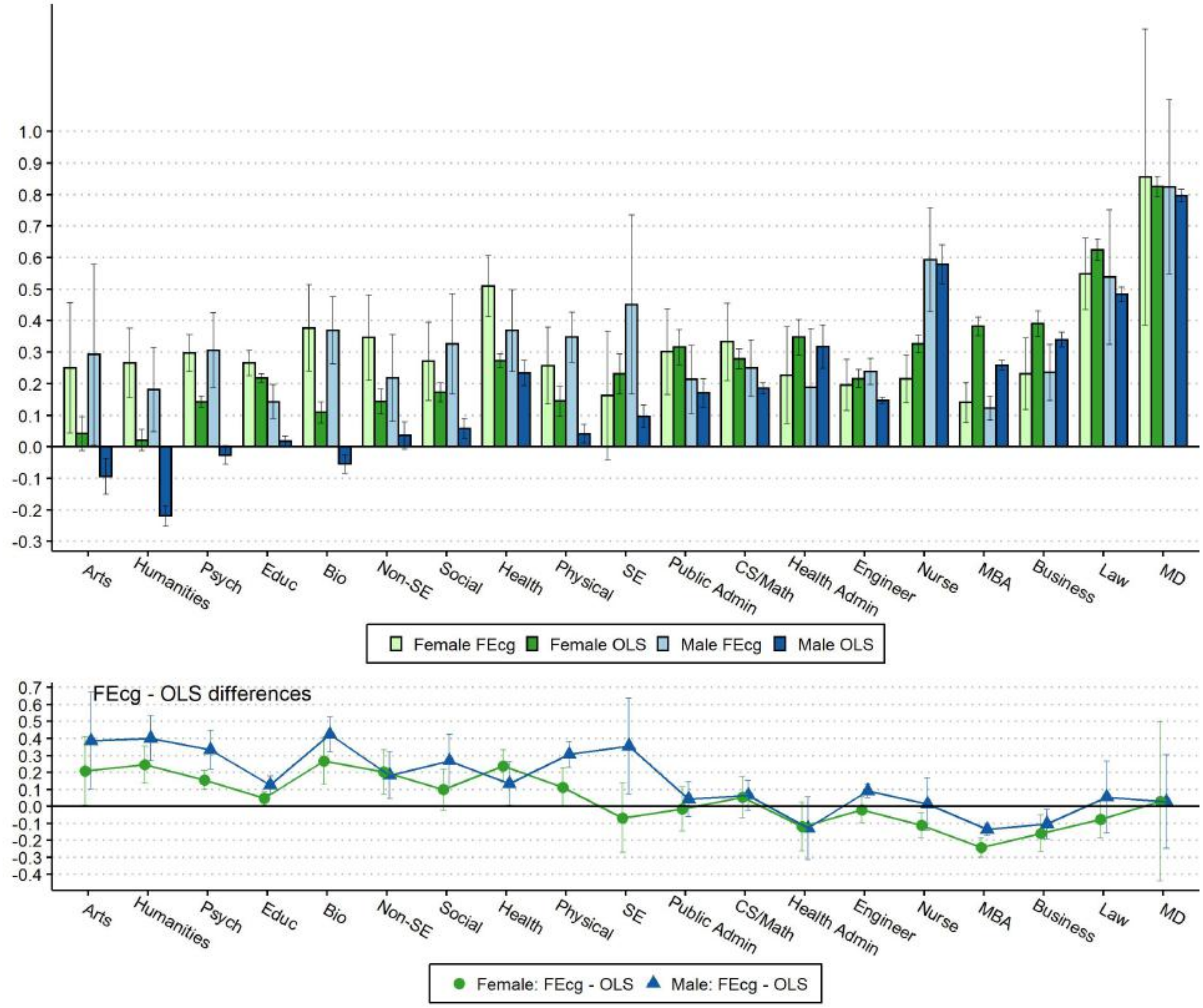
Figure A9: Average log hours and employment probabilities by graduate field



Notes: The figure shows the average difference in various outcomes between graduate degree holders and college graduates for 19 different graduate degrees. The orange triangles and crosses show the average difference in employment for females and males. The green triangles and crosses show the average difference in log hours worked for full-time females and males.

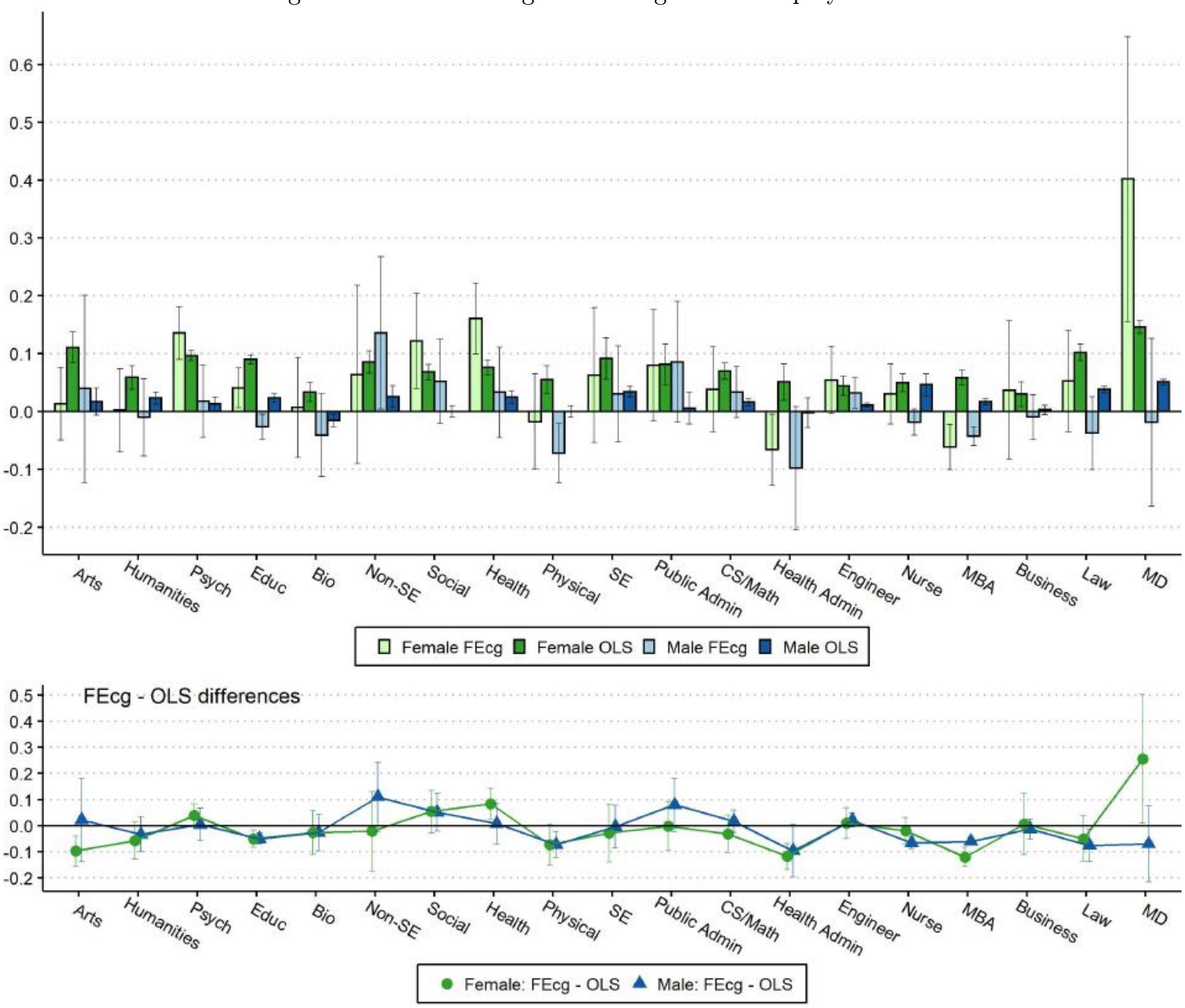
A10

Figure A10: The effects of graduate degrees on log earnings, all workers



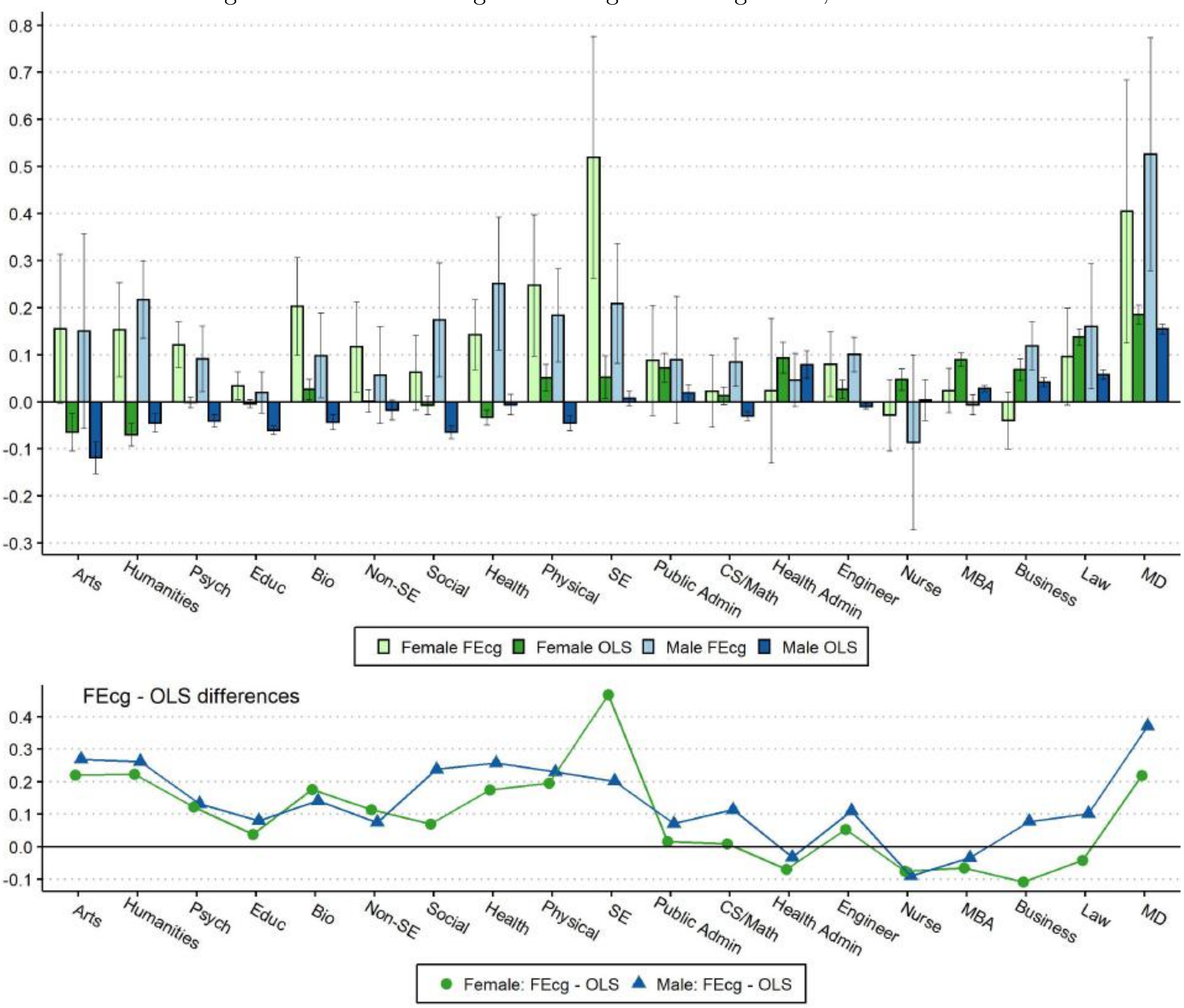
Notes: The figure shows OLS and FEcg estimates of the effects of 19 graduate degrees on log earnings, not restricted to full-time workers. The top panel shows the point estimates with light green showing FEcg estimates for females, green showing OLS estimates for females, light blue showing FEcg estimates for males, and blue showing OLS estimates for males. The bottom panel shows the difference between the FEcg and OLS estimates for females (green) and males (blue). Error bars show 90 percent confidence intervals. The regressions include dummies for BA field and each advanced degree, race, Hispanic origin, parental education, calendar year, a cubic in age, and an interaction between a cubic in age and BA field.

Figure A11: Effects of graduate degrees on Employment



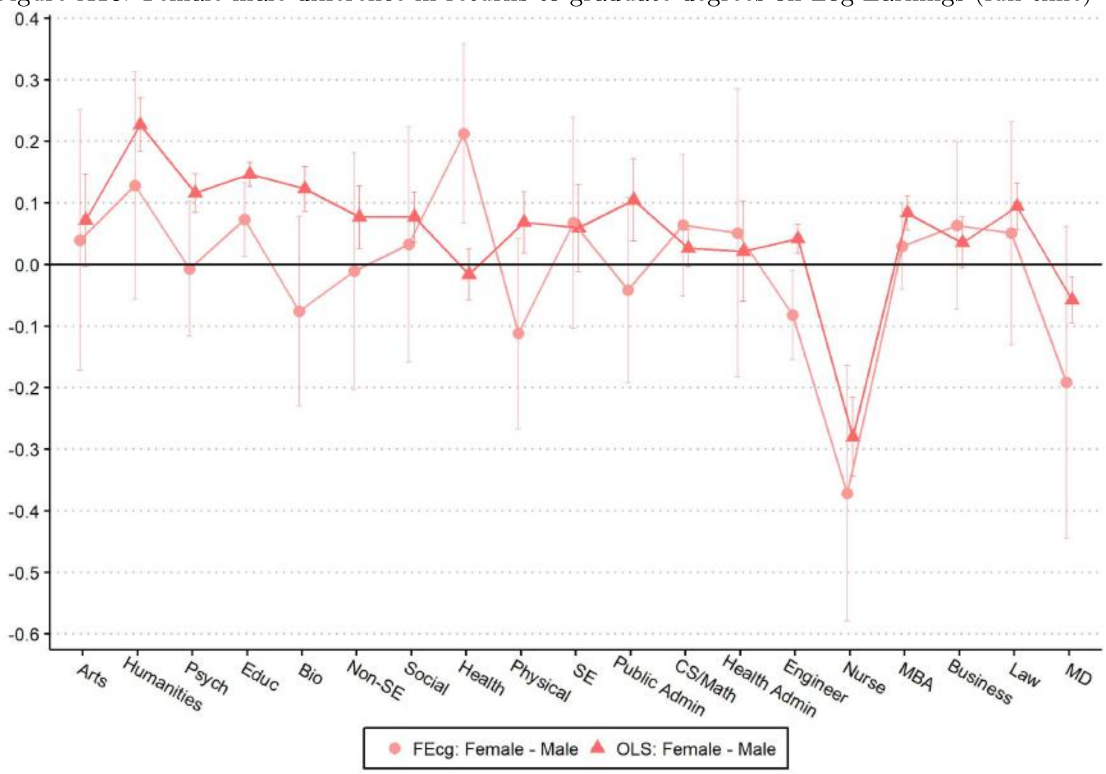
Notes: The figure shows OLS and FEcg estimates of the effects of 19 graduate degrees on employment. The top panel shows the point estimates with light green showing FEcg estimates for females, green showing OLS estimates for females, light blue showing FEcg estimates for males, and blue showing OLS estimates for males. The bottom panel shows the difference between the FEcg and OLS estimates for females (green) and males (blue). Sample weights are used. Error bars show 90 percent confidence intervals. The regressions include dummies for BA field and each advanced degree, race, Hispanic origin, parental education, calendar year, a cubic in age, and an interaction between a cubic in age and BA field.

Figure A12: Returns to graduate degrees on Log Hours, all workers



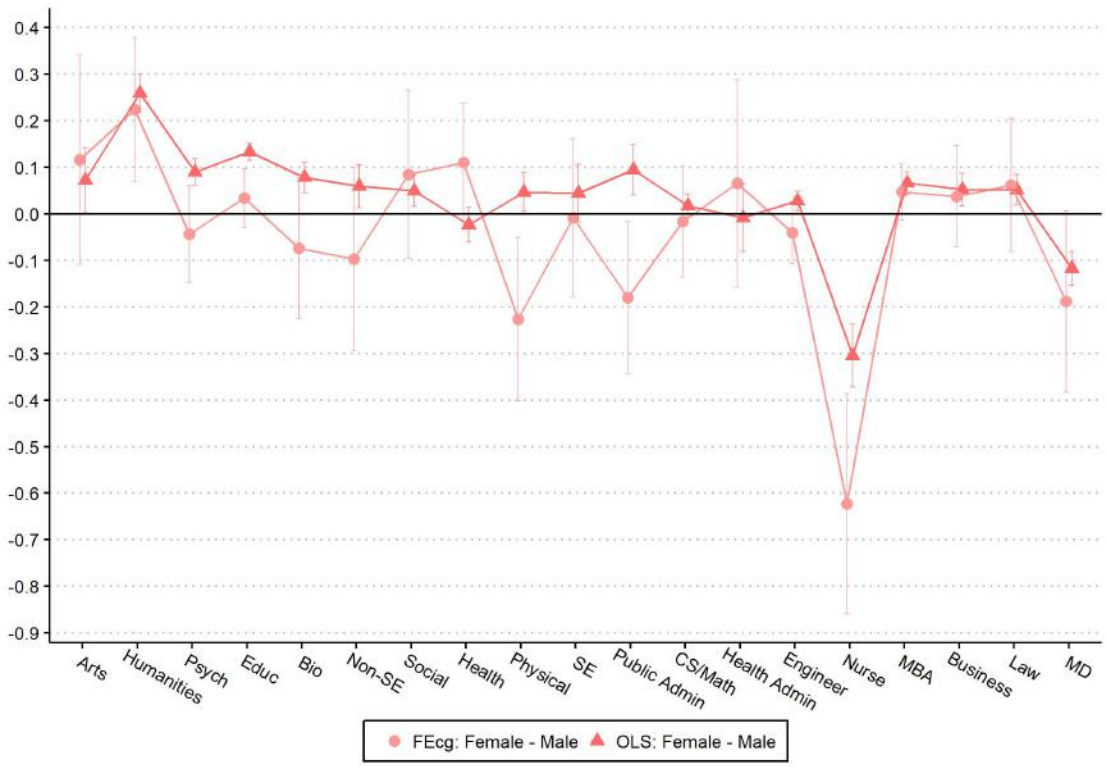
Notes: The figure shows OLS and FEcg estimates of the 19 graduate degrees for log hours worked, not restricted to full-time workers. The top panel shows the point estimates with light green showing FEcg estimates for females, green showing OLS estimates for females, light blue showing FEcg estimates for males, and blue showing OLS estimates for males. The bottom panel shows the difference between the FEcg and OLS estimates for females (green) and males (blue). Error bars show 90 percent confidence intervals. Sample weights are used. The regressions include dummies for BA field and each advanced degree, race, Hispanic origin, parental education, calendar year, a cubic in age, and an interaction between a cubic in age and BA field.

