The Labor Market Returns to Advanced Degrees*

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Abstract

We estimate the returns to a broad set of graduate degrees. To control for heterogeneity in preferences and ability, we use fixed effects for combinations of field-specific undergraduate and graduate degrees obtained by the last time we observe an individual. Basically, we compare earnings before the graduate degree to earnings after the degree. Using NSF data, we find large differences across graduate fields in earnings effects. The returns often depend on the undergraduate major. The contribution of occupational upgrading to the earnings gain varies across degrees. Finally, simple regression-based estimates of returns to graduate fields are often highly misleading.

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1 Introduction

Graduate education has grown rapidly in the U.S. and other countries. The ratio of new master's degrees awarded relative to the number of 24-year-olds in the U.S. has increased from 5.5% in 1985 to 14.7% in 2013. Over the same period, the ratio of new master's degrees to new bachelors degrees rose from about 27% to about 37%. A similar pattern has occurred in other OECD countries. For example, in the UK, the fraction of 24-year-olds with master's degrees rose from about 22% to 27% between 2005 and 2013.[1]

Many papers report estimates of the earnings differential between individuals with an advanced degree and those who stop with a bachelor's degree, but there is very little research studying differences in earnings *across* graduate degrees, even at the descriptive level. Figure 1 presents average earnings of full-time workers for the 19 graduate degree types that we focus on in the paper, and Table B1 provides values for a much more disaggregated set. The degree differentials are large. For example, on average people with a master's in education earn $66,306, while MBAs earn $115,161 and medical degree holders earn $164,302. A person deciding about graduate programs needs to know whether these estimates represent causal effects. And knowledge of the average causal effects is not enough, because returns may depend critically on undergraduate field, ability, and occupational preferences.

In this paper, we provide estimates of the returns to a broad set of graduate degrees. First, we estimate average returns to specific graduate degrees, such as an MBA, controlling for the main effects of college major. Second, we examine how these returns differ depending upon the undergraduate degree. Third, and more tentatively, we present estimates of the experience profile of the returns.

In order to credibly estimate returns to specific graduate degrees, we must account for the role of preferences and pre-determined ability in the joint determination of field of study, occupation, and earnings. Graduate education and ability shift what an individual could potentially earn in each occupation. But in a real sense, individuals choose their actual earnings by choosing job type based on both preferences and potential earnings. This can make earnings comparisons misleading as estimates of the causal effect of a degree for those who choose it. For example, an individual might prefer a master's in fine arts to an MBA because she enjoys art and would prefer to work as an artist rather than as a business analyst. Absent graduate school in fine arts, her counterfactual occupation might be a lower paying but arts-related job, not a business position. In this situation, the difference in earnings between fine arts graduates and individuals who do not go to graduate school would understate the labor market value of a fine arts degree.

The same selection issues complicate estimation of the return to a particular graduate degree for individuals with a given undergraduate degree. MBAs with a bachelor's in education are likely to differ from MBAs who majored in economics not only in the type of human capital they acquired in college but also in their preferences, predetermined ability and occupations before graduate school.

To address these issues, we use experience adjusted 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. One of the approaches we consider is to include person specific fixed effects (FE) in a regression model that includes dummy variables for graduate degrees in the current period. Abstracting from other controls, this approach identifies the return to graduate school using only people with earnings observations both before and after graduate school. Its main disadvantage is that for such people the elapsed time between when the graduate degree was obtained and when earnings are observed is typically short in our data. For this and other reasons, we rely primarily on a related approach, which we call FE-cg. For this approach, we

[1]The numbers are from Altonji et al. (2016b). Lemieux (2014) and Lindley and Machin (2016), among others, discuss the implications of the growth in graduate education for income distribution.

include fixed effects for whether an individual has obtained a particular college major c and graduate field g combination by the last time that we observe them, but we do not include person fixed effects. The main advantage of FE-cg is that it makes full use of individuals with earnings observations only before the advanced degree and the large number observed only after the advanced degree—not just individuals who are observed both before and after.

Our parameters of interest are the treatment on the treated (TT) effects of graduate field g for individuals who majored in c, for various combinations of c and g. An example is the effect on earnings of obtaining an MBA for engineering majors who get an MBA. The TT parameter is the difference between two weighted averages. The first is the weighted average of potential earnings associated with each occupation conditional on college and graduate field, ability, and preferences. The second is the weighted average for the "no graduate school" counterfactual. For the first average the weights are the actual conditional probabilities of choosing the occupations for those who obtain g. For the counterfactual average the weights are the counterfactual probabilities. Both sets of weights also depend on the conditional distributions of ability and preferences of those who have chosen the particular BA and graduate field.[2]

Using a three period model of graduate education, occupation choice, and earnings, we show how the conditional occupation choice probabilities and the conditional distributions of ability and preferences are determined. Expressions for the population values of the OLS, FE, and FE-cg estimators of the TT parameters reveal that OLS will almost certainly be biased, with the sign of the bias depending on the graduate degree. The reason is that OLS uses the wrong counterfactual earnings values. We also provide conditions under which FE-cg will be consistent. Roughly speaking, the first condition is that no new information about ability or preferences arrives between the time when pre graduate school earnings are observed and when the decision to attend graduate school is made. The second is a set of assumptions that imply a common experience profile conditional on college major. These include the effect of experience on potential earnings, the effect of experience on the occupation choice probabilities given ability and preferences, and the effects of learning about ability and preferences on earnings gains through occupational mobility. We also must restrict the role of occupation specific experience.

The data are from multiple waves of the National Survey of College Graduates (NSCG, 1993 to 2015), and the National Survey of Recent College Graduates (NSRCG, 1993 to 2010). Some individuals are surveyed more than one time. The data sets contain basic controls, earnings, occupation, and education histories that include acquired undergraduate and graduate degrees by field of study. They are large enough to support FE-cg estimation of the returns to graduate school for thirty combinations of undergraduate and graduate fields.[3] These data represent a rich and underutilized resource for the study of undergraduate and graduate education.

The empirical work starts with a descriptive analysis of the links among undergraduate field, occupation and graduate field. We document three facts. First, the link between undergraduate field and graduate field varies substantially across graduate fields. Second, both undergraduate field and occupation before graduate school have strong connections to graduate field. Finally, postgraduate occupation depends primarily on the graduate field.

We then look in more detail at the pre and post graduate school occupations for a few undergraduate and graduate degree combinations, such as bachelor's in engineering paired with a master's in education,

[2]Section 2.1 provides expressions for the TT parameters.

[3]Our main regression sample contains 863,890 observations, and includes 217,310 individuals who are observed more than once. However, we only have 8,180 pre graduate school earnings observations for people whom we later observe to obtain a graduate degree. This restricts the number of field combinations for which we can product FE-cg estimates of returns.

an MBA or a master's in engineering. These results show that the distribution of pre graduate school occupations is shifted toward the occupations that are more common for the particular advanced degree. They suggest that the counterfactual occupations for engineering majors who get an MBA are different from the occupations of engineering majors who do not attend graduate school. This means that regression models that in essence compare earnings with graduate school to those without are likely to be misleading. The occupation comparisons motivate, in part, our use of the FE-cg approach.

The heart of the paper is the estimation of the graduate school returns. The FE-cg approach shows substantial differences across graduate fields in labor market returns. There are too many fields to mention all of the results here, but a few examples may be helpful. The estimated return (in logs) for law is 0.421 (0.061) and for medicine is 0.574 (0.070), or 52% and 77.5% respectively. The return to an MBA is only 0.096 (0.021) or 10.1%, which is far below the OLS value of 0.282 (0.008). The return is 0.103 (0.018) for a masters in engineering, 0.164 (0.035) for computer and mathematical sciences, 0.247 (0.046) for health related fields, 0.236 (0.041) for nursing, 0.208 (0.029) for psychology and social work, 0.159 (0.019) for education, and essentially zero for both the arts and the humanities.

Specifications that allow the graduate degree premiums to depend on years since degree completion suggest that the premiums increase substantially with experience. The FE-cg estimate of the average premium between 1 and 28 years after degree completion are typically at least 5 log points higher than estimates that assume a constant premium. However, as we explain in section 2.3, the experience specific FE-cg estimates require the use of data on people who never attend graduate school to identify the counterfactual experience profile in the absence of a degree. We suspect that they are upward biased as a result.

We also find that the treatment on the treated effect for a given graduate field depends on the college major. For example, in the case of an MBA the FE-cg estimate of the return is 0.109 (0.067) for economics majors, 0.170 (0.069) for business majors, 0.137 (0.102) for psychology and social work majors, but only 0.078 (0.024) for engineering majors.

The FE-cg and OLS estimates of the returns differ substantially for many degrees. OLS tends to overstate the return to graduate fields that attract high paying college majors. Examples are a master's in engineering and an MBA. OLS also tends to understate returns to graduate fields that attract lower paying majors, such a master's in education or in psychology and social work. Simple earnings comparisons of those with an advanced degree to those without one are misleading.

Finally, the FE-cg estimates indicate that the extent to which the returns operate through occupational upgrading versus within occupation varies across degrees. In the cases of law and medicine, most of the return is across occupations, which make sense given licensing requirements and occupation specific skills. But in many other cases, such as engineering, most of the return is within occupation.

Our paper contributes to the vast literature on the return to higher education, and to the growing literature on the value of particular degrees. The econometric challenges have a lot in common with the problem of estimating the return to college major, and other problems in which individuals choose from multiple unordered options, although we believe they are more severe in the graduate education case.[4] The literature on the returns to college majors has grown rapidly over the past 20 years, as documented in the surveys by Altonji et al. (2012) and Altonji et al. (2016b). However, research on graduate degrees is much more limited. Using NLS72, Altonji (1993) reports regression estimates of the return to the highest degree, including some college, 10 aggregated college major categories, and 5 aggregated graduate school categories. His analysis is for a relatively young sample, and assumes that only the field of highest degree matters. Black

[4]See Heckman et al. (2008).

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. (2016b) report OLS estimates for a broader set of graduate and undergraduate degrees using the 1993, 2003, 2010, and 2013 NSCG.[5] Arcidiacono et al. (2008) study the return to an MBA using panel data on people who registered to take the GMAT exam, a standardized test that is used in MBA admissions. Sample members are observed up to 7 years after registering for the exam. They estimate that return to an MBA for men is 0.094 with basic controls, 0.063 after controlling for undergraduate GPA and the GMAT test scores, and 0.048 after controlling for individual fixed effects. Results for women are similar. These estimates are lower than what we report, but the short span between MBA completion and the post MBA earnings observation may reduce the estimates.[6] Bhattacharya (2005), Chen and Chevalier (2012) and Ketel et al. (2016) are part of a small literature that studies the return to medical degrees.

Our study is the first to provide treatment on the treated estimates of the returns to a broad set of graduate degrees and to a graduate degree for specific college majors while addressing selection bias.

The paper proceeds as follows. Section 2 uses a three period model to discuss the problem of selection bias and the estimation strategies we use. In section 3 we present the econometric specifications used. Section 4 describes the data. In section 5 we present basic facts about differences in earnings across graduate fields, and how they are related to earnings differences by bachelor degree field and by occupation. Section 6 examines links among undergraduate field, graduate field, and occupation before and after graduate school. Section 7 presents estimates of the return to graduate degrees. We conclude in section 8.

2 Addressing Selection Bias When Estimating the Return to Graduate Degrees

In this section we discuss our estimation strategy. We begin by specifying how earnings are determined and defining the TT parameters that we attempt to estimate. We then sketch a three period model of how earnings, graduate school choices, and occupation choices are determined, as functions of ability and field preferences. With the model as background, we present the OLS, FE, and the FE-cg estimators and discuss the conditions under which the FE and FE-cg estimators will identify the TT parameters.

2.1 The Treatment on the Treated Effect of a Graduate Degree on Earnings

First, some notation. We use i to denote the individual and for now use t to denote both the calendar year and years since college graduation. Later we use age_{it} to denote age of i in year t. The variable g, $g = 0, 1, \cdots, \mathcal{G}$, is the index of graduate degree type. Examples are a master's in engineering, a master's in education, and an MBA. The value $g = 0$ corresponds to no graduate degree. The variable G_{it} is the graduate degree that i holds in t, and the indicator G_{git} indicates that i has a graduate degree in g in period t. It is shorthand for $G_{it} = g$. The index c, $c = 1, \cdots, \mathcal{C}$, denotes undergraduate major. In the empirical work we only consider people who already have a college degree. We use the terms "major," "field," and "degree type" synonymously. We also use "BA" to refer to both bachelor of art and bachelor of science degrees, and we use MA in similar fashion. We use j, $j = 1, \cdots, \mathcal{J}$, to indicate occupation.

[5] They also report individual fixed effects estimates based on early work for the current paper. They are subject to the concerns that we raise below.

[6] Montgomery and Powell (2003) use the same data to show that the gender gap is narrower among MBA completers but do not focus on the return to an MBA. Gicheva (2013) uses the data to study earnings growth rates and shows that they are higher for individual who have obtained an MBA by the end of the sample period, although this may in part reflect the effect of obtaining an MBA on earnings levels.

Let $w_{ijcgt} = w_{jcgt}(A_{it})$ denote the value of the *potential* log of earnings that a person of ability A_{it} with degrees c and g could expect to receive in occupation j in period t.[7] When we use j and g as subscripts along with t, they refer to occupation and graduate degree status at t. Again, $g = 0$ corresponds to no graduate degree. Thus $w_{jc0t}(A_{it})$ is the log of earnings in j for someone who majored in c and had not gone to graduate school by period t. We suppress transitory shocks that influence earnings, such as luck in job search, and assume that these factors are unrelated to choice of cg. We are thus ignoring potential upward bias from Ashenfelter's dip (Ashenfelter (1978)) prior to graduate school.[8] The vector A_{it} consists of all variables that determine or are correlated with the earnings of a worker in j given c and g. The function $w_{jcgt}(A_{it})$ is not restricted, so the effect of A_i may depend on j in combination with c, g. Furthermore, cg may confer both absolute advantage and comparative advantage for a given value of A_{it}. However, the earnings function does not include occupational history, so it implicitly assumes that the effect of prior occupation on earnings does not vary with j and g. We return to this issue below.

The vector Q_{it} influences preferences for g and choice of j given cg, but does not directly influence the earnings. Some elements of A_{it} also influence preferences for particular fields of study and occupation. We typically suppress the i subscripts on these and other person specific variables that we introduce below. We define A_{it} and Q_{it} so that the influence of c and g on occupation specific earnings and nonpecuniary preferences is captured by the earnings function $w_{jcgt}(A_{it})$ and the nonpecuniary preference functions nu^{occ}_{cgjt} and nu^{grad}_{cgjt} introduced below. This definition makes it easier to distinguish between the causal effects of c and g on $w_{jcgt}(A_{it})$ and $nu^{occ}_{cgjt}(A_{it}, Q_{it})$ from the correlation that arises because the choices of c and g depend on A_{it} and Q_{it}. In the discussion of identification we treat A_{it} and Q_{it} as unobserved by the econometrician, although in practice we control for race\ethnicity, gender, parental education, and potential experience, which may be correlated with them. We abstract from the quality and selectivity of the college and graduate programs, which we do not observe.[9] We suppress the i subscript when i is not needed for clarity.

We focus on estimation of TT_{cgt}, the average treatment effect of g for c majors who eventually go on to obtain g. TT_{cgt} is the difference between the average over i of the potential earnings w_{icgjt} and the potential earnings w_{ic0jt}. The average is over the distribution of A and Q and j for c majors who choose g. Let

[7] Altonji et al. (2016b) briefly discuss the evidence on interactions between occupation and college major in earnings equations, which is limited. Some regression based studies estimate college major premiums with and without occupation fixed effects. These provide an informal assessment of the extent to which the return to major operates within occupations rather than across occupations, but they do not provide direct evidence that earnings depend on the major/occupation pair. Lemieux (2014) is one of the few papers that use multiple regression to estimate a system of potential earnings equations for c, j pairs. Robst (2007), Yuen et al. (2010), Lemieux (2014), Kinsler and Pavan (2015), Lindley and McIntosh (2015) and Altonji et al. (2016a) find that higher earnings for college graduates (1) who report that the skill requirements of their occupation is a good match for their college major or (2) who work in an occupation that is typical for their major. We do not know of papers that present such evidence for graduate field or college degree/graduate degree combinations.

[8] A negative transitory earnings shock will lower the opportunity cost of graduate school. As a result, the transitory earnings component in t will be negatively associated with graduate school attendance in t. Prior earnings of those who do attend will understate what future earnings of graduate school attendees would have been in the absence of graduate school. Arcidiacono et al. (2008) discuss the issue in the context of their individual fixed effects analysis of the return to an MBA.

[9] With quality measures and enough data, one could extend the analysis to consider program quality by redefining c and g to be field and program quality combinations.

$p_{cgt}(j|A_t, Q_t)$ be the probability of choosing j in period t given A_t, Q_t, c and g. Then TT_{cgt} is

$$TT_{cgt} = \sum_j \int_{A,Q} p_{cgt}(j|A,Q)\, w_{cgjt}(A_t)\, dF_t(A_t, Q_t|c, G_{gt}) \tag{1}$$
$$- \sum_j \int_{A,Q} p_{c0t}(j|A_t,Q_t)\, w_{c0jt}(A_t)\, dF_t(A_t, Q_t|c, G_{gt})$$
$$\equiv \overline{w}_{cgt}|G_{gt} - \overline{w}_{c0t}|G_{gt}$$

where $\overline{w}_{cgt}|G_{gt}$ is the mean of actual earnings in t for c majors with g and $\overline{w}_{c0t}|G_{gt}$ is the mean of what these individuals would have earned had they *not* gone to graduate school. The unconditional density of A_t and Q_t is $dF_t(A_t, Q_t)$. The conditional density $dF_t(A_t, Q_t|c, G_{gt})$ reflects selection based on the choice of c and g.

The causal effect of g on earnings works through two channels. First, g alters the potential earnings in each occupation j. Second, it alters the distribution of occupations that people choose conditional on c, A and Q. We directly observe the sample analog of $\overline{w}_{cgt}|G_{gt}$. It is the average of post graduate school earnings of people who choose c, g. The key econometric challenge is measuring the second term, which is the counterfactual earnings in t of those who chose c, g. The FE and FE-cg approaches, detailed in section 2.3, use earnings of c majors before graduate school who eventually obtain g to approximate counterfactual earnings. Basically, we are replacing $\overline{w}_{c0t}|G_{gt}$ with $\overline{w}_{c0t-\tau}|G_{gt}$, where $t-\tau$ is prior to graduate school. One requirement is that the distribution $dF_{t-\tau}(A_{t-\tau}, Q_{t-\tau}|c, G_{gt})$ is the same as $dF_t(A_t, Q_t|c, G_{gt})$ up to a change that can be captured by a common c-specific experience trend. We also need to account for how labor market experience influences the conditional occupation choice probabilities and earnings functions. To obtain insights into what this requires, we turn to a three period model of occupation and education choice.

2.2 A Simple Model of Occupation and Graduate Education Choice

Drawing on Altonji (1993), Arcidiacono (2004) and other papers, Altonji et al. (2012) and Altonji et al. (2016b) summarize the theoretical literature on the choice of field of study and labor market careers. The theory stresses the following features.

1. Preferences, innate ability, and knowledge at the start of college shape the expected utility of a particular education program. The decisions of whether to attend graduate school and in what field depend upon the same factors, as well as occupational experience.

2. Individuals learn gradually about preferences and ability, and about the labor market opportunities associated with particular courses of study in particular occupations.

3. Choices are made sequentially with imperfect information about preferences, ability, and labor market opportunities.

4. Education programs and occupations have different skill and knowledge prerequisites. The skill and knowledge of an individual influence how much the person learns in a particular program, and performance on the job.

5. Field of study shapes knowledge accumulation. A program of study shifts potential earnings in various occupations. Actual earnings depend on occupation choice, and occupation choice depends on potential earnings and preferences.

6. The effect of past experience in an occupation on potential earnings in other occupations varies.

A key implication is that the choices of whether to attend graduate school and what type of degree to pursue are influenced by prior choices, ability, and preferences.

We now present a simple three period model of occupation choice, graduate school, and earnings that is consistent with the first five features but assumes prior occupation has a neutral effect on the earnings. (We discuss the implications of occupation specific experience for our estimation strategy in section 3.) The timing is as follows. We consider c majors who have obtained their degree prior to t_1 and who choose to work in period t_1 rather than go directly to graduate school. This choice is in anticipation of the fact that our identification strategy involves comparisons of earnings before and after graduate school. Our parameters of interest refer to this population and not individuals who go directly to graduate school after college.

The potential earnings in each occupation in t_1 is given by $w_{c0jt_1}(A_{t1})$. In t_2, individual i either works in the optimal occupation or goes to graduate school in the optimal field. In t_3, i chooses an occupation and works. Our goal is to provide insights into what

$$E\left[w_{cgjt_3}(A_{t3})\,|c,G_{gt3}\right]-E\left[w_{c0jt_1}(A_{t1})\,|c,G_{gt3}\right]$$

corresponds to.

Let $nu^{occ}_{cgjt}(A_t,Q_t,\xi_{jt})$ be the non-pecuniary value of working in j in period t. It depends on A_t, Q_t, and the jth element ξ_{jt} of the vector ξ_t of i-specific i.i.d. occupation specific preference components. The function nu^{occ}_{cgjt} also depends on c and g because the knowledge and experiences gained in c and g may influence how satisfying j is for given values of A_t and Q_t.

We have implicitly assumed that prior occupation choice does not affect the pecuniary and nonpecuniary flow value of graduate education. As we pointed out in section 2.1, the earnings specification assumes that prior occupation does not affect future labor market opportunities in a way that depends on g or j_t. As a result, choice of occupation is separable from future education and occupation decisions. Correlation between j_{t1} and choice of g and future occupations arises from persistence in A_t, Q_t and the causal effects of c and g. We discuss relaxing these assumptions in section 2.4.

People are indifferent to the timing of consumption and income and are risk neutral.[10]

We now work backwards from the third period. The flow value from working in occupation j' in t_3 is

$$exp\left(w_{cgj't_3}(A_{t3})\right)+nu^{occ}_{cgj't_3}(A_{t3},Q_{t3},\xi_{j't3})\,,j'=1,\cdots,\mathcal{J}.$$

The individual chooses the occupation j_{t3} with the highest flow value, which we denote by $V_{cgt3}(A_{t3},Q_{t3},\xi_{t3})$. The occupation choice probabilities $p_{cgt_3}(j_{t3}|A_{t3},Q_{t3})$ are implicitly defined by the above t_3 choice problem and the distribution of the transitory occupation specific preference vector ξ_{t3}.

In t_2, i either works in the best occupation j_{t2} or attends graduate school in the best field. The net flow value of attending graduate school in field g is the non-pecuniary component $nu^{grad}_{cg}(A_{t2},Q_{t2},v_{t2})$ minus the monetary cost $COST_g(A_{t2},z_{t2})$. The non-pecuniary value depends on c, A, Q, and the preference shifter v_{t2}. The shifter v_{t2} influences utility from graduate school but is unrelated to A and Q, and has no direct influence on occupation choice. The monetary cost depends on A_{t2} and on the net tuition shifter z_{t2}. The vector z_{t2} captures tuition and grants at nearby schools and the potential for financial support from relatives.

[10]That is, we are assuming quasilinear utility and perfect credit markets. We also assume a zero rate of time preference. Given quasilinear utility and perfect credit markets, time preference would only influence choice by altering the weights on the non-pecuniary components of utility in different periods.

Adding the flow value of obtaining a g' degree to the continuation value for t_2 gives the value of going to graduate school in field g'.

$$\begin{aligned} V_{cg't2}\left(A_{t2},Q_{t2},z_{t2}\right) =& nu^{grad}_{cg'}\left(A_{t2},Q_{t2},v_{t2}\right) - COST_{g'}\left(A_{t2},z_{t2}\right), g'=1,\cdots,\mathcal{G} \\ &+ E_{t2}\left[V_{cg't3}\left(A_{t3},Q_{t3},\xi_{t3}\right)\right] \end{aligned}$$

The expectation is over the distribution of A_{t3}, Q_{t3} and ξ_{t3} conditional on A_{t2}, Q_{t2}. We do not explicitly incorporate the fact that graduate school attendance in g' is also conditional on availability and admission. However, one can think of the $nu^{grad}_{cg'}\left(A_{t2},Q_{t2},v_{t2}\right)$ and the $COST_{g'}\left(A_{t2},z_{t2}\right)$ functions as incorporating these factors.

Working in t_2 corresponds to choosing $g=0$. The flow value of working in j' is

$$exp\left(w_{c0j't_2}\left(A_{t2}\right)\right) + nu^{occ}_{j'}\left(A_{t2},Q_{t2},\xi_{t2},c,0\right), j'=1,\cdots,\mathcal{J}.$$

The value of working in t_2 is

$$\begin{aligned} V_{c0t2}\left(A_{t2},Q_{t2},\xi_{t2}\right) =& \max_j \left(exp\left(w_{c0jt2}\left(A_{t2}\right)\right) + nu^{occ}_{c0jt2}\left(A_{t2},Q_{t2},\xi_{t2}\right)\right) \\ &+ E_{t2}V_{c0t3}\left(A_{t3},Q_{t3},\xi_{t3}\right). \end{aligned}$$

Note that j does not appear in the continuation value $E_{t2}V_{c0t3}(A,Q,\xi_{t3})$ because we have ruled out effects of j on skill accumulation and the evolution of preferences.

Person i attends graduate school in program g if g is the best available graduate school option and it dominates working. The optimality conditions are

$$V_{cgt2}\left(A_{t2},Q_{t2},v_{t2},z_{t2}\right) > V_{cg't2}\left(A_{t2},Q_{t2},v_{t2},z_{t2}\right),\ g'=1,\cdots,\mathcal{G} \text{ and } g'\neq g \tag{2}$$

and

$$V_{cgt2}\left(A_{t2},Q_{t2},v_{t2},z_{t2}\right) > V_{c0t2}\left(A_{t2},Q_{t2},\xi_{t2}\right). \tag{3}$$

Note that $G_{gt3}=G_{gt2}$ because graduate education is obtained in t_2.

The above inequalities for the choice of g implicitly define the conditional pdf $dF_{t1}\left(A_{t2},Q_{t2}|c,G_{gt3}\right)$ based on the joint pdf of $\left(A_{t2},Q_{t2},v_{t2},z_{t2},\xi_{t2}\right)$ given c. The conditions (2,3) and the joint pdf of $\left(A_{t1},Q_{t1},A_{t2},Q_{t2},z_{t2},\xi_{t2},A_{t3},Q_{t3}\,|c\right)$ implicitly define the conditional pdfs $dF_{t1}\left(A_{t1},Q_{t1}|c,G_{gt3}\right)$ and $dF_{t3}\left(A_{t3},Q_{t3}|c,G_{gt3}\right)$. These distributions are central to our analysis in the next section of what OLS, FE, and FE-cg identify.

Finally, we turn to the first period. People choose the best occupation j_{t1} given that the value of working in j', $j'=1,\cdots,\mathcal{J}$ is

$$\begin{aligned} V_{c0t1}\left(j'_{t1}|A_{t1},Q_{t1},\xi_{t1}\right) = & exp\left(w_{c0j't_1}\left(A_{t1}\right)\right) + nu^{occ}_{c0j'}\left(A_{t1}\right) \\ &+ E_{t1}\left[max\left\{\max_{g'} V_{cg't2}\left(A_{t2},Q_{t2},v_{t2},z_{t2}\right), V_{c0t2}\left(A_{t2},Q_{t2},\xi_{t2}\right)\right\}\right]. \end{aligned}$$

The expectation is over the distribution of $A_{t2},Q_{t2},v_{t2},z_{t2},\xi_{t2}$ conditional on A_{t1},Q_{t1},c. The above choice problem implicitly determines the occupation choice probabilities $p_{c0t1}(j_{t1}|A_{t1},Q_{t1})$.

2.3 What Do Earnings Regressions Identify?

In this section, we discuss the earnings specifications used in the empirical work and interpret the estimators of TT_{cgt} in light of the model of occupation and education choice discussed above. We consider three main approaches. They are OLS regression, OLS regression with person fixed effects (FE), and OLS regression with fixed effects for the c, g combination reported the last time we observe an individual (FE-cg).

2.3.1 OLS Regression

We first consider the OLS regression of w_{icgjt} on a set of dummies for combinations of c and g, without controls for j or A. Expected earnings for someone who majored in c but has not gone to graduate school by period t is

$$\overline{w}_{c0t}|G_{0t} = \sum_j \int_{A,Q} p_{c0t}\left(j|A_t, Q_t\right) w_{c0jt}\left(A\right) dF_t\left(A_t, Q_t|c, G_{0t}\right), t = t_1, t_2, t_3.$$

Expected earnings in t_3 for someone who obtains g is

$$\overline{w}_{cgt_3}|G_{gt3} = \sum_j \int_{\text{A,Q}} p_{cgt_3}\left(j|A_{t3}, Q_{t3}\right) w_{cgjt3}\left(A_{t3}\right) dF_{t3}\left(A_{t3}, Q_{t3}|c, G_{gt3}\right).$$

The OLS coefficient on a dummy for G_{gt3} using just the period t_3 observations for c majors identifies

$$TT^{OLS}_{cgt3} = \overline{w}_{cgt3}|G_{gt3} - \overline{w}_{c0t3}|G_{0t3}.$$

TT^{OLS}_{cgt3} is a biased estimator of TT_{cgt3} because the education and occupation choice model implies that $dF_{t3}\left(A_{t3}, Q_{t3}|c, G_{gt3}\right)$ differs from $dF_{t3}\left(A_{t3}, Q_{t3}|c, G_{0t3}\right)$. Consequently, TT^{OLS}_{cgt3} differs from TT_{cgt3} for two main reasons. First, differences in the distribution of A between the c, G_{gt3} and the c, G_{0t3} populations will lead earnings to differ even if A and Q do not alter the occupation choice probabilities. Second, A and Q influence occupation choice, and occupation matters for earnings.[11] Intuitively, a person who majors in English and chooses to go to law school has different occupational preferences and abilities than an English major who does not go to law school. The law school graduate would have followed a different career path in the absence of a law degree.

2.3.2 Person Fixed Effects (FE)

The second specification controls for person fixed effects. The earnings gain from g for a given c is identified from people who are observed working both before and after obtaining g.[12] Consider the subset of individuals who majored in c, work in period t_1, obtain g in t_2 and work in t$_3$. They identify

[11] Here we consider OLS when only t_3 observations are used to simplify the discussion of bias, but the argument extends directly to the case when observations from all three periods are used. We use all periods in the empirical work.

