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THE LABOR MARKET RETURNS TO ADVANCED DEGREES

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ABSTRACT

We estimate the labor market return to an MBA, a JD, and master's in engineering, nursing, education, psychology and social work, and thirteen other 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. We find large differences across graduate fields in earnings effects, and more moderate differences in internal rates of return that account for program length and tuition. 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 bachelor's 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 $66,174, while MBAs earn $113,177 and medical degree holders earn $164,317. 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 on undergraduate field, ability, and occupational preferences.

This paper provides 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. Instead of person fixed

[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.

effects, FE-cg includes 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. 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 identification strategy only applies to people who work between college and graduate school, but they account for 85% of those who obtain graduate degrees.

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 corresponding 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.

Expressions for 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 unbiased. 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 31 combinations of undergraduate and graduate fields. These data are 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, the effect of graduate field on postgraduate occupation is about twice as large as undergraduate 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 bachelors in engineering paired with a master's in education, 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 0.416 (0.059) and for medicine is 0.549 (0.072), or 51.6% and 73.2% respectively. The return to an MBA is only 0.110 (0.021) or 11.6%, which is far below the OLS value of 0.282 (0.008). The return is 0.103 (0.018) for a masters in engineering, 0.179 (0.033) for computer and mathematical sciences, 0.227 (0.053) for health related fields, 0.235 (0.041) for nursing, 0.202 (0.029) for psychology and social work, 0.162 (0.019) for education, and essentially zero for both the arts and the humanities. Estimates of the internal rate of return under assumptions about public school tuition and program length vary less. For example, the values are 0.148 for law, 0.160 for medicine, and 0.059 for an MBA.

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 estimates of the average premium between 1 and 28 years after degree completion is typically at least 5 log points higher than estimates that assume a constant premium. For an MBA, the estimate is 0.181. However, as section 5.2 explains, 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, although it is also possible that constraining the graduate school returns to be a constant leads to a downward bias in the average return. Estimates of internal rates of return are closer to and sometimes below estimates assuming a constant earnings premium because of the effects of discounting future earnings.

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 (in logs) is 0.098 (0.070) for economics majors, 0.157 (0.065) for business majors, 0.140 (0.102) for psychology and social work majors, but only 0.083 (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 as 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, including 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 (Heckman et al. (2008)), although we believe they are more severe in the graduate education case. The literature on the returns to college majors has grown rapidly over the past 20 years, as Altonji et al. (2012) and Altonji et al. (2016b) document. 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, with controls for family background, test scores, high school grades, and other 12th grade aptitude measures. His analysis is for a relatively young sample, and assumes that only the field of highest degree matters. Black et al. (2003) report OLS estimates of the return to a few graduate degree types for different majors using the 1993 NSCG. Altonji et al. (2016b) report OLS estimates for a broader set of graduate and undergraduate degrees using the 1993, 2003, 2010, and 2013 NSCG.[2] 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 the 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 post MBA earnings observation may reduce the estimates.[3] Bhattacharya (2005), Chen and Chevalier (2012) and Ketel et al. (2016) are part of small literature that studies the return to medical degrees.

To the best of our knowledge we are 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 describes the data. In section 3 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 4 examines links among undergraduate field, graduate field, and occupation before and after graduate school. Section 5 discusses the problem of selection bias and the estimation strategies we use. In section 6 we present the econometric specifications. Section 7 presents estimates of the return to graduate degrees. We conclude in section 8.

2 Data

2.1 Data Sources

We employ data from the NSCG (1993 to 2015) and the NSRCG (1993 to 2010). They are part of the Scientists and Engineers Statistical Data System (SESTAT) sponsored by the National Center for Science and Engineering Statistics (NCSES) within the National Science Foundation (NSF). The NSCG 1993 and 2003 are, respectively, subsamples of the 1990 and 2000 decennial census long form respondents who had a bachelor's degree. In the 1990s and 2000s, NSF only follows people who have a BA field, advanced field, or occupation that is Science and Engineering related (S&E) in their first observation in the data system. We denote this selection criterion by the phrase "SESTAT-eligible".[4] From 2010 on, the NSCG employs a new rotating sampling strategy. The NSCG 2010 includes respondents from previous waves but is drawn primarily from respondents to the 2009 American Community Survey (ACS). The samples for the NSCG 2013 and the 2015 surveys combine a subset of the interviewees from the 2010 and 2013 NSCG and a subset of interviewees with a BA degree from the 2010 and 2013 waves of the ACS. The NSCG 1993, 2003, 2010, 2013, and 2015 can be weighted to be representative of the U.S. population with bachelor's degree.[5] The NSRCG 1993, 1995, 1997, 1999, 2001, 2003, 2006, 2008, and 2010 surveys add additional interviewees to the

[2] 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.