Figure A13: Female-male difference in returns to graduate degrees on Log Earnings (full-time)



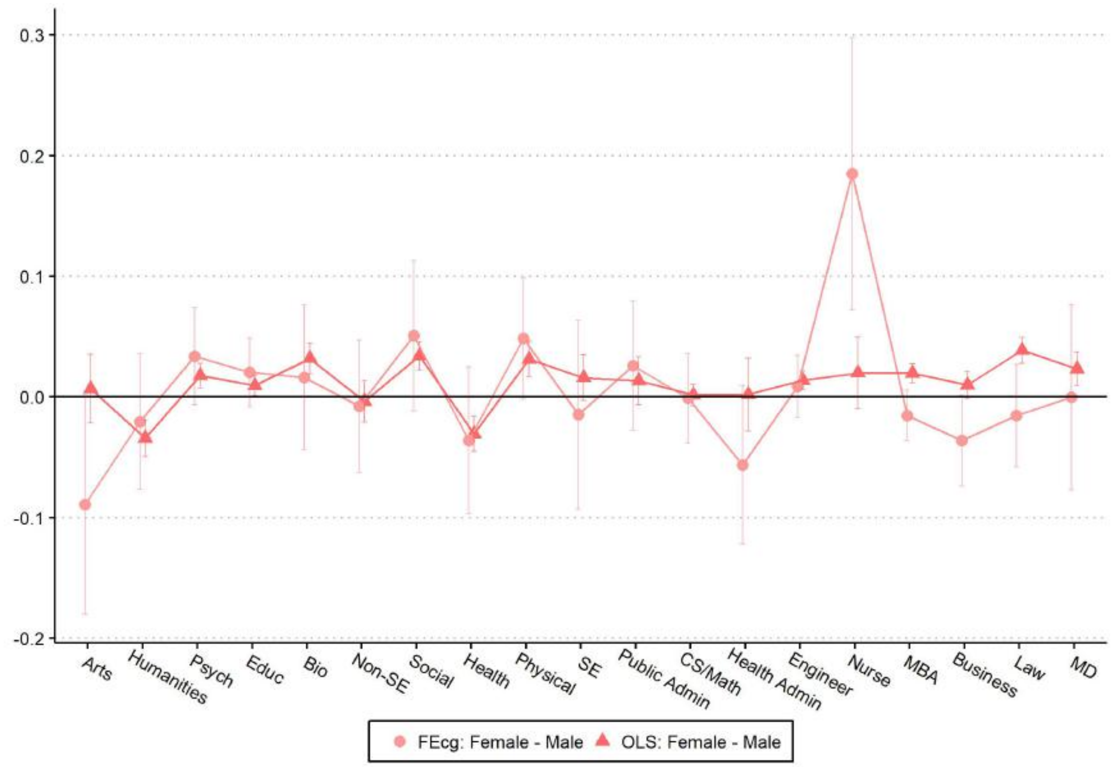
Notes: The figure shows the female-male difference in OLS and FEcg estimates of the 19 graduate degrees for log earnings of full-time workers. The light red lines with circles show the difference in the FEcg estimates and the red lines with triangles show the difference in the OLS estimates. Error bars show 90 percent confidence intervals. Sample weights are used. The regressions include dummies for BA field and each advanced degree, race, Hispanic origin, parental education, calendar year, a cubic in age, and an interaction between a cubic in age and BA field.

Figure A14: Female-male difference in returns to graduate degrees on Log Hourly Wage (full-time)



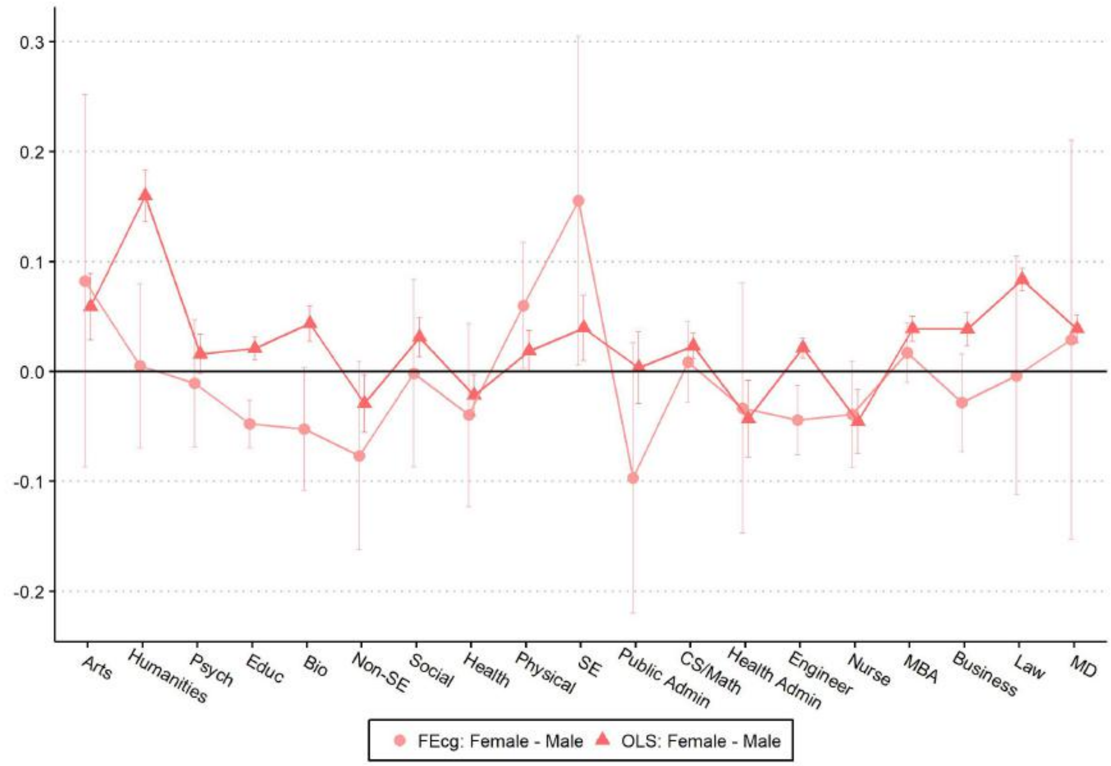
Notes: The figure shows the female-male difference in OLS and FEcg estimates of the 19 graduate degrees for log hourly wage. The light red lines with circles show the difference in the FEcg estimates and the red lines with triangles show the difference in the OLS estimates. Error bars show 90 percent confidence intervals. Sample weights are used. The regressions include dummies for BA field and each advanced degree, race, Hispanic origin, parental education, calendar year, a cubic in age, and an interaction between a cubic in age and BA field.

Figure A15: Female-male difference in returns to graduate degrees on Log Hours (full-time)



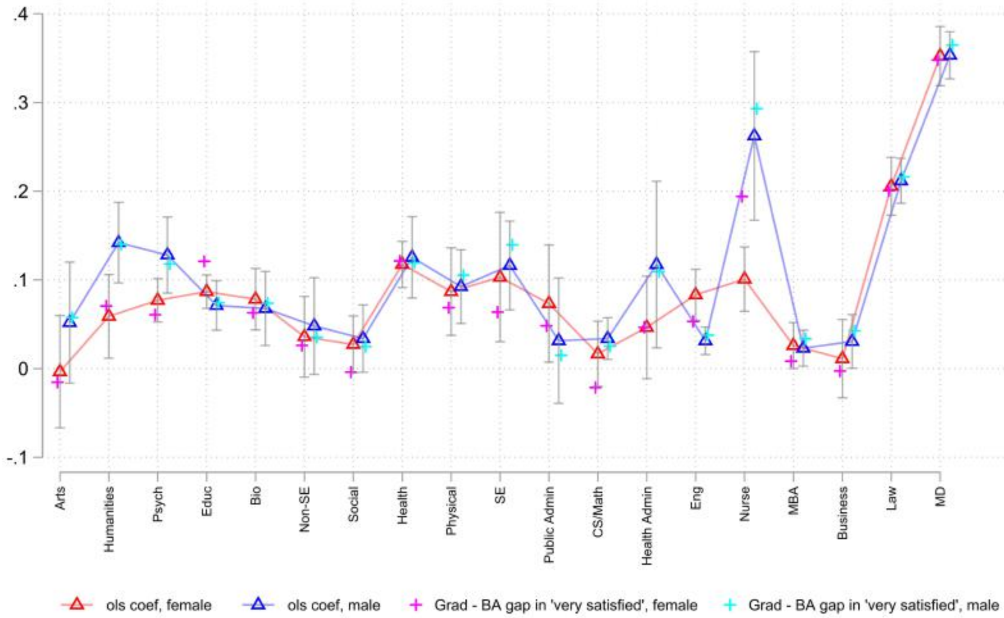
Notes: The figure shows the female-male difference in OLS and FEcg estimates of the 19 graduate degrees for log hours of full-time workers. The light red lines with circles show the difference in the FEcg estimates and the red lines with triangles show the difference in the OLS estimates. Error bars show 90 percent confidence intervals. Sample weights are used. The regressions include dummies for BA field and each advanced degree, race, Hispanic origin, parental education, calendar year, a cubic in age, and an interaction between a cubic in age and BA field.

Figure A16: Female-male difference in returns to graduate degrees on Log Occupation Premium

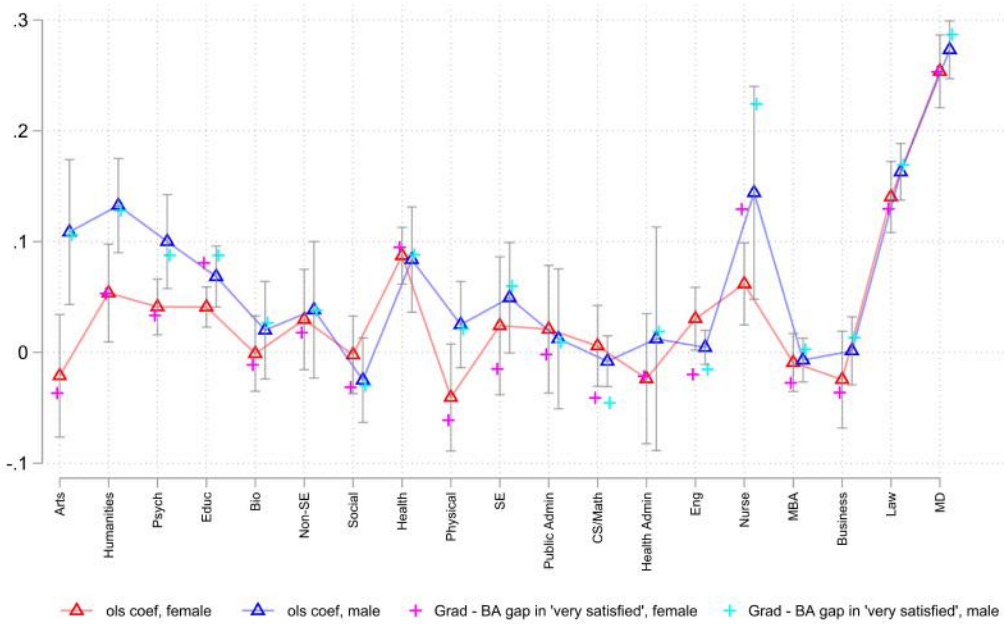


Notes: The figure shows the female-male difference in OLS and FEcg estimates of the 19 graduate degrees for log occupational premium. The light red lines with circles show the difference in the FEcg estimates and the red lines with triangles show the difference in the OLS estimates. Error bars show 90 percent confidence intervals. Sample weights are used. The regressions include dummies for BA field and each advanced degree, race, Hispanic origin, parental education, calendar year, a cubic in age, and an interaction between a cubic in age and BA field.

Figure A17: OLS estimates of effects of graduate degrees on job satisfaction.
(A) Dep. variable: "very satisfied" with intellectual challenge.

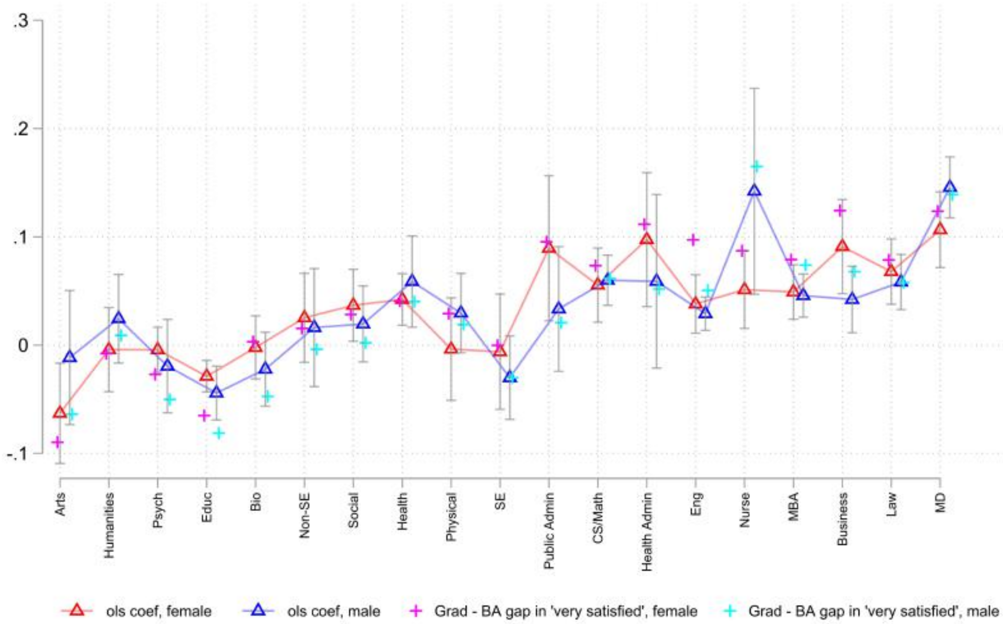


(B) Dep variable: "very satisfied" with responsibility.



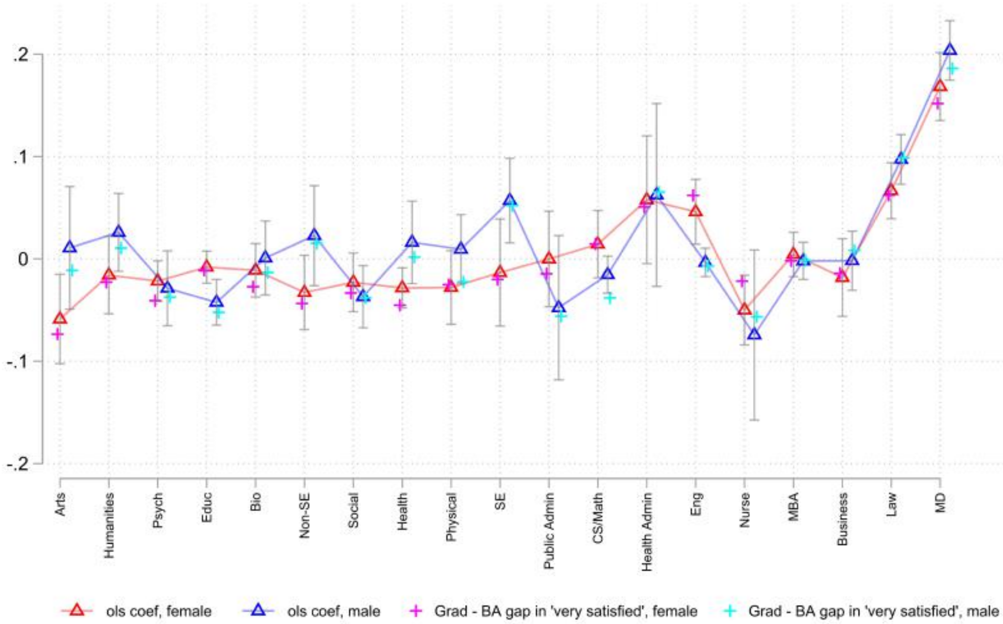
Notes: The figure reports estimates of the effect of completing advanced degrees on job satisfaction in terms of intellectual challenge (panel A) and responsibility (panel B) by graduate degree field. The dependent variable is an indicator for if the individual responded that they were "very satisfied". Sample weights are used. Standard errors are clustered by person. The red line and triangles report the OLS estimates for women and blue line with triangles report the OLS estimates for men. The pink crosses report the raw differences between the mean response of women with the particular graduate degree and women with only a BA. The light-blue crosses report the corresponding differences for men.

Figure A18: OLS estimates of effects of graduate degrees on job satisfaction. Dep variable: "very satisfied" with salary.

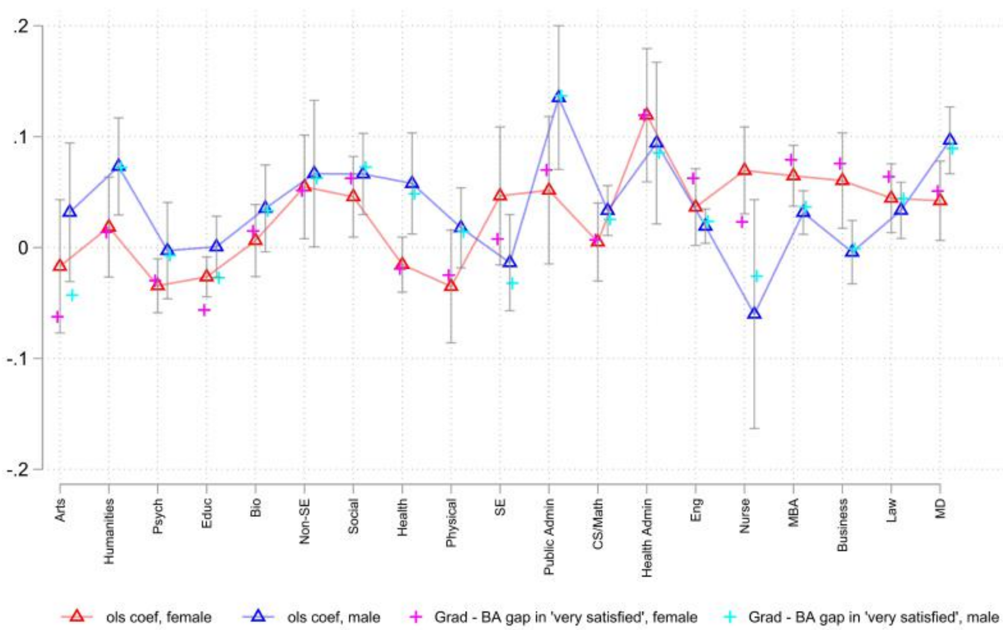


Notes: The figure reports estimates of the effect of completing advanced degrees on job satisfaction in terms of salary by graduate degree field. The dependent variable is an indicator for whether the individual responded that they were "very satisfied". Sample weights are used. Standard errors are clustered by person. The red line and triangles report the OLS estimates for women and blue line with triangles report the OLS estimates for men. The pink crosses report the raw differences between the mean response of women with the particular graduate degree and women with only a BA. The light-blue crosses report the corresponding differences for men.

Figure A19: OLS estimates of effects of graduate degrees on job satisfaction.
(A) Dep variable: "very satisfied" with career advancement.