[12] The main effects of college majors are not identified. They are absorbed by the person effects.

$$\begin{aligned} TT^{FE}_{cgt3} &= E\left[w_{icgjt3} - w_{ic0jt_1} | c, G_{git3}\right] \qquad (4) \\ &= \sum_j \int_{A,Q} p_{cgt3}\left(j|A_{t3}, Q_{t3}\right) w_{cgjt3}\left(A_{t3}\right) dF_{t3}\left(A_{t3}, Q_{t3}|c, G_{gt3}\right) \\ &\quad -\sum_j \int_{A,Q} p_{c0t1}\left(j|A_{t1}, Q_{t1}\right) w_{c0jt1}\left(A_{t1}\right) dF_{t1}\left(A_{t1}, Q_{t1}|c, G_{gt3}\right). \end{aligned}$$

Comparing the above equation with equation (1), one can see that differences could arise from three sources. The first is the difference between dF_{t3} and dF_{t1}. The second is the effect of experience on occupation choice. The third is the effect of experience on occupation specific earnings.

First consider dF_{t3} and dF_{t1}. To focus on the selection issue, assume for now that years since college graduation do not affect the w and p functions. Then $TT^{FE}_{cgt3} = TT_{cgt3}$ provided that the distribution of A and Q does not change between t_1 and t_3. This condition is

$$dF_{t1}\left(A_{t1}, Q_{t1}|c, G_{gt3}\right) = dF_{t3}\left(A_{t3}, Q_{t3}|c, G_{gt3}\right). \qquad (5)$$

Note that the distributions of A and Q do not shift with the attainment of g because A and Q are defined to be net of the effects of cg. Thus, the fact that dF_{t1} is from the period before g is obtained and dF_{t3} is from the period after g is obtained does not lead $dF\left(A_{t1}, Q_{t1}|c, g_{t3}\right)$ to differ from $dF\left(A_{t3}, Q_{t3}|c, g_{t3}\right)$. If ability and preferences do not change after college, then the condition obviously holds. In reality, one would expect permanent changes in A and Q (or updating of beliefs about A and Q) to occur in the years after college.

To see the implications, consider a change in Q that would induce individuals to move toward higher paying occupations as well as induce the individual to get a degree g, say an MBA. Then

$$\overline{w}_{cgt_3}|G_{gt3} = \sum_j \int_{A,Q} p_{c0t1}\left(j|A_{t1}, Q_{t1}\right) w_{c0jt1}\left(A_{t1}\right) dF_{t1}\left(A_{t1}, Q_{t1}|c, G_{gt3}\right)$$

is likely to understate the counterfactual earnings of someone who obtains an MBA. For example, an education major who starts out as a teacher but finds she has a taste for business would be likely to move toward better paying business related occupations even if she does not pursue an MBA. Her taste for business would also make her more likely to seek an advanced degree that provides skills that are valued in business, such as an MBA. The differences between her earnings as a teacher and her earnings after her MBA would overstate the causal effect of the MBA.

The problem is lessened if earnings are available *after* her preferences have changed but *before* she goes to graduate school. In this case, her earnings (and occupation choices) prior to graduate school will reflect her new beliefs.[13] In the context of the three period model above, this amounts to assuming

Assumption A1 *(Constant ability and preference)*:

$$dF_{t1}\left(A_{t1}, Q_{t1}|c, G_{gt3}\right) = dF_{t2}\left(A_{t2}, Q_{t2}|c, G_{gt3}\right).$$

In this case, $\overline{w}_{cgt_1}|G_{gt3}$ is based on the distribution of ability and preferences that governed the decision to obtain g.

[13] Our data does include measures of preferences as well as occupation, so in principle one could examine changes in preferences for those observed more than once before graduate school. Sample size consideration would limit how much one could do along these lines.

2.3.3 Age Profiles

Because we do not observe the counterfactual $\overline{w}_{cgt_1}|G_{gt3}$, we also need additional assumptions that allow us to adjust for age. In our basic specification, we assume that the graduate degree does not alter the experience profile for c majors. This requires three additional assumptions. The first concerns the effects of new information about A and Q. New information arriving between t_2 and t_3 could still lead to a difference between $dF_{t1}(A_{t1}, Q_{t1}|c, G_{gt3})$ and $dF_{t3}(A_{t3}, Q_{t3}|c, G_{gt3})$ even if $dF_{t1}(A_{t1}, Q_{t1}|c, G_{gt3}) = dF_{t2}(A_{t2}, Q_{t2}|c, G_{gt3})$. The additional information will induce a change in earnings, as individuals optimize across occupations. We assume that on average the earnings change from additional information about A and Q would have been the same in the counterfactual case in which the person did not attend g.

Assumption A2 (*Neutral contribution of updating about A_t, Q_t to earnings trends*):

$$\begin{aligned}
&\sum_j \int_{A,Q} p_{cgt3}(j|A_{t3}, Q_{t3})\, w_{cgjt3}(A_{t3}) \left[dF_{t3}(A_{t3}, Q_{t3}|c, G_{gt3}) - dF_{t1}(A_{t1}, Q_{t1}|c, G_{gt3})\right] \\
=&\sum_j \int_{A,Q} p_{c0t3}(j|A_{t3}, Q_{t3})\, w_{c0jt3}(A_{t3}) \left[dF_{t3}(A_{t3}, Q_{t3}|c, G_{gt3}) - dF_{t1}(A_{t1}, Q_{t1}|c, G_{gt3})\right].
\end{aligned}$$

The occupation probability functionand earnings functions on the left hand side are evaluated at $G_{t3} = g$ while those on the right hand side are evaluated at $G_{t3} = 0$. This is the only difference.

The next assumption concerns experience effects within occupations.

Assumption A3 *(Earnings trends do not depend on occupation)*: *$w_{cgjt}(A_t)$ and $w_{c0jt}(A_t)$ follow parallel trends that depend on A_{t1} but not the occupation. That is,*

$$E\left[w_{cgjt}(A_t)\,|c, G_{gt3}\right] = w_{cgjt1}(A_{t1}) + a_c(A_{t1}, A_{\mathrm{t}} - A_{t1}),\, g = 0, 1, ..., \mathcal{G},$$

where $a_c(\cdot, \cdot)$ is some college major specific funtion.

The final assumption, A4, concerns the earnings growth due to predictable shifts in occupation with experience.

Assumption A4 (*Occupational earnings progression*): *Evaluated at $dF_{t1}(A, Q|c, G_{t3}^{g})$, the contribution of occupational progression to earnings growth for those who choose g would have been the same if they had not gone to graduate school. To be specific,*

$$\begin{aligned}
&\sum_j \int_{A,Q} \left[p_{cgt3}(j|A_{t3}, Q_{t3})\, dF_{t1}(A_{t3}, Q_{t3}|c, G_{gt3}) - p_{cgt1}(j|A_{t1}, Q_{t1})\right] w_{cgjt1}(A)\, dF_{t1}(A_{t1}, Q_{t1}|c, G_{gt3}) \\
=&\sum_j \int_{A,Q} \left[p_{c0t3}(j|A_{t3}, Q_{t3})\, dF_{t1}(A_{t3}, Q_{t3}|c, G_{gt3}) - p_{c0t1}(j|A_{t1}, Q_{t1})\right] w_{c0jt1}(A)\, dF_{t1}(A_{t1}, Q_{t1}|c, G_{gt3}) \\
=&\int_{A,Q} \phi_c(A, Q, t_3 - t_1)\, dF_{t1}(A, Q|c, G_{gt3})
\end{aligned}$$

for $g = 0, 1, ..., \mathcal{G}$ and some college major specific function $\phi_c(\cdot, \cdot, \cdot)$.

The upshot of A2-A4 is that people who chose G_{gt3} would have experienced the same age profile of earnings had they been forced to choose G_{0t3} even though their earnings level would differ. In the empirical work we allow the experience profile to depend on the choice of graduate degree.

2.3.4 OLS Regression with Final Degree Fixed Effects (FE-cg)

Our main econometric approach is closely related to the person fixed effects approach but makes more complete use of the available data. We stick with the three period example. Now assume that some people are only observed through t_2 and others are observed only in t_3. Assume that either way, we know whether they obtained g by the time they exited the sample. We make an additional assumption, which is that the distribution of A and Q is not related to when individuals are observed.

Assumption A5 *(Random data availability): The ability and preference distributions $dF_{t3}\left(A_{t3}, Q_{t3}|c, G_{gt3}\right)$ and $dF_{t1}\left(A_{t1}, Q_{t1}|c, G_{0t3}\right)$ do not depend on whether we observe the earnings of an individual in t_1 only, t_3 only, or both t_1 and t_3.*

Consider the estimator

$$TT^{\text{FEcg}}_{cgt3} = E\left[w_{cgjt3}|G_{0t1}, G_{gt3}\right] - E\left[w_{c0jt1}|G_{0t1}, G_{gt3}\right]$$

where we have made explicit the fact that all individual in the analysis are observed in t_1 prior to obtaining g and are known to have obtained g in t_2. This is true even if they contribute an earnings observation only in t_1 or t_2. Under assumptions A1-A5, $TT^{FEcg}_{cgt} = TT_{cgt}$. We denote this estimator by FE-cg and sometimes refer to it as the "degree combination fixed effects" estimator. We implement it using regression with the indicator variables $C_{c(i)}$ for $c, G_{g(i)t}$ for having g in t and $C_{c(i)}G_{g(i)}$ for whether the individual i ever obtained c and g. People who are never observed to obtain a graduate degree do not contribute to TT^{FEcg}_{cgt} other than by helping to identify effects of control variables. In our main specification, we exclude them from the sample.

2.4 Occupation Specific Effects and the Challenge of Identifying the Causal Effect of Graduate Education

The earnings model assumes that occupation does not have g specific or occupation specific effects on earnings. The choice model also rules out an effect of j_{t1} on the nonpecuniary costs of graduate school and the effect of a graduate program on occupation specific potential earnings. These assumptions imply that the choice of first period occupation is separable from future education and occupation decisions. Separability means that plans to go to graduate school do not directly influence choice of j_{t1}, given A_{t1} and Q_{t1}. This is important for our use of pre graduate school earnings to estimate counterfactual earnings of those who go to graduate school.

To see the consequences if separability does not hold, consider economics BAs who are the considering a PhD in Economics. Such individual sometimes works as a research assistant for a year or two, in part because of occupational preferences but in part because the experience and connections the work provides are complementary with PhD studies and an academic career. Research assistant positions typically pay less than the business and finance jobs that economics majors often choose. Individuals who obtained a PhD in economics would probably have chosen a different mix of occupations in t_1 if one had eliminated PhD studies as an option.

We suspect the violations of separability are likely to be the strongest for PhD studies, which we do not consider in this paper. But it is unlikely to hold perfectly. Consider the case in which the earnings in t in occupation j for a given A_t would depend not only on c and g but also on j_{t1}.[14] Write the earnings function

[14]For evidence of occupation specific experience, see Poletaev and Robinson (2008), Gathmann and Schönberg (2010), and Yamaguchi (2012).

as $w_{cgjt}(A_t, j_{t_1})$. One may define the treatment on the treated effect of attending g for a person with c who worked in j_{t_1} as

$$TT_{cgj_{t1}t} = \sum_{j'_t} \int_{A,Q} p_{cgj_{t1}t}(j'_t|A_t, Q_t)\, w_{cgjt}(A_t, j_{t1})\, dF_t(A, Q|c, g, j_{t1}) \\ - \sum_{j'_t} \int_{A,Q} p_{c0j_{t1}t}(j'_t|A_t, Q)\, w_{c0jt}(A_t, j_{t1})\, dF_t(A, Q|c, g, j_{t1}). \tag{6}$$

One could use FE or FE-cg to estimate $TT_{cgj_{t1}t}$ by allowing a separate treatment effect for each c, g, j_{t1} combination. One could modify FE-cg to estimate $TT_{cgj_{t1}t}$ controlling for fixed effects for each c, g, j_{t1} combination provided that j_{t1} is observed for all individuals. A halfway house is to control for the main effect of j_{t1}.[15] In practice, sample size considerations and lack of information about occupation prior graduate school for those who are only surveyed after graduate school limits our ability to estimate the returns to graduate school that depend on early occupations. But even if one did obtain estimates of $TT_{cgj_{t1}t}$ for various values of j_{t1}, one might be concerned about using pre graduate school earnings in j_{t1} as a measure of earnings in the absence of graduate school later in a career.

Consideration of a randomized controlled trial provides insights into the challenge of identifying the causal effect of graduate education when multiple fields are available. Suppose at the end of t_1, a set of economics majors are offered the opportunity to get an MBA for free. The intent-to-treat effect of the tuition subsidy offer is identified, and one could identify such effects for each value of j_{t1}. But these effects mix gains from an MBA relative to no advanced degree with gains relative to alternative graduate degrees. The counterfactual for the treatment on the treated parameter would be a complicated mix of alternative education choices. Without multiple sources of field specific exogenous variation in incentives, it would be difficult to make progress using an IV strategy.[16] Consequently, while we have pointed out the limitations of the FE-cg and FE approaches, they also have the advantage of providing a way to control for alternative graduate school options.

3 Econometric Specification

We work with a parsimonious additive specification in which the effects of college and graduate school are independent of each other. We also use an interactive specification in which the return to graduate school depends upon the undergraduate major. The additive specification is

$$w_{it} = a_1 + \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{g=1}^{\mathcal{G}} \gamma_g G_{g(i)t} + X_{it}\beta + u_{it}. \tag{7}$$

We use t to denote the year. Here $\alpha_0^c + \alpha_{age_{it}}^c, c = 1, \cdots, \mathcal{C}$, is the return to c at age_{it} relative to the reference major (education), and $C_{c(i)}$ is a dummy variable that takes on the value 1 if 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, $g = 1, \cdots, \mathcal{G}$ is the premium for graduate degree g relative to no graduate degree and $G_{g(i)t}$ is the associated indicator for

[15] Note the FE estimators implicitly control for earnings differences across individuals in time invariant factors that are associated with early occupation.

[16] Similar issues arise in the estimation of the return to a college major, as discussed in Altonji et al. (2016b) and Kirkeboen et al. (2016). The latter makes progress on the issue by exploiting the fact that in some countries, university admission is centralized and in on the basis of test scores with program specific cutoffs.

whether i holds a g degree in t. The vector X_{it} is the set of control variables. It consists of the full set of interactions between gender and race\ethnicity indicators, a gender specific cubic in age_{it}, which we measure relative to age 35, and year dummies. The equation says that the effect of graduate degrees on log earnings does not depend on the undergraduate degree.

The term u_{it} may be written as

$$u_{it} = e_i + \varepsilon_{it}. \tag{8}$$

We further decompose the permanent component e_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,

$$e_i = \sum_{c=1}^{\mathcal{C}} \sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)} + v_i \tag{9}$$

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 FE specification treats e_i as a fixed effect in estimation. The α_0^c coefficients are not separately identified. The FE-cg specification adds $\sum_{c=1}^{\mathcal{C}} \sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)}$ to equation (7) and applies OLS to

$$w = a_1 + \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{g=1}^{\mathcal{G}} \gamma_g G_{g(i)t} + X_{it}\beta + \sum_{c=1}^{\mathcal{C}} \sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)} + v_i + \varepsilon_{it} \tag{10}$$

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.[17]

The interactive specification is

$$w = a_1 + \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{c=1}^{\mathcal{C}} \sum_{g=1}^{\mathcal{G}} \gamma_{cg} C_{c(i)} G_{g(i)t} + X_{it}\beta + e_i + \varepsilon_{it}. \tag{11}$$

In the above model, γ_{cg} is the premium for graduate degree g for individuals with a BA in c. The FE estimator again treats e_i as a person fixed effect. The FE-cg estimator applies OLS to

$$w = a_1 + \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{c=1}^{\mathcal{C}} \sum_{g=1}^{\mathcal{G}} \gamma_{cg} C_{c(i)} G_{g(i)t} + X_{it}\beta + \sum_{c=1}^{\mathcal{C}} \sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)} + v_i + \varepsilon_{it}. \tag{12}$$

In the OLS case, the estimates of α_c and γ_{cg} are based on both cross-sectional and panel data variation. They will be biased by correlations among BA major and graduate degree and e_i.

In the FE case, we can estimate γ_{cg} only if at least one sample member with $c(i) = c$ is observed both before and after obtaining g. In the FE-cg case, we can estimate γ_{cg} only if at least one person with a $c(i) = c$ who eventually obtains g is observed before graduate school, and at least one person is observed after graduate school. The before and after observations need not be for the same individual.

A numerical example may clarify how observations contribute to the FE and FE-cg estimates. We abstract from age and time effects and other covariates. Table 1 presents earnings data for three individuals

[17] Differences across cohorts in selection patterns into graduate school might affect the FE-cg estimates, given that the $C_{c(i)} G_{g(i)}$ fixed effects in the model are not interacted with cohort. We do not have any evidence on the importance of this.

who obtained of BA in economics and are known to have obtained an MBA. Barry 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 FE estimate of $\gamma_{\text{Econ,MBA}}$ is the change in Barry's earnings — \$35,000. The FE-cg 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 Barry's.

3.1 Allowing Experience Profiles to Depend on Graduate Field

We also estimate models in which the potential experience profile of earnings depends on g. In the additive case, the FE-cg specification is

$$\begin{aligned} w_{it} = a_1 + \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{g=1}^{\mathcal{G}} \gamma_{gx_{it}} G_{g(i)t} \\ + X_{it}\beta + \sum_{c=1}^{\mathcal{C}}\sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)} + v_i + \varepsilon_{it}, \end{aligned} \tag{13}$$

where x_{it} is years since i obtained the advance degree. The variable x_{it} is 0 for those without an advanced degree in t. The return γ_{gx} to g at x years after graduate school completion is given by $\gamma_{gx} = \gamma_{g0} + \gamma_{g1}x + \gamma_{g2}x^2$. The term γ_{g0} is the effect of graduate degree at the time of graduation. Linear and quadratic slope parameters γ_{g1} and γ_{g2} govern how the return to the graduate degree changes with experience after graduate school. In the OLS case, we exclude the term $\sum_{c=1}^{\mathcal{C}}\sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)}$. We add experience interactions to the models with cg interactions using the parsimonious specification[18]

$$\gamma_{cgx} = \gamma_{gc0} + \gamma_{g1}x + \gamma_{g2}x^2. \tag{14}$$

If the return to g varies with time since graduate school, then the estimates of γ_g based on equations (7) and (10) identify an average of the experience specific effects γ_{gx} weighted by the sample distribution of x_{it} for those who chose g. In Table 2 below we report γ_g based on equations (7) and (10). 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 (13) with or without the $C_{c(i)}G_{g(i)}$ controls.[19] As we discuss below, γ_{g1_28} typically exceeds γ_g by about 0.04, and sometimes by more, especially in the FE-cg case. Table B2 reports more detailed information about the experience profile of graduate school effects.

The choice of whether or not 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 assuming that college graduates without advanced degrees are an appropriate control group. Consequently, we include them when we use OLS whether or not we include the x_{it} interactions. When using FE-cg without the x_{it} interactions (i.e., equation (10)) we exclude individuals who never get a graduate

[18] We have too few observations to allow γ_{g1} and γ_{g2} to vary with both c and g.

[19] 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.

degree. We exclude them because the parameter of interest is treatment on the treated. However, when we allow for x_{it} interactions using equation (13), we include those who do not get a graduate degree 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. 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.[20] We show below that inclusion of the college only sample leads to larger FE-cg estimates of γ_g that are usually closer to the OLS estimates.

4 Data

4.1 Data Sources

We employ restricted-use data from the National Survey of College Graduates (NSCG, 1993 to 2015) and the National Survey of Recent College Graduates (NSRCG, 1993 to 2010). They are part of the Scientists and Engineers Statistical Data System (SESTAT), a collection of three biennial surveys sponsored by the National Center for Science and Engineering Statistics (NCSES) within the National Science Foundation (NSF). The sample frame for all waves of the NSCG and the NSRCG consists of people who are under 76 years of age, live in the U.S.- and have at least a bachelor's degree as of the survey reference date. The NSCG 1993 and 2003 are, respectively, subsamples of the 1990 and 2000 decennial census long form respondents. In the 1990's and 2000's, only individuals- who have a BA degree, an advanced degree, and/or an occupation that is science and engineering related (S&E) at the time of their first NSCG observation are eligible for followup NSCG surveys. We denote this selection criterion by the phrase "SESTAT-eligible". From 2003 on, health related degrees and occupations are also SESTAT-eligible.

From 2010 on, NSCG employs a new rotating sampling strategy. The NSCG 2010 is drawn from respondents to the 2009 American Community Survey (ACS). The samples for the NSCG 2013 and the 2015 surveys combine a subsample of the interviewees from the 2010 and 2013 NSCG, and a subsample of interviewees with postsecondary education from the 2010 and 2013 waves of the ACS. Therefore, the NSCG 1993, 2003, 2010, 2013, 2015 are stratified random- samples of the U.S. population with at least a BA degree.

The NSRCG samples- are based on a two stage stratified random sampling procedure. First, schools are selected and then a set of recent graduates from the selected schools are chosen. The NSRCG samples are- restricted to individuals who have obtained a BA or master's degree in a S&E field (including health related fields after 2003) within three years prior to the survey reference date. Thus, all interviewees from the NSRCG surveys are SESTAT-eligible.[21]

We also use a version of the NSCG 1993 that is available from the Inter-university Consortium for Political and Social Research (ICPSR). The ICPSR version includes several variables from the 1990 Census, including occupation based on the census classification, employment, and earnings in 1989. To use this data, we created occupation categories that are consistent across the census and the SESTAT surveys. Table B3 reports the shares of the 363 disaggregated fields in the 66 consistent categories (from column (3) to column (2)), and

[20] We do not allow the counterfactual experience profile to depend on $C_{c(i)}G_{g(i)}$, rather than just on $C_{c(i)}$ for two reasons. First, given limited panel data, to estimate a $C_{c(i)}G_{g(i)}$ specific profile one would have to rely primarily on cross sectional variation in the number of years between college and graduate school. This is unattractive. More importantly, because data are of course missing for the counterfactual, one would have to extrapolate the pre graduate school profile many years past the age at which most people complete advanced degrees.

[21] The NSRCG survey was discontinued after 2010. Beginning in- 2013 the NSCG- oversamples recent college graduates. Followups to the 2010 and 2013 NSCG are not restricted to individuals who had a SESTAT-eligible degree when are first surveyed.

the shares of those 66 consistent categories in the 21 aggregated occupations (from column (2) to column (1)).[22]

We append all waves of both the NSCG and NSRCG and build a panel data set focusing on people in the US labor market with at least a bachelor's degree. The combined dataset has detailed information on postsecondary education history, current and past employment, occupation, and basic demographic variables. The latter include gender, race\Hispanic origin and parents' education. We use 19 aggregated BA categories and 19 aggregated graduate categories in most of our analysis. Tables B1 and B4 provide the shares of the disaggregated fields in the aggregated categories of the graduate degrees and BA respectively. The tables report the mean and standard deviation of earnings and the regression coefficients from estimating (7) using the disaggregated categories.

Individuals have a unique identifier, which permits us to track individuals across surveys and waves of a given survey. The availability of 1990 Census information for NSCG 1993 sample members is an additional source of panel data observations. In addition to using the 1990 Census information, we obtain information about occupation in 1988 from a NSCG 1993 question. In the panel dataset, age of initial interview and follow up duration varies across individuals.[23]

The NSCG 1993 and NSCG 2003 surveys and the followups to these surveys oversample individuals in S&E occupations. This leads to oversampling of S&E majors. Furthermore, only individuals who had an S&E degree or were in a S&E occupation as of 1993 (2003) were eligible for the followups to the NSCG 1993 (NSCG 2003). As a result, we have very large samples for some STEM majors, such as engineering. The downside is that sample sizes for many pairs of specific– majors and graduate degrees are too small to support the use of FE-cg for the interactive specification. We only report FE-cg estimates of the pair specific parameter γ_{cg} for degree combinations for which we have sufficient observations. The constraint is the number of individuals with earnings observations before graduate school. For a given cg pair, we impose a minimum of 31 individuals with pre-graduate school observations. Because sampling probabilities depend in part on occupation choice and on degree field, we use sample weights unless otherwise noted.[24]

The earnings data are based on two separate questions. The first asks about annualized salary at the main employer. It refers to the survey date. The second asks about the sum of earnings from all jobs in the prior calendar year. This provides a source of additional panel observations for many individuals.[25]

The occupational earnings premiums are constructed using the 2009-2014 waves of the ACS. We estimate the premiums using full time workers with– at least a BA degree who are between 24 and 59 years old.[26] The

[22]Table A1 uses the 21 categories and Tables 6–8 use the 66 category classification.

[23]We cleaned the panel data to ensure consistent values for the demographic variables. We also cleaned the data to ensure consistency of information about the degrees. Specifically, we ensure that a given postsecondary educational degree that an individual reports in multiple surveys has coherent information for completion date, location and fields of study.

[24]We account for relative sample sizes across surveys and waves by rescaling the original survey weights so that they sum to the number of observations for each survey-wave. This has the effect of overweighting STEM degrees (relative to the full population) in the followups to the NSCG 1993 and NSCG 2003. In the next draft, we will construct and use weights for the pooled sample of observations from NSCG and NSRCG samples so as to match the population distribution of undergraduate and advanced degrees (excluding PhDs) over the period of our sample. We will also exclude followup observations on individuals who did not have a STEM degree in 1993 or 2003 but were followed because they worked in a STEM occupation. Preliminary results indicate that estimates of the returns to advanced degrees are not very sensitive to the alternative sampling scheme. Note that to improve efficiency of the sample, we winsorized the weights to be no smaller than 0.1 of the median weight and no larger than 10 times the median weight. This did not make much difference in practice.

[25]The timing of the surveys is such that in a given year only one of two measures are available. Consequently, the minor differences in the means of the two measures are absorbed by the year dummies. Measurement error is likely to be correlated across the two measures. This will contribute to correlation in the earning regression error term but this will not lead to bias if the measurement error is uncorrelated with the regressors. We cluster standard errors at the individual level throughout the paper.

[26]The regression controls include cubic 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. Unfortunately, the ACS does not report field of advanced degree.

estimates are merged into the NSCG-NSRCG dataset by occupation. The imported premiums are reported in Table B3. We use the occupational premiums associated with 66 category classification in column (2) as the dependent variable in our analysis of the effects of graduate degrees on occupational earnings.

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 as well as people who obtain a BA before age 20 or after age 55. We also exclude people who obtain their advanced degree after age 49.[27] We also restrict the earnings analysis to full-time workers.[28]

In addition, we exclude individuals who go directly to graduate school to help insure comparability between the people we observe before graduate school and those we observe after. In the case of FE-cg, we also restrict the sample to individuals who have an advanced degree when we last observe them. We do this because the parameter of interest is TT, and so it makes sense to estimate effects of control variables and age only for individuals who ultimately get an advanced degree. However, we cannot impose this restriction when we allow the effects of advanced degrees to depend on time since the degree. Our main OLS regression sample contains 863,890 observations, and includes 217,310 individuals who are observed more than once. The sample used for FE-cg contains 296,440 observations and includes 8,180 pre advanced degree observations on 4,810 individuals.[29] All observation counts reported in the paper and tables are rounded to the nearest 10.

Definitions and descriptive statistics for the key control variables that appear in our regression models are in Table A2 and the distribution across years is in Table B5.

4.2 The Timing of the Earnings Observations and Degree Completion

In this section, we provide information about the timing of earnings observations relative to BA completion and advanced degree completion. Unfortunately, we do not know the start date of graduate school. Consequently, we determine whether an observation is prior to graduate school by subtracting an assumed typical number of years required to obtain the degree for a full time student.[30] This restriction and our exclusion of part time workers should eliminate most of the problem of using earnings measured when people are attending graduate school. Column 1 of Table 3 reports the minimum, maximum, mean, and 10th, 25th, 50th, 75th, and 90th quantiles of the number of years from BA completion for earnings observations that precede graduate school enrollment. All statistics in the table are unweighted. The 10th, 50th, and 90th quantiles are 1, 4, and 12. Column 2 reports that 90% of pre graduate school earnings observations occur between 1 and 5 years before completion of the advanced degree, although the maximum is 13. Column 3 reports that the 10th, 50th, and 90th quantiles of time from advanced degree completion to post advanced degree earnings observations are 2, 11, and 25. In column 5 the corresponding values are much lower for individuals with earnings observations both before and after the advanced degree. The short period between the advanced degree and earnings is likely to lead the FE estimates to understate the returns to graduate school if the returns rise with time since graduation. This is particularly true for programs such as medicine,

[27] We code BA based on the report of the primary field of the first BA obtained. Thus, we do not account for a second major, or a minor. One could extend the FE-cg approach to treat BA combinations as an additional type of BA, but we have not explored this. We drop individuals who obtain multiple BA degrees in different years.

[28] We code an individual as full-time if she reported working full-time or if she worked at least 41 weeks per year and 35 hours per week. We used 41 weeks to accommodate the employment arrangements of many teachers. When the earnings measure refers to the year prior to the survey, we assume that full-time status in the prior year is the same as the survey year. We do so because we lack data on full time status in the prior year.

[29] "The min, mean, median, and maximum number of observations per person in the main OLS earnings sample are __, __, __, and __. The corresponding values in the FE-cg sample are __, __, __, and __.

[30] We assumed 4 years for Medicine, 3 for Law, 2 for an MBA, and 1 for all other master's degrees.

which typically involve a multiyear medical residency at relatively low pay. In part for this reason, we place little emphasis on the FE estimates. Finally, column 4 presents time from BA to advanced degree completion for those who obtained an advanced degree. This column does not condition on availability of a pre advanced observation. The 10th, median and 90th quantiles are 2, 5, and 12.

Table 4 presents the unweighted age distribution of the earnings observations. The first column refers to the full sample. The 10th, 50th and 90th quantiles are 26, 39, and 53. The 10th, median and 90th quantiles of the age distribution of the 8,180 pre advanced degree observations of people with a graduate degree by the last interview are 23, 27, and 38 (column 3). The mean is 29.1. As expected, 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 291,880 post advanced degree earnings observations. The 10th, 50th, and 90th percentiles are 29, 41, and 54.