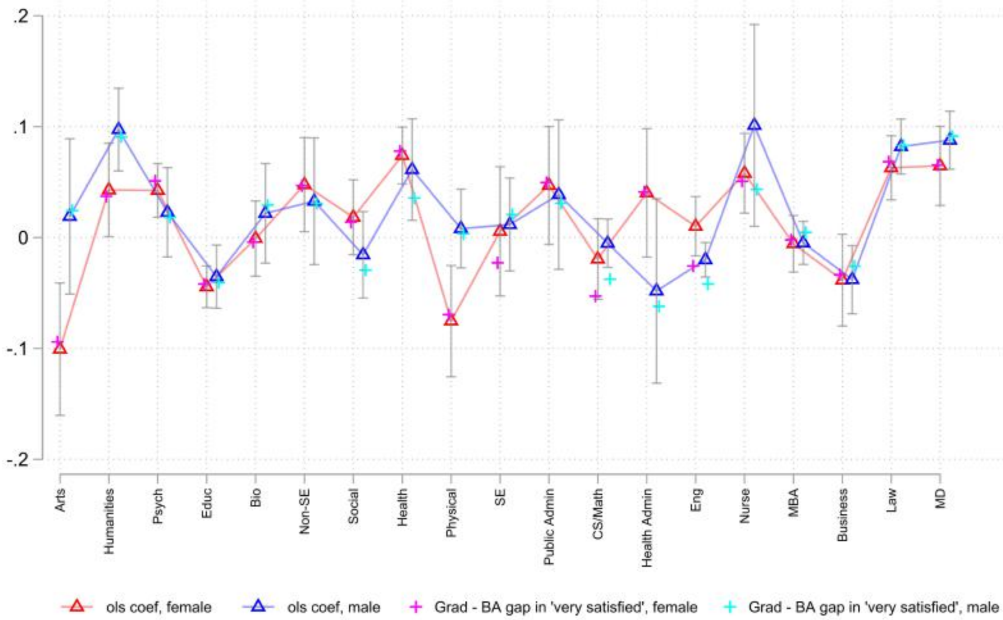


(B) Dep variable: "very satisfied" with benefits.

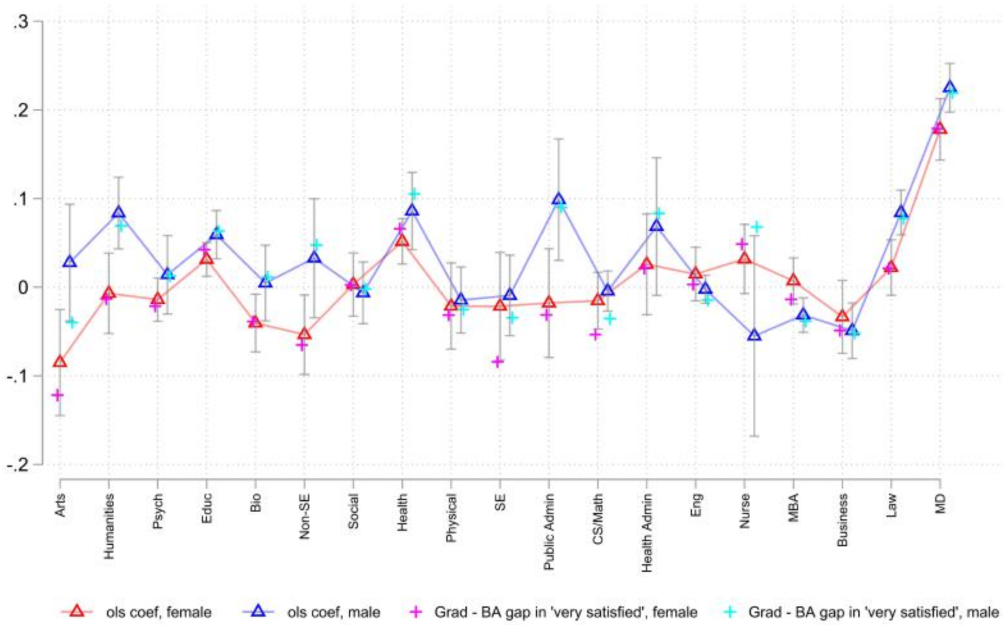


Notes: The figure reports estimates of the effect of completing advanced degrees on job satisfaction (panel A) and benefits (panel (B) in terms of career advancement by graduate degree field. The dependent variable is an indicator for if the individual responded that they were "very satisfied". Sample weights are used. Standard errors are clustered by person. The red line and triangles report the OLS estimates for women and blue line with triangles report the OLS estimates for men. The pink crosses report the raw differences between the mean response of women with the particular graduate degree and women with only a BA. The light-blue crosses report the corresponding differences for men.

Figure A20: OLS estimates of effects of graduate degrees on job satisfaction.
(A) Dep variable: "very satisfied" with independence.

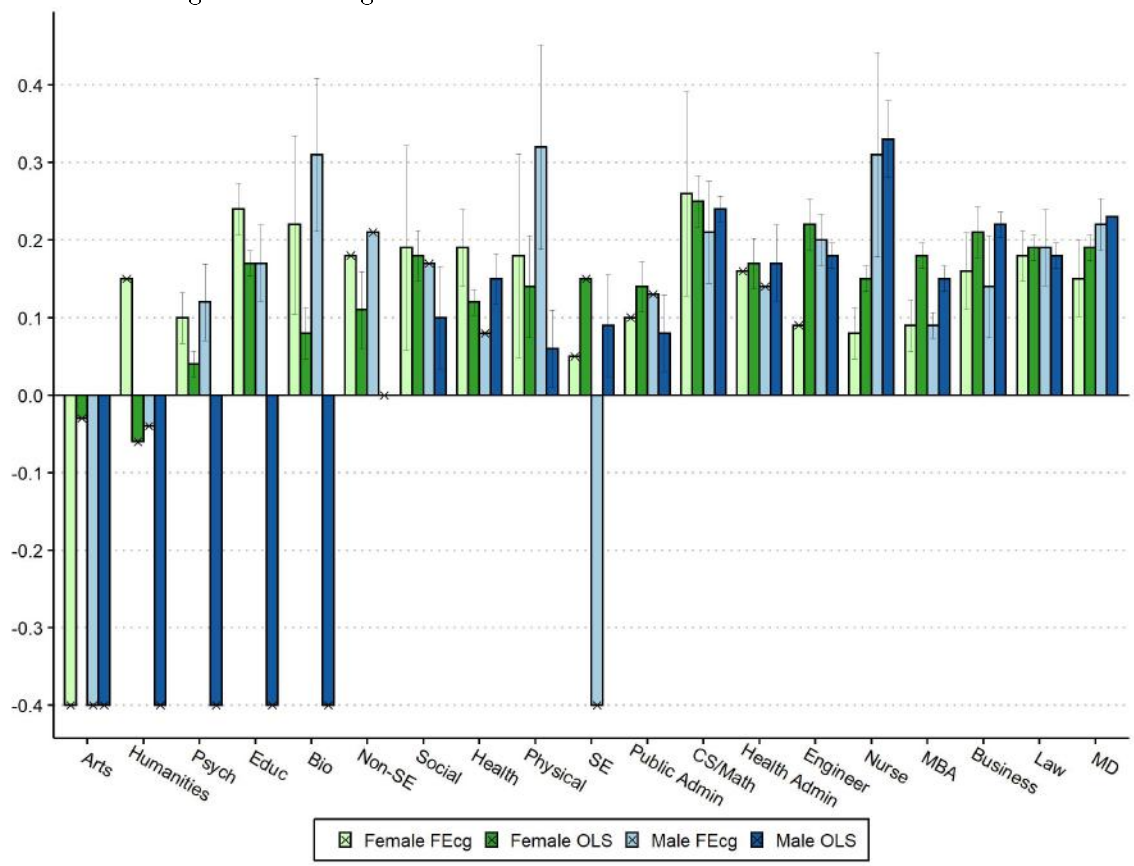


(B) Dep variable: "very satisfied" with job security.



Notes: The figure reports estimates of the effect of completing advanced degrees on job satisfaction in terms of independence (panel A) and job security (panel B), by graduate degree field. The dependent variable is an indicator for whether the individual responded that they were "very satisfied". Sample weights are used. Standard errors are clustered by person. The red line and triangles report the OLS estimates for women and blue line with triangles report the OLS estimates for men. The pink crosses report the raw differences between the mean response of women with the particular graduate degree and women with only a BA. The light-blue crosses report the corresponding differences for men.

Figure A21: FEcg and OLS estimates of the internal rate of return.



Notes: The figure reports the FEcg and OLS estimates of the internal rate of return for men and women by graduate degree. The estimates assume full-time enrollment with no wage income while enrolled. See Table 7 for details on the IRR estimates. Standard errors show 90% confidence intervals calculated via bootstrap. Cases where one or more of the bootstrap estimates did not converge or found corner solutions do not report confidence intervals are marked with an x. Light green bars show FEcg estimates for females, green bars show OLS estimates for females, light blue bars show FEcg estimates for males, and blue bars show OLS estimates for females.

12 Additional Tables

Table A1: Aggregation of advanced fields and degree type: Women

Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occ prem.		OLS Earnings prem.		Perc. in sample	Cell count
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Law	Law/prelaw/legal studies	Master	75,193	41,079	-0.65	0.28	0.29	0.08	0.11	160
		Prof	119,463	97,165	-0.33	0.16	0.57	0.02	7.67	7,520
MBA	Business, general	Master	106,570	70,193	-0.51	0.24	0.42	0.04	1.71	2,350
	Business administration and management	Master	93,496	61,921	-0.51	0.23	0.31	0.02	6.14	8,050
		Prof								
	Business and managerial economics	Master	102,683	60,463	-0.51	0.25	0.41	0.09	0.13	180
	Other business management/administrative services	Master	93,995	100,726	-0.53	0.23	0.32	0.04	1.67	2,170
		Prof								
Medicine	Medicine (e.g., dentistry, optometry, osteopathic, podiatry, veterinary)	Master	90,020	41,443	-0.52	0.19	0.37	0.07	0.28	560
		Prof	146,584	108,744	-0.13	0.19	0.74	0.02	4.94	6,470
Master's in arts	Dramatic arts	Master	74,534	139,897	-0.68	0.24	0.09	0.08	0.26	190
	Fine arts, all fields	Master	52,237	26,255	-0.78	0.20	-0.07	0.05	0.51	420
	Music, all fields	Master	56,611	28,504	-0.78	0.21	0.13	0.04	0.45	330
		Prof								
	Other visual and performing arts	Master	67,372	43,769	-0.74	0.21	0.08	0.08	0.40	370
		Prof								
Master's in biological/ agricultural/ environmental/ life sciences	Animal sciences	Master	62,387	77,769	-0.69	0.23	0.21	0.05	0.07	260
	Biochemistry and biophysics	Master	65,072	60,648	-0.70	0.21	0.02	0.06	0.15	600
	Biology, general	Master	60,250	29,993	-0.73	0.18	0.06	0.03	0.47	1,700
	Botany	Master	46,013	19,922	-0.81	0.14	-0.17	0.07	0.05	220
	Cell and molecular biology	Master	66,875	57,225	-0.74	0.13	0.06	0.05	0.12	500
	Ecology	Master	56,363	22,126	-0.72	0.16	0.01	0.07	0.14	500
	Environmental science or studies	Master	67,611	31,280	-0.66	0.21	0.17	0.04	0.29	1,060
	Food sciences and technology	Master	69,962	32,151	-0.66	0.17	0.15	0.06	0.12	500
	Forestry sciences	Master	63,709	24,286	-0.65	0.25	0.12	0.10	0.03	140
	Genetics, animal and plant	Master	61,954	24,088	-0.74	0.22	0.09	0.06	0.07	240
	Microbiological sciences and immunology	Master	64,093	33,803	-0.68	0.18	0.03	0.05	0.15	720
	Nutritional sciences	Master	66,640	24,248	-0.55	0.16	0.18	0.04	0.27	760
	Other agricultural sciences	Master	55,027	16,746	-0.63	0.31	0.10	0.07	0.07	250
	Other biological sciences	Master	63,292	34,669	-0.72	0.19	0.07	0.04	0.25	960
	Other conservation and natural resources	Master	68,834	88,269	-0.62	0.22	0.09	0.07	0.08	300
	Pharmacology, human and animal	Master	89,164	46,346	-0.67	0.18	0.22	0.13	0.05	160
		Prof								
	Physiology and pathology, human and animal	Master	62,318	29,313	-0.65	0.19	0.07	0.05	0.09	340
	Plant sciences	Master	52,137	29,834	-0.75	0.22	-0.02	0.07	0.08	350
	Zoology, general	Master	51,202	26,803	-0.73	0.17	-0.13	0.07	0.07	280

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occ prem.		OLS Earnings prem.		Perc. in sample	Cell count
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Master's in business-related fields	Accounting	Master Prof	84,272	66,570	-0.51	0.17	0.21	0.04	0.99	890
	Actuarial science	Master	108,311	50,612	-0.09	0.18	0.34	0.17	0.02	40
	Agricultural economics	Master	73,473	39,836	-0.62	0.21	0.18	0.20	0.08	210
	Business marketing/marketing management	Master	96,503	62,469	-0.50	0.22	0.32	0.05	0.94	1,170
	Financial management	Master Prof	113,162	77,999	-0.47	0.21	0.48	0.03	1.80	1,970
	Marketing research	Master	80,785	44,253	-0.51	0.14	0.20	0.07	0.18	200
	Other agricultural business and production	Master	46,502	13,291	-0.70	0.26	-0.18	0.12	0.03	40
Master's in computer and mathematical sciences	Applied mathematics	Master	83,008	56,862	-0.54	0.25	0.22	0.05	0.10	420
	Computer and information sciences, general	Master	81,504	34,400	-0.50	0.17	0.21	0.03	0.36	1,060
	Computer programming	Master	75,626	28,464	-0.50	0.16	0.13	0.12	0.06	130
	Computer science	Master	93,684	47,668	-0.45	0.14	0.27	0.02	1.20	3,410
	Computer systems analysis	Master	102,097	45,049	-0.44	0.13	0.49	0.10	0.07	140
	Data processing	Master	74,343	30,213	-0.42	0.11	0.20	0.08	0.01	40
	Information services and systems	Master	85,765	41,124	-0.56	0.21	0.26	0.04	0.45	1,250
	Mathematics, general	Master	65,581	34,348	-0.70	0.23	0.04	0.03	0.60	1,750
	Other computer and information sciences	Master	90,280	38,543	-0.51	0.19	0.28	0.07	0.16	460
	Other mathematics	Master	71,811	36,537	-0.67	0.23	0.09	0.12	0.04	120
	Operations research	Master	105,618	66,181	-0.48	0.19	0.39	0.11	0.11	360
	Statistics	Master	88,139	48,482	-0.53	0.19	0.26	0.05	0.28	1,090
Master's in education fields	Computer teacher education	Master	63,961	19,942	-0.81	0.15	0.13	0.05	0.29	280
	Counselor education and guidance	Master	59,727	35,814	-0.86	0.18	0.10	0.02	2.64	2,690
	Education administration	Master Prof	69,713	48,288	-0.74	0.23	0.25	0.02	3.17	2,620
	Educational psychology	Master	65,372	30,930	-0.78	0.21	0.19	0.02	1.71	1,990
	Elementary teacher education	Master Prof	61,966	37,649	-0.87	0.13	0.17	0.01	5.94	3,540
	Mathematics teacher education	Master Prof	64,595	25,072	-0.80	0.18	0.11	0.04	0.76	1,110
	Other education	Master Prof	60,255	22,499	-0.81	0.19	0.14	0.01	5.80	4,760
	Physical education and coaching	Master	57,672	19,310	-0.79	0.17	0.09	0.04	0.46	320
	Pre-school/kindergarten/early childhood teacher education	Master Prof	56,445	21,956	-0.93	0.23	0.14	0.03	0.58	450
	Science teacher education	Master Prof	62,319	27,225	-0.82	0.13	0.13	0.04	0.62	1,000
	Secondary teacher education	Master Prof	61,369	26,907	-0.82	0.15	0.11	0.02	2.37	2,330
	Social science teacher education	Master	59,516	16,613	-0.83	0.14	0.17	0.03	0.22	250
	Special education	Master Prof	60,947	21,745	-0.83	0.16	0.17	0.02	3.97	2,840

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occ prem.		OLS Earnings prem.		Perc. in sample	Cell count
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Master's in engineering	Aerospace, aeronautical, astronautical/space engineering	Master	90,436	37,059	-0.41	0.14	0.19	0.05	0.07	920
	Agricultural engineering	Master	54,908	24,645	-0.59	0.21	0.01	0.14	0.01	60
	Architectural engineering	Master	72,240	23,050	-0.53	0.13	0.13	0.07	0.03	170
	Bioengineering and biomedical engineering	Master	68,886	33,545	-0.64	0.19	-0.03	0.06	0.07	610
	Chemical engineering	Master	82,020	39,213	-0.42	0.23	0.02	0.04	0.12	1,330
	Civil engineering	Master	79,270	56,188	-0.45	0.17	0.12	0.03	0.31	2,550
	Computer and systems engineering	Master	108,930	81,512	-0.43	0.13	0.34	0.03	0.32	1,550
	Electrical, electronics and communications engineering	Master	97,631	61,670	-0.40	0.12	0.24	0.03	0.40	2,410
	Engineering, general	Master	109,144	55,475	-0.45	0.18	0.34	0.16	0.05	260
	Engineering sciences, mechanics and physics	Master	86,587	55,842	-0.44	0.15	0.17	0.09	0.03	140
	Environmental engineering	Master	76,814	29,228	-0.46	0.18	0.12	0.03	0.14	1,000
	Geophysical and geological engineering	Master	87,795	23,648	-0.42	0.11	0.27	0.08	0.01	70
	Industrial and manufacturing engineering	Master	91,901	49,971	-0.48	0.17	0.27	0.03	0.19	1,760
	Materials engineering, including ceramic and textile sciences	Master	78,596	33,549	-0.48	0.16	0.11	0.06	0.06	460
	Mechanical engineering	Master	85,288	34,176	-0.45	0.12	0.16	0.03	0.21	2,030
	Metallurgical engineering	Master	115,385	32,265	-0.44	0.07	0.52	0.07	0.02	80
	Mining and minerals engineering	Master								
	Naval architecture and marine engineering	Master	71,934	15,246	-0.47	0.12	0.18	0.09	0.00	20
	Nuclear engineering	Master	92,550	28,710	-0.44	0.14	0.18	0.07	0.02	100
	Other engineering	Master	86,118	33,972	-0.45	0.16	0.21	0.03	0.14	970
	Petroleum engineering	Master	93,130	41,437	-0.11	0.26	0.29	0.14	0.01	70
Master's in health services admin	Health services administration	Master	87,414	62,144	-0.54	0.23	0.30	0.03	1.32	1,780
		Prof								
Master's in health-related fields	Audiology and speech pathology	Master	64,552	33,827	-0.60	0.19	0.26	0.03	1.69	2,400
		Prof	64,408	8,598	-0.08	0.00	0.44	0.07	0.01	10
	Health/medical assistants	Master	89,394	28,088	-0.52	0.18	0.57	0.09	0.27	460
		Prof								
	Health/medical technologies	Master	79,494	30,061	-0.65	0.19	0.22	0.07	0.08	180
		Prof	81,843	56,743	-0.51	0.33	0.31	0.19	0.02	30
	Medical preparatory programs (e.g., pre-dentistry, pre-medical, pre-veterinary)	Master	64,370	24,652	-0.60	0.20	0.10	0.09	0.01	40
		Prof	90,413	55,391	-0.06	0.03	0.55	0.18	0.01	10
	Other health/medical sciences	Master	71,275	47,358	-0.66	0.24	0.19	0.03	1.31	2,090
		Prof	96,978	61,895	-0.33	0.24	0.44	0.12	0.01	20
	Pharmacy	Master	88,863	62,385	-0.64	0.18	0.12	0.06	0.07	180
		Prof	112,840	30,954	-0.52	0.11	0.58	0.04	0.42	630
	Physical therapy and other rehabilitation/therapeutic services	Master	66,248	32,683	-0.60	0.20	0.23	0.02	1.83	2,600
		Prof	71,457	19,376	-0.49	0.14	0.38	0.05	0.11	110
	Public health (including environmental health and epidemiology)	Master	68,107	36,373	-0.64	0.21	0.19	0.03	1.11	2,590
		Prof								

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occ prem.		OLS Earnings prem.		Perc. in sample	Cell count
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Master's in humanity fields	English Language, literature and letters	Master	59,523	31,031	-0.79	0.18	0.05	0.03	1.16	1,060
		Prof								
	History, other	Master	60,689	81,251	-0.75	0.23	-0.03	0.05	0.61	530
		Prof								
	Liberal arts/general studies	Master	69,097	34,427	-0.76	0.24	0.16	0.06	0.34	340
		Prof	89,695	30,500	-0.49	0.04	0.37	0.10	0.01	10
	Linguistics	Master	58,729	25,288	-0.78	0.18	0.04	0.06	0.23	290
	Other foreign languages and literature	Master	60,026	34,212	-0.77	0.21	0.00	0.04	0.56	640
		Prof								
	Other philosophy, religion, theology	Master	52,961	28,700	-0.94	0.28	-0.09	0.04	0.67	570
		Prof	57,325	50,802	-1.03	0.24	-0.08	0.17	0.03	20
Master's in other non-science and engineering fields	Communications, general	Master	65,915	35,063	-0.67	0.24	0.10	0.06	0.42	430
	Criminal justice/protective services	Master	61,524	28,275	-0.74	0.32	0.14	0.06	0.37	620
		Prof	252,435	284,889	-0.28	0.00	1.09	0.41	0.03	30
	Journalism	Master	68,481	37,187	-0.69	0.16	0.13	0.06	0.31	290
	Library science	Master	60,743	22,696	-0.86	0.19	0.10	0.02	1.67	1,180
		Prof								
	Non-Science & Engineering (suppressed)	Master								
	Other communication	Master	73,003	60,189	-0.66	0.21	0.18	0.05	0.42	350
	Parks, recreation, leisure, and fitness studies	Master	53,853	21,660	-0.77	0.26	0.01	0.04	0.27	340
Master's in nursing	Nursing (4 years or longer program)	Master	92,658	43,776	-0.51	0.17	0.27	0.01	3.27	4,890
		Prof	84,626	52,373	-0.45	0.14	0.35	0.15	0.02	20
Master's in physical and related sciences	Astronomy and astrophysics	Master	53,056	30,958	-0.56	0.22	-0.14	0.11	0.01	120
	Atmospheric sciences and meteorology	Master	66,209	27,793	-0.47	0.14	0.12	0.09	0.02	180
	Chemistry, except biochemistry	Master	73,286	48,140	-0.65	0.19	0.13	0.04	0.43	2,590
	Earth sciences	Master	70,176	41,834	-0.67	0.19	0.19	0.07	0.03	190
	Geological sciences, other	Master	74,177	51,095	-0.60	0.17	0.15	0.11	0.07	430
	Geology	Master	75,510	37,756	-0.58	0.15	0.22	0.05	0.14	850
	Other physical sciences	Master	68,250	35,055	-0.74	0.17	0.15	0.08	0.06	220
	Oceanography	Master	59,669	27,622	-0.62	0.17	-0.01	0.10	0.02	130
	Physics, except biophysics	Master	68,745	46,269	-0.61	0.21	0.04	0.06	0.13	740
	Science, unclassified	Master	57,717	18,117	-0.78	0.16	0.03	0.05	0.03	100

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occ prem.		OLS Earnings prem.		Perc. in sample	Cell count
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Master's in psychology and social work	Clinical psychology	Master	55,427	36,134	-0.77	0.21	-0.01	0.04	0.63	1,370
		Prof	81,091	45,810	-0.74	0.11	0.30	0.09	0.02	50
	Counseling psychology	Master	57,384	36,542	-0.81	0.21	0.05	0.02	2.56	4,720
	Educational psychology	Prof								
	Experimental psychology	Master	100,248	165,112	-0.69	0.24	0.28	0.14	0.08	180
		Prof								
	General psychology	Master	58,688	40,464	-0.75	0.21	0.08	0.03	0.74	1,360
		Prof	61,755	38,248	-0.53	0.27	0.03	0.35	0.02	20
	Industrial/Organizational psychology	Master	81,253	60,992	-0.61	0.21	0.31	0.07	0.29	580
	Other psychology	Master	59,200	29,064	-0.76	0.21	0.14	0.03	0.78	1,800
		Prof	54,604	21,380	-0.85	0.03	0.08	0.11	0.01	20
	Social Work	Master	61,127	38,171	-0.82	0.22	0.14	0.01	4.26	6,860
		Prof								
	Social psychology	Master	48,926	22,120	-0.80	0.24	-0.10	0.08	0.05	140
		Prof								
Master's in public admin	Other public affairs	Master	65,855	31,013	-0.60	0.30	0.15	0.06	0.14	200
	Public administration	Master	77,230	46,030	-0.60	0.27	0.25	0.03	1.35	1,870
Master's in other science and engineering -related fields	Architecture/environmental design	Master	75,132	35,996	-0.59	0.24	0.17	0.04	0.68	1,260
		Prof								
	Electrical and electronics technologies	Master	84,949	37,457	-0.48	0.21	0.19	0.22	0.03	80
	Industrial production technologies	Master	82,737	53,530	-0.53	0.15	0.19	0.07	0.02	70
	Mechanical engineering-related technologies	Master	84,847	15,740	-0.42	0.05	0.18	0.06	0.01	30
	Other engineering-related technologies	Master	80,935	34,278	-0.61	0.28	0.18	0.10	0.07	220
	All Science & Engineering (suppressed)	Master								
Master's in other social and related sciences	Anthropology and archaeology	Master	51,657	24,073	-0.70	0.22	-0.06	0.06	0.21	810
	Area and ethnic studies	Master	54,729	23,475	-0.76	0.24	-0.01	0.04	0.19	590
	Criminology	Master	61,816	28,850	-0.81	0.30	0.17	0.08	0.09	340
	Economics	Master	90,985	69,617	-0.56	0.25	0.25	0.06	0.40	1,560
	Geography	Master	62,333	28,539	-0.63	0.21	0.13	0.06	0.14	420
	History of science	Master								
	Home Economics	Master	57,431	24,774	-0.76	0.24	0.13	0.04	0.25	390
	International relations	Master	72,213	43,413	-0.61	0.23	0.20	0.05	0.41	1,140
	Other social sciences	Master	62,045	30,705	-0.68	0.27	0.11	0.03	0.49	1,280
	Philosophy of science	Master	54,372	19,347	-0.85	0.04	0.01	0.12	0.01	20
	Political science and government	Master	61,164	-0.71	0.23	0.26	0.03	0.05	0.36	850
	Public policy studies	Master	84,010	53,644	33,604	-0.54	0.33	0.04	0.45	1,440
	Sociology	Master	67,142	52,940	-0.72	0.24	0.18	0.04	0.48	1534

Note: The table presents the statistics of the disaggregated advanced degrees for women. Column 1 presents 19 aggregated advanced degree fields that are constructed from 168 disaggregated advanced degrees. For each disaggregated advanced degree, columns 2-11 present its field, type (Master or Professional Degree), mean and standard deviation of earnings, the mean and standard deviation of occupational premiums, its coefficient and standard error from a disaggregated additive earnings regression, percentage in the sample, and the rounded observation count. The reference category of advanced fields in the disaggregated additive earnings regression is no advanced degree. The reference category of the occupational premium is top level managers. Disaggregated advanced degrees with less than 10 observations are removed from the table. The specification is Table 2 col. (2), with disaggregated BA and advanced fields. Sample weights are used. Standard errors are clustered at the person level.

Table A2: Aggregation of BA fields: Women

Aggregated BA major	Disaggregated BA major	Earnings		BA earnings prem.		Perc. in sample	Cell count
		Mean	SD	Mean	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Biological/ agricultural/ environmental sciences	Animal sciences	52,046	35,180	-0.00	0.03	0.36	2,110
	Biochemistry and biophysics	78,984	77,657	0.22	0.03	0.37	2,750
	Biology, general	73,823	64,636	0.19	0.02	3.19	18,640
	Botany	52,295	35,588	-0.02	0.06	0.05	310
	Cell and molecular biology	82,150	59,791	0.29	0.05	0.12	990
	Ecology	63,372	53,847	0.17	0.06	0.15	1,170
	Environmental science or studies	60,376	44,797	0.19	0.04	0.29	2,400
	Food sciences and technology	68,430	40,693	0.30	0.06	0.11	1,010
	Forestry sciences	51,361	23,609	-0.01	0.07	0.06	410
	Genetics, animal and plant	78,920	84,671	0.23	0.11	0.03	240
	Microbiological sciences and immunology	73,784	61,395	0.23	0.04	0.33	2,210
	Nutritional sciences	64,032	57,927	0.17	0.03	0.27	1,540
	Other agricultural sciences	47,740	28,535	0.06	0.07	0.07	590
	Other biological sciences	64,426	63,481	0.20	0.04	0.28	1,740
	Other conservation and natural resources	64,985	54,884	0.15	0.06	0.08	680
	Pharmacology, human and animal	83,962	68,370	0.44	0.09	0.02	140
	Physiology and pathology, human and animal	77,648	59,800	0.26	0.04	0.11	680
	Plant sciences	53,858	35,621	0.00	0.05	0.17	1,150
	Zoology, general	70,515	52,754	0.11	0.03	0.29	1,570
Business	Accounting	74,104	50,993	0.38	0.02	3.81	6,900
	Actuarial science	93,589	124,159	0.51	0.13	0.11	290
	Agricultural economics	52,614	31,075	0.08	0.06	0.20	530
	Business, general	69,529	59,615	0.25	0.02	1.97	4,090
	Business administration and management	66,317	47,301	0.25	0.02	4.47	9,660
	Business and managerial economics	72,347	50,373	0.31	0.04	0.41	1,080
	Financial management	79,436	62,662	0.39	0.03	1.25	2,740
	Other agricultural business and production	59,282	41,830	0.09	0.08	0.11	330
	Other business management/administrative services	64,819	44,993	0.24	0.02	1.46	3,430
Communications/ Journalism	Communications, general	62,654	44,424	0.21	0.03	1.69	3,410
	Journalism	66,720	49,832	0.23	0.03	1.26	2,480
	Other communication	59,242	36,880	0.18	0.03	0.86	1,710
Computer and mathematical sciences	Applied mathematics	78,608	72,243	0.36	0.05	0.21	1,490
	Computer and information sciences, general	73,906	38,619	0.38	0.03	0.48	3,200
	Computer science	81,407	48,346	0.47	0.02	1.44	10,240
	Computer systems analysis	80,326	43,820	0.47	0.06	0.08	510
	Information services and systems	73,084	52,112	0.38	0.02	0.52	3,470
	Mathematics, general	69,713	48,538	0.25	0.02	1.57	10,450
	Other computer and information sciences	68,088	63,736	0.32	0.06	0.09	520
	Other mathematics	75,998	47,262	0.35	0.06	0.10	620
	Operations research	82,677	49,381	0.48	0.09	0.04	270
	Computer & Info Sci. (suppressed)						
	Statistics	82,741	58,089	0.41	0.05	0.14	1,160
Economics	Economics	84,813	86,130	0.38	0.03	1.74	9,800

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Aggregated BA major	Disaggregated BA major	Earnings		BA earnings prem.		Perc. in sample	Cell count
		Mean	SD	Mean	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	Computer teacher education	57,789	23,824	0.08	0.06	0.02	60
	Counselor education and guidance	59,002	44,078	0.05	0.07	0.07	160
	Education administration	55,044	32,624	-0.02	0.07	0.08	180
	Educational psychology	58,422	41,347	0.06	0.04	0.56	1,340
	Elementary teacher education	53,268	33,204	0.00		5.13	7,780
	Mathematics teacher education	56,738	28,110	0.06	0.03	0.45	1,420
	Other education	54,006	28,554	0.01	0.01	2.20	4,420
	Physical education and coaching	57,508	46,290	0.07	0.02	0.96	1,840
	Pre-school/kindergarten/early childhood teacher education	47,241	20,009	-0.10	0.03	0.61	870
	Science teacher education	57,845	27,627	0.07	0.04	0.40	1,120
	Secondary teacher education	53,383	25,590	0.02	0.02	1.18	2,420
	Social science teacher education	55,398	25,328	0.02	0.03	0.45	1,000
	Special education	55,031	34,197	0.04	0.02	1.56	2,660
Engineering	Aerospace, aeronautical, astronautical/space engineering	85,969	41,081	0.54	0.06	0.09	2,410
	Agricultural engineering	63,643	47,958	0.20	0.16	0.02	210
	Architectural engineering	69,120	37,886	0.34	0.06	0.06	600
	Bioengineering and biomedical engineering	77,216	45,952	0.41	0.06	0.08	1,200
	Chemical engineering	93,664	57,503	0.60	0.03	0.47	7,320
	Civil engineering	77,309	43,958	0.46	0.02	0.45	7,040
	Computer and systems engineering	88,226	40,047	0.53	0.03	0.23	2,390
	Electrical, electronics and communications engineering	89,230	49,167	0.53	0.02	0.62	7,930
	Engineering, general	87,198	40,292	0.52	0.06	0.04	460
	Engineering sciences, mechanics and physics	93,606	56,198	0.52	0.07	0.03	410
	Environmental engineering	77,089	39,398	0.46	0.04	0.05	730
	Geophysical and geological engineering	70,888	48,779	0.33	0.06	0.01	140
	Industrial and manufacturing engineering	86,752	47,730	0.51	0.03	0.29	4,710
	Materials engineering, including ceramic and textile sciences	81,785	51,168	0.43	0.06	0.06	870
	Mechanical engineering	82,382	41,166	0.51	0.03	0.42	7,080
	Metallurgical engineering	111,582	54,415	0.59	0.08	0.02	240
	Mining and minerals engineering	81,437	56,868	0.51	0.10	0.00	60
	Naval architecture and marine engineering	75,208	33,423	0.48	0.15	0.00	60
	Nuclear engineering	90,963	34,250	0.65	0.08	0.01	160
	Other engineering	84,200	44,406	0.47	0.06	0.07	800
	Petroleum engineering	86,592	47,336	0.52	0.12	0.03	250
English/ Languages/ Literature	English Language, literature and letters	64,104	52,831	0.14	0.02	4.10	9,560
	Linguistics	52,792	29,333	0.05	0.07	0.17	460
	Other foreign languages and literature	62,164	45,711	0.15	0.02	1.77	5,090
Fine/ Performing Arts	Dramatic arts	54,597	47,867	0.02	0.05	0.33	640
	Fine arts, all fields	55,538	39,298	0.06	0.03	1.39	2,780
	Music, all fields	54,861	55,543	-0.02	0.03	0.67	1,260
	Other visual and performing arts	61,266	70,217	0.13	0.03	0.99	1,880
Health Related Fields	Audiology and speech pathology	59,865	27,473	0.07	0.03	0.72	2,660
	Health/medical assistants	56,178	22,904	0.27	0.08	0.07	230
	Health/medical technologies	68,643	46,404	0.29	0.02	0.79	3,540
	Medical preparatory programs (e.g., pre-dentistry, pre-medical, pre-veterinary)	112,501	106,275	0.27	0.04	0.38	1,510
	Medicine (e.g., dentistry, optometry, osteopathic, podiatry, veterinary)	109,742	86,336	0.35	0.07	0.26	940
	Other health/medical sciences	63,282	46,078	0.20	0.03	0.86	2,830
	Pharmacy	100,083	45,271	0.61	0.03	0.49	1,730
	Physical therapy and other rehabilitation/therapeutic services	65,973	43,331	0.26	0.02	1.22	3,350
	Public health (including environmental health and epidemiology)	52,074	28,728	0.07	0.04	0.29	1,140