5 Facts about Earnings Differences across Graduate Fields

Table 5 displays basic facts about earnings differences across graduate degrees. The statistics are for people who work full time, earn at least $5,000 per year, graduated from college at least one year earlier, and are age 23 to 59. All statistics are weighted. Columns 1 and 2 display the mean of earnings and the log of earnings, respectively. One can easily observe the large differences across fields. Column 3 provides information about the role of occupation in field differences in earnings. It reports the mean and standard deviation of occupation coefficients given the occupation distribution for each graduate field. The values are expressed as deviations from the average for the sample with graduate degrees. Figure 2 graphs the relationship between the occupation mean for each graduate field and mean of the log of earnings for each field. The points are tightly clustered around the regression line displayed in the graph, which has a slope of 1.34 (0.10).

Earnings differences across graduate fields are in part a reflection of earnings differences across the undergraduate majors that lead to them. Column 4 provides information about earnings levels in the college majors that lead to the specified graduate degree. It reports the mean and standard deviation of the BA premiums for each advanced degree based on the OLS estimates of (7) using the disaggregated BA and advanced degree categories.[31] Figure 3 graphs average earnings by advanced degree against the BA premiums. There is a positive relationship, with a slope coefficient of 1.40 (0.29). It is notable that earnings of those with advanced degrees in STEM fields such as engineering, biology and the physical sciences tend to be below the regression line. These advance degrees pay less than one would expect given earnings associated with the BA degrees that lead to them. Medicine is a notable exception to this pattern. It pays extremely well but draws heavily from biology and other life science majors, which are not especially high paying.

Figures 4 and 5 provide facts about male-female differences in earnings of graduate degree holders. Figure 4 plots advanced degree specific gender differences in the average occupational premium against the degree specific gender difference in average earnings. The gender gaps in earnings are centered around 0.23, while the gender gaps in the occupational premium are centered around 0.05. The slope of the relationship is 0.60. In the cases of biology and the arts, the earnings gaps are about 0.12, while the occupational earnings gap is very small. In the case of medicine, the overall gap is 0.34, while the occupation gap is only 0.02. Discrimination, gender differences in work hours, gender differences in medical specialty, and heterogeneity within the medicine category (which includes MD, optometry, dentistry, osteopathic, podiatry, and veterinary) may all contribute to the gap.[32]

[31] The BA premiums are reported in Table B4.

[32] See Sasser (2005); Bertrand et al. (2010); Goldin and Katz (2011, 2016) for analyses of the gender gaps in various professional

Figure 5 plots the earnings gap for each advanced degree against the corresponding gender difference in the mean of the BA premium. By construction, the gender gap in BA premiums is entirely due to gender differences in the mix of BA degrees for a given graduate degree. The figure suggests that only a small portion of the gender gap among advanced degree holders is due to differences in undergraduate degree. The slope of the relationship is 0.76 (0.61), but the gender gaps in average BA premiums within graduate fields are relatively small.

6 Links among BA Field, Occupation, and Graduate Fields

The introduction and section 2 emphasize that ability A and preferences Q influence earnings differences across graduate fields by inducing a link between graduate field and occupation. That interdependence arises not only because of the heterogeneity in A and Q but also because undergraduate and graduate fields are occupation specific to varying degrees. Here we document three facts. First, the link between undergraduate field and graduate field varies substantially across graduate fields. Second, both undergraduate field and occupation before graduate school have strong connections to graduate field. Finally, graduate field is the main influence on post graduate occupation. We then look in more detail at the pre and post graduate school occupations for a few undergraduate and graduate degree combinations. We show that the distribution of pre graduate school occupation is related to the occupations that are common for a particular advanced degree. Finally, for engineering, we use information about whether and why an individual's job is not related to BA field to shed light on the importance of preferences and labor market opportunities in determining occupation before graduate school and graduate field of study.

6.1 The Link Between BA Field and Graduate Field Varies

Here we draw on Table 4 of Altonji et al. (2016b), which reports the ratio of the share of a specified graduate degree accounted for by a specified undergraduate major to the share of that major of all undergraduate degrees. If majors are equally represented in all graduate degrees, then this ratio would be 1.0, aside from sampling error. The table shows that particular undergraduate majors are heavily overrepresented in certain graduate programs. For example, the relative share of undergraduate nursing majors in a master's in nursing is 26.9. Nursing BAs are also overrepresented among those with a master's in health services administration (5.3). They are underrepresented in all other fields. Similarly, the ratio for BA in engineering in a master's in engineering is 11.0. The relative shares of economics BAs are less concentrated. The highest value is 4.95 for a master's in social science, and the value is 3.1 for a master's in business, 2.83 for law and 2.2 for health services administration.

It is also instructive to compare shares across graduate degree type. The relative shares for law and MBA programs, which have few prerequisites, are much more even across majors than the shares for master's in nursing, or engineering.

6.2 Both Undergraduate Field and Early Occupation Predict Graduate Field

We estimate probit regressions for the probability of attending graduate school in field g as a function of 19 indicators for undergraduate field and 21 indicators for occupation before graduate school (not reported). The sample consists of pre graduate school observations on individuals who eventually obtain an advanced

occupations, including pharmacist and doctor, and for MBA holders.

degree. Separate F tests indicate that both the undergraduate field indicators and the occupation dummies are highly significant predictors of graduate field.

6.3 Graduate Field is the Primary Determinant of Occupation after Graduate School

We match 1990 Census with 1993 and 1995 NSCG to construct a subsample. The subsample includes 1,430 people with pre advanced degree observations in 1988 and post advanced degree observations in 1993, as well as 300 people with pre advanced degree observations in 1990 and post advanced degree observations in 1995. We regress estimates of the conditional occupation probability $p_{c(i)g(i)}(j_{it}|j_{it-5})$ on a constant, $p_{c(i)}(j_{it})$ and $p_{g(i)}(j_{it})$. The estimates of the coefficient on $p_{c(i)}(j_{it})$ is 0.024 (0.025), and the coefficient on $p_{g(i)}(j_{it})$ is 0.365 (0.024). If one excludes $p_{g(i)}(j_{it})$, the coefficient on $p_{c(i)}(j_{it})$ is 0.163 (0.029). Thus while BA field has a strong link to graduate field, post graduate school occupation is determined primarily by graduate field.

6.4 Case Studies of the Relationship among Major, Advanced Degree and Occupation

The regressions provide an overall sense of the relationship among c, g, and j, but it is also useful to take a closer look at a few cases. Table 6 examines the occupation choices before graduate school and after graduate school for individuals with a BA in engineering. Cell sizes are small for the pre graduate degree samples in some cases. In Table 6 as well as Tables 7 and 8, we only report results for occupation categories containing at least 10 cases, and in some instances aggregate occupations. For comparison, the top panel of Table 6 lists the five most common occupations for engineering graduates who have not obtained an advanced degree by age 35.[33] The first four are all engineering occupations and account for 48.8% of all graduates. The fifth is software developer, which is also engineering related. The next panels of the table examines the pre graduate school occupations of engineering majors who go on to get an MBA, a master's in education, or a master's in engineering. Engineers also dominate among pre MBA occupations, but top level managers account for 5.61%. Post MBA, managerial occupations are the first, fourth and fifth most common.

The sample of engineers who get a master's in education is relatively small, so we only broadly characterize the occupations. Prior to graduate school, about one third of this group work in engineering related occupations and about 25% work as primary or secondary school teachers. Thus, the early occupations of engineers who go on to a master's in education are quite different from engineers as a whole. After an education master's, about 50% work as secondary school teachers and another 10% work as postsecondary school teachers. The other three most common occupations are managerial.

Engineers who eventually pursue a master's in engineering follow a different path. Prior to graduate school, the 5 most popular occupations are all engineering, and they account for 60.4% of the cases. After the master's in engineering, the 5 most popular occupations are in engineering and computer science. Managerial occupations are not represented.

Table 7 provides similar sets of tabulations for education majors who pursue an MBA or a master's in education. Teaching dominates the most common occupations for education majors who have not obtained an advanced degree by age 35, although the 4rth and 5th most common occupations are secretary (3.91%) and salesperson (2.53%). The number of pre MBA education majors is too small to break out occupations

[33]We impose the sample restrictions used in the earnings analysis below. The tables also report average earnings, although we do not discuss this information in the text, because cell sizes are relatively small in some cases.

in detail, but none works as a teacher. Post MBA, the top 4 occupations are all business related. Secondary school teacher is number 5.

On the other hand, education majors who pursue a master's in education are overwhelmingly concentrated in teaching occupations both before and after getting a master's degree. After the degree, teaching occupations account for 64.7% of the total. Interestingly, top level manager is the fourth most common post master's occupation, with 6.53% of the total. A few of these individuals may hold high level management positions within the education system, but we lack the industry codes needed to check.[34]

Table 8 considers individuals with a BA in physical and related sciences. The occupations of individuals who have not pursued an advanced degree by age 35 are less concentrated than those of engineers or teachers. Four of the top five occupations are science related, with a share of 37.49%. The other is secondary school teacher, which of course may include science teachers (4.46%). Physical science and engineering related occupations account for 70.37% of the pre MBA jobs, but manager and clerical occupations account for 18.52%. Post MBA, manager and service occupations have the largest shares, and business related occupations is also in the top five. Those who pursue a master's in education are heavily concentrated in teaching both before and after doing so. Finally, those who pursue a master's in the physical sciences are heavily concentrated in the sciences to a much greater extent than those who only pursue a BA. They remain concentrated in the sciences after the master's degree, although postsecondary teacher is the fourth most common occupation.

Overall, these examples show that the pre graduate school career paths of individuals who pursue advanced degrees depend on the specific advanced degree and may be quite different from the early career paths of those who do not go to graduate school. They are consistent with the regression analysis of the link between occupation after graduate school and undergraduate major and graduate field.

6.5 Additional Evidence Concerning Occupational Selection

The NSCG respondents are asked whether their work is closely related to their highest degree. Those who say "no" are asked to choose from a number of reasons why. We consider engineering BAs who have not yet attended graduate school but eventually do so. The top panel of Table A1 reports that 83% of engineering BAs are in the "work closely related" group. These individuals earned an average of $69,459. The 17% in the "work not closely related" group includes 4.46% who gave "pay and promotion opportunities" as the reason. This group earned $84,997. It also includes 5.56% who gave "change in career or professional interests" as the reason. They earned $63,331. Working conditions, job location, family related reasons, lack of availability of jobs in the degree field, and "other" account for the rest. Panel B tabulates the shares of the most common advanced degrees. Master's in engineering accounts for 31.0% of the closely related group, but only 18.2% of the not closely related group. Those with an MBA or a business related master's degree account for 55.5% of the "work closely related" group but 63.7% of those in the "work not closely related" group. The table also displays the most common pre occupations and the percentages that they account for. Not surprisingly, the fraction working as engineers is higher for those working in jobs related to BA field prior to going to graduate school.

Taken together, these results show that pay varies substantially with the nature of the work people are doing, and that both pay and preferences drive pre graduate school job choice as well as graduate field choice. They are consistent with our emphasis on the relationship between the type of work people do after college

[34] The detailed definition of top level managers from SESTAT codebook (footnote 1 of Table B3) indicates that the category includes presidents and provosts. Also, both the SESTAT occupation codes and the 1990 Census codes include managers in education and related fields as a detailed category. We treat it as separate from top level manager in the 66 more aggregated categories that we use. See Table B3.

and the graduate degree that they pursue.

Overall, the evidence in section 6 indicates that simple comparisons of earnings of those with an advanced degree with those without an advanced degree are likely to be misleading. They also suggest that the FE-cg approaches, while far from perfect, are likely to be superior to simple OLS.

7 Estimates of the Return to Graduate Degree

In this section we report estimates of returns to graduate education. In section 7.1 we start with the additive specification for men and women combined. Section 7.2 presents rough internal rate of return estimates that account for tuition and program length. Section 7.3 presents results by gender. In section 7.4 we allow returns to depend on BA field.

7.1 Results for the Additive Specification

Columns 1 and 2 of Table 2 report FE-cg estimates of γ_g for the additive specification with age profiles that depend only on c. The log of earnings is the dependent variable. They are based on equation (10). The control vector X_{it} includes race\Hispanic origin interacted with gender, gender specific cubics in age, a college major specific cubic in age, mother's education (8 categories, including missing), and father's education (7 categories) and year dummies.[35] We use 19 aggregated BA categories and 19 aggregated graduate categories in most of our analysis.

Column 1 restricts the sample to individuals who obtain a graduate degree, which is our preferred sample for FE-cg. Column 2 uses the same sample as OLS, which also includes the college only subsample. Column 3 presents the corresponding OLS estimates based on equation (7). Columns 4 and 5 present FE-cg and OLS estimates of γ_{g1_28} based on (13) which includes g-specific interactions with post graduate school potential experience x_{it}. 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. To facilitate comparison to the results in columns 2 and 3, column 6 presents the average of $\hat{\gamma}_{gx_{it}}$ over the distribution of x_{it} in the FE-cg regression sample.

We typically find that $\widehat{\gamma}_{g1\_28}$ exceeds $\widehat{\gamma}_g$, especially for the FE-cg estimates. In part, this reflects the fact that $\widehat{\gamma}_g$ is a sample weighted average of returns at various values of x_{it}. The sample distribution of x_{it} is typically skewed 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.[36] Columns 7-11 correspond to columns 1-5 but are for the occupational component of earnings.

Before turning to Table 2, we note that Tables B1 and B4 report OLS estimates of α_c and γ_g for 168 advanced fields and 144 BA fields, respectively. The tables also report the composition of each of the 19 aggregated BA and graduate categories. To our knowledge, it is the first time such a disaggregated set of estimates has been presented. It is a step toward the objective of providing estimates that can be used to guide the decisions of individuals, institutions, and the government about investments in graduate education. The estimates show large differences across degrees, with substantial heterogeneity within the 19 categories that we feature.[37] However, they should be viewed as descriptive rather than causal. This is especially true for the graduate degrees, for which we believe selection bias in the OLS estimates is particularly serious.

[35] We observe undergraduate GPA for some people in our sample. In preliminary work, we find that controlling for GPA does not alter our results qualitatively.

[36] $\widehat{\gamma}_{g1\_28}$ is indirectly influenced by observations with $x_{it} > 28$ through estimation of the experience polynomial parameters.

[37] For example, for engineering the estimates of $\hat{\gamma}_g$ range from 0.311 (0.034) for agricultural engineering to 0.594 (0.046) for petroleum engineering.

Figure 6 graphs the FE-cg and the OLS estimates of γ_g with 90% confidence intervals (vertical axis). The degrees are ordered along the horizontal axis from lowest to highest mean of the log of earnings, but are equally spaced to improve readability. Not surprisingly, the FE-cg estimates are considerably less precise than OLS.

Regressing the FE-cg estimates on the OLS estimates yields a slope of 0.605 (0.102) and a constant of 0.071 (0.027). Thus the FE-cg estimate tends to be small relative to the OLS estimate when OLS is large, and vice versa.[38] The gap between the FE-cg and OLS estimates has a strong negative relationship with the average for the graduate degree of the BA premiums.[39] The results are consistent with a theme, which is that OLS tends to overstate (understate) returns to advanced degrees that attract students from high (low) paying majors.

7.1.1 Medicine

In the case of medicine, the FE-cg estimate of γ_g is 0.574 (0.070) and the OLS estimate is 0.697 (0.016). The FE-cg estimate rises to 0.625 when the OLS sample is used (column 2). This points to the fact that part of the difference between OLS and FE-cg is the use of college only cases to estimate the counterfactual.

In columns 4 and 5 we report estimates of γ_{g1_28} using the specification with g-specific experience profiles. The FE-cg estimate is 0.685 and the OLS estimate is 0.747. Tables B2 and B6 report FE-cg and OLS estimates of the return when x_{it} is 1, 5, 10, 20, and 30 years. The FE-cg estimate of the return is only 0.091 (0.080) at one year, but rises to 0.687 (0.076) at 10 years and 0.897 (0.077) at 20 before declining to 0.633 (0.085) at 30 years. Including the college only observations accounts for part of the difference between column 1 and column 4. When we use the specification with the experience interactions to estimate γ_{gx} and then compute $\hat{\gamma}_g$ as the sample weighted average of γ_{gx} (column 6), we obtain a larger value than when we exclude the experience interactions (column 2).[40] Consequently, the specification of the quadratic functional form for γ_{gx} as well as the choice of sample contribute to differences in the FE-cg estimates.

Columns 7-11 present a corresponding set of results for the occupational component of earnings. The FE-cg estimate is 0.510 (0.036) and the OLS estimate is 0.508 (0.005). The effects decline by about 0.04 over the first 20 years (not reported). This makes sense when one thinks about the careers of medical doctors. They typically enter residency programs right after graduation, working as doctors but at relatively low pay. Later, some fraction may migrate to other occupations, such as manager. Managers are paid less on average than doctors.

Table B7 reports individual fixed effects estimates of γ_g. For the log of earnings, the FE point estimate is actually negative: -0.198 (0.112). We believe that the FE estimate substantially understates the returns to medicine, because most of the post graduate school observations that identify this effect are for low values of x_{it}, when many doctors are in residency programs. For occupational earnings, the FE estimate is 0.581 (0.075) which is actually above the corresponding OLS and FE-cg estimates. Medicine is an extreme case, but it illustrates the difficulty of estimating returns using individual fixed effects when panel length is relatively

[38] Adjusting the slope for the effect of sampling error in the OLS estimates makes almost no difference because the OLS estimates are very precise. We performed the adjustment under the assumption that the sampling errors in the OLS and FE-cg estimators are independent, which is approximately true. The bias corrected estimator is the product of the OLS coefficient and the adjustment factor

$$\hat{\rho} = \frac{var\left(\hat{\gamma}_{gOLS}\right)}{var\left(\hat{\gamma}_{gOLS}\right) - \frac{1}{19}\Sigma_{g=1}^{19}\left(\hat{se}_{\gamma_{gOLS}}\right)^2},$$

where $\hat{se}_{\gamma_{gOLS}}$ is the standard error of $\hat{\gamma}_{gOLS}$ and $var\left(\hat{\gamma}_{gOLS}\right)$ is the unweighted variance of the OLS estimates across fields.

[39] The coefficient relating the gap to the g-specific average of the BA premiums is -0.671 (0.228).

[40] Here we use the sample distribution of x_{it} to construct $\widehat{\gamma}_g$ from the estimates of γ_{gx}.

short and the payoff to the graduate degree takes a few years to be fully realized. Consequently, we place little emphasis on the FE estimates in this paper. The approach would be valuable in a longer panel, which could be created by merging the data that we use with administrative earnings records. We hope to pursue this possibility in future work.

7.1.2 Law

The FE-cg estimate of γ_g for a law degree is 0.421 (0.061). It is slightly below the OLS estimate. The estimate of γ_{g1_28} is 0.473 (0.059) in the case of FE-cg. Both approaches indicate that the return rises with time since graduation, as is documented in Table B2. The FE-cg estimates rise from 0.287 (0.062) one year after law school to 0.544 (0.061) at 20 years. OLS and FE-cg agree that much of the return comes from occupational upgrading.

As was the case for medical degrees, the FE estimate of γ_g appears to greatly understate the return to law. The value is only 0.039 (0.065), although the FE results indicate that occupational upgrading is important and are in line with the other approaches. Because of the importance of on the job training and learning by doing in the first few years of a legal career as well as the partnership system, one might expect that the short time between law school and the earnings observations in the effective sample for the FE estimates leads to understatement of the returns to a law degree while capturing the occupation related component. To save space, we will not discuss the FE estimates for the other graduate degrees.

Overall, the evidence indicates that the TT effect of a law degree is large – about 0.14 per year for a 3 year degree. Of course these estimates do not account for tuition costs, which are substantial especially at private universities.[41]

7.1.3 MBA and Other Business Related Master's Degrees

Row 4 of the table reports estimates of the return to an MBA. The FE-cg estimate of γ_g is 0.096 (0.021). This estimate suggests only a modest return to an MBA, in sharp contrast to the OLS estimate of 0.282 (0.008). The FE-cg and OLS values of $\widehat{\gamma}_{g1\_28}$ are larger: 0.169 and 0.308 respectively, reflecting the fact that the return rises over time and that γ_g places more weight on the earlier years. However, in the case of FE-cg, a comparison of columns 1 and 2 indicates that the need to include the college only subsample when estimating γ_{g1_28} accounts for about half of the difference between the FE-cg estimates of $\hat{\gamma}_g$ and $\widehat{\gamma}_{g1\_28}$.

The FE-cg estimates show that an MBA improves occupational earnings by an average of only 2.8% over the first 28 years. The comparable OLS estimate is 10%. We believe that selection on ability and occupational preferences lead to a large bias in the OLS estimates. The high post MBA earnings implied by the OLS estimates are a reflection of relatively high pre MBA market opportunities and business/management related preferences of many of those who obtain an MBA.

The business related master's degree category consists of financial management (43.5%), business marketing and business management (22.7%), accounting (15.4%), marketing research (3.3%), agricultural economics (2.6%), other agricultural business and production (0.8%), and actuarial science (0.4%). (See Table B1). As a group, they are more technical than an MBA degree, and we suspect that they have more specific prerequisites. The FE-cg estimate of γ_g is 0.195 (0.042). This is a healthy return assuming that these programs take one or even two years if pursued full time. Occupation accounts for about 0.046 (0.016) of the return. The OLS estimate of γ_g is again much larger than FE-cg: 0.350 (0.013). Of this 0.116 (0.005) is through occupation alone. As was the case with the MBA degree, the gap between FE-cg and OLS is narrower for

[41] We not know whether the graduate institution was private not for profit, private for profit, or public.

γ_{g1_28}. The estimates are 0.252 (0.041) versus 0.365 (0.014). Most of the relative increase in the FE-cg estimate is due to the addition of the college only sample, which we believe leads to upward bias.

7.1.4 Health Services Administration, and Public Administration

We next consider two other management and administrative services related degrees. The FE-cg estimate of γ_g for a master's in health administration is 0.278 (0.082). The OLS estimate is similar: 0.308 (0.026). Occupational returns account for 40% and 44% (respectively) of these effects.

The FE-cg and OLS estimates of γ_g for public administration are about two thirds as large — 0.167 (0.052) and 0.209 (0.021), respectively. The corresponding estimates for the occupation premium are 0.116 (0.031) and 0.123 (0.011), so a large fraction of the return is through occupation.

7.1.5 MA in Nursing

The FE-cg and OLS estimates of γ_g are 0.236 (0.041) and 0.315 (0.014) respectively, a large difference. The FE-cg estimate of γ_{g1_28} is 0.163 (0.038), which is about 55 percent of the corresponding OLS estimate. FE-cg and OLS show similar occupation premiums of 0.03 and 0.04. The substantial difference between FE-cg and OLS for earnings and the small difference for occupation suggest substantial earnings related selection among nurses who obtain a master's degree.

7.1.6 MA in Health Related Fields

The health related category consists primarily of physical therapy (27.8%), public health (20.8%), audiology and speech pathology (18.3%), other health/medical sciences (18.3%), pharmacy (9.8%), and health/medical assistant (4.7%). Both FE-cg and OLS show a return of about 0.28, with little variation with x_{it}. The FE-cg estimate is that 0.094 of the return is through occupational upgrading. This makes sense given the importance of occupation specific training and licensing requirements in most of the subfields in the category.

7.1.7 Engineering and Computer Science/Math

The FE-cg and OLS estimates of γ_g for a master's in engineering are 0.103 (0.018) and 0.144 (0.005). For computer science and math, the FE-cg and OLS estimates are 0.164 (0.035) versus 0.196 (0.008). OLS shows a larger effect operating through occupation. To some degree, OLS misses the fact that people who obtain a degree in these two fields were in relatively high paying occupations prior to graduate school.

Table B2 reports the estimates of γ_{gx}. In both fields the estimates rise over the first few years after the degree. The FE-cg and OLS estimates of γ_{g1_28} are larger and more similar than the estimates of γ_g. Placing more of the weight on the FE-cg estimates, we conclude that a master's degree in these two fields yields a healthy return that comes a number of years after graduate school.

7.1.8 MA in Other Science\Engineering Related Fields

The other science and engineering category is dominated by architecture and environmental design (73%). The remainder consists of engineering technologies, electrical and electronics technologies, or industrial production technologies. The FE-cg estimate is only 0.010 (0.058) but the 90% confidence interval includes modest positive returns. The OLS estimate is 0.107 (0.020). We suspect that returns are higher in the engineering related fields, for which average earnings and the OLS estimates are substantially larger than for architecture (Table B1).

7.1.9 Biology\Agriculture\Environmental Sciences and Physical Sciences

For master's degrees in biology, agricultural, environmental and life sciences, the FE-cg estimate is 0.239 (0.046). The estimate for the physical sciences is 0.156 (0.054), which is also substantial. The estimates of γ_{g1_28} are about 0.09 and 0.13 higher. Most of these returns are within occupation. In sharp contrast, the corresponding OLS estimates are only 0.017 (0.011) and 0.054 (0.015) respectively. Almost all of the difference between the estimators is within occupation. We are surprised by the large difference between FE-cg and OLS in this case, especially because it is not associated with a large difference in the occupational return estimates.

7.1.10 Education

The results for a master's in education are particularly interesting. Teacher contracts often mandate higher salaries for teachers with master's degrees. For example, the 2018 salary schedule for New York City specifies base salaries of \$56,711 for a teacher with 1 year of experience and \$105,394 for a teacher with 22 years of experience. The corresponding values for a teacher with an approved master's degree are \$63,751 and \$112,434.[42] The implied premium in logs are 0.117 for new teachers and 0.065 for teachers with 22 years of experience. Note that the average gain may be larger if the master's facilitates movement into higher paying administrative or specialized teaching positions. The FE-cg estimate of γ_g is 0.159 (0.019), of which 0.030 (0.008) is due to occupational advancement. The earnings effect seems high, but the fact that a small component is through occupation seems reasonable given that a master's in educational administration accounts for 15.9% of the education category, and it pays better (Table B1). When we add the college only observations and allow the return to depend on x_{it}, the effect rises from 0.107 (0.020) when $x_{it} = 1$ to 0.259 (0.021) when $x_{it} = 20$. The increase seems implausibly large.

In contrast, the OLS estimate is 0.083 (0.006), and it is only 0.029 (0.007) five years after the degree. OLS shows a substantial *negative* effect on occupational pay of -0.082 (0.003). The estimate is -0.015 (0.011) one year after degree attainment. We think this reflects the fact that getting a master's in education is an indication that an individual has chosen to continue as a teacher or to switch into teaching from a higher paying occupation. That is, those who get a master's in education, even conditional on undergraduate major, have talents and preferences that lead them toward a relatively low paying (but socially valuable) profession. This negative occupational selection takes away from the positive, and contractually based "treatment on the treated" effect of a master's in education. The gap between FE-cg and OLS widens with experience (see Tables B2 and B6).

7.1.11 Psychology\Social Work, the Humanities, "Not science or engineering related" and Social Sciences

The FE-cg 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. The FE-cg estimate indicates a substantial return of 0.208 (0.029), while the OLS value is only 0.058 (0.009). About 0.096 of the gap is because FE-cg implies a 0.026 (0.017) occupational return while OLS implies a loss of -0.070 (0.005).

The relative values of the OLS and FE-cg estimates of γ_g for a master's in Humanities also follow a similar pattern, although the FE-cg approach indicates a return of only 0.004 (0.066). The small return is associated with an estimate of -0.081 (0.031) for occupational earnings. One interpretation of this finding is

[42] See https://www.schools.nyc.gov/careers/working-at-the-doe/benefits-and-pay.

that the humanities degree enables an individual to find work in occupations that value the degree, and these are relatively low paying. Getting a master's in humanities has a modest positive effect within occupation. In contrast, the OLS estimate is -0.163 (0.015) and is driven by a huge -0.218 (0.009) effect on occupational earnings.

The results for master's degrees in the "Not science or engineering related" category are qualitatively similar. This category consists of communications (25.4%), library science (37.7%), criminal justice/protective services (16.2%), and journalism (8.0%). The FE-cg estimate is 0.136 (0.057) while the OLS estimate is 0.051 (0.016). About 0.03 of the difference arises from the more negative OLS estimate of the occupation return.

Social science (excluding psychology) is the exception within this group, in that the FE-cg and OLS estimates of γ_g are very similar: about 0.1 for the earnings premium and about 0.03 for the occupational premium.[43]

7.2 Internal Rates of Return Estimates Based on the FE-cg Regressions

Table 9 reports the present discounted values (PDV) of lifetime income net of tuition for each advanced degree, the counterfactual PDV for people who chose various advanced degree had they not gone for graduate school and the percentage gain from the advanced degree. It also reports the calculated internal rate of return ρ_g for each advanced field.

The estimates are based on the following assumptions. Column 1 shows the assumed duration of each degree. We use average tuition in 2012 at public institutions, in 2013 dollars.[44] We assume graduate programs are full-time, and students have zero earnings when they are enrolled. 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, the parental education variables to their weighted sample means and the calendar year to 2012. We set the race\ethnicity indicators to non-Hispanic white, but take a population weighted average over the distribution of gender and undergraduate major for each advanced degree. The PDV calculation assumes that the interest rate is 0.05.[45]

For medicine, the percentage gain in PDV (with tuition accounted for) is 45.1% for medicine. It is a 4 year degree, and $\hat{\rho}_g$ is 0.167. For law, the values are 29.3% and 0.150, while the percentage gain for an MBA is essentially 0 and $\hat{\rho}_g$ is 0.048. The internal rate of return is above 10% for all other degrees, except arts, humanities, and other science and engineering related fields, for which it is negative. A master's in the life sciences has the highest internal rate of return. sing average private tuition lowers $\hat{\rho}_g$ to about 0.14 for

[43]The FE-cg estimate for a master's in arts is too noisy to support a meaningful comparison to OLS.

[44]The tuition information is from the National Center of Education Statistics.

[45]The formula for the actual PDV calculation is

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

where

$$net\ income_{cgi}(age) = \begin{cases} -tuition_g & \text{if } age-27 \leq \text{duration of } g \\ exp\left(\hat{a_1} + X_{it}\hat{\beta} + \left(\hat{\alpha_0^c} + \hat{\alpha_{age}^c}\right) + \hat{\gamma}_g + \hat{b_{cg}}\right) & otherwise \end{cases}.$$

The interest rate is denoted by r. The formula for counterfactual PDV is

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

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

$$\sum_c weight_i \times \left[PDV_{cgi}^{\text{actual}}(\rho_g) - PDV_{cgi}^{\text{counterfactual}}(\rho_g)\right] = 0$$

where $weight_i$ is the sample weight.

medicien, and about 0.13 for law. It leads to a reduction of about 0.01 or 0.02 for the other fields. In a future draft, we will explore sensitivity to our assumptions about earnings while enrolled, program length of the master's programs, and produce standard errors of the estimates.

7.3 Returns by Gender

Tables B8 and B9 report summary statistics about earnings for men and women, by graduate field. In Table 10, we report FE-cg and OLS estimates of γ_g and γ_{g1_28} based upon separate models for men and women. In all other respects, the specifications are identical to the pooled specifications that form the basis for Table 2. Figure 7 displays the FE-cg estimates and 90% confidence bands for γ_g. The blue diamonds are for men and the red circles are for women. The advanced degrees are in increasing order (from left to right) of average earnings in the pooled sample. Not surprisingly, there is a strong relationship between the FE-cg estimates for men and for women. A regression of the estimate for women on the corresponding estimate for men yields a sampling error corrected slope coefficient of 0.605.[46] There are a few interesting differences that are worth pointing out. First, on average women receive larger returns than men. The difference in the simple averages of coefficients for women and for men is 0.050. When one weights the coefficients using the shares of the advanced degrees in the pooled sample of men and women, the difference is 0.029. We do not control for actual experience, and so cannot address the possibility that the higher estimates for women reflect a larger effect for women on the full-time work probability.[47] If one uses a full-time work indicator in place of the log of earnings as the dependent variable in equation (10), the FE-cg estimates indicate a stronger casual effect of obtaining an advanced degree on full time work for women than men in 17 of the 19 graduate degree categories (Table B10). It is interesting to note that women obtain a substantially larger return to an MBA than men do: 0.155 (0.039) versus 0.119 (0.022), although the difference is not statistically significant. One should keep in mind that because the earnings of women are below those of men prior to the advanced degree, the gain in dollars from an advanced degree implied by the log of earnings model is smaller in some cases for women even when γ_g is higher. A full exploration of gender differences in the causal effect of graduate education on labor market outcomes will require a separate paper.

7.4 Graduate Returns by Undergraduate Field

We now turn to estimates of graduate returns by undergraduate field. As we have already mentioned, we only have 8,180 pre advanced degree observations on 4,810 individuals who ultimately obtain an advanced degree. These observations tend to be concentrated in STEM undergraduate fields because of the sample design of the surveys. This fact, together with strong selection between undergraduate field and graduate field, limits the cg combinations for which we can produce FE-cg estimates. We report results for cases with pre advanced observations on at least 31 individuals, but do not discuss all cases in the text. We organize the discussion by the graduate degrees. Columns 1 and 2 of Table 11 report FE-cg and OLS estimates of the treatment effect for earnings. For completeness, columns 3 and 4 reports the FE-cg estimates of γ_{cg} and γ_{cg1-28} using the sample with college only observations included. In column 4 the effect of x_{it} on earnings after graduate school depends on g but not c, as given in (14). We do not discuss these estimates, but both are typically larger than the FE-cg estimate of $\hat{\gamma}_{cg}$ when the college only observations are excluded (column 1). These estimates are probably upward biased due to lack of comparability between individuals who obtain graduate

[46] See footnote 38. The correction factor is 1.6647.

[47] The NSCG does contain information on number of years of full time and number of years of part time work, but actual experience is endogenous, and so isolating its role is not straightforward.

degrees and those who do not. However, the sample weighted γ_{cg} parameter probably underestimates the average return per year over the full period after graduate degree attainment.

Columns 5 and 6 report FE-cg and OLS estimates of γ_{cg} for the occupation premium. Column 7 reports the number of pre graduate school person-year observations on earnings and column 8 reports the number of individuals who contribute. The number of pre graduate school occupation observations is not displayed, but is typically higher because of the availability of occupation data in 1988 for the NSCG 1993 sample.

7.4.1 MBA and Business Related Master's Degrees.

Table 11 first presents estimates of the return to an MBA for 10 undergraduate fields. We can do so in part because MBA is a popular degree and in part because it draws individuals from a variety of majors. The second row is for Business major. The FE-cg estimate is 0.170 (0.069), while the OLS estimate is 0.245 (0.018). For economics majors the FE-cg estimate is 0.109 (0.067) and the OLS estimate is 0.277 (0.036). We had expected that the return would be larger for economics majors under the assumption they would benefit more from basics in accounting, management, marketing, and finance that business majors may typically take as undergraduates. The difference in the estimates is not significant even at the 10% level. OLS appears to substantially overstate the return to an MBA for both majors. In both cases OLS shows a substantial occupation related return of about 0.072, but FE-cg does not.

Next we consider STEM majors. The FE-cg estimate for biological, agricultural, and environmental sciences is -0.099 (0.087). The value for engineering is 0.078 (0.024) . In contrast, the OLS estimates range from 0.220 (0.013) for engineering to a whopping 0.337 (0.038) for bio/agricultural/environmental sciences. OLS appears to vastly overstate the value of an MBA for these fields, just as it understates the value of a science related master's degree. We find the same pattern for physical science majors.

The table reports substantial FE-cg estimates of 0.154 (0.076) and 0.137 (0.103) for other social sciences and psychology. The corresponding OLS estimates are much larger—0.405 (0.048) and 0.397 (0.042). It is interesting to note that we find substantial FE-cg effects on the occupational returns in the cases of other social sciences and psychology, but only a small effect for the business related majors. Overall, the results show substantial heterogeneity across college majors in the value of an MBA.

The second panel reports estimates for business related master's degrees for three majors. The return for engineering and economics majors is below the return for business majors, although standard errors are substantial. The OLS estimates are far above the FE-cg estimates in two of the three cases.

7.4.2 Education

Table 11 panel 3 presents estimates of the return to a master's in education for 7 majors. In some cases, the estimates are imprecise, because of small cell sizes. The most important estimate is for education majors, for whom an education master's is common. FE-cg indicates a return of 0.141 (0.030), of which 0.014 (0.009) is an occupational premium. The corresponding OLS estimate is even larger: 0.208 (0.009). In all other cases, the FE-cg estimate is substantially above the OLS estimate. The gap is particularly large for Physical and Related Sciences and computer and mathematical sciences as well as for engineering (not reported). OLS shows a negative occupational premium in all cases. It is often large, especially for higher paying STEM fields.

Overall, the evidence points to a substantial positive return to a master's degree in education, as one would expect given teacher contracts. OLS seems to be a very unreliable guide. The results for the occupational earnings suggest that the reason is that in many cases those in a given major who pursue a master's in education chose lower paying occupations prior to graduate school than those who do not.

7.4.3 Engineering, Computer Science and Math

The return to a master's in engineering is 0.115 (0.021), of which 0.016 (0.015) is occupational upgrading. In this case, the OLS estimates are similar. We obtain a healthy return of 0.146 (0.055) to a graduate degree in computer science/math for those who majored in those disciplines. The return for engineering majors is smaller. The OLS estimates of the returns are around 0.14 in both cases.

7.4.4 Physical and Related Sciences and Life Sciences

The FE-cg estimate indicates that physical and related sciences majors who go on to get a master's degree receive a return of 0.148 (0.061). The FE-cg estimate of the return to a biology/agriculture/environmental master's degree for those who majored in this field is also large. In both cases, the FE-cg estimates are far above OLS and most of the return is within occupation.

7.4.5 Nursing and Health Related Master's Degrees

The FE-cg estimates show a return of 0.248 (0.045) to a master's in nursing for people with a nursing BA. Almost all of the return is within occupation. Life science majors obtain a return of 0.334 (0.048) from a health related master's, and the occupational component is 0.191. In both cases, the OLS estimate is even larger.

7.4.6 Psychology or Social Work

The FE-cg estimates show a return of about 0.23 for social science majors and for psychology or social work majors. For both majors, the OLS estimate is about 0.095. Most of the difference in the FE-cg and OLS estimates is due to differences in the occupational returns, which are negative in the OLS case.

7.5 Patterns in the FE-cg estimates by undergraduate field

Here we highlight how FE-cg estimates of the major specific returns to advanced degrees are related to the OLS estimates of the BA and advanced degree earnings premia and occupation premia. We estimate a series of weighted regressions of the FE-cg estimate of $\hat{\gamma}_{cg}$ on the OLS estimate for the 83 cg combinations for which at least 10 individuals are observed prior to graduate school on the OLS estimates of γ_c and γ_g for the additive specification (not reported).[48] The OLS estimates may be biased as estimates of causal effects, but they do measure differences across fields in the conditional mean of earnings.

When only $\hat{\gamma}_c$ is included, the coefficient is -0.238 (0.075), When both $\hat{\gamma}_c$ and $\hat{\gamma}_g$ are included, they enter with coefficients of -0.334 (0.098) and 0.361 (0.122) respectively. The negative coefficient on $\hat{\gamma}_c$ indicates that the return to graduate degrees tends to be lower for individuals with higher paying majors. Adding the product of the deviations of $\hat{\gamma}_c$ and $\hat{\gamma}_g$ and from their averages across the 19 undergraduate and graduate fields to the regression indicates that the association of $\hat{\gamma}_{cg}$ with $\hat{\gamma}_c$ is more negative for graduate degrees with high pay, although the p-value on the interaction terms is only 0.107. When the the FE-cg estimates of γ_{cg}^{occ} for the occupation premium are used in place of the effects on earnings, the estimates again indicate that the

[48]The weights are the inverse of square of the standard error of $\hat{\gamma}_{cg}$.

effect of g is smaller for those with high paying undergraduate degrees, especially for graduate degrees that pay well.

8 Concluding Remarks

Many people face the decision of whether to go to graduate school, and what to study. Unfortunately, information about the labor market value of alternative graduate degrees is both critical to that decision and in short supply. Part of the reason is lack of data, but the biggest challenge is that ability and preferences influence both job choice and graduate field. This makes simple earnings comparisons a poor guide to the causal effects of the degrees.

We address the selection problem by controlling for fixed effects for whether an individual has obtained a particular college major and graduate degree combination by the last time that we observe her. Basically, the FE-cg approach compares earnings before graduate school with earnings after graduate school. We implement the approach using multiple waves of the National Survey of College Graduates and the National Survey of Recent College Graduates.

In the empirical sections we start with a set of facts about the linkages between BA field, graduate field, and occupation. Our main contribution is to provide treatment on the treated estimates of the returns for 19 graduate fields as well as 30 estimates of returns to graduate fields that are for specific undergraduate majors. The online appendix provides descriptive information about earnings premiums for 168 graduate fields. We provide highlights of the results in the introduction and a detailed discussion in section 7, so here we simply characterize the results rather than review point estimates.

First, the FE-cg estimates differ substantially across fields. Second, we obtain somewhat larger estimates when we allow the return to graduate school to depend on time since degree completion, and for most fields annual returns appear to rise with post graduate school experience. However, we suspect that the experience specific estimates are biased because they require the use of data on people who never attend graduate school to identify the counterfactual experience profile.

Third, the return to a given graduate field, such as an MBA, depends on the college major. Fourth, the FE-cg estimates indicate that the extent to which the returns operate through occupational upgrading varies across degrees. In the cases of law and medicine, most of the returns are across occupations. But in many other cases, such as a master's in engineering, most of the returns are within occupation.

Finally, the FE-cg and OLS estimates of the effects on earnings and on the occupational upgrading differ substantially for many degrees. OLS tends to overstate the returns to graduate fields that attract high paying college majors, such as a master's in engineering and an MBA. OLS also tends to understate the returns to graduate fields that attract lower paying majors, such a master's in psychology and social work. The simple earnings comparisons of those with an advanced degree to those with only a BA can be very misleading.

We close with a few caveats. The FE-cg approach requires that earnings observed prior to the advanced degree must provide an unbiased estimate of what a person would have earned had she not gone to graduate school, after accounting for differences in experience. As we explained above, this will only be true under some strong assumptions. Because the fundamental problem is that we do not observe counterfactual earnings after graduate school, further progress would seem to require either a more structural approach or a source of quasi-experimental variation in which a set individuals who are intending to pursue an MBA, say, are induced at random not to go to graduate school *in any field* without altering earnings prospects in the absence of a graduate degree. This is a tall order.[49]

We stress that our estimates are averages across a wide range of institutions. The return to a law degree may depend on the school. Our approach could incorporate program quality if the data were available. It is also important to keep in mind that our results are for people who work before going to graduate school. It is possible that returns are different for those who go immediately to graduate school. Finally, one should keep in mind that our treatment on the treated estimates may of course be different from average treatment effects. For example, the estimated effect for an MBA, say, may be only a rough guide to what the return would be for someone with talents and preferences that are quite different from typical business school graduates. And the treatment on the treated estimates for medicine and other selective programs are for those who are able to obtain admission to medical programs.

We believe that our paper is an important step toward the goal of providing information about graduate school returns that individuals can rely on, but we have a long way to go.

[49]Another possibility is to use geographical proximity to particular graduate programs as a source of variation. Alternatively, there may be settings in which grades or test scores have a discontinuous relationship with admission to a graduate program at a particular institution, although we suspect that it will be difficult to define the counterfactual using such a design given the large number of alternative programs and institutions.

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Figures

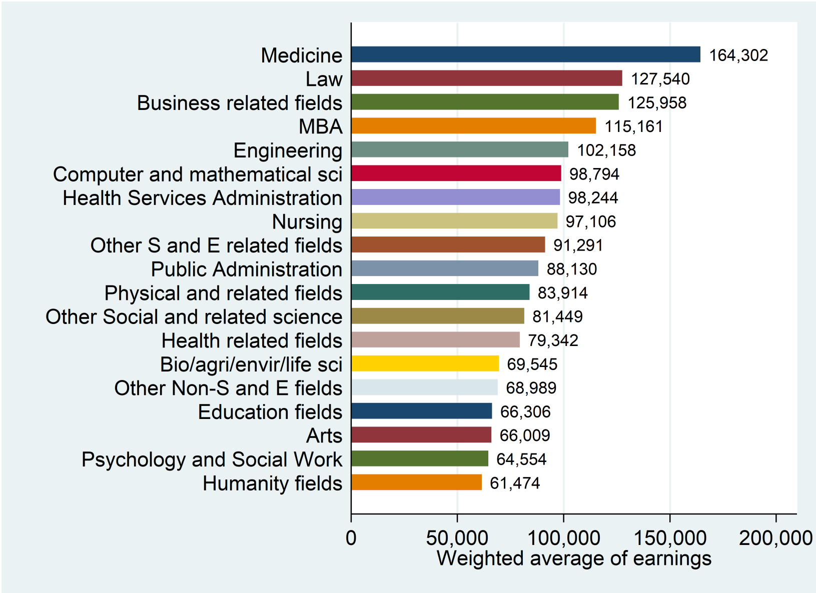

Figure 1: Average earnings by advanced field

Note: The figure presents the weighted average of earnings by advanced fields, in descending order of earnings (in 2013 dollars). Medicine is highest paid and humanities fields are lowest paid.

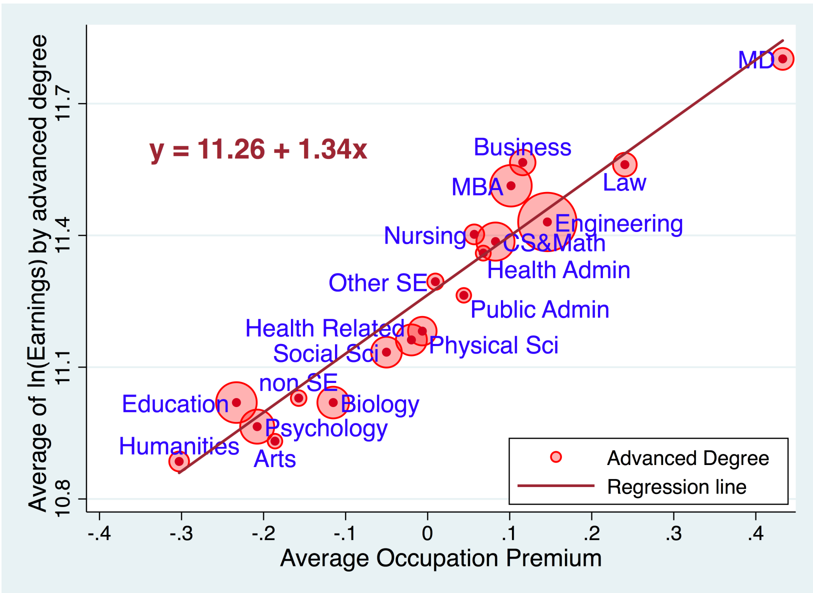

Figure 2: Average ln(earnings) of advanced fields by average occupation premium

Note: The figure presents the relationship between the averages of the log of earnings (in 2013 dollars) and the occupation premium for each advanced field, using sample weights. The dots are the averages. The shaded circles around the dots indicate the share of each advanced field among all graduate degree holders. The straight line is the fitted simple regression line between the two averages, with the shares of the advanced fields as weights. The standard error of the slope is 0.10. The figure shows that much of the variation in earnings across advanced degrees is associated with occupational sorting.

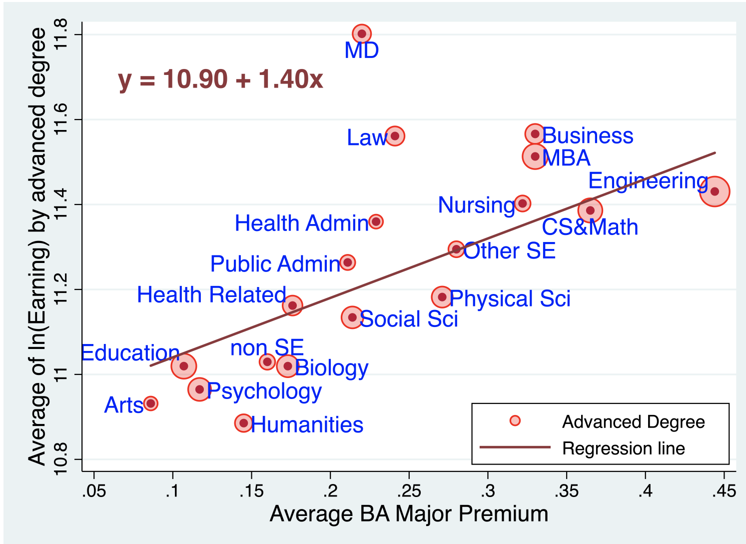

Figure 3: Average ln(earnings) of advanced fields by average BA major premium

Note: The figure presents the relationship between the averages of the log of earnings (in 2013 dollars) and the averages of BA major premium of each advanced field, using sample weights. The dots indicate the averages. The shaded circles indicate the share of each advanced field among all graduate degree holders. The straight line is the fitted simple regression line between the two averages, with the shares of the advanced fields as weights. The standard error of the slope is 0.29. The figure shows a positive relationship between the log of earnings and the BA major premium. Therefore, those who choose a high-paying advanced field tend to have majored in a high-paying BA field.

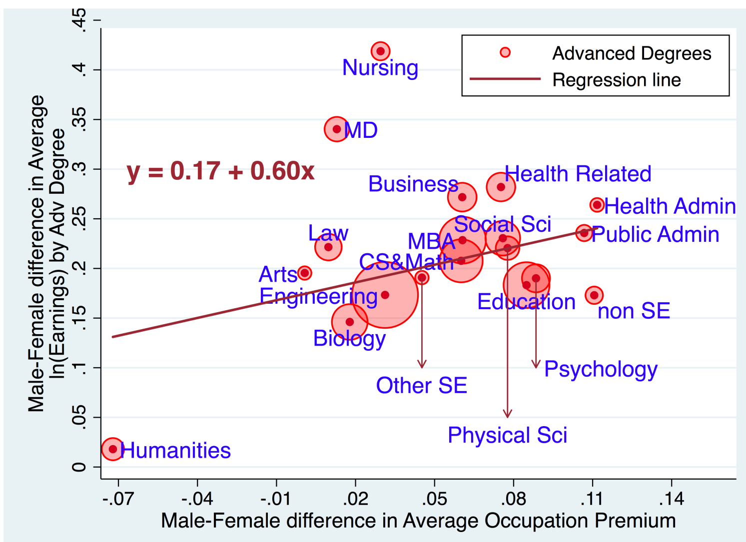

Figure 4: Gender differences in average ln(earnings) by differences in the average occupation premiums of advanced fields

Note: The figure plots the male-female difference for each advanced field in the average of the log of earnings (in 2013 dollars) against the difference in the average occupation premium, using sample weights. The dots indicate the gender differences. The shaded circles indicate the share of each advanced field among all graduate degree holders. The straight line is the fitted simple regression line between the two averages, with the shares of the advanced fields as weights. The standard error of the slope is 0.44. The figure shows that men are in higher paying occupations than women in all advanced fields except for humanities and arts, but only a small fraction of the earnings differentials are accounted for by gender differences in occupation choices.

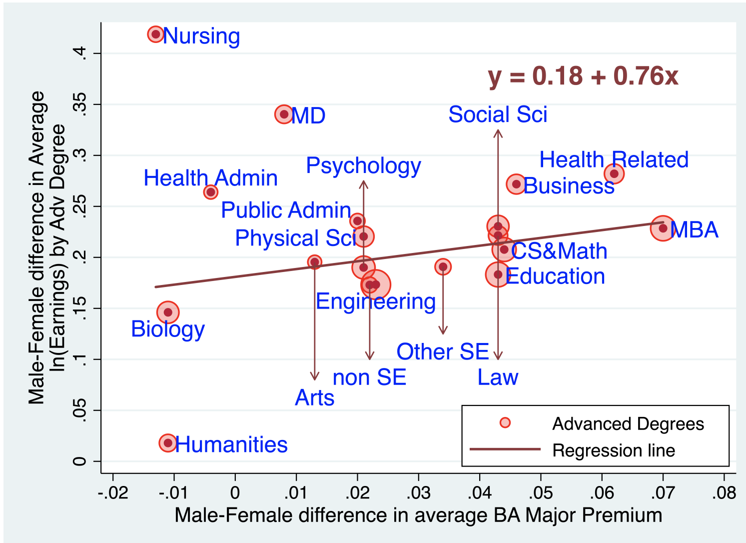

Figure 5: Gender differences in average ln(earnings) by differences in the average BA major premiums of advanced fields

Note: The figure plots the male-female difference for each advanced field in the average of the log of earnings against the difference in the average BA major premium, using sample weights. The BA premiums are OLS estimates for the pooled sample of males and females and are reported in Table B4. The dots indicate the gender differences. The shaded circles indicate the share of each advanced field among all graduate degree holders. The straight line is the fitted simple regression line between the two averages, with the shares of the advanced fields as weights. The standard error of the slope is 0.61. The figure shows men have higher earnings than women in all advanced fields. The gender gap in the BA major premium is scattered around 0.03. The poor fit of the regression line shows that gender differences in the link between BA field and graduate field do not explain much of the gender gap in earnings.

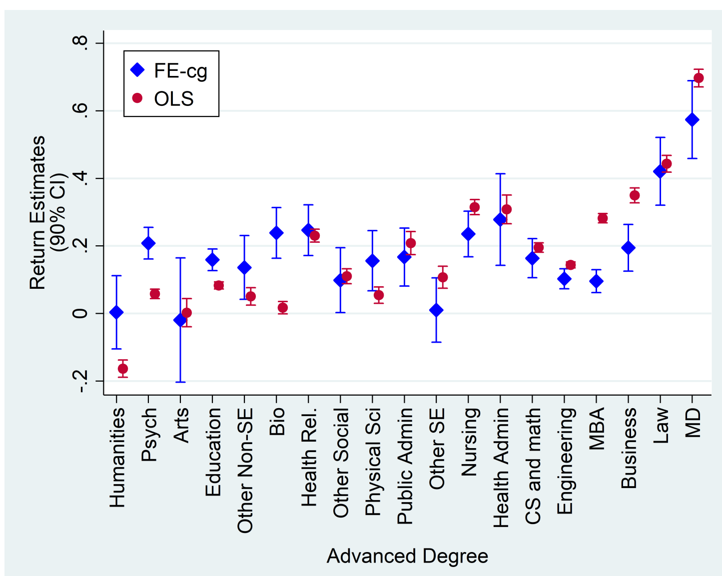

Figure 6: FE-cg and OLS estimates of the Advanced degree premiums

Note: The figure compares the FE-cg and OLS coefficients from sample weighted additive regressions of the log of earnings based on (10) and (7). The figure also presents 90% confidence intervals of the estimates. The horizontal axis lists advanced fields in ascending order of the sample weighted average of earnings of the advanced fields. It shows that OLS underestimates the returns to low-paying fields (e.g. humanities, psychology, education, and biology), while it overestimates the returns to high-paying fields (e.g. medicine, business, MBA, nursing, and other science and engineering related fields).

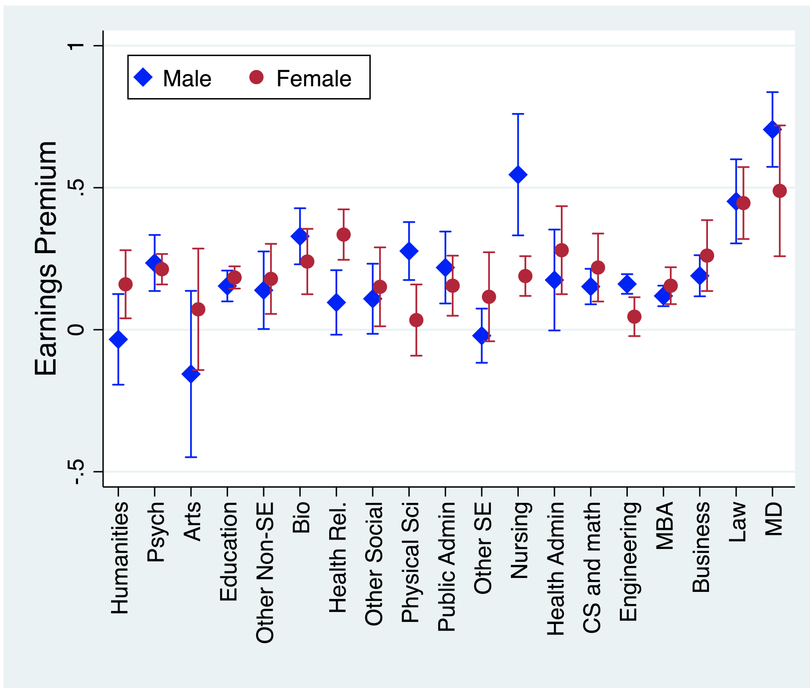

Figure 7: FE-cg estimates of advanced degree premiums, by gender

Note: The figure presents FE-cg coefficients from sample weighted additive regressions of the log of earnings for women and for men. The specification is (10). The figure also presents 90% confidence intervals of the estimates. The horizontal axis lists advanced fields in ascending order of the weighted average of earnings of the advanced fields.

Table 1: Example of FE-cg estimator

Observation	BA-Econ, MBA at last obs.?	Post BA, Pre-MBA Earnings	Post-MBA Earnings	Post MBA minus Pre-MBA Earnings
Barry	Yes	\$55,000	\$90,000	\$35,000
Ebony	Yes	NA	\$80,000	NA
Mary	Yes	\$65,000	NA	NA
Column Mean		\$60,000	\$85,000	\$25,000

Note: FE-cg estimate of return to MBA for economics major is: \$25,000 (=\$85,000−\$60,000). FE estimate is \$35,000 (=\$90,000−\$55,000)

Table 2: Returns to graduate education

Dependent variable:	ln(earnings)						Occupational Premium				
				w/ post Adv exp. interaction						w/ post Adv exp. interaction	
	FE-cg	FE-cg large†	OLS	FE-cg $1\sim28$ yrs*	OLS $1\sim28$ yrs*	FE-cg all years$^\#$	FE-cg	FE-cg large†	OLS	FE-cg $1\sim28$ yrs*	OLS $1\sim28$ yrs*
Medicine	0.574	0.625	0.697	0.685	0.747	0.666	0.510	0.500	0.508	0.485	0.493
	(0.070)	(0.075)	(0.016)	(0.076)	(0.015)	(0.076)	(0.036)	(0.040)	(0.005)	(0.039)	(0.005)
Law	0.421	0.444	0.444	0.473	0.460	0.469	0.342	0.325	0.298	0.318	0.290
	(0.061)	(0.058)	(0.015)	(0.059)	(0.015)	(0.058)	(0.030)	(0.030)	(0.004)	(0.029)	(0.004)
Master's in Business related fields	0.195	0.225	0.350	0.252	0.365	0.241	0.048	0.047	0.116	0.052	0.117
	(0.042)	(0.041)	(0.013)	(0.041)	(0.014)	(0.041)	(0.016)	(0.016)	(0.005)	(0.016)	(0.005)
MBA	0.096	0.129	0.282	0.169	0.308	0.153	0.024	0.023	0.097	0.028	0.100
	(0.021)	(0.020)	(0.008)	(0.021)	(0.009)	(0.020)	(0.008)	(0.008)	(0.004)	(0.008)	(0.004)
Master's in Engineering	0.103	0.146	0.144	0.198	0.180	0.162	0.021	0.028	0.065	0.030	0.067
	(0.018)	(0.019)	(0.005)	(0.019)	(0.007)	(0.019)	(0.013)	(0.015)	(0.002)	(0.014)	(0.003)
Master's in Computer and mathematical sciences	0.164	0.173	0.196	0.210	0.223	0.183	0.012	0.008	0.063	0.008	0.062
	(0.035)	(0.035)	(0.008)	(0.035)	(0.010)	(0.035)	(0.010)	(0.010)	(0.003)	(0.010)	(0.004)
Master's in Health Services Administration	0.278	0.268	0.308	0.307	0.348	0.277	0.112	0.098	0.134	0.112	0.150
	(0.082)	(0.080)	(0.026)	(0.082)	(0.031)	(0.079)	(0.038)	(0.037)	(0.012)	(0.038)	(0.013)
Master's in Nursing	0.236	0.181	0.315	0.163	0.294	0.180	0.034	0.021	0.044	0.019	0.034
	(0.041)	(0.036)	(0.014)	(0.038)	(0.018)	(0.036)	(0.013)	(0.011)	(0.006)	(0.012)	(0.008)
Master's in Other Science and Engineering related fields	0.010	0.027	0.107	0.054	0.116	0.047	0.034	0.021	0.023	0.023	0.023
	(0.058)	(0.055)	(0.020)	(0.055)	(0.019)	(0.055)	(0.051)	(0.050)	(0.010)	(0.049)	(0.011)
Master's in Public Administration	0.167	0.192	0.209	0.235	0.239	0.210	0.116	0.110	0.123	0.123	0.133
	(0.052)	(0.052)	(0.021)	(0.053)	(0.021)	(0.052)	(0.031)	(0.030)	(0.011)	(0.030)	(0.011)
Master's in Physical and related sciences	0.156	0.224	0.054	0.283	0.091	0.245	-0.012	-0.021	0.010	-0.023	0.008
	(0.054)	(0.053)	(0.015)	(0.054)	(0.016)	(0.053)	(0.017)	(0.017)	(0.006)	(0.017)	(0.007)
Master's in Other Social and related sciences	0.099	0.128	0.110	0.171	0.139	0.143	0.034	0.026	0.031	0.034	0.036
	(0.058)	(0.057)	(0.013)	(0.058)	(0.017)	(0.057)	(0.028)	(0.028)	(0.006)	(0.028)	(0.007)
Master's in Health related fields	0.247	0.256	0.231	0.270	0.224	0.263	0.094	0.080	0.084	0.069	0.070
	(0.046)	(0.045)	(0.012)	(0.047)	(0.015)	(0.045)	(0.021)	(0.021)	(0.006)	(0.022)	(0.007)
Master's in Bio/agricultural/ environmental/life sciences	0.239	0.280	0.017	0.331	0.050	0.299	0.036	0.039	-0.021	0.045	-0.016
	(0.046)	(0.046)	(0.011)	(0.046)	(0.012)	(0.046)	(0.015)	(0.015)	(0.006)	(0.015)	(0.006)
Master's in Other Non-Science and Engineering fields	0.136	0.165	0.051	0.205	0.073	0.190	-0.021	-0.022	-0.054	-0.020	-0.055
	(0.057)	(0.057)	(0.016)	(0.058)	(0.016)	(0.057)	(0.026)	(0.026)	(0.010)	(0.027)	(0.010)
Master's in Education fields	0.159	0.185	0.083	0.216	0.100	0.207	0.030	0.022	-0.082	0.029	-0.075
	(0.019)	(0.019)	(0.006)	(0.019)	(0.007)	(0.019)	(0.008)	(0.008)	(0.003)	(0.008)	(0.004)
Master's in Arts	-0.019	-0.017	0.002	0.034	0.029	0.014	0.001	-0.011	-0.059	-0.009	-0.058
	(0.112)	(0.118)	(0.025)	(0.119)	(0.025)	(0.118)	(0.056)	(0.057)	(0.012)	(0.056)	(0.011)
Master's in Psychology and Social Work	0.208	0.206	0.058	0.258	0.093	0.225	0.026	0.007	-0.070	0.019	-0.061
	(0.029)	(0.028)	(0.009)	(0.029)	(0.010)	(0.028)	(0.017)	(0.017)	(0.005)	(0.017)	(0.006)
Master's in Humanity fields	0.004	0.020	-0.163	0.043	-0.157	0.045	-0.081	-0.088	-0.218	-0.084	-0.213
	(0.066)	(0.064)	(0.015)	(0.065)	(0.016)	(0.065)	(0.031)	(0.031)	(0.009)	(0.030)	(0.009)

(† large sample, including people without an advanced degree by their last observation; * γ_{g1-28}; $^\#$ sample weighted average of γ_{gx})

Note: The table reports estimates of returns to advanced degrees for a set of additive regression specifications. Sample weights are used and standard errors are clustered at the person level. The dependent variable is earnings in columns 1-6 and the occupation premium in columns 7-11. The regressions include dummies for each BA field (OLS only) and each advanced degree, as well as parental education, year of the earnings/occupation observation, interactions between a cubic in age and gender, a cubic in age and BA field, and between race\ethnicity and gender. Note that a linear birth cohort effect is embedded in the indicator for the year of earnings/occupation observations. The linear term on age, on the other hand, is net of the heterogeneity across the birth cohorts. The nonlinear effect of the birth cohort is partially accounted for by the non-linear effect of age on earnings/occupations.