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Aggregated BA major	Disaggregated BA major	Earnings		BA earnings prem.		Perc. in sample	Cell count
		Mean	SD	Mean	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Marketing	Business marketing/marketing management	72,564	63,812	0.34	0.03	2.46	4,380
	Marketing research	61,849	35,194	0.25	0.05	0.18	320
Nursing	Nursing (4 years or longer program)	74,691	46,982	0.37	0.02	6.55	17,190
Other Humanities	History, other	69,154	67,014	0.17	0.02	2.56	6,100
	Liberal arts/general studies	68,358	62,063	0.20	0.03	1.35	3,320
	Other philosophy, religion, theology	51,888	32,194	0.00	0.04	0.45	990
Other Non-S and E fields	Criminal justice/protective services	53,252	34,496	0.08	0.03	1.04	2,800
	Health services administration	68,961	66,072	0.25	0.04	0.61	1,760
	Library science	57,049	25,764	0.09	0.08	0.02	80
	Non-Science & Engineering (suppressed)	63,972	28,893	0.28	0.06	0.04	140
	Parks, recreation, leisure, and fitness studies	52,785	29,664	0.04	0.04	0.46	1,110
Other S and E-Related Fields	Architecture/environmental design	70,762	49,857	0.32	0.04	0.55	2,290
	Computer programming	75,718	47,439	0.46	0.05	0.22	1,150
	Data processing	73,529	26,667	0.44	0.05	0.04	210
	Electrical and electronics technologies	74,211	38,554	0.33	0.15	0.07	390
	Industrial production technologies	81,168	68,633	0.46	0.10	0.08	370
	Mechanical engineering-related technologies	73,973	27,563	0.44	0.07	0.03	230
	Other engineering-related technologies	92,313	54,347	0.53	0.09	0.07	440
	All Science & Engineering (suppressed)	30,274	14,078	-0.54	0.10	0.01	20
Other Social and related sciences	Anthropology and archaeology	58,341	55,339	0.06	0.03	0.45	2,530
	Area and ethnic studies	62,797	46,032	0.18	0.03	0.46	2,520
	Criminology	49,056	25,649	0.04	0.03	0.26	1,250
	Geography	54,618	32,668	0.08	0.04	0.28	1,400
	History of science	71,289	46,168	0.25	0.09	0.07	220
	Home Economics	54,399	33,024	0.02	0.03	0.64	2,520
	International relations	78,731	79,484	0.29	0.03	0.53	2,890
	Other social sciences	54,369	30,677	0.06	0.03	0.88	3,600
	Philosophy of science	69,988	42,521	0.18	0.08	0.09	290
	Public policy studies	87,466	120,715	0.27	0.09	0.08	500
	Sociology	55,884	38,892	0.09	0.02	3.95	16,750
Physical and related sciences	Astronomy and astrophysics	79,241	79,847	0.35	0.13	0.01	170
	Atmospheric sciences and meteorology	66,039	37,910	0.20	0.12	0.03	350
	Chemistry, except biochemistry	73,791	57,745	0.26	0.02	1.48	13,940
	Earth sciences	49,272	24,735	0.02	0.07	0.06	690
	Geological sciences, other	61,185	36,776	0.18	0.12	0.02	360
	Geology	66,751	36,822	0.23	0.04	0.24	3,040
	Other physical sciences	63,022	38,505	0.12	0.05	0.12	890
	Oceanography	61,036	24,440	0.31	0.08	0.01	130
	Physics, except biophysics	71,742	46,697	0.27	0.03	0.23	3,120
	Physical & Related Sci (suppressed)						
	Science, unclassified	49,601	27,245	0.08	0.05	0.06	350
Political science	Law/prelaw/legal studies	68,433	62,370	0.11	0.05	0.25	930
	Other public affairs	52,328	24,360	0.05	0.05	0.09	330
	Political science and government	76,558	65,810	0.25	0.02	3.06	13,010
	Public administration	63,389	42,740	0.17	0.05	0.10	540
Psychology or Social Work	Clinical psychology	72,992	60,474	0.21	0.04	0.48	2,260
	Counseling psychology	56,549	37,379	0.10	0.03	0.45	1,850
	Experimental psychology	77,151	59,225	0.15	0.08	0.16	660
	General psychology	54,159	40,878	0.10	0.02	4.89	20,020
	Industrial/Organizational psychology	63,623	44,187	0.22	0.05	0.20	830
	Other psychology	58,615	40,413	0.12	0.02	0.65	2,690
	Social Work	54,272	42,471	0.03	0.02	0.95	4,070
	Social psychology	59,519	34,943	0.11	0.03	0.38	1,500

Note: The table presents the statistics of the disaggregated BA fields of study. Column 1 presents 19 aggregated BA fields that are constructed from 144 disaggregated BA fields. For each disaggregated field, columns 2-8 present its field name, mean and standard deviation of earnings, its coefficient and standard error from a disaggregated additive earnings regression, percentage in the sample, and cell counts. The reference category of the disaggregated additive earnings regression is elementary teacher education. Disaggregated BA fields with less than 10 observations are removed from the table. See notes for Table A1.

Table A3: Aggregation of advanced fields and degree type: Men

Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occ prem.		OLS Earnings prem.		Perc. in sample	Cell count
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Law	Law/prelaw/legal studies	Master	108,014	66,282	-0.47	0.26	0.20	0.13	0.17	200
		Prof	153,808	129,547	-0.31	0.13	0.48	0.01	11.94	12,810
MBA	Business, general	Master	134,407	100,428	-0.44	0.25	0.30	0.02	2.84	5,290
		Prof								
	Business administration and management	Master	126,779	103,786	-0.45	0.22	0.25	0.01	11.50	20,690
		Prof	67,698	22,870	-0.57	0.31	0.00	0.03	0.01	10
	Business and managerial economics	Master	122,434	101,193	-0.46	0.22	0.16	0.05	0.43	650
		Prof								
	Other business management/administrative services	Master	111,125	107,684	-0.50	0.23	0.17	0.03	1.86	3,120
		Prof	112,627	61,679	-0.47	0.10	0.14	0.24	0.02	20
Medicine	Medicine (e.g., dentistry, optometry, osteopathic, podiatry, veterinary)	Master	142,137	110,187	-0.31	0.26	0.45	0.09	0.14	320
		Prof	206,621	154,102	-0.12	0.17	0.79	0.01	10.55	17,760
Master's in arts	Dramatic arts	Master	75,091	38,729	-0.71	0.21	0.04	0.08	0.18	200
		Prof								
	Fine arts, all fields	Master	69,682	44,900	-0.73	0.22	-0.10	0.05	0.50	490
		Prof								
	Music, all fields	Master	65,960	72,732	-0.80	0.22	-0.05	0.05	0.49	480
	Other visual and performing arts	Master	93,307	105,705	-0.72	0.25	0.07	0.11	0.22	240
Master's in biological/agricultural/environmental/life sciences	Animal sciences	Master	53,941	33,795	-0.78	0.26	-0.06	0.07	0.06	280
	Biochemistry and biophysics	Master	81,641	61,452	-0.65	0.21	0.02	0.07	0.11	550
	Biology, general	Master	70,288	37,495	-0.71	0.22	-0.10	0.04	0.45	1,580
	Botany	Master	58,797	26,422	-0.71	0.21	-0.17	0.06	0.04	210
	Cell and molecular biology	Master	63,097	46,446	-0.72	0.18	-0.10	0.05	0.07	410
	Ecology	Master	72,082	49,842	-0.68	0.21	-0.12	0.05	0.12	580
	Environmental science or studies	Master	79,778	38,224	-0.59	0.21	0.03	0.04	0.25	1,150
		Prof								
	Food sciences and technology	Master	99,725	70,128	-0.59	0.21	0.23	0.08	0.08	360
	Forestry sciences	Master	74,059	33,705	-0.71	0.26	-0.08	0.09	0.13	610
	Genetics, animal and plant	Master	81,748	45,532	-0.65	0.23	0.03	0.09	0.06	190
	Microbiological sciences and immunology	Master	82,405	49,334	-0.67	0.20	0.01	0.07	0.12	550
	Nutritional sciences	Master	60,134	33,663	-0.68	0.25	-0.18	0.16	0.02	60
	Other agricultural sciences	Master	69,667	30,687	-0.73	0.20	-0.03	0.06	0.14	520
	Other biological sciences	Master	82,174	67,980	-0.63	0.26	0.05	0.04	0.21	970
		Prof								
	Other conservation and natural resources	Master	75,340	35,586	-0.68	0.18	-0.03	0.04	0.15	650
	Pharmacology, human and animal	Master	93,046	36,471	-0.57	0.19	0.13	0.07	0.03	140
	Physiology and pathology, human and animal	Master	70,967	48,427	-0.63	0.23	-0.18	0.17	0.10	340
	Plant sciences	Master	61,650	45,063	-0.72	0.20	-0.11	0.06	0.18	760
	Zoology, general	Master	74,665	47,734	-0.68	0.21	-0.08	0.07	0.11	490

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occ prem.		OLS Earnings prem.		Perc. in sample	Cell count
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Master's in business-related fields	Accounting	Master	135,336	116,285	-0.44	0.19	0.28	0.04	1.37	1,360
		Prof								
	Actuarial science	Master	203,586	225,494	-0.23	0.21	0.53	0.14	0.03	70
	Agricultural economics	Master	105,324	71,666	-0.50	0.22	0.27	0.07	0.22	480
	Business marketing/marketing management	Master	135,844	118,740	-0.44	0.22	0.30	0.04	1.46	2,160
	Financial management	Master	152,760	142,711	-0.42	0.19	0.37	0.02	4.83	6,810
		Prof	161,917	68,053	-0.38	0.12	0.64	0.09	0.03	20
	Marketing research	Master	115,226	70,580	-0.46	0.20	0.20	0.06	0.34	390
	Other agricultural business and production	Master	79,462	46,041	-0.73	0.33	0.02	0.14	0.10	160
Master's in computer and mathematical sciences	Applied mathematics	Master	101,251	61,539	-0.52	0.25	0.15	0.04	0.17	760
	Computer and information sciences, general	Master	102,851	49,486	-0.47	0.16	0.19	0.02	0.74	2,470
	Computer programming	Master	104,678	48,536	-0.44	0.14	0.19	0.06	0.11	330
	Computer science	Master	108,730	62,287	-0.43	0.13	0.21	0.01	2.69	10,310
		Prof								
	Computer systems analysis	Master	111,942	48,886	-0.46	0.16	0.21	0.05	0.22	640
	Data processing	Master	103,695	52,955	-0.47	0.09	0.07	0.19	0.02	100
		Prof								
	Information services and systems	Master	108,000	57,924	-0.46	0.15	0.23	0.03	0.65	2,250
	Mathematics, general	Master	86,416	55,054	-0.61	0.25	0.00	0.03	0.58	2,050
	Other computer and information sciences	Master	119,815	88,483	-0.49	0.15	0.29	0.06	0.25	960
	Other mathematics	Master	115,479	85,386	-0.49	0.18	0.18	0.07	0.06	210
	Operations research	Master	116,126	55,521	-0.45	0.18	0.22	0.03	0.40	1,260
		Prof								
	Statistics	Master	93,472	48,709	-0.50	0.20	0.12	0.04	0.24	1,350
Master's in education fields	Computer teacher education	Master	70,344	19,076	-0.73	0.18	-0.03	0.06	0.10	170
	Counselor education and guidance	Master	70,939	34,936	-0.79	0.23	-0.01	0.02	0.94	1,230
	Education administration	Master	81,802	39,486	-0.66	0.24	0.10	0.02	3.08	3,160
		Prof								
	Educational psychology	Master	70,215	30,509	-0.77	0.25	-0.02	0.04	0.51	790
	Elementary teacher education	Master	70,812	50,029	-0.79	0.19	-0.05	0.04	0.60	580
		Prof								
	Mathematics teacher education	Master	74,502	34,611	-0.77	0.19	-0.05	0.05	0.41	670
		Prof								
	Other education	Master	72,187	33,444	-0.75	0.22	-0.02	0.02	2.05	2,390
		Prof	109,847	77,577	-0.71	0.44	0.13	0.44	0.02	20
	Physical education and coaching	Master	67,156	29,136	-0.77	0.19	-0.04	0.03	0.49	460
		Prof								
	Pre-school/kindergarten/early childhood teacher education	Master	59,093	19,594	-0.78	0.25	-0.15	0.12	0.04	40
	Science teacher education	Master	65,646	29,486	-0.81	0.17	-0.17	0.05	0.36	650
		Prof								
	Secondary teacher education	Master	70,787	46,803	-0.78	0.20	-0.06	0.02	1.45	1,790
		Prof								
	Social science teacher education	Master	71,045	27,593	-0.81	0.19	-0.05	0.04	0.26	360
	Special education	Master	77,274	40,254	-0.77	0.20	0.08	0.03	0.70	680
		Prof								

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occ prem.		OLS Earnings prem.		Perc. in sample	Cell count
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Master's in engineering	Aerospace, aeronautical, astronautical/space engineering	Master	104,215	48,361	-0.44	0.20	0.13	0.03	0.45	3,800
	Agricultural engineering	Master	82,472	42,585	-0.51	0.21	0.03	0.05	0.06	290
	Architectural engineering	Master	102,838	88,249	-0.52	0.17	0.05	0.06	0.07	350
	Bioengineering and biomedical engineering	Master	96,196	77,545	-0.58	0.23	0.08	0.06	0.11	860
	Chemical engineering	Master	114,708	61,126	-0.34	0.16	0.14	0.03	0.47	3,760
	Civil engineering	Master	100,514	69,777	-0.42	0.14	0.09	0.01	1.35	8,950
	Computer and systems engineering	Master	116,980	55,689	-0.41	0.12	0.23	0.01	1.06	5,500
	Electrical, electronics and communications engineering	Master	112,013	67,986	-0.39	0.13	0.19	0.01	2.97	16,980
	Engineering, general	Master	108,001	65,054	-0.41	0.18	0.13	0.05	0.15	870
	Engineering sciences, mechanics and physics	Master	115,792	74,431	-0.43	0.14	0.19	0.04	0.16	900
	Environmental engineering	Master	101,101	43,365	-0.40	0.13	0.13	0.02	0.39	2,160
	Geophysical and geological engineering	Master	102,600	52,830	-0.42	0.18	0.06	0.05	0.04	310
	Industrial and manufacturing engineering	Master	101,892	54,291	-0.45	0.15	0.16	0.02	0.53	3,930
	Materials engineering, including ceramic and textile sciences	Master	96,501	40,024	-0.43	0.13	0.12	0.04	0.21	1,180
	Mechanical engineering	Master	100,129	53,166	-0.44	0.14	0.10	0.01	1.57	11,000
	Metallurgical engineering	Master	107,417	39,611	-0.43	0.15	0.15	0.07	0.09	450
	Mining and minerals engineering	Master	102,492	32,566	-0.29	0.32	0.14	0.09	0.03	140
	Naval architecture and marine engineering	Master	101,916	40,981	-0.42	0.12	0.07	0.08	0.03	200
	Nuclear engineering	Master	109,988	43,353	-0.41	0.13	0.14	0.03	0.12	700
	Other engineering	Master	100,311	39,938	-0.43	0.15	0.13	0.02	0.56	3,110
	Petroleum engineering	Master	150,943	124,169	-0.19	0.26	0.29	0.08	0.06	280
Master's in health services admin	Health services administration	Master	110,512	76,732	-0.44	0.24	0.28	0.04	0.63	1,010
		Prof								
Master's in health-related fields	Audiology and speech pathology	Master	86,290	54,155	-0.57	0.17	0.14	0.09	0.11	230
		Prof								
	Health/medical assistants	Master	95,615	25,849	-0.53	0.18	0.33	0.08	0.09	170
		Prof								
	Health/medical technologies	Master	113,756	106,261	-0.64	0.24	0.21	0.12	0.04	130
		Prof								
	Medical preparatory programs (e.g., pre-dentistry, pre-medical, pre-veterinary)	Master	167,840	104,052	-0.39	0.46	0.54	0.28	0.00	20
		Prof	168,972	75,616	-0.10	0.15	0.74	0.07	0.09	190
	Other health/medical sciences	Master	92,075	95,591	-0.64	0.27	0.09	0.06	0.30	640
		Prof	166,548	128,642	-0.14	0.17	0.61	0.10	0.09	150
	Pharmacy	Master	115,290	50,453	-0.48	0.20	0.21	0.11	0.07	210
		Prof	132,061	71,920	-0.50	0.11	0.54	0.05	0.28	460
	Physical therapy and other rehabilitation/therapeutic services	Master	79,700	37,812	-0.60	0.20	0.10	0.04	0.52	940
		Prof	97,077	82,994	-0.48	0.20	0.44	0.08	0.03	40
	Public health (including environmental health and epidemiology)	Master	87,907	72,092	-0.58	0.22	0.13	0.04	0.37	960
		Prof								

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occ prem.		OLS Earnings prem.		Perc. in sample	Cell count
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Master's in humanity fields	English Language, literature and letters	Master	72,650	54,307	-0.76	0.23	-0.08	0.04	0.50	630
		Prof								
	History, other	Master	81,343	78,645	-0.73	0.28	-0.06	0.04	0.68	740
		Prof	111,007	40,688	-0.34	0.17	0.33	0.08	0.07	40
	Liberal arts/general studies	Master	73,432	35,297	-0.76	0.29	-0.03	0.06	0.17	220
		Prof								
	Linguistics	Master	63,168	27,469	-0.77	0.17	-0.10	0.07	0.07	140
	Other foreign languages and literature	Master	86,135	76,766	-0.73	0.26	-0.00	0.08	0.24	330
		Prof								
	Other philosophy, religion, theology	Master	55,783	36,667	-0.97	0.29	-0.29	0.02	2.19	2,110
		Prof	52,820	36,035	-1.02	0.26	-0.45	0.09	0.20	160
Master's in other non-science and engineering fields	Communications, general	Master	81,828	51,634	-0.62	0.24	0.04	0.08	0.22	350
		Prof								
	Criminal justice/protective services	Master	84,764	86,010	-0.64	0.28	0.11	0.05	0.40	510
		Prof	140,239	105,353	-0.32	0.08	0.58	0.14	0.05	30
	Journalism	Master	92,154	60,006	-0.67	0.20	0.08	0.06	0.19	210
	Library science	Master	66,400	27,621	-0.79	0.24	-0.12	0.04	0.40	400
	Non-Science & Engineering (suppressed)	Master								
	Other communication	Master	86,170	49,132	-0.60	0.28	0.05	0.08	0.27	360
	Parks, recreation, leisure, and fitness studies	Master	68,798	29,905	-0.68	0.22	-0.03	0.05	0.37	380
Master's in nursing	Nursing (4 years or longer program)	Master	139,404	58,733	-0.46	0.15	0.55	0.04	0.38	690
Master's in physical and related sciences	Astronomy and astrophysics	Master	82,639	73,377	-0.50	0.19	-0.07	0.15	0.02	170
	Atmospheric sciences and meteorology	Master	88,894	44,900	-0.47	0.13	0.08	0.06	0.09	620
	Chemistry, except biochemistry	Master	82,620	52,153	-0.60	0.19	0.01	0.04	0.51	3,270
	Earth sciences	Master	75,002	30,171	-0.73	0.17	0.02	0.04	0.08	350
	Geological sciences, other	Master	93,410	47,306	-0.52	0.18	0.12	0.05	0.11	670
	Geology	Master	92,455	55,223	-0.58	0.20	0.10	0.03	0.42	2,540
	Other physical sciences	Master	80,925	34,011	-0.64	0.28	0.05	0.05	0.08	310
	Oceanography	Master	97,589	142,619	-0.52	0.21	-0.02	0.11	0.03	150
	Physics, except biophysics	Master	95,604	60,646	-0.50	0.19	0.04	0.03	0.49	3,080
		Prof								
	Science, unclassified	Master	72,958	26,995	-0.68	0.21	-0.13	0.05	0.03	150

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occ prem.		OLS Earnings prem.		Perc. in sample	Cell count
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Master's in psychology and social work	Clinical psychology	Master	77,242	52,919	-0.66	0.28	0.01	0.06	0.28	690
		Prof	82,448	31,405	-0.72	0.22	0.08	0.15	0.01	40
	Counseling psychology	Master	66,507	34,739	-0.77	0.29	-0.10	0.03	0.88	1,940
		Prof								
	Experimental psychology	Master	69,449	49,933	-0.69	0.21	-0.23	0.20	0.07	200
		Prof								
	General psychology	Master	73,223	43,454	-0.64	0.25	0.01	0.05	0.31	710
		Prof	111,090	48,368	-0.69	0.36	0.23	0.32	0.01	10
	Industrial/Organizational psychology	Master	99,156	85,545	-0.53	0.20	0.27	0.06	0.20	380
	Other psychology	Master	71,417	37,122	-0.73	0.22	-0.04	0.05	0.23	580
	Social Work	Master	73,058	33,196	-0.74	0.28	0.01	0.03	0.99	1,960
		Prof	129,648	62,616	-0.46	0.27	0.44	0.15	0.01	20
	Social psychology	Master	85,448	44,626	-0.76	0.33	0.11	0.14	0.05	100
		Prof								
Master's in public admin	Other public affairs	Master	69,616	36,604	-0.68	0.29	-0.13	0.10	0.09	180
	Public administration	Master	94,429	46,644	-0.49	0.26	0.15	0.03	1.43	2,030
Master's in other science and engineering -related fields	Architecture/environmental design	Master	93,979	71,602	-0.56	0.21	0.07	0.03	1.34	2,220
		Prof	89,188	58,615	-0.63	0.11	0.03	0.14	0.01	20
	Electrical and electronics technologies	Master	103,113	47,805	-0.45	0.17	0.17	0.09	0.14	440
		Prof	92,999	28,795	-0.46	0.20	0.22	0.09	0.00	10
	Industrial production technologies	Master	84,485	42,437	-0.58	0.29	-0.07	0.07	0.13	320
	Mechanical engineering-related technologies	Master	112,056	42,615	-0.48	0.25	0.18	0.08	0.15	450
		Prof								
	Other engineering-related technologies	Master	107,318	78,427	-0.49	0.19	0.17	0.04	0.26	800
		Prof								
Master's in other social and related sciences	Anthropology and archaeology	Master	68,061	45,616	-0.69	0.21	-0.07	0.07	0.10	560
	Area and ethnic studies	Master	65,854	38,814	-0.76	0.23	-0.16	0.14	0.11	340
	Criminology	Master	78,170	34,273	-0.69	0.26	0.15	0.08	0.10	280
	Economics	Master	116,941	101,565	-0.47	0.22	0.18	0.04	0.73	2,770
	Geography	Master	80,222	44,495	-0.60	0.25	0.02	0.06	0.28	830
	History of science	Master	75,760	36,488	-0.65	0.20	-0.10	0.18	0.03	40
	Home Economics	Master	62,951	33,818	-0.53	0.28	-0.31	0.21	0.02	80
	International relations	Master	111,639	84,759	-0.55	0.29	0.27	0.07	0.36	1,140
	Other social sciences	Master	66,700	34,229	-0.69	0.24	-0.12	0.06	0.24	720
	Philosophy of science	Master	41,540	19,825	-0.81	0.29	-0.47	0.09	0.02	40
	Political science and government	Master	91,319	71,069	-0.61	0.26	0.04	0.04	0.57	1,330
	Public policy studies	Master	114,268	94,989	-0.48	0.26	0.29	0.05	0.26	1,040
	Sociology	Master	74,745	57,802	-0.69	0.26	-0.02	0.04	0.34	1,060

Note: The table present statistics for disaggregated advanced degrees for men. See the notes to Table A1.