Col. 1 and 7 report FE-cg estimates of γ_g on the sample of people who have an advanced degree when they are last observed. The specification is equation (10). Cell counts by major for the FE-cg sample range from 2,410 for a master's in Arts to 64,810 for a master's in Engineering. Col. 2 and 8 report FE-cg estimates of γ_g including people who only have a BA when they are last observed. Columns 3 and 9 report OLS estimates of γ_g based on (7). Col. 4-5 and 10-11 report FE-cg 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 obtainment. They are based on equation (13), with degree combination fixed effects excluded in the OLS case. Col. 6 reports the sample weighted average of γ_{gx}. A detailed explanation of the construction of these averages is provided in the notes

Table 3: 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)
Min	1	1	1	2	1	2
10th quantile	1	1	2	2	1	4
25th quantile	2	2	4	3	1	5
Mean	5.07	2.30	12.13	6.38	2.35	8.49
Median	4	3	11	5	2	7
75th quantile	7	4	18	8	3	11
90th quantile	12	5	25	12	5	15
Max	19	13	37	20	8	20
count	8,180	8,180	290,560	298,740	7,560	15,740

Note: Summary statistics of the time gaps reported for the regression sample, but exclude observations based on the annual earnings in the previous year. Columns 3-4 are estimated from the subsample in which the individuals obtain advanced degrees by the last time they were observed. 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. Unweighted cell counts are rounded to the nearest 10.

Table 4: Age distribution of the earnings observations

	Full sample	Individuals without Adv. Degree	Individuals with Adv. Degree in the future	Individuals with advanced degree
	(1)	(2)	(3)	(4)
Min	23	23	23	23
10th quantile	26	25	24	28
25th quantile	30	29	25	32
Mean	38.72	38.28	29.40	39.85
Median	38	37	28	39
75th quantile	47	46	33	47
90th quantile	53	53	38	53
Max	59	59	49	59
Count	863,890	565,150	8,180	290,560

Note: Summary statistics of individual age are reported for the additive OLS regression sample. Observations based on the survey report of earnings and annual earnings in the previous year both included. Column 4 is estimated from the subsample of individuals who obtain advanced degrees by the last time they were observed. Column 3 is estimated from the more restricted subsample of individuals who are observed working full time before they obtain the advanced degree. Unweighted cell counts are rounded to the nearest 10.

Tables

Table 5: Average earnings, occupation premium and BA premium by advanced degree

Advanced degree	Earnings	ln(Earnings)	Occupational Premium	College major premium	Number of obs	%
	(1)	(2)	(3)	(4)	(5)	(6)
Medicine	164,302 [102,773]	11.802 [0.687]	0.433 [0.185]	0.220 [0.097]	8,490	3.95
Law	127,540 [86,499]	11.561 [0.643]	0.240 [0.150]	0.241 [0.114]	9,970	6.41
Master's in Business related fields	125,958 [87,526]	11.566 [0.596]	0.116 [0.211]	0.330 [0.128]	11,370	5.87
MBA	115,161 [68,283]	11.513 [0.541]	0.102 [0.230]	0.330 [0.137]	30,430	12.86
Master's in Engineering	102,158 [51,288]	11.431 [0.471]	0.146 [0.146]	0.444 [0.085]	63,560	10.56
Master's in Computer and mathematical sciences	98,794 [50,290]	11.386 [0.499]	0.083 [0.182]	0.365 [0.127]	26,510	7.03
Master's in Health Services Admin.	98,244 [57,667]	11.360 [0.518]	0.068 [0.245]	0.229 [0.106]	2,440	1.11
Master's in Nursing	97,106 [43,601]	11.402 [0.403]	0.057 [0.164]	0.322 [0.055]	4,450	1.89
Master's in Other Science and Engineering related fields	91,291 [53,923]	11.295 [0.511]	0.009 [0.233]	0.280 [0.123]	4,490	1.59
Master's in Public Administration	88,130 [44,107]	11.264 [0.519]	0.044 [0.274]	0.211 [0.104]	3,480	1.68
Master's in Physical and related sciences	83,914 [46,917]	11.182 [0.590]	-0.007 [0.196]	0.271 [0.088]	14,700	2.41
Master's in Other Social and related sciences	81,449 [57,001]	11.134 [0.586]	-0.050 [0.267]	0.214 [0.127]	17,200	4.79
Master's in Health related fields	79,342 [45,091]	11.162 [0.487]	-0.020 [0.222]	0.176 [0.120]	11,410	4.65
Master's in Biological / agricultural / environmental / life sciences	69,545 [39,975]	11.020 [0.517]	-0.115 [0.218]	0.173 [0.096]	18,200	4.19
Master's in Other Non-Science and Engineering fields	68,989 [38,438]	11.030 [0.475]	-0.157 [0.252]	0.160 [0.101]	4,040	2.21
Master's in Education fields	66,306 [30,064]	11.020 [0.411]	-0.233 [0.206]	0.107 [0.110]	29,670	16.12
Master's in Arts	66,009 [47,334]	10.932 [0.576]	-0.186 [0.223]	0.086 [0.108]	2,370	1.18
Master's in Psychology and Social Work	64,554 [34,385]	10.965 [0.471]	-0.208 [0.245]	0.117 [0.081]	21,020	7.82
Master's in Humanity fields	61,474 [39,758]	10.885 [0.527]	-0.303 [0.286]	0.145 [0.112]	6,760	3.68

Data source: NSCG 1993-2015, NSRCG 1993-2010

Note: Weighted summary statistics reported for observations with a BA degree or higher, between the ages of 23 and 59, inclusive. Standard deviations are reported in brackets. The sample is restricted to full time workers who obtained their BA degree after age 19. The sample excludes people with PhD degrees now or in the future and people who attend graduate school directly after college. The sample also excludes observations of people enrolled in advanced degrees. Earnings statistics are based on annualized basic salary of the principal job in 2013 dollars and exclude observations based on annual earnings in the previous year. Earnings are censored to be more than $5,000 per year, and less than $1,500,000 per year. Unweighted cell counts are rounded to the nearest 10.

Table 6: Occupation choices of individuals with BA in Engineering by advanced degree choice

Educational background	Rank	Occupation before age 35	%	Average earnings
No advanced degree	1	Mechanical engineers	15.75	68,925
	2	Civil engineers	12.34	62,955
	3	Electrical engineer	12.00	71,742
	4	Not-elsewhere-classified engineers	8.68	68,699
	5	Computer software developers	6.39	80,091
Have an MBA by last observation		Pre Adv Occupation before age 45		
	1	Electrical engineer	15.27	82,875
	2	Mechanical engineers	14.80	73,267
	3	Not-elsewhere-classified engineers	10.98	73,513
	4	Industrial engineers	9.67	67,241
	5	Top-level managers, executives, administrators	5.61	87,400
		Post Adv Occupation before age 59		
	1	Top-level managers, executives, administrators	18.09	164,299
	2	Mechanical engineers	9.59	104,185
	3	Electrical engineer	8.89	107,655
	4	Other management related occupations	7.25	126,891
	5	Managers and administrators, n.e.c.	7.15	140,890
Have a Master's in Education		Pre Adv Occupation before age 45		
		1/4 are teachers		
		Post Adv Occupation before age 59		
	1	Secondary school teachers	50.00	70,149
	2	Postsecondary Teachers	10.32	63,438
	3	Other management related occupations	5.50	86,119
	4	Top-level managers, executives, administrators	5.05	83,430
	5	Managers in education and related fields	3.44	76,908
Have a Master's in Engineering		Pre Adv Occupation before age 45		
	1	Electrical engineer	23.44	67,638
	2	Mechanical engineers	15.43	70,058
	3	Not-elsewhere-classified engineers	13.67	63,838
	4	Aeronautical/aerospace/astronautical engineers	12.11	70,239
	5	Civil engineers	8.89	59,688
		Post Adv Occupation before age 59		
	1	Electrical engineer	15.92	101,477
	2	Mechanical engineers	13.87	91,651
	3	Civil engineers	11.98	88,634
	4	Not-elsewhere-classified engineers	10.37	95,646
	5	Computer software developers	8.29	102,415

Note: Tables 6-8 report occupation distributions and average earnings by BA field and advanced degree field and status. All statistics are weighted. For combinations with a small cell count, i.e. the most common occupation has less than 10 observations, the specific tabulation is replaced by a general statement. The top panel reports the five most common occupations for the BA field within the subsample of people who do not have an advanced degree when they are last observed. The lower panels reports the five most common occupations for each BA and advanced field combination, separately for pre and post advanced degree observations, on the subsample of people who have an advanced degree when they are last observed. Column 1 describes each panel. Column 2 reports the rankings of the occupations, column 3 reports the name of each occupation, column 4 reports the share of each occupation within each distinct educational background, and column 5 reports the average earnings of the individuals with each occupation and educational background combination. Table 6 focuses on people with a BA in Engineering.

Table 7: Occupation choices of individuals with BA in Education

Educational background	Rank	Occupation before age 35	%	Average earnings
No advanced degree	1	Secondary school teachers	28.74	44,409
	2	Primary school teachers	24.88	41,535
	3	Kindergarten and earlier school teachers	5.50	36,580
	4	Secretaries	3.91	36,426
	5	Salespersons, n.e.c.	2.53	69,378
Have an MBA		Pre Adv Occupation before age 45		
		Not teachers		
		Post Adv Occupation before age 59		
	1	Top-level managers, executives, administrators	11.98	145,118
	2	Computer systems analysts and computer scientists	9.59	89,617
	3	Accountants, auditors, and other financial specialists	7.84	66,159
	4	Other management related occupations	7.19	73,163
	5	Secondary school teachers	6.97	69,931
Have a Master's in Education		Pre Adv Occupation before age 45		
	1	Secondary school teachers	41.73	44,780
	2	Primary school teachers	36.22	42,283
	3	Postsecondary Teachers	5.51	48,535
	4	Kindergarten and earlier school teachers	3.41	27,640
		Post Adv Occupation before age 59		
	1	Secondary school teachers	33.06	63,036
	2	Primary school teachers	24.66	60,666
	3	Vocational and educational counselors	6.94	60,614
	4	Top-level managers, executives, administrators	6.53	84,295
	5	Managers in education and related fields	5.63	85,444

Note: This table repeats the case study presented in Table 6, but focusing on people with a BA in Education.

Table 8: Occupation choices of individuals with BA in Physical and related sciences

Educational background	Rank	Occupation before age 35	%	Average earnings
No advanced degree	1	Chemists	19.90	49,960
	2	Geologists	10.21	57,110
	3	Secondary school teachers	4.46	39,048
	4	Physicists and astronomers	3.70	38,298
	5	Biological scientists	3.68	40,800
Have an MBA		Pre-Adv Occupation before age 45		
	1	Engineer	29.63	84,701
	2,3	STEM occupations	40.74	72,299
	4,5	Manager and Clerical occupations	18.52	74,343
		Post Adv Occupation before age 59		
	1	Top-level managers, executives, administrators	21.90	154,276
	2	Chemists	7.69	88,141
	3	Accountants, auditors, and other financial specialists	7.60	89,167
	4	Salespersons, n.e.c.	7.52	110,986
	5	Other management related occupations	6.45	108,964
Have a Master's in Education		Pre Adv Occupation before age 45		
		65% are teachers		
		Post Adv Occupation before age 59		
	1	Secondary school teachers	53.51	64,169
	2	Postsecondary Teachers	5.04	59,984
	3	Top-level managers, executives, administrators	5.04	80,741
	4	Vocational and educational counselors	4.67	63,762
	5	Primary school teachers	4.18	56,891
Have a Master's in Physical Sciences		Pre Adv Occupation before age 45		
	1	Physicists and astronomers	20.77	32,916
	2	Geologists	19.67	45,004
	3	Chemists	15.30	45,453
	4	Postsecondary Teachers	9.29	22,394
		Post Adv Occupation before age 59		
	1	Geologists	22.73	89,122
	2	Chemists	20.33	76,480
	3	Physicists and astronomers	8.43	59,340
	4	Postsecondary Teachers	4.62	51,802
	5	Atmospheric and space scientists	3.86	80,194

Note: This table repeats the case study presented in Table 6, but focusing on people with a BA in Physical and related sciences.

Table 9: Internal rate of return to advanced degrees

Advanced field	Duration of the advanced degree	Annual Tuition	Net PDV Actual	PDV counterfactual	Percentage gain from the advanced degree	Internal rate of return
	(1)	(2)	(3)	(4)	(5)	(6)
Medicine	4	13,317	1,823,918	1,255,683	45.080	0.167
Law	3	16,697	1,507,279	1,164,494	29.321	0.150
Master's in Business related fields	2	6,736	1,617,182	1,462,845	10.511	0.122
MBA	2	9,311	1,510,821	1,514,925	-0.323	0.048
Master's in Engineering	1	8,131	1,615,855	1,527,885	5.748	0.128
Master's in Computer and mathematical sciences	1	8,131	1,497,761	1,335,621	12.111	0.196
Master's in Health Services Administration	2	6,736	1,326,973	1,112,356	19.209	0.163
Master's in Nursing	2	8,131	1,731,194	1,543,097	12.211	0.122
Master's in Other Science and Engineering related fields	1	8,131	1,264,376	1,314,027	-3.811	Negative
Master's in Public Administration	2	6,736	1,340,926	1,248,975	7.288	0.101
Master's in Physical and related sciences	1	8,131	1,155,757	1,033,661	11.791	0.195
Master's in Other Social and related sciences	1	6,736	1,121,509	1,066,284	5.144	0.120
Master's in Health related fields	2	8,131	1,173,007	1,016,272	15.301	0.141
Master's in Bio/agricultural/ environmental/life sciences	1	8,131	1,027,170	849,182	20.935	0.274
Master's in Other Non-Science and Engineering fields	1	6,736	1,016,031	931,541	9.042	0.161
Master's in Education fields	1	6,736	977,044	877,099	11.367	0.182
Master's in Arts	2	6,736	882,213	995,566	-11.466	Negative
Master's in Psychology and Social Work	2	6,736	902,510	813,132	10.906	0.118
Master's in Humanity fields	1	6,736	849,901	890,164	-4.550	Negative

Note: The statistics are calculated from regression coefficients underlying the FE-cg estimates reported in Table 2, column 1. 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\ethnicity indicators to nonHispanic 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 people's actual income to obtain net income. We assume graduate programs are full-time, and students have zero earnings when they are enrolled. The assumed duration of the degree is in Column 1. The average tuition at public institutions in 2012 from the National Center of Education Statistics is in column 2. Then we calculate the present discounted value of the lifetime net income, assuming the interest rate is 0.05. Column 3 is the PDV of actual income net of tuition. Column 4 is the PDV of counterfactual income. All monetary values in the table are in 2013 dollars. Column 5 is percentage increase in net income 100×((Col. 3-Col. 4)/Col. 4). In column 6, we report estimates of the internal rate of return of each advanced field. The internal rate of return is the discount factor that equates actual and counterfactual lifetime net income.

Table 10: FE-cg Estimates of the returns to graduate education, by gender

Gender:	Female						Male					
Dependent variable:	ln(Earnings)			Occupational Premium			ln(Earnings)			Occupational Premium		
	FE-cg	OLS	FE-cg Avg over 28 years	FE-cg	OLS	FE-cg Avg over 28 years	FE-cg	OLS	FE-cg Avg over 28 years	FE-cg	OLS	FE-cg Avg over 28 years
Medicine	0.489	0.650	0.610	0.538	0.549	0.483	0.705	0.713	0.733	0.495	0.490	0.494
	(0.140)	(0.028)	(0.157)	(0.064)	(0.008)	(0.076)	(0.080)	(0.019)	(0.082)	(0.045)	(0.006)	(0.043)
Law	0.446	0.506	0.532	0.368	0.361	0.345	0.452	0.408	0.469	0.339	0.268	0.325
	(0.077)	(0.025)	(0.074)	(0.039)	(0.007)	(0.039)	(0.090)	(0.019)	(0.090)	(0.046)	(0.005)	(0.044)
Master's in Business related fields	0.261	0.382	0.338	0.065	0.143	0.073	0.190	0.335	0.211	0.038	0.106	0.044
	(0.076)	(0.026)	(0.081)	(0.032)	(0.010)	(0.033)	(0.044)	(0.016)	(0.044)	(0.015)	(0.006)	(0.015)
MBA	0.155	0.362	0.244	0.046	0.133	0.050	0.119	0.250	0.154	0.015	0.083	0.022
	(0.040)	(0.017)	(0.041)	(0.018)	(0.008)	(0.018)	(0.022)	(0.009)	(0.023)	(0.009)	(0.004)	(0.009)
Master's in Engineering	0.046	0.180	0.191	-0.006	0.085	-0.005	0.161	0.136	0.206	0.025	0.061	0.035
	(0.042)	(0.014)	(0.046)	(0.017)	(0.005)	(0.019)	(0.021)	(0.006)	(0.021)	(0.015)	(0.002)	(0.016)
Master's in Computer and mathematical sciences	0.219	0.221	0.259	0.020	0.081	0.015	0.152	0.184	0.185	0.010	0.055	0.005
	(0.073)	(0.017)	(0.072)	(0.023)	(0.007)	(0.024)	(0.038)	(0.010)	(0.039)	(0.010)	(0.004)	(0.011)
Master's in Health Services Administration	0.280	0.301	0.310	0.088	0.109	0.083	0.175	0.329	0.215	0.141	0.169	0.140
	(0.094)	(0.028)	(0.096)	(0.039)	(0.013)	(0.038)	(0.108)	(0.045)	(0.113)	(0.098)	(0.020)	(0.095)
Master's in Nursing	0.189	0.278	0.117	0.034	0.040	0.014	0.546	0.578	0.579	0.031	0.081	0.075
	(0.043)	(0.014)	(0.038)	(0.013)	(0.006)	(0.013)	(0.130)	(0.040)	(0.139)	(0.038)	(0.016)	(0.039)
Master's in Other Science and Engineering related fields	0.116	0.148	0.205	0.163	0.042	0.162	-0.021	0.090	-0.012	-0.039	0.015	-0.047
	(0.095)	(0.042)	(0.100)	(0.082)	(0.018)	(0.076)	(0.058)	(0.022)	(0.058)	(0.042)	(0.013)	(0.042)
Master's in Public Administration	0.155	0.266	0.221	0.096	0.121	0.089	0.219	0.169	0.248	0.135	0.125	0.148
	(0.064)	(0.033)	(0.069)	(0.051)	(0.018)	(0.050)	(0.077)	(0.027)	(0.076)	(0.035)	(0.013)	(0.033)
Master's in Physical and related sciences	0.034	0.097	0.182	-0.002	0.016	-0.021	0.277	0.037	0.329	-0.016	0.007	-0.025
	(0.076)	(0.025)	(0.088)	(0.026)	(0.010)	(0.027)	(0.062)	(0.018)	(0.062)	(0.021)	(0.008)	(0.021)
Master's in Other Social and related sciences	0.151	0.166	0.236	0.039	0.047	0.036	0.109	0.067	0.141	0.036	0.018	0.045
	(0.085)	(0.017)	(0.086)	(0.031)	(0.009)	(0.032)	(0.075)	(0.020)	(0.077)	(0.047)	(0.009)	(0.045)
Master's in Health related fields	0.335	0.232	0.317	0.095	0.084	0.055	0.096	0.243	0.139	0.093	0.092	0.087
	(0.054)	(0.013)	(0.057)	(0.023)	(0.006)	(0.024)	(0.069)	(0.023)	(0.072)	(0.048)	(0.011)	(0.048)
Master's in Bio/agricultural /environmental /life sciences	0.240	0.078	0.305	0.035	0.001	0.040	0.329	-0.032	0.376	0.039	-0.039	0.048
	(0.070)	(0.015)	(0.071)	(0.022)	(0.007)	(0.023)	(0.060)	(0.016)	(0.060)	(0.020)	(0.008)	(0.020)
Master's in Other Non-Sci and Engineering fields	0.179	0.095	0.253	-0.070	-0.067	-0.071	0.139	0.003	0.168	0.054	-0.036	0.054
	(0.075)	(0.019)	(0.078)	(0.030)	(0.012)	(0.030)	(0.083)	(0.026)	(0.085)	(0.046)	(0.015)	(0.046)
Master's in Education fields	0.184	0.138	0.243	0.021	-0.070	0.020	0.154	-0.003	0.177	0.044	-0.098	0.048
	(0.024)	(0.008)	(0.024)	(0.010)	(0.004)	(0.010)	(0.033)	(0.011)	(0.033)	(0.012)	(0.006)	(0.012)
Master's in Arts	0.072	0.023	0.162	0.031	-0.025	0.020	-0.156	-0.012	-0.112	-0.058	-0.088	-0.050
	(0.130)	(0.035)	(0.133)	(0.083)	(0.016)	(0.083)	(0.178)	(0.036)	(0.177)	(0.055)	(0.017)	(0.061)
Master's in Psychology and Social Work	0.213	0.104	0.271	0.021	-0.064	0.006	0.235	-0.018	0.268	0.041	-0.073	0.044
	(0.033)	(0.010)	(0.033)	(0.019)	(0.006)	(0.019)	(0.060)	(0.017)	(0.059)	(0.037)	(0.010)	(0.037)
Master's in Humanity fields	0.160	0.002	0.231	-0.047	-0.115	-0.050	-0.034	-0.259	-0.016	-0.090	-0.274	-0.089
	(0.073)	(0.021)	(0.072)	(0.030)	(0.012)	(0.029)	(0.097)	(0.020)	(0.097)	(0.042)	(0.012)	(0.041)

Note: The table reports FE-cg and OLS estimates of returns to advanced degrees by gender for a set of additive regression specifications. The control variables include dummies for each BA field (in OLS only) and each advanced degree, as well as a set of demographic variables including parental education, year of the survey, and interactions of cubic in age with race/ethnicity and with BA field. Columns 1, 4 (women) and 7, and 10 (men) report estimates of γ_g, the effects of advanced degrees on earnings and on the occupation premium from a FE-cg regression on the sample of people who have an advanced degree when last observed. The specification is equation (10). Cell counts for this FE-cg regression specification are identical to the cell counts reported in Table B8 and Table B9. Columns 2, 5, 8, and 11 report OLS estimates of γ_g based on equation (7). Columns 3, 6, 9, and 12 report FE-cg estimates for earnings and the occupation premium of γ_{g1-28}, which is simple average of return to each advanced degree between 1 and 28 years after degree obtainment. The specification is equation (13) and the sample includes individuals who did not obtain a graduate degree by the last observation. A detailed explanation for the construction of these averages are provided in the notes for Table B2.

Table 11: Returns to graduate education by undergraduate fields

	Advanced field	Undergraduate field	ln(earnings)				Occupation premium		# of pre Adv earnings obs	
			FE-cg	FE-cg large sample	OLS	FE-cg Avg 1∼28 years γ_{g1-28}	FE-cg	OLS	person-year	person
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	**MBA**	Bio/agricultural/environmental sciences	-0.099	-0.045	0.337	0.009	0.122	0.173	140	70
			(0.087)	(0.089)	(0.038)	(0.090)	(0.043)	(0.017)		
		Business	0.170	0.195	0.245	0.225	0.021	0.072	110	90
			(0.069)	(0.066)	(0.018)	(0.066)	(0.019)	(0.008)		
		Computer and mathematical sciences	0.091	0.086	0.244	0.126	0.011	0.054	220	120
			(0.053)	(0.053)	(0.026)	(0.053)	(0.018)	(0.011)		
		Economics	0.109	0.176	0.277	0.232	0.001	0.073	100	60
			(0.067)	(0.055)	(0.036)	(0.054)	(0.029)	(0.014)		
		Engineering	0.078	0.125	0.220	0.157	0.007	0.042	870	460
			(0.024)	(0.023)	(0.013)	(0.024)	(0.012)	(0.006)		
		Other Social and related sciences	0.154	0.204	0.405	0.242	0.049	0.194	80	40
			(0.076)	(0.075)	(0.048)	(0.075)	(0.042)	(0.021)		
		Physical and related sciences	0.127	0.158	0.291	0.200	0.092	0.108	60	40
			(0.123)	(0.119)	(0.049)	(0.118)	(0.053)	(0.023)		
		Psychology or Social Work	0.137	0.131	0.397	0.180	0.055	0.207	80	50
			(0.102)	(0.100)	(0.042)	(0.100)	(0.051)	(0.021)		
(2)	**Master's in Business related fields**	Business	0.342	0.367	0.292	0.389	0.059	0.092	70	60
			(0.114)	(0.112)	(0.024)	(0.113)	(0.026)	(0.009)		
		Economics	0.048	0.117	0.361	0.158	-0.001	0.107	70	40
			(0.104)	(0.092)	(0.044)	(0.088)	(0.031)	(0.016)		
		Engineering	0.081	0.137	0.269	0.154	0.010	0.033	150	70
			(0.051)	(0.050)	(0.030)	(0.050)	(0.023)	(0.010)		
(3)	**Master's in Education**	Bio/agricultural/environmental sciences	0.103	0.165	0.036	0.215	0.022	-0.083	160	80
			(0.061)	(0.060)	(0.025)	(0.060)	(0.020)	(0.014)		
		Computer and mathematical sciences	0.173	0.153	-0.146	0.172	0.074	-0.205	180	100
			(0.066)	(0.066)	(0.026)	(0.066)	(0.032)	(0.018)		
		Education	0.142	0.179	0.208	0.178	0.014	-0.016	230	180
			(0.030)	(0.026)	(0.009)	(0.027)	(0.009)	(0.005)		
		Other Social and related sciences	0.172	0.231	0.110	0.253	0.023	-0.065	170	90
			(0.047)	(0.048)	(0.024)	(0.048)	(0.025)	(0.014)		
		Physical and related sciences	0.166	0.228	-0.131	0.272	0.056	-0.222	90	50
			(0.077)	(0.074)	(0.044)	(0.072)	(0.038)	(0.020)		
		Political science	0.031	0.025	-0.057	0.079	0.062	-0.136	80	40
			(0.095)	(0.095)	(0.049)	(0.095)	(0.043)	(0.023)		
		Psychology or Social Work	0.241	0.225	0.088	0.262	0.048	-0.079	190	120
			(0.043)	(0.043)	(0.018)	(0.043)	(0.020)	(0.010)		

	Advanced field	Undergraduate field	ln(earnings)				Occupation premium		# of pre Adv earnings obs	
			FE-cg	FE-cg large sample	OLS	FE-cg Avg 1∼28 years γ_{g1-28}	FE-cg	OLS	person-year	person
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(4)	**Master's in Engineering**	Engineering	0.115 (0.021)	0.166 (0.021)	0.109 (0.006)	0.201 (0.021)	0.016 (0.015)	0.041 (0.002)	1070	630
		Physical and related sciences	0.074 (0.085)	0.135 (0.083)	0.246 (0.022)	0.190 (0.083)	0.043 (0.039)	0.148 (0.007)	60	40
(5)	**Master's in Computer and mathematical sciences**	Computer and mathematical sciences	0.146 (0.055)	0.135 (0.053)	0.141 (0.012)	0.168 (0.054)	-0.001 (0.015)	0.026 (0.005)	330	180
		Engineering	0.052 (0.050)	0.091 (0.047)	0.131 (0.015)	0.127 (0.048)	0.000 (0.016)	0.033 (0.005)	150	80
(6)	**Master's in Physical and related sciences**	Physical and related sciences	0.148 (0.061)	0.238 (0.058)	0.056 (0.018)	0.319 (0.059)	0.004 (0.021)	0.011 (0.007)	190	130
(7)	**Master's in Bio/agri/ env/life sciences**	Bio/agricultural/environmental sciences	0.283 (0.054)	0.338 (0.054)	0.017 (0.013)	0.400 (0.054)	0.048 (0.017)	-0.015 (0.007)	190	120
(8)	**Master's in Nursing**	Nursing	0.248 (0.045)	0.186 (0.038)	0.305 (0.015)	0.161 (0.041)	0.031 (0.014)	0.018 (0.006)	150	90
(9)	**Master's in Health related fields**	Bio/agricultural/environmental sciences	0.334 (0.048)	0.364 (0.049)	0.429 (0.022)	0.390 (0.051)	0.191 (0.027)	0.177 (0.010)	90	50
		Health related fields	0.064 (0.134)	0.045 (0.131)	0.106 (0.020)	0.063 (0.132)	0.013 (0.046)	0.046 (0.010)	70	40
(10)	**Master's in Psychology and Social Work**	Other Social and related sciences	0.232 (0.065)	0.262 (0.067)	0.102 (0.019)	0.291 (0.066)	0.025 (0.030)	-0.079 (0.012)	90	50
		Psychology or Social Work	0.236 (0.035)	0.208 (0.034)	0.090 (0.012)	0.270 (0.034)	0.022 (0.022)	-0.051 (0.007)	290	180
(11)	**Master's in Other Social and related sci.**	Other Social and related sciences	0.149 (0.083)	0.198 (0.081)	0.139 (0.020)	0.236 (0.081)	0.084 (0.043)	0.048 (0.011)	60	40

Note: Estimates of returns to advanced degree by undergraduate fields are reported. Columns 1-4 present estimates from earnings regressions, and columns 5-6 present output from occupation premium regressions. Columns 1 and 5 present the returns to each advanced degree by each BA field from the FE-cg regression. Column 2 presents the returns from the FE-cg regression, when the sample includes people who only have a BA by the last time they are observed. Columns 3 and 6 present the OLS estimates. Column 4 presents γ_{g1-28}, the average of return to each advanced degree by BA field from 1 to 28 years of post advanced degree experience. A detailed explanation of the construction of these averages is provided in the notes for Table B2. Column 7 presents the observation-level cell count of pre advanced degree earnings observations for the FE-cg earnings regression (col. 1), which is the regression with smallest sample among all regressions reported in this table. Column 8 presents the individual-level cell count of the same regression, which counts multiple observations of one individual as one. Unweighted cell counts are rounded to the nearest 10.