Table A4: Aggregation of BA fields: Men

Aggregated BA major	Disaggregated BA major	Earnings		BA earnings prem.		Perc. in sample	Cell count
		Mean	SD	Mean	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Biological/ agricultural/ environmental sciences	Animal sciences	75,754	56,215	-0.06	0.04	0.38	2,510
	Biochemistry and biophysics	140,314	140,518	0.25	0.04	0.41	3,260
	Biology, general	120,319	114,420	0.14	0.03	2.95	19,650
	Botany	69,299	47,676	-0.10	0.10	0.04	330
	Cell and molecular biology	137,936	175,270	0.25	0.08	0.13	1,010
	Ecology	83,168	97,232	0.08	0.07	0.16	1,400
	Environmental science or studies	69,024	55,025	0.05	0.04	0.33	3,270
	Food sciences and technology	83,239	50,873	0.23	0.05	0.08	800
	Forestry sciences	77,364	56,548	0.08	0.04	0.30	3,120
	Genetics, animal and plant	97,839	69,016	0.10	0.07	0.02	210
	Microbiological sciences and immunology	130,316	159,595	0.19	0.06	0.20	1,740
	Nutritional sciences	97,316	90,238	0.08	0.08	0.03	180
	Other agricultural sciences	70,056	40,363	0.02	0.04	0.30	2,090
	Other biological sciences	99,098	98,678	0.14	0.04	0.27	2,130
	Other conservation and natural resources	68,934	36,839	0.01	0.04	0.19	1,930
	Pharmacology, human and animal	112,892	131,492	0.30	0.09	0.02	190
	Physiology and pathology, human and animal	103,260	83,716	0.21	0.04	0.14	910
	Plant sciences	68,165	60,367	0.00	0.04	0.37	2,890
	Environmental Sciences (suppressed)						
	Zoology, general	130,529	115,712	0.14	0.04	0.42	2,710
Business	Accounting	111,049	101,750	0.40	0.03	4.99	11,840
	Actuarial science	139,676	107,840	0.73	0.06	0.10	470
	Agricultural economics	84,275	62,419	0.19	0.04	0.90	2,260
	Business, general	94,187	81,187	0.23	0.03	2.50	6,710
	Business administration and management	93,638	81,251	0.25	0.03	6.14	17,280
	Business and managerial economics	106,057	89,269	0.36	0.03	0.99	2,900
	Financial management	118,139	119,460	0.43	0.03	2.80	7,300
	Other agricultural business and production	66,724	49,493	-0.02	0.05	0.31	1,020
	Other business management/administrative services	90,289	65,787	0.27	0.03	1.53	4,890
Communications/ Journalism	Communications, general	82,218	95,746	0.13	0.04	1.05	2,780
	Journalism	84,663	71,700	0.18	0.04	0.81	2,010
	Other communication	80,176	59,776	0.15	0.04	0.59	1,670
Computer and mathematical sciences	Applied mathematics	105,072	89,886	0.36	0.04	0.38	3,350
	Computer and information sciences, general	87,838	50,090	0.36	0.03	0.89	7,060
	Computer science	97,858	61,961	0.44	0.03	3.37	31,520
	Computer systems analysis	89,930	55,619	0.38	0.04	0.15	1,290
	Information services and systems	86,833	54,898	0.33	0.03	0.77	6,160
	Mathematics, general	95,147	77,794	0.25	0.03	1.74	13,950
	Other computer and information sciences	66,069	36,358	0.11	0.04	0.22	1,480
	Other mathematics	91,590	51,723	0.30	0.04	0.14	1,100
	Operations research	97,779	66,996	0.41	0.05	0.10	750
	Computer & Info Sci. (suppressed)						
	Statistics	104,678	68,996	0.39	0.05	0.19	1,650
Economics	Economics	115,478	111,454	0.41	0.03	3.93	22,560

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Aggregated BA major	Disaggregated BA major	Earnings		BA earnings prem.		Perc. in sample	Cell count
		Mean	SD	Mean	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Education	Computer teacher education	76,727	29,983	0.16	0.09	0.01	60
	Counselor education and guidance	60,199	32,754	-0.06	0.09	0.03	100
	Education administration	72,598	41,338	0.03	0.06	0.04	140
	Educational psychology	76,553	46,033	0.04	0.05	0.19	500
	Elementary teacher education	66,491	39,663	0.00		0.47	1,130
	Mathematics teacher education	67,261	31,332	-0.02	0.04	0.27	990
	Other education	72,883	51,919	0.02	0.03	1.04	3,070
	Physical education and coaching	72,833	63,930	0.03	0.03	1.22	3,210
	Pre-school/kindergarten/early childhood teacher education	55,140	21,473	-0.06	0.07	0.02	30
	Science teacher education	75,543	60,646	0.01	0.05	0.29	1,150
	Secondary teacher education	68,099	46,072	-0.01	0.03	0.61	1,770
	Social science teacher education	73,034	56,725	-0.01	0.04	0.41	1,280
	Special education	67,374	42,198	0.01	0.04	0.12	340
Engineering	Aerospace, aeronautical, astronautical/space engineering	100,490	57,220	0.41	0.03	0.67	10,650
	Agricultural engineering	83,302	43,904	0.27	0.04	0.15	1,770
	Architectural engineering	94,093	68,116	0.35	0.04	0.23	2,460
	Bioengineering and biomedical engineering	122,623	137,826	0.38	0.05	0.09	1,430
	Chemical engineering	116,995	86,661	0.50	0.03	1.18	18,990
	Civil engineering	98,668	70,726	0.40	0.03	2.37	34,900
	Computer and systems engineering	107,150	63,994	0.54	0.03	1.01	12,950
	Electrical, electronics and communications engineering	104,051	64,101	0.46	0.03	4.71	64,880
	Engineering, general	108,304	83,089	0.38	0.03	0.29	2,850
	Engineering sciences, mechanics and physics	98,210	73,500	0.34	0.04	0.22	2,610
	Environmental engineering	91,568	47,529	0.36	0.04	0.11	1,430
	Geophysical and geological engineering	103,432	94,122	0.39	0.06	0.03	450
	Industrial and manufacturing engineering	103,318	73,300	0.39	0.03	0.91	11,550
	Materials engineering, including ceramic and textile sciences	89,520	48,419	0.34	0.04	0.18	2,510
	Mechanical engineering	100,745	62,376	0.44	0.03	3.90	57,450
	Metallurgical engineering	102,557	58,907	0.34	0.04	0.15	1,820
	Mining and minerals engineering	99,166	78,005	0.32	0.05	0.08	870
	Naval architecture and marine engineering	101,696	51,609	0.40	0.05	0.12	1,350
	Nuclear engineering	112,245	57,562	0.50	0.04	0.10	1,300
	Other engineering	109,043	83,846	0.42	0.04	0.41	4,250
	Petroleum engineering	130,107	118,349	0.58	0.06	0.13	1,630
English/ Languages/ Literature	English Language, literature and letters	86,497	87,052	0.10	0.04	1.83	5,610
	Linguistics	69,130	46,402	0.03	0.10	0.07	260
	Other foreign languages and literature	83,282	68,151	0.14	0.04	0.55	2,110
Fine/ Performing Arts	Dramatic arts	74,002	56,530	0.02	0.07	0.18	500
	Fine arts, all fields	75,642	77,710	0.09	0.05	0.81	2,190
	Music, all fields	70,050	87,336	0.01	0.05	0.58	1,700
	Other visual and performing arts	73,988	59,665	0.10	0.04	0.76	1,880
Health Related Fields	Audiology and speech pathology	82,267	54,873	0.14	0.08	0.04	200
	Health/medical assistants	146,596	182,840	0.45	0.13	0.03	110
	Health/medical technologies	81,354	52,895	0.13	0.05	0.22	1,300
	Medical preparatory programs (e.g., pre-dentistry, pre-medical, pre-veterinary)	194,239	165,932	0.25	0.04	0.55	2,590
	Medicine (e.g., dentistry, optometry, osteopathic, podiatry, veterinary)	182,855	185,465	0.27	0.07	0.24	1,170
	Other health/medical sciences	91,506	83,548	0.18	0.05	0.23	1,160
	Pharmacy	116,428	67,294	0.47	0.04	0.50	2,180
	Physical therapy and other rehabilitation/therapeutic services	80,539	60,639	0.14	0.05	0.31	1,280
	Public health (including environmental health and epidemiology)	77,150	42,954	0.07	0.05	0.14	690

....continued

Aggregated BA major	Disaggregated BA major	Earnings		BA earnings prem.		Perc. in sample	Cell count
		Mean	SD	Mean	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Marketing	Business marketing/marketing management	100,206	85,042	0.35	0.03	2.65	6,300
	Marketing research	85,957	73,205	0.23	0.05	0.25	560
Nursing	Nursing (4 years or longer program)	89,460	55,969	0.28	0.04	0.54	2,240
Other Humanities	History, other	92,415	87,584	0.14	0.03	3.69	10,980
	Liberal arts/general studies	94,592	94,078	0.09	0.04	0.87	3,230
	Other philosophy, religion, theology	67,149	63,774	-0.08	0.04	0.91	2,580
Other Non-S and E fields	Criminal justice/protective services	71,732	48,788	0.11	0.03	1.11	3,260
	Health services administration	76,726	56,867	0.11	0.06	0.18	720
	Library science	47,651	17,451	-0.15	0.09	0.01	20
	Non-Science & Engineering (suppressed)	96,816	63,185	0.28	0.08	0.06	250
	Parks, recreation, leisure, and fitness studies	66,201	62,496	-0.00	0.04	0.38	1,120
Other S and E-Related Fields	Architecture/environmental design	92,740	73,746	0.26	0.03	1.20	5,760
	Computer programming	95,941	64,277	0.39	0.04	0.45	2,610
	Data processing	85,070	30,871	0.32	0.06	0.05	350
	Electrical and electronics technologies	86,802	45,592	0.34	0.03	0.62	5,320
	Industrial production technologies	83,728	48,802	0.20	0.04	0.56	2,950
	Mechanical engineering-related technologies	89,668	40,239	0.35	0.03	0.44	3,480
	Other engineering-related technologies	91,200	67,181	0.30	0.04	0.49	2,950
	All Science & Engineering (suppressed)	114,218	57,684	0.46	0.23	0.01	40
Other Social and related sciences	Anthropology and archaeology	74,467	80,695	-0.02	0.05	0.23	1,770
	Area and ethnic studies	92,640	117,778	0.12	0.07	0.15	1,120
	Criminology	68,805	35,392	0.12	0.04	0.30	1,450
	Geography	73,273	53,144	0.09	0.04	0.45	3,030
	History of science	93,160	75,372	0.12	0.07	0.09	400
	Home Economics	79,797	73,305	0.13	0.09	0.05	280
	International relations	93,772	81,295	0.27	0.04	0.31	1,960
	Other social sciences	75,510	64,047	0.11	0.04	0.56	2,960
	Philosophy of science	101,666	94,736	0.22	0.05	0.19	930
	Public policy studies	87,067	76,666	0.07	0.08	0.05	320
	Sociology	76,522	67,383	0.09	0.03	1.73	9,160
Physical and related sciences	Astronomy and astrophysics	63,748	43,365	-0.02	0.10	0.02	220
	Atmospheric sciences and meteorology	78,841	43,850	0.17	0.04	0.07	1,510
	Chemistry, except biochemistry	110,983	93,207	0.21	0.03	2.00	21,490
	Earth sciences	67,486	37,881	0.06	0.07	0.09	1,130
	Geological sciences, other	86,377	80,372	0.22	0.06	0.05	890
	Geology	87,865	70,216	0.18	0.03	0.60	8,360
	Other physical sciences	92,056	64,311	0.13	0.05	0.18	1,530
	Oceanography	75,349	40,314	0.06	0.13	0.03	290
	Physics, except biophysics	99,053	73,818	0.29	0.03	0.90	12,520
	Physical & Related Sci (suppressed)						
	Science, unclassified	87,732	51,602	0.24	0.05	0.11	860
Political science	Law/prelaw/legal studies	100,003	99,140	0.16	0.05	0.17	940
	Other public affairs	105,134	64,693	0.29	0.17	0.04	150
	Political science and government	106,347	100,724	0.24	0.03	3.84	19,020
	Public administration	107,969	105,474	0.28	0.07	0.15	750
Psychology or Social Work	Clinical psychology	84,870	87,164	0.05	0.05	0.23	1,170
	Counseling psychology	69,509	39,903	-0.02	0.05	0.16	850
	Experimental psychology	102,748	103,125	0.19	0.06	0.13	760
	General psychology	78,158	71,863	0.08	0.03	1.84	9,220
	Industrial/Organizational psychology	95,788	60,249	0.25	0.06	0.11	630
	Other psychology	92,126	73,800	0.13	0.04	0.26	1,380
	Social Work	65,175	34,068	-0.04	0.06	0.18	950
	Social psychology	79,708	49,555	0.11	0.06	0.14	810

Note: The table repeats the statistics presented in Table A2 for men.

Table A5: Summary statistics of the control variables

	Male	Female
	(1)	(2)
Panel A: Gender composition of the regression sample		
Sample composition	58.240	41.760
Panel B: Father's Education		
Less than high school	14.370	14.013
High school diploma	27.539	26.868
Associate degree	17.588	20.105
College Degree	21.471	20.065
Masters degree (incl. MBA)	6.456	6.980
Professional degree	10.414	9.864
Doctorate	2.160	2.105
Panel C: Mother's Education		
Less than high school	11.782	11.554
High school diploma	38.733	33.954
Associate degree	20.646	24.734
College Degree	18.793	18.503
Masters degree (incl. MBA)	5.091	6.255
Professional degree	4.270	4.330
Doctorate	0.606	0.613
Missing	0.081	0.057
Panel D: Race and Ethnicity		
Asian	6.758	6.913
Black, Hispanic	0.151	0.268
Black, Non-Hispanic	4.682	8.752
Native American	0.580	0.728
White, Hispanic	3.788	4.796
White, Non-Hispanic	82.787	76.815
Other	1.253	1.727

Note: Weighted summary statistics for demographic controls for the regression sample, by gender. The values are percentages.

Table A6: Distribution of time gaps between educational experience and earnings observation

	Time from BA completion to pre-Adv obs.	Time from pre-Adv obs. To Adv. Completion	Time from Adv completion to post Adv obs.	Time from BA to Adv completion	Time from Adv completion to post Adv obs. (for individuals with pre and post Adv observations)	Time from BA to Adv completion (for individuals with pre and post Adv observations)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Men + Women						
5th quantile	1	1	1	1	1	3
10th quantile	1	2	2	2	1	4
25th quantile	2	2	4	3	1	5
Mean	5.52	3.12	11.46	5.40	2.25	8.42
Median	4	3	9	4	2	7
75th quantile	8	4	18	7	3	11
90th quantile	12	5	25	11	4	15
95th quantile	14	6	28	14	5	17
count	9,820	9,770	388,270	398,040	9,350	19,120
Panel B: Men						
5th quantile	1	1	1	1	1	3
10th quantile	1	2	2	2	1	4
25th quantile	2	2	5	3	1	5
Mean	5.69	3.16	12.41	5.34	2.27	8.63
Median	5	3	11	4	2	8
75th quantile	8	4	19	7	3	11
90th quantile	12	5	26	11	4	15
95th quantile	14	6	29	14	5	17
count	5,450	5,420	232,690	238,110	5,310	10,730
Panel C: Women						
5th quantile	1	1	1	1	1	3
10th quantile	1	2	2	2	1	4
25th quantile	2	2	3	3	1	5
Mean	5.32	3.07	10.04	5.48	2.23	8.15
Median	4	3	8	4	2	7
75th quantile	7	4	15	7	3	10
90th quantile	11	5	22	11	4	14
95th quantile	14	6	27	14	5	17
count	4,370	4,350	155,580	159,930	4,040	8,390

Note: Unweighted summary statistics of the time gaps reported for the regression sample. Panel A shows the statistics of the full sample including men and women. Panels B and C show the statistics of men and women samples separately. Columns 3-4 are estimated from the graduate degree sample, which excludes people never are observed with a graduate degree. Columns 1, 2, 5, and 6 are estimated from a more-restricted subsample in which the individuals are observed working full time before they obtain the advanced degree. Our sample selection rules impose a minimum of 1 for the time gap variables in columns 1-5. Column 2 excludes about 50 pre advanced earnings observations on individuals for whom we dropped post advanced observations because they were reinterviewed only because of occupation. See footnote 12. Unweighted cell counts are rounded to the nearest 10.