Appendix

Table A1: Graduate Field Choice and Occupation and Earnings Before and After Graduate School, by Whether pre Graduate School Job is Related to a BA in Engineering

Panel A: Reasons for choosing pre adv occupation

	pre adv obs.		pre adv earnings			post adv earnings		
	count	%	count	mean	sd	count	mean	sd
Closely related	1,490	83	1,440	69,459	26,578	1,140	94,047	30,626
If not closely related:								
Pay and promotion opportunities	80	4.46	60	84,997	25,932	50	103,911	32,077
Working conditions	-	-	-	-	-	-	-	-
Job location	-	-	-	-	-	-	-	-
Change in career/prof. interests	100	5.56	70	63,331	20,024	40	84,856	29,822
Family-related reasons	-	-	-	-	-	-	-	-
Job in BA field not available	-	-	-	-	-	-	-	-
Other reasons	50	2.74	-	-	-	-	-	-
Total	1,803	100	1,680	69,543	26,635	1,300	93,276	31,721

Panel B: Pre adv occupation

Closely related	Freq.	%	Not Closely related	Freq.	%
Engineer	1,090	70.93	Engineer	500	47.23
Computer scientist	140	9.41	Manager	160	15.27
Manager	110	7.04	Computer scientist	160	14.90
Blue collar	40	2.39	Farmers, foresters, fishermen	50	4.87
			Blue Collar	50	4.33

Panel C: Advanced field choice

Advanced field	Not closely related		Closely related	
	Freq.	%	Freq.	%
MBA	400	54.36	530	49.76
Master's in Engineering	130	18.16	330	31.02
Master's in Business related fields	70	9.37	60	5.71
Master's in Computer and mathematical sciences	30	4.60	50	4.84

Panel D: Pre adv average earnings by advanced field

Advanced field	Not closely related			Closely related		
	count	mean	sd	count	mean	sd
MBA	480	79,499	32,915	480	77,556	22,380
Master's in Business related fields	80	80,772	84,329	50	93,372	42,167
Master's in Computer and mathematical sciences	50	73,801	22,307	60	68,290	25,574
Master's in Engineering	260	65,795	26,099	580	60,482	25,331

Note: A case study is presented for people with BA in Engineering. The term "closely related" refers to whether the pre adv occupation is closely related to the educational training provided by the BA in Engineering. "-" indicates fewer than 10 cases.

Table A2: Summary statistics of the control variables

Gender		
	Percentage	Frequency
(1)	(2)	(3)
Female	36.74	317,410
Male	63.26	546,480
Total		863,890
Gender and Race		
Asian, Female	4.01	34,620
Asian, Male	7.04	60,830
Black Hispanic, Female	0.16	1,340
Black Hispanic, Male	0.15	1,280
Black Non-hispanics, Female	4.23	36,540
Black Non-hispanics, Male	3.44	29,750
Native American, Female	0.46	3,940
Native American, Male	0.59	5,130
Other race, Female	0.93	8,010
Other race, Male	1.09	9,380
Unknown race, Female	2.4	20,760
Unknown race, Male	4.87	42,090
White Hispanic, Female	3.03	26,170
White Hispanic, Male	3.91	33,820
White Non-hispanic, Female	21.53	186,040
White Non-hispanic, Male	42.16	364,200
Father's education attainment		
Less than high school	14.39	124,300
High school diploma	26.11	225,600
Some college, vocational, trade school, 2-year college	18.26	157,750
College Degree	22.00	190,040
Master's degree (incl. MBA)	7.07	61,090
Professional degree (e.g. JD, LLB, MD, DDS, etc.)	9.82	84,800
Doctorate (e.g. PhD, DSc, EdD, etc.)	2.35	20,310
Mother's education attainment		
Less than high school	13.06	112,850
High school diploma	35.03	302,590
Some college, vocational, trade school, 2-year college	21.49	185,660
College Degree	19.19	165,820
Master's degree (incl. MBA)	5.99	51,750
Professional degree (e.g. JD, LLB, MD, DDS, etc.)	4.47	38,590
Doctorate (e.g. PhD, DSc, EdD, etc.)	0.69	5,920
Missing	0.08	720

Note: Weighted summary statistics of the demographics for the OLS regression sample. Unweighted cell counts are rounded to the nearest 10.

Online Appendix

Table B1: Aggregation of advanced fields and degree type

Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		OLS Earnings premium		Perc. in sample
			Mean	SD	Coef	SE	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Law	Law/prelaw/legal studies	Master	104,314	64,949	0.210	0.120	0.098
	Law/prelaw/legal studies	Prof	127,901	86,746	0.427	0.015	6.310
MBA	Business, general	Master	125,356	72,338	0.305	0.022	1.850
	Business, general	Prof	70,355	7,932	-0.453	0.013	0.004
	Business administration and management	Master	115,964	68,897	0.225	0.010	9.087
	Business and managerial economics	Master	123,765	88,721	0.223	0.054	0.212
	Other business management/admin services	Master	98,689	52,931	0.188	0.020	1.688
	Other business management/admin services	Prof	113,468	64,807	0.371	0.215	0.020
Medicine	Medicine[1]	Master	104,176	63,089	0.244	0.104	0.093
	Medicine[1]	Prof	165,758	103,113	0.678	0.016	3.855
Master's in Arts	Dramatic arts	Master	65,852	36,317	0.000	0.056	0.164
	Fine arts, all fields	Master	63,013	39,922	-0.070	0.040	0.430
	Music, all fields	Master	60,873	31,681	-0.023	0.038	0.369
	Other visual and performing arts	Master	80,387	77,790	0.062	0.074	0.218
Master's in Biological/ Agricultural/ Environmental/ Life Sciences	Animal sciences	Master	59,265	37,497	-0.026	0.074	0.103
	Biochemistry and biophysics	Master	79,416	58,131	0.031	0.064	0.162
	Biology, general	Master	66,337	32,272	-0.021	0.023	0.816
	Botany	Master	56,386	23,418	-0.156	0.051	0.112
	Cell and molecular biology	Master	71,627	51,671	0.012	0.046	0.163
	Ecology	Master	64,753	31,195	-0.060	0.045	0.257
	Environmental science or studies	Master	73,897	36,048	0.069	0.031	0.431
	Food sciences and technology	Master	78,653	38,727	0.111	0.045	0.139
	Forestry sciences	Master	71,475	33,677	-0.027	0.076	0.157
	Genetics, animal and plant	Master	72,680	40,518	-0.016	0.061	0.072
	Microbiological sciences and immunology	Master	76,743	44,574	0.022	0.048	0.215
	Nutritional sciences	Master	66,998	39,887	0.064	0.043	0.222
	Other agricultural sciences	Master	63,906	24,478	-0.052	0.044	0.167
	Other biological sciences	Master	73,342	61,795	0.044	0.030	0.338
	Other conservation and natural resources	Master	72,475	34,914	0.004	0.041	0.206
	Pharmacology, human and animal	Master	88,915	37,894	0.082	0.079	0.047
	Physiology and pathology, human and animal	Master	74,784	40,536	0.010	0.050	0.151
	Plant sciences	Master	60,840	31,035	-0.053	0.044	0.237
	Zoology, general	Master	65,295	34,640	-0.087	0.041	0.188
Master's in Business related fields	Accounting	Master	112,389	79,009	0.181	0.035	1.016
	Actuarial science	Master	148,137	135,584	0.367	0.158	0.024
	Agricultural economics	Master	101,253	71,509	0.168	0.069	0.170
	Business marketing/marketing management	Master	120,847	75,949	0.295	0.027	1.495
	Financial management	Master	136,613	96,346	0.355	0.018	2.866
	Financial management	Prof	156,763	69,803	0.617	0.121	0.016
	Marketing research	Master	113,123	67,460	0.310	0.055	0.219
	Other agricultural business and production	Master	75,148	46,255	0.049	0.149	0.056
Master's in Computer and Mathematical Sciences	Applied mathematics	Master	89,307	49,333	0.102	0.039	0.169
	Computer and information sciences, general	Master	98,813	47,338	0.188	0.020	0.951
	Computer programming	Master	94,893	46,492	0.161	0.074	0.091
	Computer science	Master	101,840	46,856	0.206	0.011	2.949
	Computer systems analysis	Master	109,435	45,002	0.230	0.052	0.161
	Data processing	Master	110,198	45,919	0.199	0.122	0.014
	Information services and systems	Master	101,700	53,166	0.214	0.025	0.816
	Mathematics, general	Master	79,341	44,747	-0.029	0.025	0.855
	Other computer and information sciences	Master	110,954	77,520	0.176	0.052	0.284
	Other mathematics	Master	84,765	41,719	0.153	0.066	0.071
	Operations research	Master	109,115	50,649	0.194	0.032	0.376
	Statistics	Master	95,397	55,969	0.189	0.046	0.286

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		OLS Earnings premium		Perc. in sample
			Mean	SD	Coef	SE	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Master's in Education fields	Computer teacher education	Master	67,288	19,959	-0.024	0.049	0.153
	Counselor education and guidance	Master	63,478	33,435	0.031	0.016	1.566
	Education administration	Master	76,407	32,825	0.120	0.014	2.567
	Educational psychology	Master	66,882	29,933	0.104	0.023	0.802
	Elementary teacher education	Master	62,646	29,980	0.080	0.014	2.828
	Mathematics teacher education	Master	69,325	29,868	-0.054	0.034	0.511
	Other education	Master	64,561	26,703	0.030	0.012	3.128
	Other education	Prof	142,222	81,199	0.246	0.287	0.011
	Physical education and coaching	Master	64,123	26,741	0.013	0.028	0.428
	Pre-school/kindergarten/early childhood teacher education	Master	57,889	20,835	0.041	0.033	0.275
	Science teacher education	Master	65,434	29,263	-0.032	0.046	0.452
	Science teacher education	Prof	110,711	100,057	0.525	0.308	0.008
	Secondary teacher education	Master	64,083	28,368	-0.019	0.017	1.503
	Secondary teacher education	Prof	37,561	5,638	-0.426	0.065	0.008
	Social science teacher education	Master	67,407	26,465	-0.061	0.034	0.157
	Special education	Master	65,185	27,908	0.088	0.018	1.713
	Special education	Prof	64,482	2,783	0.202	0.059	0.004
Master's in Engineering	Aerospace, aeronautical, astronautical/space engineering	Master	104,731	48,415	0.077	0.032	0.408
	Agricultural engineering	Master	80,884	32,287	0.000	0.046	0.067
	Architectural engineering	Master	95,807	66,604	0.033	0.063	0.079
	Bioengineering and biomedical engineering	Master	88,667	61,182	-0.015	0.051	0.165
	Chemical engineering	Master	105,682	52,603	0.011	0.025	0.497
	Civil engineering	Master	93,878	43,897	0.057	0.012	1.397
	Computer and systems engineering	Master	112,168	58,119	0.213	0.014	0.927
	Electrical, electronics and communications engineering	Master	107,567	55,258	0.164	0.010	2.886
	Engineering, general	Master	106,606	62,998	0.109	0.056	0.174
	Engineering sciences, mechanics and physics	Master	106,183	59,255	0.080	0.038	0.159
	Environmental engineering	Master	96,532	41,983	0.103	0.020	0.414
	Geophysical and geological engineering	Master	103,282	58,695	0.094	0.060	0.032
	Industrial and manufacturing engineering	Master	97,480	51,158	0.118	0.018	0.614
	Materials engineering, including ceramic and textile sciences	Master	95,200	39,221	0.077	0.030	0.257
	Mechanical engineering	Master	98,885	48,343	0.088	0.012	1.613
	Metallurgical engineering	Master	101,356	37,328	0.072	0.080	0.085
	Mining and minerals engineering	Master	101,527	30,264	0.187	0.097	0.031
	Naval architecture and marine engineering	Master	101,587	44,751	-0.017	0.092	0.032
	Nuclear engineering	Master	106,031	42,710	0.090	0.037	0.106
	Other engineering	Master	97,441	38,457	0.136	0.015	0.562
	Petroleum engineering	Master	123,671	65,444	0.186	0.067	0.055
Master's in Health Serv. Admin.	Health services administration	Master	98,254	57,677	0.284	0.026	1.110

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		OLS Earnings premium		Perc. in sample
			Mean	SD	Coef	SE	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Master's in Health related fields	Audiology and speech pathology	Master	65,173	24,694	0.196	0.028	0.811
	Audiology and speech pathology	Prof	64,449	8,492	0.388	0.078	0.008
	Health/medical assistants	Master	92,082	26,551	0.510	0.056	0.212
	Health/medical technologies	Master	90,197	71,787	0.222	0.061	0.065
	Health/medical technologies	Prof	95,807	67,342	0.375	0.200	0.011
	Medical preparatory programs[2]	Master	135,245	96,265	0.340	0.224	0.006
	Medical preparatory programs[2]	Prof	171,868	76,282	0.824	0.063	0.051
	Other health/medical sciences	Master	76,690	52,847	0.169	0.027	0.790
	Other health/medical sciences	Prof	154,124	109,068	0.633	0.089	0.078
	Pharmacy	Master	103,631	47,840	0.102	0.098	0.073
	Pharmacy	Prof	118,552	35,112	0.549	0.034	0.369
	Physical therapy and other rehabilitation/ therapeutic services	Master	70,386	30,122	0.160	0.020	1.169
	Physical therapy and other rehabilitation/ therapeutic services	Prof	80,865	47,957	0.397	0.039	0.077
	Public health (including environmental health and epidemiology)	Master	72,082	36,422	0.145	0.024	0.931
Master's in Humanity fields	English Language, literature and letters	Master	65,364	46,029	-0.074	0.029	0.661
	English Language, literature and letters	Prof	149,354	168,339	-0.024	0.579	0.006
	History, other	Master	68,248	50,014	-0.090	0.038	0.500
	Liberal arts/general studies	Master	71,725	36,626	0.097	0.056	0.209
	Linguistics	Master	61,378	24,265	-0.101	0.045	0.144
	Other foreign languages and literature	Master	68,188	48,478	-0.006	0.053	0.246
	Other philosophy, religion, theology	Master	56,260	31,492	-0.240	0.023	1.749
	Other philosophy, religion, theology	Prof	53,549	32,612	-0.371	0.070	0.160
Master's in Other Non-Science and Engineering fields	Communications, general	Master	77,112	44,039	0.058	0.054	0.263
	Criminal justice/protective services	Master	71,856	35,419	0.084	0.045	0.339
	Criminal justice/protective services	Prof	199,275	187,672	1.039	0.276	0.018
	Journalism	Master	71,361	38,896	0.057	0.051	0.176
	Library science	Master	61,884	23,226	-0.007	0.022	0.829
	Library science	Prof	72,001	41,359	0.318	0.124	0.005
	Other communication	Master	74,294	36,984	0.077	0.045	0.279
	Parks, recreation, leisure, and fitness studies	Master	64,031	27,141	-0.082	0.036	0.298
Master's in Nursing	Nursing (4 years or longer program)	Master	97,209	43,555	0.269	0.014	1.880
	Nursing (4 years or longer program)	Prof	82,631	48,651	0.410	0.099	0.013
Master's in Physical and related sciences	Astronomy and astrophysics	Master	78,084	66,889	-0.200	0.113	0.042
	Atmospheric sciences and meteorology	Master	84,421	39,920	0.078	0.046	0.108
	Chemistry, except biochemistry	Master	79,346	42,711	0.000	0.031	0.780
	Earth sciences	Master	74,751	32,616	0.013	0.037	0.076
	Geological sciences, other	Master	84,735	50,096	0.068	0.056	0.153
	Geology	Master	88,947	50,339	0.138	0.028	0.499
	Other physical sciences	Master	78,286	35,229	0.035	0.045	0.088
	Oceanography	Master	68,932	36,603	-0.053	0.075	0.057
	Physics, except biophysics	Master	90,414	51,527	-0.049	0.028	0.539
	Science, unclassified	Master	79,234	38,641	-0.008	0.067	0.066

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		OLS Earnings premium		Perc. in sample
			Mean	SD	Coef	SE	
Master's in Psychology and Social Work	Clinical psychology	Master	63,275	41,749	-0.046	0.030	0.625
	Clinical psychology	Prof	83,099	39,412	0.290	0.080	0.013
	Counseling psychology	Master	60,357	30,322	-0.020	0.014	2.315
	Experimental psychology	Master	75,792	54,605	0.016	0.126	0.105
	General psychology	Master	66,062	38,193	0.026	0.025	0.668
	General psychology	Prof	89,213	44,512	0.297	0.231	0.025
	Industrial/Organizational psychology	Master	86,164	51,072	0.211	0.044	0.280
	Other psychology	Master	65,145	33,535	0.057	0.033	0.614
	Other psychology	Prof	57,729	12,317	0.127	0.036	0.011
	Social Work	Master	64,374	30,176	0.091	0.012	3.083
	Social Work	Prof	118,777	66,024	0.296	0.120	0.016
	Social psychology	Master	71,344	39,701	-0.004	0.092	0.060
	Social psychology	Prof	135,660	20,577	0.527	0.036	0.005
Master's in Public Admin	Other public affairs	Master	75,033	39,355	0.115	0.068	0.111
	Public administration	Master	89,054	44,281	0.182	0.022	1.568
Master's in Other Science and Engineering related fields	Architecture/environmental design	Master	87,856	49,900	0.093	0.024	1.157
	Architecture/environmental design	Prof	69,843	21,699	-0.120	0.063	0.007
	Electrical and electronics technologies	Master	101,852	46,947	0.170	0.089	0.089
	Industrial production technologies	Master	86,671	40,658	0.059	0.058	0.089
	Mechanical engineering-related technologies	Master	105,028	40,677	0.140	0.116	0.072
	Other engineering-related technologies	Master	106,576	83,341	0.166	0.044	0.172
Master's in Other Social and Related Sciences	Anthropology and archaeology	Master	58,170	33,224	-0.081	0.044	0.229
	Area and ethnic studies	Master	66,644	36,112	-0.001	0.052	0.268
	Criminology	Master	68,467	32,622	0.054	0.059	0.114
	Economics	Master	105,634	76,347	0.157	0.032	0.773
	Geography	Master	75,996	42,809	0.027	0.049	0.324
	History of science	Master	67,085	29,920	-0.182	0.141	0.028
	Home Economics	Master	59,462	26,578	0.045	0.050	0.184
	International relations	Master	96,893	67,990	0.201	0.042	0.600
	Other social sciences	Master	63,871	30,014	0.026	0.028	0.614
	Philosophy of science	Master	49,583	26,820	-0.202	0.126	0.031
	Political science and government	Master	77,738	47,947	0.011	0.035	0.652
	Public policy studies	Master	102,049	75,889	0.277	0.037	0.458
	Sociology	Master	69,554	37,306	0.018	0.036	0.518

Note: Column 1 presents 19 aggregated advanced degree fields that are constructed from 168 disaggregated advanced degrees. For each disaggregated advanced degree, columns 2-8 present its field, type (Master or Professional Degree), mean and standard deviation of earnings, its coefficient and standard error from a disaggregated additive earnings regression, and percentage in the sample. Disaggregated advanced degrees with less than 10 observations are removed from the table. The specification is Table 2 col. (3), with disaggregated BA and advanced fields. Sample weights are used for all statistics. Standard errors are clustered at the person level.

[1] Medicine includes dentistry, optometry, osteopathic, podiatry, veterinary, etc.

[2] Medical preparatory programs include pre-dentistry, pre-medical, pre-veterinary etc.

Table B2: Return to advanced degrees by years of post adv experience, FE-cg

	Averages			Return to advanced degree by years of post Adv experience				
	γ_x 1~28 years, sample weighted	$\bar{\gamma_x}$ All years, sample weighted	γ_{g1-28} 1~28 years equally weighted	1	5	10	20	30
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	0.676	0.666	0.685	0.091	0.403	0.687	0.897	0.633
	(0.076)	(0.076)	(0.076)	(0.080)	(0.076)	(0.076)	(0.077)	(0.085)
Law	0.460	0.469	0.473	0.287	0.364	0.442	0.544	0.570
	(0.058)	(0.058)	(0.059)	(0.062)	(0.059)	(0.060)	(0.061)	(0.073)
Master's in Business related fields	0.237	0.241	0.252	0.087	0.162	0.235	0.314	0.303
	(0.041)	(0.041)	(0.041)	(0.045)	(0.041)	(0.042)	(0.045)	(0.056)
MBA	0.147	0.153	0.169	0.087	0.107	0.136	0.203	0.284
	(0.020)	(0.020)	(0.021)	(0.023)	(0.020)	(0.021)	(0.023)	(0.039)
Master's in Engineering	0.157	0.162	0.198	0.045	0.112	0.178	0.255	0.258
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.026)
Master's in Computer and mathematical sciences	0.183	0.183	0.210	0.090	0.152	0.209	0.252	0.201
	(0.034)	(0.035)	(0.035)	(0.035)	(0.034)	(0.036)	(0.037)	(0.047)
Master's in Health Services Administration	0.278	0.277	0.307	0.165	0.248	0.321	0.356	0.245
	(0.079)	(0.079)	(0.082)	(0.080)	(0.078)	(0.082)	(0.088)	(0.128)
Master's in Nursing	0.184	0.180	0.163	0.181	0.203	0.208	0.150	-0.001
	(0.036)	(0.036)	(0.038)	(0.038)	(0.036)	(0.039)	(0.042)	(0.071)
Master's in Other Science and Engineering related fields	0.029	0.047	0.054	-0.165	-0.095	-0.012	0.141	0.278
	(0.055)	(0.055)	(0.055)	(0.063)	(0.057)	(0.057)	(0.059)	(0.068)
Master's in Public Administration	0.209	0.210	0.235	0.009	0.119	0.224	0.318	0.262
	(0.052)	(0.052)	(0.053)	(0.060)	(0.053)	(0.055)	(0.059)	(0.086)
Master's in Physical and related sciences	0.236	0.245	0.283	0.036	0.147	0.256	0.375	0.361
	(0.053)	(0.053)	(0.054)	(0.053)	(0.053)	(0.055)	(0.056)	(0.067)
Master's in Other Social and related sciences	0.133	0.143	0.171	0.032	0.080	0.135	0.226	0.293
	(0.057)	(0.057)	(0.058)	(0.056)	(0.056)	(0.059)	(0.061)	(0.067)
Master's in Health Related Fields	0.265	0.263	0.270	0.244	0.262	0.277	0.278	0.243
	(0.045)	(0.045)	(0.047)	(0.046)	(0.045)	(0.047)	(0.050)	(0.065)
Master's in Biological /agricultural /environmental/life sciences	0.296	0.299	0.331	0.151	0.237	0.319	0.398	0.362
	(0.046)	(0.046)	(0.046)	(0.046)	(0.045)	(0.047)	(0.048)	(0.058)
Master's in Other Non-Science and Engineering fields	0.184	0.190	0.205	0.073	0.125	0.179	0.256	0.289
	(0.057)	(0.057)	(0.058)	(0.061)	(0.058)	(0.059)	(0.061)	(0.073)
Master's in Education fields	0.202	0.207	0.216	0.107	0.148	0.192	0.259	0.296
	(0.019)	(0.019)	(0.019)	(0.020)	(0.019)	(0.020)	(0.021)	(0.026)
Master's in Arts	0.009	0.014	0.034	-0.182	-0.083	0.012	0.114	0.097
	(0.118)	(0.118)	(0.119)	(0.124)	(0.119)	(0.120)	(0.123)	(0.139)
Master's in Psychology and Social Work	0.221	0.225	0.258	0.077	0.158	0.238	0.326	0.319
	(0.028)	(0.028)	(0.029)	(0.029)	(0.028)	(0.029)	(0.031)	(0.039)
Master's in Humanity fields	0.032	0.045	0.043	0.017	0.003	0.003	0.058	0.187
	(0.065)	(0.065)	(0.065)	(0.066)	(0.064)	(0.066)	(0.068)	(0.075)

Note: Returns to each advanced degree by years of post advanced degree experience are reported. We run an additive FE-cg regression of the log of earnings on BA fields interacted with a cubic function of (age-35), advanced degrees interacted with a quadratic function of number of years x since graduate school completion, and a set of demographics as controls. The specification is equation (13). Sample weights are used and inference is based on clustering at the individual level. Then the estimate for the return to a specific advanced degree and a specific value of experience is calculated from the regression coefficients on the advanced degree and the interaction between this advanced degree and the quadratic in years since graduate school. Column 1 presents the average of γ_{gx} over first 28 years after graduate school completion, weighted by the distribution of observations in the regression sample. Column 2 presents the corresponding averages, but over all possible years after graduate school completion, again weighted by the sample distribution of observations. Column 3 presents γ_{g1-28}, the equally average of γ_{gx} from 1 year to 28 years of post advanced degree experience. Columns 4-8 present the return γ_{gx} for x= 1, 5, 10, 20, and 30 years of post advanced experience.

Table B3: Aggregation of occupations

Aggregated occupation	Consistent disaggregated occupation	Raw occupation names	Source	Earnings		Occupation premium	%	Freq.
				Mean	SD			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Biological Scientist	Agri. and food scientists	Agricultural and food scientists	Census	59,514	23,844	-0.754	0.01	180
		Agricultural and food scientists	SESTAT	61,971	34,226	-0.754	0.27	3,620
	Biological scientists	Biochemists and biophysicists	SESTAT	52,889	29,414	-0.781	0.17	2,870
		Biological scientists	Census	55,091	19,570	-0.781	0.02	410
		Biological scientists (e.g., botanists, ecologists, zoologists)	SESTAT	55,540	30,716	-0.781	0.47	6,870
		Other biological and life scientists	SESTAT	64,590	38,889	-0.781	0.19	2,910
	Foresters and conservation scientists	Foresters and conservation scientists	Census	60,600	26,526	-0.789	0.01	250
		Forestry and conservation scientists	SESTAT	62,389	26,285	-0.789	0.17	2,450
	Medical scientists	Medical scientists	Census	74,401	83,664	-0.670	0.01	140
		Medical scientists (excluding practitioners)	SESTAT	64,354	45,747	-0.670	0.31	3,790
Blue Collar	Construction and extraction occupations	Carpenters	Census	44,685	18,835	-1.256	0.01	40
		Construction and extraction occupations	SESTAT	69,929	44,807	-1.041	0.77	4,580
		Construction trades, n.e.c.	Census					
		Drillers of oil wells	Census					
		Electric power installers and repairers	Census					
		Electricians	Census	51,485	22,748	-0.913	0.01	30
		Explosives workers	Census					
		Glaziers	Census					
		Insulation workers	Census					
		Masons, tilers, and carpet installers	Census					
		Miners	Census					
		Painters, construction and maintenance	Census					
		Plasterers	Census					
		Plumbers, pipe fitters, and steamfitters	Census					
		Roofers and slaters	Census					
		Structural metal workers	Census					
		Supervisors of construction work	Census	78,824	50,146	-0.623	0.02	250
	Installation, maintenance, and repair occupations	Aircraft mechanics	Census					
		Automobile mechanics	Census	72,133	37,455	-1.117	0.00	20
		Bus, truck, and stationary engine mechanics	Census					
		Elevator installers and repairers	Census					
		Heating, air conditioning, and refigeration mechanics	Census					
		Heavy equipment and farm equipment mechanics	Census					
		Industrial machinery repairers	Census	59,010	23,629	-0.892	0.00	30
		Installation, maintenance, and repair occupations	SESTAT	58,724	31,144	-0.917	0.57	3,360
		Locksmiths and safe repairers	Census					
		Machinery maintenance occupations	Census					
		Mechanics and repairers, n.e.c.	Census	58,367	30,065	-0.995	0.01	30
		Millwrights	Census					

....continued

Aggregated occupation	Consistent disaggregated occupation	Raw occupation names	Source	Earnings Mean	Earnings SD	Occupation premium	%	Freq.
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Blue Collar (continued)	Installation, maintenance, and repair occupations (continued)	Precision makers, repairers, and smiths	Census					
		Repairers of data processing equipment	Census	63,922	19,681	-0.893	0.01	40
		Repairers of electrical equipment, n.e.c.	Census					
		Repairers of household appliances and power tools	Census					
		Repairers of industrial electrical equipment	Census	59,183	35,770	-0.933	0.00	70
		Small engine repairers	Census					
		Telecom and line installers and repairers	Census					
	Precision/production occupations (e.g., metal workers, woodworkers, butchers, bakers, assemblers, printing occupations, tailors, shoemakers, photographic process)	Assemblers of electrical equipment	Census	47,696	24,002	-1.234	0.01	40
		Bakers	Census					
		Butchers and meat cutters	Census					
		Cabinetmakers and bench carpenters	Census					
		Dental laboratory and medical appliance technicians	Census					
		Dressmakers and seamstresses	Census					
		Engravers	Census					
		Furnace, kiln, and oven operators, apart from food	Census					
		Graders and sorters in manufacturing	Census					
		Grinding, abrading, buffing & polishing workers	Census					
		Hand molders and shapers, except jewelers	Census					
		Knitters, loopers, and toppers textile operatives	Census					
		Laundry workers	Census					
		Machine operators, n.e.c.	Census	48,987	29,013	-1.063	0.01	40
		Machinists	Census	46,062	19,426	-1.037	0.00	20
		Misc textile machine operators	Census					
		Mixing and blending machine operatives	Census					
		Molders, and casting machine operators	Census					
		Motion picture projectionists	Census					
		Optical goods workers	Census					
		Other plant and system operators	Census					
		Other woodworking machine operators	Census					
		Packers, fillers, and wrappers	Census					
		Painting machine operators	Census					
		Patternmakers and model makers	Census					
		Photographic process workers	Census					
		Plant and system operators, stationary engineers	Census	76,723	29,868	-0.641	0.01	110
		Power plant operators	Census					
		Precision/production occupations (e.g., metal workers, woodworkers, butchers, bakers, assemblers, printing occupations, tailors, shoemakers, photographic process)	SESTAT	56,717	36,343	-0.920	0.72	4,470
		Pressing machine operators (clothing)	Census					
		Printing machine operators, n.e.c.	Census	48,641	29,821	-1.310	0.01	30

....continued

Aggregated occupation	Consistent disaggregated occupation	Raw occupation names	Source	Earnings		Occupation premium	%	Freq.
				Mean	SD			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Blue Collar (continued)	Precision/production occupations (e.g., metal workers, woodworkers, butchers, bakers, assemblers, printing occupations, tailors, shoemakers, photographic process) (continued)	Printing machine operators, n.e.c.	Census	48,641	29,821	-1.310	0.01	30
		Production supervisors or foremen	Census	84,483	62,718	-0.571	0.07	310
		Punching and stamping press operatives	Census					
		Sawing machine operators and sawyers	Census					
		Separating, filtering & clarifying machine operators	Census					
		Shoe repairers	Census					
		Supervisors of mechanics and repairers	Census	88,650	108,650	-0.588	0.01	70
		Textile sewing machine operators	Census					
		Tool and die makers and die setters	Census					
		Typesetters and compositors	Census					
		Upholsterers	Census					
		Water and sewage treatment plant operators	Census					
		Welders and metal cutters	Census					
		Wood lathe, routing & planing machine operators	Census					
	Protective services (e.g., fire fighters, police, guards, wardens, park rangers)	Fire fighting, prevention, and inspection	Census	71,681	22,748	-0.564	0.01	60
		Guards, watchmen, doorkeepers	Census	49,374	24,020	-1.061	0.02	110
		Other law enforcement: sheriffs, bailiffs, correctional institution officers	Census	63,733	26,628	-0.810	0.01	50
		Police, detectives, and private investigators	Census	68,802	23,528	-0.518	0.05	270
		Protective services, n.e.c.	Census					
		Protective services (e.g., fire fighters, police, guards, wardens, park rangers)	SESTAT	65,710	34,263	-0.641	1.25	6,540
		Supervisors of guards	Census	54,034	26,697	-0.640	0.00	20
	Transportation and material moving occupations	Bus drivers	Census					
		Construction laborers	Census	68,016	37,869	-1.177	0.01	40
		Crane, derrick, winch, and hoist operators	Census					
		Excavating and loading machine operators	Census					
		Freight, stock, and materials handlers	Census	45,622	18,095	-1.025	0.00	20
		Garage and service station related occupations	Census					
		Garbage and recyclable material collectors	Census					
		Helpers, constructions	Census					
		Helpers, surveyors	Census					
		Laborers outside construction	Census	44,765	21,834	-1.294	0.01	40
		Locomotive operators (engineers and firemen)	Census					
		Misc material moving occupations	Census					
		Operating engineers of construction equipment	Census					
		Packers and packagers by hand	Census					
		Parking lot attendants	Census					
		Production helpers	Census					
		Railroad conductors and yardmasters	Census					

....continued

Aggregated occupation	Consistent disaggregated occupation	Raw occupation names	Source	Earnings		Occupation premium	%	Freq.
				Mean	SD			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Blue Collar (continued)	Transportation and material moving occupations (continued)	Ship crews and marine engineers	Census					
		Supervisors of motor vehicle transportation	Census	59,340	19,164	-0.725	0.00	20
		Taxi cab drivers and chauffeurs	Census					
		Transportation and material moving occupations	SESTAT	71,349	52,626	-1.148	0.73	4,430
		Truck, delivery, and tractor drivers	Census	52,440	19,843	-1.172	0.02	100
		Vehicle washers and equipment cleaners	Census					
Business related occupations	Accountants, auditors, and other financial specialists	Accountants, auditors & other financial specialists	SESTAT	87,722	59,766	-0.475	4.72	26,090
		Accountants and auditors	Census	70,528	47,900	-0.521	0.41	1,980
		Other financial specialists	Census	82,038	72,812	-0.359	0.13	580
	Actuaries	Actuaries	Census	102,751	44,698	-0.022	0.01	40
		Actuaries	SESTAT	112,304	77,452	-0.022	0.15	1,220
	Insurance, securities, real estate and business services	Advertising and related sales jobs	Census	74,752	51,219	-0.471	0.03	110
		Financial services sales occupations	Census	141,951	172,077	-0.078	0.06	240
		Insurance, securities, real estate and business services	SESTAT	96,090	76,116	-0.452	2.90	14,680
		Insurance sales occupations	Census	92,753	77,660	-0.565	0.09	400
		Real estate sales occupations	Census	90,461	89,342	-0.687	0.08	340
	Personnel, training, and labor relations specialists	Personnel, HR, training & labor relations specialists	Census	61,518	35,241	-0.566	0.09	460
		Personnel, training, and labor relations specialists	SESTAT	72,271	42,543	-0.566	1.57	9,780
Clerical occupations	Bookkeepers and accounting and auditing clerks	Accounting clerks and bookkeepers	SESTAT	44,077	25,673	-0.956	0.67	3,530
		Bookkeepers and accounting and auditing clerks	Census	42,666	23,867	-0.956	0.05	240
	Legal assistants, paralegals, legal support, etc	Legal assistants, paralegals, legal support, etc	Census	51,683	27,369	-0.745	0.03	120
	Secretaries	Other admin. (e.g. record clerks, telephone operators)	SESTAT	45,924	24,818	-0.992	3.05	18,360
		Secretaries	Census	36,339	12,796	-0.992	0.09	440
		Secretaries, receptionists, typists	SESTAT	39,087	23,789	-0.992	0.99	5,230
Computer Scientist	Computer software developers	Computer programmers (business, scientific, process control)	SESTAT	80,429	34,451	-0.359	1.31	13,140
		Computer software developers	Census	67,203	26,383	-0.359	0.17	2,300
		Computer system analysts	SESTAT	98,985	42,547	-0.359	2.57	32,310
	Computer systems analysts and computer scientists	Computer system analysts	SESTAT	84,346	40,441	-0.513	2.93	30,470
		Computer systems analysts and computer scientists	Census	75,491	28,785	-0.514	0.14	3,030
		Other computer information science occupations	SESTAT	83,153	39,429	-0.512	0.87	8,150
	Operations and systems researchers and analysts	Computer system analysts	SESTAT	85,989	38,384	-0.512	1.14	12,570
		Other computer information science occupations	SESTAT	84,283	39,474	-0.506	1.80	18,920
		Operations and systems researchers & analysts	Census	71,219	31,500	-0.504	0.06	1,270

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Aggregated occupation	Consistent disaggregated occupation	Raw occupation names	Source	Earnings		Occupation premium	%	Freq.
				Mean	SD			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Doctor	Diagnosing/treating practitioners [2]	Dentists	Census	126,433	82,535	-0.172	0.01	30
		Diagnosing/treating practitioners [2]	SESTAT	153,482	100,283	-0.078	1.35	9,970
		Optometrists	Census					
		Physicians	Census	164,683	160,833	-0.007	0.05	710
		Podiatrists	Census					
		Veterinarians	Census	77,521	40,643	-0.607	0.00	40
Engineer	Aeronautical/aerospace/astronautical engineers	Aeronautical/aerospace/astronautical engineers	SESTAT	96,453	33,741	-0.380	0.50	10,930
		Aerospace engineer	Census	85,687	26,645	-0.300	0.05	1,050
	Architects	Architects	Census	79,657	63,049	-0.615	0.04	580
		Architects	SESTAT	82,898	47,608	-0.615	0.55	4,370
	Chemical engineers	Chemical engineers	Census	86,946	29,082	-0.247	0.02	500
		Chemical engineers	SESTAT	94,973	39,661	-0.247	0.47	10,350
	Civil engineers	Civil, including architectural/sanitary engineers	SESTAT	82,171	36,328	-0.416	1.45	25,840
		Civil engineers	Census	82,338	50,759	-0.416	0.08	1,800
	Electrical engineer	Electrical and electronics engineers	SESTAT	93,261	35,518	-0.358	2.01	33,520
		Electrical engineer	Census	83,665	29,411	-0.358	0.14	3,270
	Industrial engineers	Industrial engineers	Census	75,212	25,329	-0.461	0.04	970
		Industrial engineers	SESTAT	79,157	29,156	-0.461	0.56	9,530
	Mechanical engineers	Mechanical engineers	Census	81,127	28,787	-0.445	0.05	1,170
		Mechanical engineers	SESTAT	86,505	32,968	-0.445	1.86	33,640
	Metallurgical and materials engineers	Materials and metallurgical engineers	SESTAT	84,320	33,190	-0.435	0.20	3,650
		Metallurgical and materials engineers, variously phrased	Census	76,329	21,767	-0.435	0.01	120
	Not-elsewhere-classified engineers	Agricultural engineers	SESTAT	78,367	34,046	-0.754	0.03	430
		Bioengineers or biomedical engineers	SESTAT	74,116	38,050	-0.781	0.10	1,830
		Computer engineer - hardware	SESTAT	96,763	42,777	-0.380	0.34	4,790
		Environmental engineers	SESTAT	81,389	34,408	-0.380	0.48	7,330
		Marine engineers and naval architects	SESTAT	93,401	40,291	-0.380	0.05	810
		Not-elsewhere-classified engineers	Census	82,548	49,378	-0.380	0.10	2,180
		Nuclear engineers	SESTAT	100,040	38,477	-0.380	0.11	1,680
		Other engineers	SESTAT	90,920	34,509	-0.380	0.45	8,130
	Petroleum, mining, and geological engineers	Mining and geological engineers	SESTAT	83,615	33,755	0.003	0.04	650
		Petroleum, mining, and geological engineers	Census	100,504	38,518	0.003	0.01	190
		Petroleum engineers	SESTAT	115,475	56,442	0.003	0.11	1,800
	Sales engineers	Sales engineers	Census	93,375	43,040	-0.276	0.01	260
		Sales engineers	SESTAT	103,453	53,785	-0.276	0.38	4,200

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Aggregated occupation (1)	Consistent disaggregated occupation (2)	Raw occupation names (3)	Source (4)	Earnings Mean (5)	Earnings SD (6)	Occupation premium (7)	% (8)	Freq. (9)
Farmers, Foresters and Fishermen	Farmers, Foresters and Fishermen	Animal caretakers except on farms	Census					
		Farm managers, except for horticultural farms	Census	51,679	26,070	-1.042	0.01	30
		Farm workers	Census	35,518	22,763	-1.307	0.00	20
		Farmers, Foresters and Fishermen	SESTAT	60,395	54,236	-1.095	0.53	3,690
		Farmers (owners and tenants)	Census					
		Gardeners and groundskeepers	Census	46,216	22,151	-1.339	0.01	30
		Supervisors of agricultural occupations	Census	40,272	18,621	-0.942	0.00	20
		Weighers, measurers, and checkers	Census					
Law related occupations	Lawyers, judges	Lawyers	Census	122,405	127,410	-0.284	0.12	520
		Lawyers, judges	SESTAT	129,175	84,597	-0.284	1.65	8,930
Manager	Managers and administrators, n.e.c.	Computer and information systems managers	SESTAT	135,021	58,382	-0.514	0.48	4,400
		Engineering managers	SESTAT	131,230	57,707	-0.354	0.52	8,130
		Financial managers	Census	96,878	87,681	-0.291	0.15	700
		Funeral directors	Census					
		Human resources and labor relations managers	Census	83,235	43,251	-0.383	0.05	250
		Managers and administrators, n.e.c.	Census	107,162	93,189	-0.354	0.84	3,780
		Managers and specialists in marketing, advertising, and public relations	Census	100,958	56,908	-0.325	0.15	650
		Managers of properties and real estate	Census	96,602	94,754	-0.601	0.03	160
		Managers of service organizations, n.e.c.	Census	60,057	31,622	-0.686	0.05	230
		Natural sciences managers	SESTAT	98,625	51,813	-0.354	0.06	1,070
		Supervisors and proprietors of sales jobs	Census	84,664	79,460	-0.619	0.31	1,360
	Managers in education and related fields	Education admin. (e.g. registrar, dean & principal)	SESTAT	86,990	31,085	-0.653	0.34	2,300
		Managers in education and related fields	Census	69,233	33,280	-0.653	0.13	650
		Managers of medicine and health occupations	Census	72,221	35,476	-0.445	0.04	190
		Medical and health services managers	SESTAT	106,842	62,710	-0.445	0.38	2,820
	Other management related occupations	Business and promotion agents	Census	73,695	80,314	-0.567	0.00	20
		Buyers, wholesale and retail trade	Census	63,350	37,528	-0.675	0.02	80
		Construction inspectors	Census	57,646	18,603	-0.821	0.00	60
		Inspectors and compliance officers, outside construction	Census	59,156	25,382	-0.493	0.03	420
		Insurance underwriters	Census	59,170	22,507	-0.491	0.01	60
		Management analysts	Census	93,831	74,482	-0.368	0.05	580
		Management support occupations	Census	54,457	24,134	-0.572	0.03	140
		Other management related occupations	SESTAT	81,045	48,931	-0.503	4.07	31,370
		Purchasing agents and buyers, of farm products	Census					
		Purchasing managers, agents and buyers, n.e.c.	Census	61,559	41,911	-0.526	0.04	160
	Top-level managers [1]	Chief executives and public administrators	Census	89,508	42,022	0.000	0.00	10
		Top-level managers [1]	SESTAT	158,365	102,619	0.000	2.51	16,230
		Top & mid-level managers, executives, admin	SESTAT	108,811	55,479	-0.354	6.90	42,500

....continued

Aggregated occupation	Consistent disaggregated occupation	Raw occupation names	Source	Earnings Mean	Earnings SD	Occupation premium	%	Freq.
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Marketing	Retail sales clerks	Retail sales clerks	Census	49,578	33,293	-0.887	0.00	20
		Sales occupations - retail (e.g., furnishings, clothing, motor vehicles, cosmetics)	SESTAT	53,903	39,929	-0.887	1.70	8,700
	Salespersons, n.e.c.	Door-to-door sales, street sales, and news vendors	Census	64,061	35,174	-1.117	0.01	40
		Other marketing and sales occupations	SESTAT	81,364	55,788	-0.446	2.90	17,600
		Sales demonstrators / promoters / models	Census					
		Sales occupations - Commodities except retail (e.g., industrial machinery/equipment/supplies, medical and dental equip./supplies)	SESTAT	90,978	54,487	-0.446	2.09	11,520
		Salespersons, n.e.c.	Census	54,034	35,071	-0.446	0.05	210
Math Scientist	Mathematicians and mathematical scientists	Mathematicians	SESTAT	65,159	43,731	-0.475	0.02	260
		Mathematicians and mathematical scientists	Census	69,617	23,574	-0.475	0.00	30
		Other mathematical scientists	SESTAT	79,540	53,701	-0.475	0.02	260
		Statisticians	SESTAT	76,407	33,243	-0.475	0.12	2,250
Other health occupations	Health technologists and technicians, n.e.c.	Clinical laboratory technologies and technicians	Census	53,606	16,112	-0.760	0.05	720
		Dental hygenists	Census	49,851	16,466	-0.658	0.00	20
		Health record tech specialists	Census	39,541	12,629	-0.991	0.00	30
		Health technologists and technicians, n.e.c.	Census	51,762	27,296	-0.752	0.02	100
		Health technologists and technicians[3]	SESTAT	55,275	35,339	-0.751	1.22	9,190
		Licensed practical nurses	Census	50,673	18,692	-0.971	0.00	30
		Other health occupations	SESTAT	56,918	42,834	-0.752	1.03	7,300
		Radiologic tech specialists	Census	59,354	22,975	-0.638	0.00	70
	Registered nurses, pharmacists, dieticians, therapists, physician assistants, nurse practitioners	Dietitians and nutritionists	Census	48,224	15,901	-0.767	0.01	190
		Occupational therapists	Census	55,173	15,732	-0.586	0.01	50
		Pharmacists	Census	79,998	26,395	-0.217	0.05	230
		Physical therapists	Census	66,309	43,510	-0.614	0.02	90
		Registered nurses	Census	61,454	18,568	-0.504	0.20	1,020
		Registered nurses, pharmacists, dieticians, therapists, physician assistants, nurse practitioners	SESTAT	74,752	34,291	-0.518	4.55	25,280
		Respiratory therapists	Census	51,465	11,246	-0.677	0.00	20
		Speech therapists	Census	48,179	18,492	-0.706	0.01	40
		Therapists, n.e.c.	Census	42,114	14,216	-0.923	0.01	70

....continued

Aggregated occupation	Consistent disaggregated occupation	Raw occupation names	Source	Earnings		Occupation premium	%	Freq.
				Mean	SD			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Other service occupations	Food preparation and service (e.g., cookes, waitresses, bartenders)	Cooks, variously defined	Census	39,623	25,412	-1.246	0.01	30
		Food preparation and service (e.g., cookes, waitresses, bartenders)	SESTAT	39,498	29,546	-1.312	0.61	3,280
		Kitchen workers	Census					
		Misc food prep workers	Census					
		Waiter's assistant	Census					
		Waiter/waitress	Census	30,366	14,114	-1.318	0.01	40
	Other service occupations, except health (e.g., probation officers, human services workers)	Cashiers	Census	63,886	146,819	-1.355	0.02	90
		Hairdressers and cosmetologists	Census					
		Hotel clerks	Census					
		Other service occupations, except health (e.g., probation officers, human services workers)	SESTAT	49,097	32,317	-1.371	1.38	8,140
		Personal service occupations, nec	Census	49,581	47,443	-1.371	0.00	20
Other social service occupations	Clergy and religious workers	Clergy and other religious workers	SESTAT	48,977	26,250	-1.156	0.54	2,540
		Clergy and religious workers	Census	41,556	19,487	-1.156	0.08	340
	Librarians, archivists, curators	Archivists and curators	Census	63,684	59,023	-0.909	0.00	60
		Librarians	Census	46,342	15,373	-0.939	0.03	150
		Librarians, archivists, curators	SESTAT	53,156	22,002	-0.939	0.33	1,860
		Library assistants	Census	35,681	13,164	-1.288	0.01	30
	Other teachers and instructors	Other teachers and instructors (e.g., private tutors, dance or flying instructors, martial arts instructors)	SESTAT	52,374	32,611	-1.118	0.26	1,760
		Teachers , n.e.c.	Census	54,436	28,972	-1.118	0.05	270
	Social workers	Recreation workers	Census	43,417	17,337	-1.056	0.00	20
		Social Workers	SESTAT	47,957	21,697	-0.918	2.20	15,690
		Social workers	Census	48,156	18,480	-0.918	0.15	2,260
	Vocational and educational counselors	Counselors (Educational, vocational health, and substance abuse)	SESTAT	50,024	23,038	-0.955	1.28	10,270
		Vocational and educational counselors	Census	53,627	20,775	-0.955	0.04	580
Physical Scientist	Atmospheric and space scientists	Atmospheric and space scientists	Census	70,488	26,663	-0.470	0.00	50
		Atmospheric and space scientists	SESTAT	73,227	37,995	-0.470	0.06	1,520
	Chemists	Chemists	Census	66,563	24,979	-0.601	0.04	820
		Chemists, except biochemists	SESTAT	66,700	32,395	-0.601	0.62	11,790
	Geologists	Geologists	Census	76,468	48,739	-0.571	0.02	390
		Geologists, including earth scientists	SESTAT	80,131	44,861	-0.571	0.33	6,760
		Oceanographers	SESTAT	60,489	40,165	-0.571	0.01	270
	Physical scientists, n.e.c.	Other physical scientists	SESTAT	64,991	28,399	-0.663	0.17	3,040
		Physical scientists, n.e.c.	Census	62,817	22,026	-0.663	0.01	150
	Physicists and astronomers	Astronomers	SESTAT	37,566	21,018	-0.525	0.01	240
		Physicists, except biophysicists	SESTAT	62,650	42,642	-0.525	0.08	2,050
		Physicists and astronomers	Census	80,270	34,288	-0.525	0.00	130

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Aggregated occupation	Consistent disaggregated occupation	Raw occupation names	Source	Earnings		Occupation premium	%	Freq.
				Mean	SD			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post-secondary Teachers	Postsecondary Teachers	Post-sec teachers - physical education	SESTAT	59,475	49,112	-0.833	0.03	250
		Postsecondary Teachers: Agriculture	SESTAT	60,797	20,336	-0.833	0.03	280
		Postsecondary Teachers: Art, Drama, and Music	SESTAT	55,154	25,157	-0.833	0.05	570
		Postsecondary Teachers: Biological Sciences	SESTAT	43,080	23,581	-0.833	0.06	840
		Postsecondary Teachers: Business Commerce and Marketing	SESTAT	67,716	31,105	-0.833	0.04	420
		Postsecondary Teachers: Chemistry	SESTAT	39,997	24,010	-0.833	0.04	510
		Postsecondary Teachers: Computer Science	SESTAT	64,997	33,021	-0.833	0.05	540
		Postsecondary Teachers: Earth, Environmental, and Marine Science	SESTAT	49,466	30,602	-0.833	0.02	280
		Postsecondary Teachers: Economics	SESTAT	71,252	66,583	-0.833	0.01	150
		Postsecondary Teachers: Education	SESTAT	54,984	28,367	-0.833	0.03	340
		Postsecondary Teachers: Engineering	SESTAT	61,504	35,577	-0.833	0.04	720
		Postsecondary Teachers: English	SESTAT	46,015	20,643	-0.833	0.05	590
		Postsecondary Teachers: Foreign Language	SESTAT	53,761	21,614	-0.833	0.02	240
		Postsecondary Teachers: Health and related sci.	SESTAT	79,228	65,173	-0.833	0.13	1,440
		Postsecondary Teachers: History	SESTAT	47,580	27,641	-0.833	0.01	140
		Postsecondary Teachers: Mathematics and Statistics	SESTAT	49,937	25,239	-0.833	0.08	1,300
		Postsecondary Teachers: other Natural Sciences	SESTAT	82,341	52,669	-0.833	0.02	220
		Postsecondary Teachers: other Postsecondary fields	SESTAT	61,667	30,292	-0.833	0.15	1,590
		Postsecondary Teachers: other Social Sciences	SESTAT	54,174	35,054	-0.833	0.02	270
		Postsecondary Teachers: Physics	SESTAT	45,918	26,849	-0.833	0.02	360
		Postsecondary Teachers: Political Science	SESTAT	55,240	36,860	-0.833	0.01	120
		Postsecondary Teachers: Psychology	SESTAT	47,749	28,851	-0.833	0.02	270
		Postsecondary Teachers: Sociology	SESTAT	59,557	27,996	-0.833	0.01	160
		Subject instructors (HS/college)	Census	56,630	33,907	-0.833	0.04	590
Primary and secondary teachers	Kindergarten and earlier school teachers	Kindergarten and earlier school teachers	Census	32,242	17,036	-1.145	0.01	50
		Teachers: Pre-kindergarten and kindergarten	SESTAT	43,387	23,465	-1.145	0.61	2,640
	Primary school teachers	Primary school teachers	Census	50,954	21,157	-0.875	0.39	1,930
		Special education teachers	Census	47,650	19,410	-0.882	0.01	40
		Teachers: Elementary	SESTAT	52,882	22,005	-0.875	2.59	12,050
	Secondary school teachers	Secondary school teachers	Census	53,552	19,067	-0.859	0.10	940
		Teachers: other precollegiate area	SESTAT	50,056	26,361	-0.859	0.34	2,170
		Teachers: Secondary - computer, math or sciences	SESTAT	55,249	20,602	-0.859	1.57	14,560
		Teachers: Secondary - other subjects	SESTAT	55,607	21,921	-0.859	1.17	7,730
		Teachers: Secondary - social sciences	SESTAT	55,345	22,523	-0.859	0.52	3,660
		Teachers: Special education - primary and secondary	SESTAT	52,922	20,890	-0.859	0.81	4,410

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Aggregated occupation	Consistent disaggregated occupation	Raw occupation names	Source	Earnings		Occupation premium	%	Freq.
				Mean	SD			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Social Scientist	Economists, market researchers, and survey researchers	Economists	SESTAT	89,266	57,969	-0.384	0.15	2,200
		Economists, market researchers, and survey researchers	Census	83,106	51,929	-0.384	0.04	860
	Psychologists	Psychologists	Census	53,651	47,142	-0.788	0.03	550
		Psychologists, including clinical	SESTAT	55,053	29,724	-0.788	0.53	5,790
	Social scientists, n.e.c.	Anthropologists	SESTAT	45,276	23,566	-0.748	0.04	770
		Historian, science and technology	SESTAT	67,524	37,327	-0.748	0.00	20
		Historians	SESTAT	54,714	21,205	-0.748	0.01	190
		Other social scientists	SESTAT	76,105	50,580	-0.748	0.31	3,370
		Political scientists	SESTAT	69,037	47,866	-0.748	0.08	820
		Social scientists, n.e.c.	Census	64,905	70,260	-0.748	0.01	140
		Sociologists	SESTAT	51,646	33,914	-0.748	0.03	470
		Urban and regional planners	Census	67,020	26,300	-0.628	0.01	30
Technician	Biological technicians	Biological technicians	Census	52,130	23,288	-0.869	0.00	60
		Technologists and technicians in the bio/life sciences	SESTAT	46,847	23,331	-0.869	0.46	4,800
	Drafters	Drafters	Census	59,033	26,152	-0.830	0.02	320
		Drafting occupations, including computer drafting	SESTAT	59,365	25,754	-0.830	0.13	1,360
	Engineering technicians, n.e.c.	Electrical, electronic, industrial, and mechanical technicians	SESTAT	69,540	32,526	-0.805	0.53	5,960
		Engineering technicians, n.e.c.	Census	65,804	18,344	-0.805	0.00	40
		Other engineering technologists and technicians	SESTAT	73,498	35,033	-0.805	0.27	3,820
	Other science technicians	Air traffic controllers	Census	84,480	34,324	-0.227	0.00	20
		Airplane pilots and navigators	Census	95,343	57,159	-0.282	0.03	410
		Broadcast equipment operators	Census					
		Chemical technicians	Census	61,823	25,476	-0.758	0.01	110
		Other science technicians	Census	58,642	31,673	-0.544	0.01	80
		Programmers of numerically controlled machine tools	Census					
		Technologists and technicians in the math sciences	SESTAT	70,404	43,757	-0.544	0.01	60
		Technologists and technicians in the physical sciences	SESTAT	54,134	28,400	-0.544	0.17	1,980
	Surveyors, cartographers, mapping scientists and technicians	Surveying and mapping technicians	SESTAT	55,027	27,238	-0.809	0.06	610
		Surveyors, cartographers, mapping scientists and technicians	Census	53,664	19,759	-0.809	0.01	60
		Surveyors, cartographers, photogrammetrists	SESTAT	63,855	29,531	-0.809	0.08	790

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Aggregated occupation	Consistent disaggregated occupation	Raw occupation names	Source	Earnings		Occupation premium	%	Freq.
				Mean	SD			
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Writers and Artists	Writers, editors, public relations specialists, artists, entertaininers, broadcasters	Actors, directors, producers	Census	85,273	131,303	-0.584	0.02	80
		Announcers	Census	97,115	80,788	-0.702	0.00	20
		Art/entertainment performers and related	Census	39,402	18,459	-1.004	0.00	20
		Art makers: painters, sculptors, craft-artists, and print-makers	Census	46,838	26,888	-0.726	0.01	50
		Athletes, sports instructors, and officials	Census	73,159	91,582	-0.878	0.01	30
		Dancers	Census					
		Designers	Census	61,652	45,106	-0.729	0.06	300
		Editors and reporters	Census	56,682	29,731	-0.726	0.06	280
		Musician or composer	Census	45,633	32,438	-1.089	0.01	50
		Photographers	Census	58,968	63,086	-1.085	0.01	40
		Technical writers	Census	65,509	44,315	-0.631	0.02	210
		Writers, editors, public relations specialists, artists, entertaininers, broadcasters	SESTAT	67,162	47,988	-0.745	1.85	9,290
		Writers and authors	Census	62,819	42,243	-0.702	0.01	50

Note: Column 1 presents 20 aggregated occupation categories that are constructed from 66 disaggregated occupations that are available in both Census 1990 and SESTAT 1993-2015. Column 2 presents the occupation names of the 66 disaggregated fields. The 66 disaggregated fields are constructed from 122 occupation categories from SESTAT and 290 occupation categories from Census 1990. Column 3-4 present the name and source of each most detailed-level occupation. For each detailed-level occupation, column 5-9 present its mean and standard deviation of earnings, the occupational premium we imported from an earnings regression in ACS 2009-2014, its percentage in the sample, and the number of observations with this occupation in the regression sample. If a disaggregated occupation has 10 or fewer observations, the name is left in the table, but all quantitative information is removed from the table. Cell counts are rounded to the nearest 10.