Table A7: Age distribution of the earnings observations

	Full sample (1)	Individuals without Adv. Degree (2)	Individuals with Adv. Degree in the future (3)	Individuals with advanced degree (4)
Panel A: Men+Women				
count	1,020,640	622,560	9,820	388,270
1st quantile	23	23	23	25
10th quantile	26	26	24	28
25th quantile	30	29	25	32
Mean	38.82	38.44	29.29	39.68
Median	38	37	28	39
75th quantile	47	47	32	47
90th quantile	53	53	37	54
99th quantile	59	59	46	59
Panel B: Men				
count	642,550	404,420	5,450	232,690
1st quantile	23	23	23	25
10th quantile	27	26	24	28
25th quantile	31	30	25	32
Mean	39.54	39.12	29.43	40.50
Median	39	38	28	40
75th quantile	47	47	32	48
90th quantile	54	54	37	54
99th quantile	59	59	45	59
Panel C: Women				
count	378,090	218,130	4,370	155,590
1st quantile	23	23	23	24
10th quantile	26	25	23	27
25th quantile	29	28	25	31
Mean	37.61	37.17	29.12	38.46
Median	36	35	27	37
75th quantile	45	45	32	46
90th quantile	52	52	38	53
99th quantile	58	59	46	59

Note: Unweighted summary statistics of individual age are reported for the additive OLS regression sample. Panel A shows the statistics of the pooled sample of men and women. Panels B and C show the statistics of men and women samples separately. Observations based on the survey report of earnings and annual earnings in the previous year are both included. Column 4 is estimated from the graduate degree sample. Column 3 is estimated from the more restricted subsample of individuals who are observed working full time before they obtain an advanced degree. Unweighted cell counts are rounded to the nearest 10.

Table A8: FEcg estimates of effects of advanced degrees by gender: graduate sample

	ln(earnings)		Occ.Prem.		ln(hourly wage)		ln(annual hours)	
	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	.548	.464	.539	.495	.334	.235	.229	.285
	(.118)	(.102)	(.088)	(.052)	(.082)	(.088)	(.025)	(.039)
Law	.525	.415	.350	.351	.445	.322	.087	.112
	(.070)	(.088)	(.044)	(.049)	(.066)	(.059)	(.021)	(.016)
Master's in business-related fields	.248	.153	.016	.046	.176	.109	.020	.062
	(.068)	(.050)	(.022)	(.015)	(.06)	(.032)	(.020)	(.012)
MBA	.145	.097	.026	.006	.126	.060	.026	.047
	(.037)	(.022)	(.015)	(.008)	(.031)	(.022)	(.011)	(.007)
Master's in nursing	.208	.565	.030	.066	.175	.878	.006	-.190
	(.039)	(.106)	(.011)	(.034)	(.034)	(.132)	(.024)	(.054)
Master's in engineering	.054	.123	-.009	.025	.052	.080	.034	.025
	(.039)	(.020)	(.015)	(.011)	(.036)	(.021)	(.013)	(.008)
Master's in health services administration	.296	.201	.085	.126	.284	.135	.028	.103
	(.087)	(.129)	(.038)	(.059)	(.079)	(.136)	(.026)	(.033)
Master's in computer and mathematical sciences	.232	.151	.031	.016	.163	.155	.019	.026
	(.062)	(.034)	(.019)	(.013)	(.063)	(.036)	(.020)	(.011)
Master's in public administration	.160	.173	.009	.100	.113	.266	.012	-.009
	(.062)	(.069)	(.055)	(.051)	(.055)	(.082)	(.020)	(.025)
Master's in other science and engineering-related fields	.024	-.056	.164	-.001	0.000	.002	-.012	.006
	(.088)	(.051)	(.088)	(.038)	(.089)	(.05)	(.032)	(.035)
Master's in physical and related sciences	.114	.173	.014	-.040	-.003	.178	.072	.030
	(.072)	(.066)	(.024)	(.025)	(.087)	(.063)	(.023)	(.020)
Master's in health-related fields	.350	.066	.110	.144	.331	.133	.021	.069
	(.056)	(.070)	(.022)	(.048)	(.046)	(.062)	(.017)	(.033)
Master's in other social and related sciences	.150	.084	.071	.065	.180	.071	.013	-.031
	(.072)	(.091)	(.027)	(.046)	(.08)	(.072)	(.024)	(.030)
Master's in other non-science and engineering fields	.135	.113	-.040	.035	.029	.101	-.008	.008
	(.069)	(.096)	(.035)	(.037)	(.063)	(.102)	(.022)	(.025)
Master's in biological/agricultural/ environmental/life sciences	.164	.138	-.005	.045	.103	.079	.025	.023
	(.065)	(.068)	(.025)	(.023)	(.060)	(.078)	(.024)	(.026)
Master's in education fields	.199	.096	.013	.057	.164	.105	.017	.002
	(.021)	(.030)	(.008)	(.010)	(.021)	(.033)	(.009)	(.015)
Master's in psychology and social work	.194	.148	.015	.018	.169	.168	.029	.003
	(.030)	(.062)	(.018)	(.03)	(.035)	(.056)	(.012)	(.022)
Master's in humanity fields	.121	-.033	-.048	-.060	.148	-.090	.018	.039
	(.066)	(.093)	(.031)	(.034)	(.064)	(.069)	(.023)	(.026)
Master's in arts	-.010	-.094	.081	-.016	.077	-.107	-.017	.083
	(.074)	(.105)	(.085)	(.043)	(.084)	(.112)	(.034)	(.048)

Note: The table reports FEcg estimates of the effects advanced degrees for each dependent variable and gender. The sample is restricted to full time workers who eventually get an advanced degree. The sample for the log of annual hours only uses the current year observation. Sample weights are used. Standard errors are clustered by person. The dependent variable is log earnings in 2013 dollars. The 4 dependent variables are the log of earnings, occupational premiun, log of hourly wage rate, and log of annual hours. For each dependent variable, the column on the left is for women and the column on the right is for men. The regressions include dummies for each BA field (OLS only) and each advanced degree, as well as race/Hispanic, parental education, the year, a cubic in age, and interactions between a cubic in age and BA field. The age polynomials and the year dummies control for linear birth cohort trend and partially control for nonlinear birth cohort effects. The ln(earnings), occupational premium, and ln(hourly wage) samples have 377,835 and 641,263 observations for females and males, respectively. The ln(annual hours) samples have 196,376 females and 334,648 males, respectively.

Table A9: Internal Rate of Return to Advanced Degrees by Gender: public institution with zero earnings when enrolled, FEcg

	Female				Male			
	PDV actual	PDV counter-factual	%Gain in PDV	IRR	PDV actual	PDV counter-factual	%Gain in PDV	IRR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	1.54	1.12	37.01	0.15	2.18	1.25	73.61	0.22
	[0.03]	[0.12]	[17.63]	[0.03]	[0.03]	[0.10]	[13.60]	[0.02]
Law	1.37	0.94	45.07	0.18	1.71	1.21	41.93	0.19
	[0.03]	[0.05]	[6.65]	[0.02]	[0.03]	[0.09]	[9.99]	[0.03]
Master's in business-related fields	1.31	1.11	18.11	0.16	1.75	1.53	14.01	0.14
	[0.04]	[0.06]	[6.89]	[0.03]	[0.03]	[0.10]	[7.88]	[0.04]
MBA	1.24	1.17	6.58	0.09	1.59	1.51	5.43	0.09
	[0.02]	[0.04]	[3.42]	[0.02]	[0.02]	[0.03]	[2.15]	[0.01]
Master's in nursing	1.26	1.22	3.79	0.08	1.90	1.25	52.03	0.31
	[0.02]	[0.04]	[3.88]	[0.02]	[0.07]	[0.15]	[19.57]	[0.08]
Master's in engineering	1.38	1.34	3.01	0.09	1.66	1.48	12.35	0.20
	[0.02]	[0.05]	[3.99]	[0.07†]	[0.01]	[0.03]	[2.22]	[0.02]
Master's in health services administration	1.17	0.97	19.80	0.16	1.45	1.26	14.70	0.14
	[0.04]	[0.11]	[12.96]	[0.08†]	[0.07]	[0.13]	[11.89]	[0.10†]
Master's in computer and mathematical sciences	1.23	1.03	19.55	0.26	1.60	1.42	13.11	0.21
	[0.02]	[0.07]	[8.81]	[0.08]	[0.02]	[0.05]	[4.03]	[0.04]
Master's in public administration	1.04	0.97	7.03	0.10	1.27	1.13	12.68	0.13
	[0.04]	[0.06]	[6.35]	[0.05†]	[0.04]	[0.07]	[6.87]	[0.07†]
Master's in other science and engineering-related fields	1.08	1.09	-0.28	0.05	1.34	1.43	-6.24	-0.40
	[0.04]	[0.09]	[8.43]	[0.24†]	[0.03]	[0.08]	[5.26]	[0.21†]
Master's in physical and related sciences	1.02	0.92	10.91	0.18	1.26	1.01	24.88	0.32
	[0.03]	[0.06]	[7.80]	[0.08]	[0.03]	[0.07]	[9.21]	[0.08]
Master's in health-related fields	1.05	0.83	26.41	0.19	1.39	1.33	4.44	0.08
	[0.02]	[0.05]	[7.38]	[0.03]	[0.04]	[0.10]	[7.32]	[0.10†]
Master's in other social and related sciences	1.00	0.89	12.05	0.19	1.27	1.16	9.71	0.17
	[0.02]	[0.06]	[7.93]	[0.08]	[0.03]	[0.09]	[9.73]	[0.11†]
Master's in other non-science and engineering fields	0.93	0.83	11.51	0.18	1.13	1.00	13.04	0.21
	[0.02]	[0.07]	[9.98]	[0.11†]	[0.04]	[0.10]	[11.48]	[0.16†]
Master's in biological/agricultural/environmental/life sciences	0.94	0.81	15.75	0.22	1.05	0.84	24.87	0.31
	[0.01]	[0.05]	[6.80]	[0.07]	[0.02]	[0.05]	[7.30]	[0.06]
Master's in education fields	0.92	0.78	17.70	0.24	1.07	0.97	10.26	0.17
	[0.01]	[0.02]	[2.37]	[0.02]	[0.01]	[0.03]	[3.06]	[0.03]
Master's in psychology and social work	0.84	0.78	8.72	0.10	1.00	0.90	10.81	0.12
	[0.01]	[0.03]	[3.67]	[0.02]	[0.02]	[0.05]	[6.51]	[0.03]
Master's in humanity fields	0.83	0.76	8.66	0.15	0.87	0.91	-3.71	-0.04
	[0.02]	[0.05]	[6.98]	[0.12†]	[0.03]	[0.08]	[8.04]	[0.22†]
Master's in arts	0.77	0.88	-13.05	-0.40	0.94	1.12	-16.54	-0.40
	[0.04]	[0.08]	[8.62]	[0.21†]	[0.04]	[0.13]	[9.85]	[0.22†]

Note: This table reports the same statistics as Table 7 for the earnings model (3), which excludes post-advanced degree experience regression coefficients. The regressions specifications are in Table 2, column 1 for female and column 5 for male.

Table A10: Internal Rate of Return to Advanced Degrees by Gender: public institution with zero earnings when enrolled, OLS

	Female				Male			
	PDV actual	PDV counter-factual	%Gain in PDV	IRR	PDV actual	PDV counter-factual	%Gain in PDV	IRR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	1.53	0.93	65.06	0.19	2.18	1.19	83.43	0.23
	[0.03]	[0.01]	[3.63]	[0.01]	[0.03]	[0.01]	[2.76]	[0.00]
Law	1.36	0.92	48.13	0.19	1.73	1.25	38.46	0.18
	[0.03]	[0.01]	[3.40]	[0.01]	[0.03]	[0.01]	[2.49]	[0.01]
Master's in business-related fields	1.29	0.99	30.13	0.21	1.74	1.35	29.35	0.22
	[0.04]	[0.01]	[3.53]	[0.02]	[0.03]	[0.01]	[2.25]	[0.01]
MBA	1.23	0.99	24.77	0.18	1.58	1.36	16.53	0.15
	[0.02]	[0.01]	[2.37]	[0.01]	[0.02]	[0.01]	[1.35]	[0.01]
Master's in nursing	1.26	1.08	17.22	0.15	1.90	1.21	57.07	0.33
	[0.02]	[0.01]	[1.84]	[0.01]	[0.07]	[0.03]	[6.30]	[0.03]
Master's in engineering	1.37	1.19	15.03	0.22	1.66	1.50	10.69	0.18
	[0.02]	[0.02]	[2.06]	[0.02]	[0.01]	[0.01]	[0.74]	[0.01]
Master's in health services	1.16	0.95	21.91	0.17	1.45	1.21	20.47	0.17
administration	[0.04]	[0.01]	[4.07]	[0.02]	[0.07]	[0.02]	[6.47]	[0.03]
Master's in computer and	1.23	1.04	18.64	0.25	1.61	1.38	16.17	0.24
mathematical sciences	[0.02]	[0.01]	[2.18]	[0.02]	[0.02]	[0.01]	[1.32]	[0.01]
Master's in public administration	1.04	0.91	14.12	0.14	1.27	1.23	3.68	0.08
	[0.04]	[0.01]	[4.39]	[0.02]	[0.04]	[0.01]	[3.42]	[0.03]
Master's in other science and	1.07	0.99	8.43	0.15	1.34	1.30	2.93	0.09
engineering-related fields	[0.04]	[0.02]	[4.37]	[0.06†]	[0.03]	[0.02]	[2.41]	[0.04]
Master's in physical and	1.03	0.96	6.82	0.14	1.26	1.25	0.41	0.06
related sciences	[0.03]	[0.02]	[3.37]	[0.04]	[0.03]	[0.01]	[2.13]	[0.03]
Master's in health-related fields	1.04	0.92	12.37	0.12	1.38	1.19	16.19	0.15
	[0.02]	[0.01]	[1.88]	[0.01]	[0.03]	[0.01]	[2.93]	[0.02]
Master's in other social and	1.00	0.90	11.19	0.18	1.27	1.23	3.61	0.10
related sciences	[0.02]	[0.01]	[2.21]	[0.02]	[0.03]	[0.01]	[2.65]	[0.04]
Master's in other non-science and	0.93	0.88	5.03	0.11	1.14	1.17	-2.59	-0.00
engineering fields	[0.02]	[0.01]	[2.41]	[0.03]	[0.04]	[0.01]	[3.12]	[0.17†]
Master's in biological/agricultural/	0.93	0.91	2.17	0.08	1.05	1.16	-9.44	-0.40
environmental/life sciences	[0.01]	[0.01]	[1.57]	[0.02]	[0.02]	[0.01]	[1.96]	[0.12†]
Master's in education fields	0.92	0.84	9.87	0.17	1.08	1.13	-4.66	-0.40
	[0.01]	[0.01]	[1.14]	[0.01]	[0.01]	[0.01]	[1.26]	[0.05†]
Master's in psychology and	0.84	0.85	-1.15	0.04	1.00	1.12	-11.01	-0.40
social work	[0.01]	[0.01]	[1.17]	[0.01]	[0.02]	[0.01]	[1.72]	[0.14†]
Master's in humanity fields	0.84	0.88	-4.55	-0.06	0.88	1.15	-23.60	-0.40
	[0.02]	[0.01]	[2.20]	[0.09†]	[0.03]	[0.01]	[2.09]	[0.00†]
Master's in arts	0.78	0.84	-7.86	-0.03	0.93	1.08	-13.69	-0.40
	[0.04]	[0.01]	[4.44]	[0.19†]	[0.04]	[0.03]	[4.00]	[0.13†]

Note: This table reports the same statistics as Table 8 for earnings model (1), which excludes post graduate degree experience coefficients.

Table A11: Internal Rate of Return to Advanced Degrees by Gender: public institution with estimated earnings when enrolled, FEcg with post-adv experience

	Female				Male			
	PDV actual	PDV counter-factual	%Gain in PDV	IRR	PDV actual	PDV counter-factual	%Gain in PDV	IRR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	1.56	1.10	41.78	0.12	2.04	1.21	68.58	0.17
	[0.04]	[0.13]	[19.14]	[0.03]	[0.03]	[0.10]	[13.07]	[0.02]
Law	1.38	0.92	50.44	0.18	1.69	1.19	41.78	0.18
	[0.03]	[0.05]	[7.00]	[0.02]	[0.03]	[0.09]	[9.89]	[0.03]
Master's in business-related fields	1.37	1.09	25.54	0.22	1.81	1.51	20.13	0.22
	[0.04]	[0.06]	[7.19]	[0.06]	[0.03]	[0.09]	[8.06]	[0.22†]
MBA	1.35	1.14	18.09	0.20	1.68	1.48	13.81	0.21
	[0.03]	[0.04]	[3.72]	[0.06]	[0.02]	[0.03]	[2.24]	[0.04]
Master's in nursing	1.33	1.21	9.21	0.17	1.96	1.24	58.39	0.43
	[0.02]	[0.04]	[4.06]	[0.06]	[0.11]	[0.15]	[22.00]	[0.18†]
Master's in engineering	1.42	1.29	10.47	0.12	1.68	1.45	15.69	0.23
	[0.02]	[0.05]	[4.23]	[0.04]	[0.01]	[0.03]	[2.18]	[0.06]
Master's in health services	1.25	0.96	30.06	0.29	1.53	1.24	23.72	0.30
administration	[0.04]	[0.12]	[14.18]	[0.19†]	[0.07]	[0.12]	[12.32]	[0.21†]
Master's in computer and	1.23	1.02	21.12	0.25	1.62	1.40	16.09	0.25
mathematical sciences	[0.02]	[0.07]	[8.83]	[0.26†]	[0.02]	[0.05]	[4.25]	[0.10]
Master's in public administration	1.09	0.95	15.07	0.15	1.33	1.11	19.77	0.22
	[0.04]	[0.05]	[6.83]	[0.07†]	[0.04]	[0.07]	[7.03]	[0.10†]
Master's in other science and	1.03	1.04	-0.94	0.05	1.28	1.41	-9.24	-0.01
engineering-related fields	[0.04]	[0.09]	[8.58]	[0.05]	[0.03]	[0.08]	[5.39]	[0.04]
Master's in physical and	1.03	0.90	14.33	0.13	1.23	0.97	26.40	0.23
related sciences	[0.03]	[0.06]	[7.71]	[0.05]	[0.02]	[0.06]	[9.01]	[0.22†]
Master's in health-related fields	1.04	0.81	27.95	0.23	1.40	1.29	7.80	0.09
	[0.02]	[0.05]	[7.53]	[0.05]	[0.04]	[0.09]	[7.54]	[0.06†]
Master's in other social and	0.99	0.87	13.14	0.13	1.25	1.13	10.37	0.14
related sciences	[0.02]	[0.06]	[7.96]	[0.07]	[0.03]	[0.09]	[9.54]	[0.14†]
Master's in other non-science and	0.92	0.81	14.39	0.16	1.15	0.98	17.08	0.50
engineering fields	[0.02]	[0.06]	[10.01]	[0.21†]	[0.04]	[0.10]	[12.07]	[0.34†]
Master's in biological/agricultural/	0.93	0.78	19.61	0.19	1.03	0.81	26.80	0.20
environmental/life sciences	[0.01]	[0.05]	[6.80]	[0.09]	[0.02]	[0.05]	[7.28]	[0.06]
Master's in education fields	0.92	0.76	20.61	0.31	1.07	0.95	12.52	0.20
	[0.01]	[0.01]	[2.35]	[0.06]	[0.01]	[0.03]	[3.05]	[0.08]
Master's in psychology and	0.88	0.76	15.76	0.14	1.03	0.89	15.98	0.15
social work	[0.01]	[0.02]	[3.88]	[0.03]	[0.02]	[0.05]	[6.59]	[0.05]
Master's in humanity fields	0.82	0.75	10.06	0.13	0.87	0.89	-2.64	0.02
	[0.02]	[0.05]	[6.92]	[0.09†]	[0.02]	[0.07]	[7.86]	[0.13†]
Master's in arts	0.78	0.86	-8.61	-0.02	0.94	1.08	-12.73	-0.04
	[0.04]	[0.08]	[10.22]	[0.22†]	[0.04]	[0.13]	[12.52]	[0.14†]

Note: This table reports the same statistics as Table 7 without the full-time enrollment assumption.