[1] Top-level managers also include executives, administrators (e.g., CEO/COO/CFO, president, district manager, general manager, legislator, chancellor, provost).

[2] Diagnosing/treating practitioners include dentists, optometrists, physicians, podiatrists, surgeons, veterinarians.

[3] Health technologists and technicians include dental hygienist, health record technologists/technicians, licensed practical nurses, medical or laboratory technicians, radiological technicians.

Table B4: Aggregation of BA fields

Aggregated BA major	Disaggregated BA major	Earnings		BA earnings prem.		Perc. in sample
		Mean	SD	Coef	SE	
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biological/ Agricultural/ Environmental Sciences	Animal sciences	61,837	43,139	0.024	0.024	0.612
	Biochemistry and biophysics	85,378	73,248	0.265	0.028	0.415
	Biology, general	77,124	61,669	0.180	0.014	4.166
	Botany	64,431	41,867	0.008	0.051	0.097
	Cell and molecular biology	85,338	82,749	0.290	0.044	0.16
	Ecology	69,548	57,046	0.140	0.044	0.206
	Environmental science or studies	62,113	40,589	0.129	0.022	0.513
	Food sciences and technology	76,969	44,949	0.268	0.046	0.148
	Forestry sciences	73,242	45,777	0.112	0.030	0.304
	Genetics, animal and plant	69,880	53,426	0.138	0.060	0.048
	Microbiological sciences and immunology	74,576	59,048	0.190	0.026	0.419
	Nutritional sciences	63,268	42,808	0.163	0.031	0.206
	Other agricultural sciences	64,446	36,623	0.082	0.030	0.283
	Other biological sciences	64,107	53,730	0.138	0.024	0.451
	Other conservation and natural resources	66,824	31,375	0.083	0.030	0.195
	Pharmacology, human and animal	83,748	34,996	0.346	0.074	0.025
	Physiology and pathology, human and animal	84,080	57,869	0.262	0.032	0.129
	Plant sciences	63,870	41,627	0.044	0.028	0.422
	Zoology, general	86,028	68,736	0.162	0.026	0.442
Business	Accounting	95,071	66,592	0.424	0.015	3.023
	Actuarial science	103,393	71,316	0.605	0.066	0.048
	Agricultural economics	82,240	54,968	0.252	0.030	0.453
	Business, general	84,819	59,903	0.270	0.020	1.322
	Business administration and management	81,783	56,496	0.273	0.014	4.463
	Business and managerial economics	93,405	76,747	0.358	0.027	0.343
	Financial management	98,606	78,132	0.407	0.020	1.172
	Other agricultural business and production	66,588	44,448	0.034	0.037	0.194
	Other business management/admin services	80,826	57,538	0.298	0.021	0.944
Communications/ Journalism	Communications, general	69,361	48,971	0.208	0.024	0.95
	Journalism	73,842	51,660	0.231	0.023	0.615
	Other communication	70,056	48,524	0.210	0.027	0.566
Computer and Mathematical Sciences	Applied mathematics	92,402	60,276	0.385	0.028	0.394
	Computer and information sciences, general	82,433	43,491	0.404	0.018	0.915
	Computer science	89,857	49,880	0.468	0.014	3.025
	Computer systems analysis	85,373	41,843	0.419	0.030	0.161
	Information services and systems	79,364	44,404	0.374	0.017	0.88
	Mathematics, general	84,144	55,518	0.305	0.016	2.292
	Other computer and information sciences	67,564	39,560	0.242	0.031	0.228
	Other mathematics	86,277	55,372	0.366	0.040	0.165
	Operations research	87,312	45,033	0.418	0.044	0.087
	Statistics	90,101	54,906	0.403	0.038	0.124
Economics	Economics	97,835	77,925	0.426	0.020	3.304
Education	Computer teacher education	73,068	27,023	0.165	0.051	0.009
	Counselor education and guidance	58,839	45,985	0.041	0.063	0.018
	Education administration	65,299	32,436	0.067	0.050	0.042
	Educational psychology	62,456	33,214	0.039	0.035	0.194
	Elementary teacher education	54,445	26,739	0.000	-	2.513
	Mathematics teacher education	62,929	34,015	0.038	0.025	0.259
	Other education	63,937	42,207	0.044	0.014	0.978
	Physical education and coaching	65,674	44,727	0.052	0.017	0.703
	Pre-school/kindergarten/early childhood teacher education	49,149	22,775	-0.068	0.029	0.258
	Science teacher education	64,697	30,864	0.035	0.031	0.207
	Secondary teacher education	62,549	36,186	0.042	0.015	0.821
	Social science teacher education	67,093	47,525	0.018	0.034	0.241
	Special education	58,791	31,396	0.067	0.020	0.388

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Aggregated BA major	Disaggregated BA major	Earnings		Earnings premium		Perc. in sample
		Mean	SD	Coef	SE	
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Engineering	Aerospace, aeronautical, astronautical/ space engineering	96,654	51,400	0.442	0.020	0.593
	Agricultural engineering	82,452	41,052	0.311	0.034	0.139
	Architectural engineering	88,650	55,280	0.381	0.028	0.237
	Bioengineering and biomedical engineering	89,840	75,308	0.413	0.031	0.115
	Chemical engineering	105,129	55,727	0.552	0.015	1.166
	Civil engineering	92,518	51,464	0.432	0.013	2.19
	Computer and systems engineering	99,625	50,951	0.562	0.017	0.746
	Electrical, electronics and communications engineering	99,670	50,445	0.492	0.013	4.15
	Engineering, general	97,515	57,300	0.405	0.025	0.264
	Engineering sciences, mechanics and physics	95,333	51,447	0.392	0.032	0.21
	Environmental engineering	87,079	44,815	0.402	0.031	0.113
	Geophysical and geological engineering	100,443	86,168	0.410	0.052	0.028
	Industrial and manufacturing engineering	96,014	58,507	0.434	0.017	0.888
	Materials engineering, including ceramic and textile sciences	84,291	38,709	0.373	0.029	0.177
	Mechanical engineering	96,057	51,468	0.464	0.013	3.371
	Metallurgical engineering	102,130	54,867	0.419	0.037	0.128
	Mining and minerals engineering	96,655	46,126	0.374	0.049	0.063
	Naval architecture and marine engineering	96,307	48,957	0.415	0.041	0.098
	Nuclear engineering	105,950	51,632	0.540	0.033	0.067
	Other engineering	101,256	61,503	0.444	0.026	0.315
	Petroleum engineering	112,908	66,785	0.594	0.046	0.112
English/ Languages/ Literature	English Language, literature and letters	72,838	51,392	0.169	0.021	1.613
	Linguistics	58,705	36,601	0.040	0.054	0.126
	Other foreign languages and literature	70,783	46,914	0.152	0.026	0.562
Fine/ Performing Arts	Dramatic arts	60,890	50,978	0.005	0.039	0.214
	Fine arts, all fields	62,430	46,505	0.070	0.025	0.804
	Music, all fields	58,916	35,990	-0.012	0.029	0.458
	Other visual and performing arts	63,412	44,687	0.109	0.027	0.606
Health related fields	Audiology and speech pathology	59,648	25,299	0.063	0.030	0.3
	Health/medical assistants	78,123	57,230	0.351	0.064	0.034
	Health/medical technologies	70,633	40,623	0.268	0.022	0.443
	Medical preparatory programs[2]	124,580	115,935	0.300	0.049	0.163
	Medicine[1]	126,548	108,326	0.433	0.057	0.16
	Other health/medical sciences	67,816	44,788	0.201	0.024	0.439
	Pharmacy	106,827	44,552	0.563	0.023	0.468
	Physical therapy and other rehabilitation/ therapeutic services	70,231	42,657	0.252	0.022	0.628
	Public health (including environmental health and epidemiology)	62,532	35,557	0.097	0.032	0.193
Marketing	Business marketing/marketing management	87,112	65,716	0.340	0.020	1.585
	Marketing research	77,503	59,162	0.260	0.037	0.168
Nursing	Nursing (4 years or longer program)	74,460	36,044	0.338	0.015	3.038
Other Humanities	History, other	79,999	62,928	0.172	0.022	1.294
	Liberal arts/general studies	76,161	57,136	0.186	0.025	0.747
	Other philosophy, religion, theology	62,035	49,229	-0.034	0.027	0.617
Other Non-S and E fields	Criminal justice/protective services	65,126	36,926	0.092	0.028	0.674
	Health services administration	70,714	45,916	0.195	0.036	0.278
	Library science	56,319	26,151	0.029	0.065	0.02
	Parks, recreation, leisure, and fitness studies	59,113	36,066	0.030	0.025	0.388

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Aggregated BA major	Disaggregated BA major	Earnings		Earnings premium		Perc. in sample
		Mean	SD	Coef	SE	
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Other S and E-related fields	Architecture/environmental design	85,832	56,667	0.299	0.022	0.829
	Computer programming	85,409	38,696	0.428	0.028	0.218
	Data processing	84,414	29,976	0.406	0.054	0.027
	Electrical and electronics technologies	86,949	40,561	0.393	0.022	0.382
	Industrial production technologies	83,809	45,088	0.274	0.032	0.355
	Mechanical engineering-related technologies	88,949	41,149	0.383	0.027	0.247
	Non-S & E Group	101,306	59,001	0.418	0.074	0.014
	Other engineering-related technologies	88,144	48,632	0.352	0.028	0.285
	Suppressed-All S & E Major	103,403	27,309	0.384	0.119	0.003
Other Social and Related Sciences	Anthropology and archaeology	59,991	46,467	0.056	0.023	0.663
	Area and ethnic studies	64,586	49,629	0.163	0.029	0.44
	Criminology	60,068	31,049	0.104	0.025	0.367
	Geography	66,051	45,986	0.100	0.022	0.607
	History of science	76,193	46,233	0.159	0.064	0.075
	Home Economics	57,195	32,085	0.065	0.024	0.458
	International relations	78,160	59,528	0.296	0.024	0.589
	Other social sciences	64,371	44,122	0.112	0.020	1.093
	Philosophy of science	89,784	68,309	0.230	0.055	0.114
	Public policy studies	81,737	87,243	0.252	0.078	0.075
	Sociology	63,034	43,083	0.117	0.015	3.645
Physical and Related Sciences	Astronomy and astrophysics	66,048	47,368	0.158	0.084	0.026
	Atmospheric sciences and meteorology	74,627	43,280	0.236	0.038	0.096
	Chemistry, except biochemistry	86,867	59,927	0.295	0.017	1.767
	Earth sciences	65,908	38,642	0.110	0.036	0.134
	Geological sciences, other	78,607	45,377	0.288	0.041	0.059
	Geology	82,481	52,980	0.220	0.023	0.661
	Other physical sciences	79,274	50,344	0.168	0.038	0.198
	Oceanography	65,302	33,690	0.066	0.080	0.037
	Physics, except biophysics	90,339	54,895	0.326	0.021	0.758
	Science, unclassified	78,587	46,913	0.251	0.040	0.123
Political Science	Law/prelaw/legal studies	74,946	53,727	0.135	0.038	0.206
	Other public affairs	67,234	45,673	0.099	0.064	0.068
	Political science and government	84,236	66,163	0.269	0.017	4.388
	Public administration	74,929	42,150	0.205	0.042	0.099
Psychology or Social Work	Clinical psychology	75,512	56,208	0.157	0.033	0.386
	Counseling psychology	60,275	35,216	0.068	0.024	0.397
	Experimental psychology	85,501	61,503	0.212	0.047	0.18
	General psychology	59,995	45,013	0.103	0.014	5.512
	Industrial/Organizational psychology	79,075	48,359	0.279	0.039	0.21
	Other psychology	67,369	44,959	0.134	0.021	0.591
	Social Work	53,873	26,454	0.002	0.019	0.636
	Social psychology	66,271	38,627	0.140	0.032	0.245

Note: Column 1 presents 19 aggregated BA fields that are constructed from 144 disaggregated BA fields. For each disaggregated field, columns 2-7 present its field name, mean and standard deviation of earnings, its coefficient and standard error from a disaggregated additive earnings regression, and percentage in the sample. Disaggregated BA fields with less than 10 observations are removed from the table. See notes for Table B1.

[1] Medicine includes dentistry, optometry, osteopathic, podiatry, veterinary, etc.

[2] Medical preparatory programs include pre-dentistry, pre-medical, pre-veterinary etc.

Table B5: Distribution of the regression sample by year

Year (1)	Percentage (2)	Frequency (3)
1990	7.275	62,850
1993	10.759	92,950
1994	3.481	30,070
1995	4.653	40,200
1996	3.527	30,470
1997	4.351	37,590
1998	2.974	25,690
1999	3.735	32,270
2001	0.711	6,140
2002	6.074	52,470
2003	6.287	54,310
2005	3.937	34,010
2006	4.166	35,990
2007	3.896	33,660
2008	4.146	35,820
2009	4.355	37,620
2010	4.598	39,730
2012	5.539	47,850
2013	5.561	48,040
2014	4.980	43,020
2015	4.994	43,140

Note: Tabulation of the year of survey for the regression sample (Table 2, col. 3). Both the frequency and the cell counts are unweighted. Cell counts are rounded to the nearest 10.

Table B6: Return to advanced degrees by years of post-adv experience, OLS

	Averages			Return to advanced degree by years of post Adv experience				
	γ_x 1~28 years, sample weighted	$\bar{\gamma_x}$ All years, sample weighted	γ_{g1-28} 1~28 years equally weighted	1	5	10	20	30
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Medicine	0.738	0.728	0.747	0.150	0.463	0.747	0.960	0.697
	(0.015)	(0.015)	(0.015)	(0.032)	(0.019)	(0.019)	(0.022)	(0.041)
Law	0.448	0.457	0.460	0.285	0.357	0.431	0.527	0.555
	(0.015)	(0.015)	(0.015)	(0.029)	(0.018)	(0.019)	(0.021)	(0.048)
Master's in Business related fields	0.351	0.354	0.365	0.203	0.276	0.348	0.426	0.416
	(0.013)	(0.013)	(0.014)	(0.028)	(0.017)	(0.016)	(0.020)	(0.041)
MBA	0.286	0.291	0.308	0.222	0.245	0.276	0.343	0.418
	(0.008)	(0.008)	(0.009)	(0.015)	(0.009)	(0.010)	(0.013)	(0.034)
Master's in Engineering	0.138	0.143	0.180	0.023	0.093	0.162	0.239	0.236
	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.007)	(0.009)	(0.019)
Master's in Computer and mathematical sciences	0.195	0.195	0.223	0.090	0.163	0.228	0.270	0.195
	(0.008)	(0.008)	(0.010)	(0.011)	(0.008)	(0.012)	(0.014)	(0.034)
Master's in Health Services Administration	0.312	0.311	0.348	0.178	0.275	0.359	0.407	0.292
	(0.025)	(0.025)	(0.031)	(0.034)	(0.027)	(0.037)	(0.044)	(0.100)
Master's in Nursing	0.317	0.312	0.294	0.315	0.335	0.340	0.280	0.128
	(0.014)	(0.014)	(0.018)	(0.019)	(0.015)	(0.020)	(0.025)	(0.062)
Master's in Other Science and Engineering related fields	0.093	0.109	0.116	-0.107	-0.031	0.055	0.204	0.320
	(0.019)	(0.018)	(0.019)	(0.040)	(0.024)	(0.023)	(0.028)	(0.048)
Master's in Public Administration	0.213	0.214	0.239	0.015	0.125	0.228	0.321	0.261
	(0.020)	(0.020)	(0.021)	(0.048)	(0.028)	(0.025)	(0.029)	(0.073)
Master's in Physical and related sciences	0.043	0.052	0.091	-0.162	-0.048	0.063	0.185	0.173
	(0.014)	(0.014)	(0.016)	(0.017)	(0.014)	(0.019)	(0.022)	(0.042)
Master's in Other Social and related sciences	0.100	0.111	0.139	0.001	0.047	0.101	0.194	0.266
	(0.013)	(0.013)	(0.017)	(0.015)	(0.012)	(0.020)	(0.024)	(0.037)
Master's in Health Related Fields	0.226	0.224	0.224	0.220	0.228	0.233	0.224	0.191
	(0.012)	(0.012)	(0.015)	(0.017)	(0.013)	(0.017)	(0.021)	(0.047)
Master's in Biological/ agricultural/ environmental/ life sciences	0.013	0.017	0.050	-0.134	-0.046	0.037	0.117	0.081
	(0.011)	(0.011)	(0.012)	(0.015)	(0.011)	(0.015)	(0.017)	(0.037)
Master's in Other Non-Science and Engineering fields	0.052	0.057	0.073	-0.063	-0.009	0.048	0.125	0.152
	(0.016)	(0.015)	(0.016)	(0.035)	(0.022)	(0.020)	(0.021)	(0.052)
Master's in Education fields	0.085	0.090	0.100	-0.015	0.029	0.076	0.144	0.178
	(0.006)	(0.006)	(0.007)	(0.011)	(0.007)	(0.008)	(0.009)	(0.020)
Master's in Arts	0.000	0.007	0.029	-0.211	-0.103	0.003	0.119	0.106
	(0.024)	(0.025)	(0.025)	(0.061)	(0.036)	(0.029)	(0.035)	(0.078)
Master's in Psychology and Social Work	0.057	0.061	0.093	-0.080	-0.003	0.074	0.158	0.150
	(0.008)	(0.009)	(0.010)	(0.012)	(0.008)	(0.011)	(0.014)	(0.028)
Master's in Humanity fields	-0.168	-0.156	-0.157	-0.187	-0.198	-0.196	-0.141	-0.015
	(0.015)	(0.015)	(0.016)	(0.028)	(0.018)	(0.019)	(0.023)	(0.043)

Note: The table reports OLS estimates of the returns to each advanced degree by years of post advanced degree experience x. It corresponds to Table B2 but is based on OLS rather than FE-cg. Sample weights are used and standard errors are clustered at the individual level. The specification is equation (13) with degree combination fixed effects excluded. See the notes for Table B2.

Table B7: FE estimates of the returns to graduate education

Dependent variable:	ln(earnings) (1)	Occupational Premium (2)
Medicine	-0.198	0.581
	(0.112)	(0.075)
Law	0.039	0.315
	(0.065)	(0.042)
Master's in Business related fields	0.018	0.016
	(0.027)	(0.014)
MBA	0.014	-0.002
	(0.018)	(0.008)
Master's in Engineering	0.030	0.021
	(0.021)	(0.011)
Master's in Computer and mathematical sciences	0.069	-0.006
	(0.032)	(0.011)
Master's in Health Services Administration	0.043	0.036
	(0.059)	(0.039)
Master's in Nursing	0.085	0.009
	(0.040)	(0.021)
Master's in Other Science and Engineering related fields	-0.177	-0.011
	(0.047)	(0.060)
Master's in Public Administration	0.046	0.056
	(0.033)	(0.027)
Master's in Physical and related sciences	-0.074	0.014
	(0.041)	(0.021)
Master's in Other Social and related sciences	-0.018	0.047
	(0.072)	(0.032)
Master's in Health related fields	0.069	0.027
	(0.063)	(0.020)
Master's in Biology/agricultural/ environmental/life sciences	0.077	0.012
	(0.048)	(0.019)
Master's in Other Non-Science and Engineering fields	0.123	0.008
	(0.043)	(0.027)
Master's in Education fields	0.018	-0.005
	(0.018)	(0.008)
Master's in Arts	-0.020	0.033
	(0.103)	(0.064)
Master's in Psychology and Social Work	0.065	-0.007
	(0.031)	(0.019)
Master's in Humanity fields	-0.088	-0.097
	(0.038)	(0.040)

Note: Individual fixed effects estimates of returns to advanced degrees are reported for the additive specification. Columns 1 and 2 report estimates of γ_g for the log of earnings and the occupation premium, respectively. See the note to Table 2 for list of control variables. Time invariant controls are absorbed by the person effects. Person specific averages of the sample weights across panel observations are used. Standard errors are clustered at the person level.

Table B8: Earnings related summary statistics by advanced degree: Men

	Earnings	ln(Earnings)	Average BA major premium	Average occupation premium	Advanced field composition	Fraction Working Full time
Medicine	178,711 [106,361]	11.904 [0.661]	0.222 [0.100]	0.437 [0.179]	4.75	0.907
Law	137,578 [92,330]	11.635 [0.650]	0.255 [0.116]	0.244 [0.148]	7.32	0.947
Master's in Business related fields	134,637 [91,711]	11.634 [0.595]	0.341 [0.126]	0.131 [0.209]	7.55	0.937
MBA	121,731 [71,581]	11.574 [0.527]	0.349 [0.132]	0.118 [0.227]	16.20	0.951
Master's in Engineering	104,250 [51,306]	11.453 [0.466]	0.447 [0.081]	0.150 [0.144]	15.78	0.946
Master's in Computer and mathematical sciences	104,185 [52,063]	11.446 [0.482]	0.378 [0.122]	0.100 [0.169]	8.57	0.922
Master's in Health Services Administration	116,030 [70,587]	11.511 [0.555]	0.227 [0.106]	0.132 [0.250]	0.82	0.963
Master's in Nursing	139,941 [58,799]	11.768 [0.415]	0.311 [0.067]	0.083 [0.129]	0.41	0.904
Master's in Other Science and Engineering related fields	95,463 [57,597]	11.339 [0.507]	0.288 [0.121]	0.020 [0.232]	2.09	0.935
Master's in Public Administration	96,110 [46,056]	11.360 [0.494]	0.220 [0.106]	0.089 [0.260]	1.70	0.954
Master's in Physical and related sciences	88,521 [48,573]	11.237 [0.592]	0.276 [0.086]	0.013 [0.196]	3.11	0.898
Master's in Other Social and related sciences	91,322 [65,208]	11.237 [0.612]	0.233 [0.130]	-0.016 [0.267]	4.58	0.877
Master's in Health related fields	99,952 [62,313]	11.361 [0.557]	0.220 [0.136]	0.033 [0.244]	2.34	0.903
Master's in Bio/agricultural/ environmental/life sciences	74,466 [43,509]	11.084 [0.526]	0.168 [0.095]	-0.107 [0.227]	4.03	0.913
Master's in Other Non-Science and Engineering fields	76,842 [42,245]	11.125 [0.509]	0.172 [0.105]	-0.095 [0.253]	1.69	0.910
Master's in Education fields	74,861 [34,929]	11.139 [0.412]	0.135 [0.117]	-0.178 [0.230]	9.68	0.804
Master's in Arts	73,241 [56,337]	11.024 [0.595]	0.092 [0.122]	-0.186 [0.231]	1.08	0.741
Master's in Psychology and Social Work	74,552 [39,645]	11.094 [0.510]	0.131 [0.093]	-0.147 [0.276]	4.27	0.878
Master's in Humanity fields	62,807 [44,074]	10.892 [0.548]	0.141 [0.124]	-0.329 [0.306]	4.04	0.861
Total	106,306 [70,223]	11.406 [0.584]	0.287 [0.156]	0.060 [0.270]	100	0.912

Note: Columns 1-4 repeat the statistics presented in Table 5 while restricting the sample to men. Weighted means and [standard deviations] are reported.
Column 5: Percentages reported for observations with each advanced degree and gender combination.
Column 6: The fraction of full time worker is reported for each advanced degree on the sample of people between 23 and 59 years old, and who obtained their BA degree after 19 years old. The sample excludes people with PhD degrees now or in the future and people who attend graduate school directly after college completion. The sample also excludes observations of people enrolled in advanced degrees.

Table B9: Earnings related summary statistics by advanced degree: Women

	Earnings	ln(Earnings)	Average BA major premium	Average occupation premium	Advanced field composition	Fraction Working Full time
Medicine	130,504 [84,709]	11.563 [0.689]	0.214 [0.090]	0.424 [0.197]	2.83	0.736
Law	107,624 [69,415]	11.414 [0.601]	0.212 [0.104]	0.234 [0.155]	5.14	0.840
Master's in Business related fields	100,044 [67,281]	11.363 [0.549]	0.295 [0.130]	0.071 [0.212]	3.53	0.827
MBA	97,096 [54,309]	11.346 [0.544]	0.279 [0.136]	0.057 [0.230]	8.21	0.857
Master's in Engineering	88,165 [48,921]	11.280 [0.477]	0.424 [0.105]	0.119 [0.159]	3.29	0.850
Master's in Computer and mathematical sciences	85,564 [42,867]	11.239 [0.509]	0.334 [0.133]	0.040 [0.203]	4.87	0.821
Master's in Health Services Administration	84,897 [40,853]	11.247 [0.458]	0.231 [0.106]	0.020 [0.230]	1.52	0.849
Master's in Nursing	90,879 [37,014]	11.349 [0.373]	0.324 [0.052]	0.053 [0.168]	3.96	0.742
Master's in Other Science and Engineering related fields	77,560 [36,266]	11.148 [0.494]	0.254 [0.125]	-0.025 [0.231]	0.89	0.800
Master's in Public Administration	76,612 [38,320]	11.124 [0.521]	0.200 [0.106]	-0.018 [0.281]	1.65	0.858
Master's in Physical and related sciences	70,023 [38,311]	11.017 [0.552]	0.255 [0.089]	-0.065 [0.185]	1.44	0.783
Master's in Other Social and related sciences	69,069 [41,429]	11.006 [0.525]	0.190 [0.118]	-0.092 [0.261]	5.09	0.759
Master's in Health related fields	70,801 [31,907]	11.079 [0.429]	0.158 [0.108]	-0.042 [0.208]	7.87	0.681
Master's in Bio/agricultural/ environmental/life sciences	63,271 [33,939]	10.938 [0.494]	0.179 [0.096]	-0.125 [0.205]	4.41	0.797
Master's in Other Non-Science and Engineering fields	62,663 [33,778]	10.952 [0.431]	0.150 [0.097]	-0.206 [0.239]	2.93	0.761
Master's in Education fields	61,705 [25,948]	10.955 [0.397]	0.092 [0.102]	-0.263 [0.185]	25.09	0.707
Master's in Arts	57,881 [32,687]	10.828 [0.535]	0.079 [0.090]	-0.187 [0.214]	1.34	0.614
Master's in Psychology and Social Work	59,901 [30,545]	10.904 [0.438]	0.110 [0.074]	-0.236 [0.224]	12.78	0.744
Master's in Humanity fields	59,119 [30,544]	10.874 [0.486]	0.152 [0.086]	-0.257 [0.241]	3.18	0.700
Total	75,135 [45,460]	11.093 [0.515]	0.183 [0.138]	-0.088 [0.272]	100	0.759

Note: This table repeats the statistics presented in Table B8, but restricting the sample to women.

Table B10: Logit and linear probability FE-cg regressions for full time

	Full sample		Women		Men	
	Logit	Linear	Logit	Linear	Logit	Linear
	(1)	(2)	(3)	(4)	(5)	(6)
Medicine	-0.096	-0.010	-0.040	-0.008	-0.229	-0.018
	(0.075)	(0.009)	(0.105)	(0.019)	(0.105)	(0.009)
Law	0.531	0.049	0.551	0.084	0.492	0.028
	(0.074)	(0.006)	(0.103)	(0.014)	(0.101)	(0.005)
Master's in Business related fields	0.148	0.012	0.321	0.048	-0.042	-0.003
	(0.072)	(0.006)	(0.114)	(0.016)	(0.088)	(0.005)
MBA	0.422	0.034	0.551	0.079	0.257	0.013
	(0.052)	(0.004)	(0.074)	(0.009)	(0.070)	(0.003)
Master's in Engineering	0.017	0.002	0.194	0.028	-0.078	-0.003
	(0.040)	(0.002)	(0.084)	(0.010)	(0.046)	(0.002)
Master's in Computer and mathematical sciences	-0.042	-0.002	0.125	0.019	-0.208	-0.012
	(0.048)	(0.004)	(0.071)	(0.010)	(0.062)	(0.004)
Master's in Health Services Administration	0.720	0.083	0.708	0.109	0.866	0.046
	(0.142)	(0.013)	(0.165)	(0.021)	(0.237)	(0.009)
Master's in Nursing	0.142	0.024	0.147	0.027	0.146	0.013
	(0.084)	(0.015)	(0.086)	(0.016)	(0.316)	(0.027)
Master's in Other Science and Engineering related fields	0.174	0.019	0.242	0.040	0.144	0.011
	(0.119)	(0.010)	(0.192)	(0.030)	(0.144)	(0.008)
Master's in Public Administration	0.648	0.060	0.640	0.089	0.631	0.037
	(0.126)	(0.010)	(0.172)	(0.020)	(0.166)	(0.007)
Master's in Physical and related sciences	-0.220	-0.020	-0.135	-0.021	-0.310	-0.022
	(0.069)	(0.007)	(0.107)	(0.017)	(0.090)	(0.007)
Master's in Other Social and related sciences	-0.138	-0.016	0.000	0.001	-0.388	-0.033
	(0.045)	(0.006)	(0.060)	(0.010)	(0.065)	(0.006)
Master's in Health related fields	-0.157	-0.034	-0.147	-0.031	-0.105	-0.009
	(0.050)	(0.009)	(0.055)	(0.011)	(0.122)	(0.010)
Master's in Bio/ agricultural/ environmental/ life sciences	0.102	0.013	0.191	0.031	-0.081	-0.004
	(0.051)	(0.006)	(0.066)	(0.010)	(0.080)	(0.006)
Master's in Other Non-Science and Engineering fields	0.027	0.004	0.032	0.007	-0.005	0.001
	(0.097)	(0.013)	(0.118)	(0.020)	(0.152)	(0.011)
Master's in Education fields	-0.323	-0.050	-0.151	-0.027	-0.849	-0.091
	(0.031)	(0.005)	(0.035)	(0.006)	(0.056)	(0.007)
Master's in Arts	-0.691	-0.111	-0.509	-0.099	-0.888	-0.119
	(0.108)	(0.019)	(0.134)	(0.028)	(0.162)	(0.025)
Master's in Psychology and Social Work	-0.081	-0.015	-0.021	-0.004	-0.321	-0.027
	(0.039)	(0.006)	(0.044)	(0.008)	(0.080)	(0.008)
Master's in Humanity fields	-0.306	-0.038	-0.154	-0.029	-0.508	-0.048
	(0.065)	(0.009)	(0.085)	(0.016)	(0.093)	(0.010)

Note: Logit and linear regressions of people's employment status. The dependent variable is a dummy indicating if the person is working full time. The regressions are based on the FE-cg specification. They include *cg* fixed effects, dummies for each BA field and each advanced degree, as well as a set of demographic variables including parental education, year of the survey, and interactions between age, gender, and race. The logit columns report logit coefficients, not marginal effects.