Table A12: Internal Rate of Return to Advanced Degrees by Gender: public institution with estimated earnings when enrolled, OLS with post-adv experience

	Female				Male			
	PDV actual	PDV counter-factual	%Gain in PDV	IRR	PDV actual	PDV counter-factual	%Gain in PDV	IRR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	1.55	0.92	67.84	0.16	2.04	1.20	70.77	0.17
	[0.04]	[0.01]	[3.74]	[0.00]	[0.03]	[0.01]	[2.62]	[0.01]
Law	1.38	0.92	50.07	0.18	1.70	1.25	35.51	0.16
	[0.03]	[0.01]	[3.41]	[0.01]	[0.03]	[0.01]	[2.45]	[0.01]
Master's in business-related fields	1.35	0.99	36.50	0.30	1.81	1.35	33.62	0.39
	[0.04]	[0.01]	[3.70]	[0.06]	[0.03]	[0.01]	[2.16]	[0.25†]
MBA	1.34	0.99	35.34	0.50	1.68	1.37	22.79	0.35
	[0.03]	[0.01]	[2.41]	[0.21†]	[0.02]	[0.01]	[1.29]	[0.05]
Master's in nursing	1.33	1.08	23.16	0.33	1.97	1.22	61.91	0.45
	[0.02]	[0.01]	[1.86]	[0.05]	[0.11]	[0.03]	[9.47]	[0.11†]
Master's in engineering	1.42	1.19	19.98	0.18	1.68	1.51	11.48	0.17
	[0.02]	[0.02]	[2.06]	[0.03]	[0.01]	[0.01]	[0.65]	[0.02]
Master's in health services	1.25	0.95	30.72	0.30	1.54	1.21	27.32	0.30
administration	[0.04]	[0.01]	[3.80]	[0.06]	[0.07]	[0.02]	[6.20]	[0.15†]
Master's in computer and	1.23	1.04	18.98	0.22	1.63	1.39	17.14	0.25
mathematical sciences	[0.02]	[0.01]	[2.09]	[0.06]	[0.02]	[0.01]	[1.32]	[0.04]
Master's in public administration	1.09	0.91	20.00	0.19	1.33	1.23	7.90	0.11
	[0.04]	[0.01]	[4.06]	[0.03]	[0.04]	[0.01]	[3.22]	[0.03]
Master's in other science and	1.02	0.99	3.09	0.06	1.27	1.31	-2.67	0.04
engineering-related fields	[0.04]	[0.02]	[3.79]	[0.02]	[0.03]	[0.02]	[2.27]	[0.01]
Master's in physical and	1.03	0.96	7.51	0.09	1.23	1.26	-2.33	0.04
related sciences	[0.03]	[0.01]	[2.99]	[0.02]	[0.02]	[0.01]	[1.74]	[0.01]
Master's in health-related fields	1.03	0.92	12.02	0.14	1.39	1.20	15.72	0.13
	[0.02]	[0.01]	[1.95]	[0.01]	[0.03]	[0.01]	[2.84]	[0.01]
Master's in other social and	0.99	0.90	10.00	0.11	1.25	1.24	1.20	0.06
related sciences	[0.02]	[0.01]	[2.14]	[0.02]	[0.03]	[0.01]	[2.08]	[0.02]
Master's in other non-science and	0.92	0.89	4.07	0.08	1.16	1.17	-1.31	0.03
engineering fields	[0.02]	[0.01]	[2.27]	[0.02]	[0.04]	[0.01]	[3.07]	[0.06†]
Master's in biological/agricultural/	0.93	0.91	2.07	0.06	1.03	1.17	-12.30	-0.05
environmental/life sciences	[0.01]	[0.01]	[1.55]	[0.01]	[0.02]	[0.01]	[1.68]	[0.03]
Master's in education fields	0.93	0.84	10.30	0.15	1.08	1.14	-5.11	-0.00
	[0.01]	[0.01]	[1.02]	[0.01]	[0.01]	[0.01]	[1.11]	[0.02]
Master's in psychology and	0.88	0.85	3.49	0.07	1.03	1.13	-8.54	-0.02
social work	[0.01]	[0.01]	[1.17]	[0.01]	[0.02]	[0.01]	[1.61]	[0.06†]
Master's in humanity fields	0.83	0.88	-5.74	0.00	0.87	1.16	-24.67	-0.40
	[0.02]	[0.01]	[2.15]	[0.18†]	[0.02]	[0.01]	[1.88]	[0.05†]
Master's in arts	0.79	0.84	-6.21	0.01	0.93	1.08	-13.50	-0.05
	[0.04]	[0.01]	[4.78]	[0.14†]	[0.04]	[0.03]	[3.87]	[0.11†]

Note: This table reports the same statistics as Table 8 with estimated earnings when enrolled.

Table A13: Internal Rate of Return to Advanced Degrees by Gender: private institution with zero earnings when enrolled, FEcg with post-adv experience

	Female				Male			
	PDV actual	PDV counter-factual	%Gain in PDV	IRR	PDV actual	PDV counter-factual	%Gain in PDV	IRR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	1.47 [0.03]	1.10 [0.13]	33.67 [18.02]	0.10 [0.02]	1.94 [0.03]	1.21 [0.10]	60.54 [12.46]	0.13 [0.01]
Law	1.32 [0.03]	0.92 [0.05]	43.16 [6.59]	0.14 [0.01]	1.61 [0.03]	1.19 [0.09]	35.74 [9.38]	0.14 [0.02]
Master's in business-related fields	1.31 [0.04]	1.09 [0.06]	19.56 [6.92]	0.13 [0.02]	1.71 [0.03]	1.51 [0.09]	13.17 [7.58]	0.11 [0.03]
MBA	1.27 [0.03]	1.14 [0.04]	11.09 [3.65]	0.09 [0.01]	1.59 [0.02]	1.48 [0.03]	7.53 [2.16]	0.09 [0.01]
Master's in nursing	1.25 [0.02]	1.21 [0.04]	2.69 [3.88]	0.07 [0.02]	1.93 [0.12]	1.24 [0.15]	56.17 [22.46]	0.28 [0.06]
Master's in engineering	1.44 [0.03]	1.29 [0.05]	12.08 [4.35]	0.12 [0.02]	1.67 [0.01]	1.45 [0.03]	15.06 [2.23]	0.16 [0.01]
Master's in health services administration	1.19 [0.04]	0.96 [0.12]	23.86 [13.55]	0.14 [0.05]	1.46 [0.07]	1.24 [0.12]	17.70 [12.17]	0.13 [0.06†]
Master's in computer and mathematical sciences	1.23 [0.02]	1.02 [0.07]	21.19 [8.70]	0.20 [0.05]	1.62 [0.02]	1.40 [0.05]	15.55 [4.21]	0.18 [0.03]
Master's in public administration	1.04 [0.04]	0.95 [0.05]	9.19 [6.60]	0.09 [0.04†]	1.26 [0.04]	1.11 [0.07]	13.69 [6.73]	0.10 [0.03]
Master's in other science and engineering-related fields	1.10 [0.04]	1.04 [0.09]	5.80 [9.09]	0.08 [0.05]	1.31 [0.03]	1.41 [0.08]	-7.16 [5.46]	0.01 [0.04]
Master's in physical and related sciences	1.05 [0.03]	0.90 [0.06]	16.37 [7.95]	0.14 [0.04]	1.25 [0.02]	0.97 [0.06]	28.46 [9.08]	0.20 [0.05]
Master's in health-related fields	1.02 [0.02]	0.81 [0.05]	25.15 [7.38]	0.18 [0.03]	1.39 [0.04]	1.29 [0.09]	7.39 [7.52]	0.09 [0.06†]
Master's in other social and related sciences	1.01 [0.02]	0.87 [0.06]	16.03 [8.04]	0.15 [0.05]	1.27 [0.03]	1.13 [0.09]	11.87 [9.76]	0.13 [0.07]
Master's in other non-science and engineering fields	0.93 [0.02]	0.81 [0.06]	14.67 [9.95]	0.14 [0.06]	1.13 [0.04]	0.98 [0.10]	15.12 [11.96]	0.17 [0.09]
Master's in biological/agricultural/ environmental/life sciences	0.94 [0.01]	0.78 [0.05]	21.10 [6.79]	0.18 [0.04]	1.06 [0.02]	0.81 [0.05]	30.54 [7.52]	0.22 [0.04]
Master's in education fields	0.91 [0.01]	0.76 [0.01]	19.64 [2.39]	0.18 [0.01]	1.06 [0.01]	0.95 [0.03]	11.69 [3.05]	0.13 [0.02]
Master's in psychology and social work	0.85 [0.01]	0.76 [0.02]	11.33 [3.74]	0.09 [0.01]	0.99 [0.02]	0.89 [0.05]	11.19 [6.36]	0.09 [0.02]
Master's in humanity fields	0.83 [0.02]	0.75 [0.05]	10.89 [7.15]	0.12 [0.06†]	0.87 [0.03]	0.89 [0.07]	-2.32 [8.05]	0.03 [0.10†]
Master's in arts	0.76 [0.04]	0.86 [0.08]	-11.61 [9.49]	-0.03 [0.21†]	0.91 [0.04]	1.08 [0.13]	-15.73 [12.06]	-0.04 [0.13†]

Note: This table reports the same statistics as Table 7 using the tuition rates from private institution.

Table A14: Effect of advanced degrees on job satisfactions, part 1

	Overall		Opportunities for Advancement		Benefit		Intellectual Challenges	
	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	.571	.466	-.053	1.16	-.695	-.338	.741	1.4
	(.376)	(.346)	(.322)	(.46)	(.731)	(.538)	(.261)	(.537)
Law	.327	-.0374	.323	.0352	.0119	-.302	1.43	.885
	(.149)	(.434)	(.418)	(.409)	(.262)	(.303)	(.478)	(.356)
Master's in business-related fields	.184	.247	.276	.614	.241	.185	-.0592	.22
	(.344)	(.124)	(.257)	(.222)	(.378)	(.349)	(.287)	(.283)
MBA	-.221	.222	.114	-.00367	-.128	.0689	-.247	.257
	(.128)	(.0902)	(.145)	(.107)	(.168)	(.101)	(.173)	(.11)
Master's in nursing	.00781	-.106	-.282	-.724	-.0626	.678	.00454	-4.65
	(.159)	(.57)	(.223)	(.521)	(.208)	(.426)	(.22)	(.206)
Master's in engineering	.0124	-.147	-.0551	.0448	.0678	-.34	.0707	-.025
	(.184)	(.101)	(.199)	(.144)	(.21)	(.135)	(.205)	(.162)
Master's in health services administration	-.351	-.811	-.148	-1.48	.0398	.583	.363	.384
	(.276)	(.465)	(.391)	(.536)	(.333)	(.261)	(.275)	(.334)
Master's in computer and mathematical sciences	.0965	.0476	.284	.0445	.309	-.185	-.0395	.0683
	(.236)	(.137)	(.122)	(.148)	(.258)	(.188)	(.301)	(.145)
Master's in public administration	.0458	.154	-.387	.747	.306	.762	.321	.996
	(.266)	(.186)	(.332)	(.349)	(.269)	(.373)	(.322)	(.391)
Master's in other science and engineering-related fields	.161	.683	-.314	.99	-.864	.288	1.74	.404
	(.476)	(.199)	(.672)	(.348)	(.591)	(.347)	(.652)	(.295)
Master's in physical and related sciences	-.61	.0835	.123	-.0498	.255	-.516	.156	-.643
	(.234)	(.366)	(.187)	(.431)	(.23)	(.356)	(.254)	(.334)
Master's in health-related fields	.254	.186	.223	.356	.176	.359	.239	.0757
	(.125)	(.291)	(.165)	(.308)	(.165)	(.315)	(.182)	(.243)
Master's in other social and related sciences	-.121	-.188	.0172	.357	-.109	-.346	-.156	-.159
	(.258)	(.231)	(.232)	(.225)	(.281)	(.231)	(.253)	(.225)
Master's in other non-science and engineering fields	.182	-.639	.603	-.134	.342	-.619	.0444	-.418
	(.169)	(.383)	(.376)	(.354)	(.297)	(.383)	(.441)	(.45)
Master's in biological/agricultural/ environmental/life sciences	-.242	.0993	.0779	.859	-.0968	.00586	-.0363	.589
	(.177)	(.297)	(.195)	(.334)	(.195)	(.301)	(.295)	(.205)
Master's in education fields	-.0645	.0372	-.199	-.156	.0785	-.199	-.14	-.184
	(.0989)	(.142)	(.132)	(.162)	(.111)	(.119)	(.121)	(.167)
Master's in psychology and social work	.127	-.143	.251	.0624	.305	.727	.14	.145
	(.132)	(.224)	(.143)	(.275)	(.166)	(.34)	(.135)	(.38)
Master's in humanity fields	-.206	.567	-.436	.175	.0411	-.247	.097	.558
	(.41)	(.284)	(.399)	(.348)	(.287)	(.313)	(.394)	(.354)
Master's in arts	.927	1.32	-.466	2.17	-1.85	2.25	1.85	6.19
	(.316)	(.62)	(.272)	(.845)	(.551)	(.735)	(.358)	(.426)

Note: The table reports estimates of the effect of completing advanced degrees on job satisfaction from various perspective using an ordered Probit regression. Sample weights are used. Standard errors are clustered by person. The dependent variable takes 4 values and in the order of: very satisfied, somewhat satisfied, somewhat dissatisfied, and very dissatisfied. Columns 1-2 report the overall satisfaction, columns 3-4 the satisfaction on opportunities for advancement, columns 5-6 the job benefits, and columns 7-8 the intellectual challenge.

Table A15: Effect of advanced degrees on job satisfactions, part 2

	Degree of Independence		Level of Responsibility		Salary		Contribution to the Society	
	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	.607	.791	1.2	.83	.216	.764	.818	.571
	(.34)	(.54)	(.264)	(.332)	(.138)	(.403)	(.845)	(.376)
Law	.421	.416	.903	.883	.339	.286	.25	-.417
	(.484)	(.356)	(.309)	(.332)	(.428)	(.41)	(.334)	(.331)
Master's in business-related fields	-.439	-.403	-.0319	.0685	.576	1.05	-.222	-.328
	(.26)	(.227)	(.326)	(.23)	(.288)	(.227)	(.249)	(.299)
MBA	-.162	.252	-.0238	.29	.214	.167	-.119	.303
	(.167)	(.117)	(.173)	(.116)	(.169)	(.119)	(.181)	(.113)
Master's in nursing	.196	-.465	.138	-4.8	.0447	.0715	-.0586	-4.49
	(.181)	(.651)	(.2)	(.246)	(.161)	(.452)	(.222)	(.264)
Master's in engineering	.103	-.038	-.025	-.113	.0104	-.27	.0551	-.00148
	(.2)	(.127)	(.19)	(.131)	(.146)	(.127)	(.184)	(.123)
Master's in health services	.0854	.0174	.269	-.0421	-.0888	.292	.463	.
administration	(.268)	(.439)	(.228)	(.443)	(.226)	(.278)	(.391)	(.)
Master's in computer and	.306	-.0634	.395	.0788	.00636	.214	.0648	.0772
mathematical sciences	(.266)	(.187)	(.342)	(.157)	(.222)	(.18)	(.254)	(.125)
Master's in public administration	-.234	.998	.217	.54	.454	.432	-.216	-.0861
	(.272)	(.42)	(.34)	(.265)	(.308)	(.372)	(.429)	(.423)
Master's in other science and	.264	.464	.153	.166	.392	-.176	.867	.163
engineering-related fields	(.452)	(.491)	(.488)	(.326)	(.456)	(.333)	(.26)	(.295)
Master's in physical and	-.495	-.342	-.572	-.338	.25	-.123	.182	-.441
related sciences	(.366)	(.355)	(.431)	(.356)	(.29)	(.471)	(.224)	(.355)
Master's in health-related fields	.372	.797	.255	.473	.263	-.0104	.255	.228
	(.167)	(.537)	(.188)	(.278)	(.136)	(.224)	(.164)	(.358)
Master's in other social and	-.204	-.219	.0314	-.152	.0442	-.397	-.143	.000571
related sciences	(.239)	(.231)	(.173)	(.221)	(.168)	(.271)	(.254)	(.324)
Master's in other non-science and	-.238	-.434	.0297	-.319	.576	-.5	-.0702	-.246
engineering fields	(.324)	(.416)	(.223)	(.447)	(.356)	(.527)	(.387)	(.525)
Master's in biological/agricultural/	-.262	.974	.229	.847	.127	-.0458	-.0326	.578
environmental/life sciences	(.234)	(.36)	(.26)	(.3)	(.224)	(.314)	(.238)	(.348)
Master's in education fields	-.0984	-.292	.0866	-.0769	.0241	.177	-.0382	-.12
	(.118)	(.191)	(.131)	(.199)	(.0965)	(.155)	(.148)	(.178)
Master's in psychology and	-.154	.294	.281	-.0843	.147	.079	.235	.926
social work	(.184)	(.457)	(.166)	(.344)	(.176)	(.258)	(.17)	(.493)
Master's in humanity fields	.091	.757	.0438	.354	.105	.191	.442	.411
	(.451)	(.46)	(.381)	(.246)	(.213)	(.411)	(.338)	(.338)
Master's in arts	.2	2.46	1.28	11.6	-1.17	2.21	.344	-.475
	(.497)	(.557)	(.43)	(.395)	(.457)	(.778)	(.286)	(.466)

Note: The table conducts the same regression design as Table A14. Columns 1-2 report the satisfaction on degree of independence, columns 3-4 the level of responsibility, columns 5-6 the salary, and columns 7-8 the contribution to society.