[3] Montgomery and Powell (2003) use the same data to show that the gender gap is narrower among MBA completers but does not focus on the return to an MBA. See also Gicheva (2013).

[4] Science and Engineering include the social sciences but excludes Health-related fields and occupations from 1993 to 2001. From 2003 on, Health is included. Throughout the paper, we use "BA" to refer to both bachelor's of arts and bachelor's of science degrees and use "MA" in a similar fashion.

[5] The NSCG 1993 and 2003 surveys are restricted to individuals who received a BA at least three years prior to the survey and thus exclude recent college graduates.

data system. The NSRCG samples are restricted to individuals who have obtained a BA or advanced degree in an S&E field within three years prior to the survey reference date, and thus, all interviewees from the NSRCG surveys are SESTAT-eligible.[6] All waves of the NSCG and the NSRCG are restricted to people who are under 76 years of age and who live in the U.S. as of the survey reference date.

We also use information from 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 1990 census classification, employment, and earnings and work hours in 1989. We created occupation categories that are consistent across the census and SESTAT.[7]

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. We can track individuals who are surveyed more than once. The availability of 1990 Census information for NSCG 1993 sample members is an additional source of panel data observations for both earnings and occupation. In addition to using the 1990 Census information, we obtain information about occupation in 1988 from an NSCG 1993 question. Finally, most of the surveys ask two separate questions about earnings. 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.[8]

The combined dataset also contains detailed information on postsecondary education history, current and past employment, and basic demographic variables. The latter include gender, race\Hispanic and parents' education.[9] We use 19 aggregated BA categories and 19 aggregated graduate categories in most of our analyses. Tables B1 and B2 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 equation (3) using the disaggregated degree categories.

A downside of the fact that NSCG and the NSRCG oversample people with STEM degrees is that sample sizes for many pairs of specific non-STEM majors and graduate degrees are too small to support use of FE-cg for the interactive specification. We only report FE-cg estimates of the pair specific return (parameter γ_{cg} defined below) if we observe earnings prior to graduate school for at least 31 individuals.

We construct weights to make the pooled sample representative of the US population of college graduates over the years of our sample, and we use weights unless otherwise noted.[10]

[6] In 2013 the NSRCG was merged into the NSCG. The NSCG surveys after the merge oversample recent college graduates.

[7] Table B3 reports the shares of the 363 disaggregated fields in the 66 consistent categories (from column (3) to column (2)), and the shares of those 66 consistent categories in the 21 aggregated occupations (from column (2) to column (1)). Table B6 uses the 21 categories and Tables 2–3 and Figure 2 use the 66 category classification.

[8] The timing of the surveys is such that in a given year only one of two measures is 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 earnings regression error term but will not lead to bias if the measurement error is uncorrelated with the regressors. Standard errors are clustered at the individual level throughout the paper. We divided the sample by earnings observation type and produced FE-cg estimates corresponding to the specification in Table 5. The estimates using the current earnings measure are smaller for 10 of the 19 graduate fields (Table B4). None of the differences is significant at the 5 percent level and t values are under $|1.4|$ in 16 of 19 cases.

[9] 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 degree that an individual reports in multiple surveys has coherent information for completion date, location and fields of study.

[10] The details of how we construct weights are in Appendix B.3.2. In brief, we aim to study the labor market returns to advanced degrees that represent the population of people who have a college degree in any field who are between 23 and 59 years old who live in the US. The target populations of the 1993, 2003, 2010, 2013 NSCG are individuals with at least a BA degree. We use the survey weights for each of these samples to estimate the distribution of college graduates across combinations of BA field and graduate field (including no graduate degree) over the four years combined. (We did not use the 2015 sample to avoid giving too much weight to the population distribution of college graduates from 2010 on.) The NSRCG and the other waves of the NSCG prior to 2010 are restricted to the SESTAT eligible population. Thus individuals with STEM eligible occupations and advanced degrees are overrepresented when we pool all of the data. We adjust the weights so that the weighted distribution of c, g pairs in the pooled sample matches the distribution of c, g pairs that we estimated using the 1993, 2003, 2010, and 2013 NSCG. Separate weights are constructed for the earnings regressions and the occupational premium regressions that reflect the

The occupational earnings premiums are constructed using the 2009-2014 waves of the ACS. We estimate the premiums by OLS using the sample of full time workers with BA degrees who are between 24 and 59 years old.[11] The estimates are merged into the NSCG-NSRCG dataset by occupation. The ACS based premiums are reported in Table B3. We use the occupational premiums associated with the 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, who obtain a BA before age 20 or after age 55 or who obtain their advanced degree after age 49.[12] We also restrict the earnings analysis to full-time workers.[13]

We typically exclude individuals who go directly to graduate school to help ensure comparability between the people we observe before graduate school and those we observe after. We consider such individuals in section 7.1.12. In the case of FE-cg, we also restrict the sample to individuals who have an advanced degree when we last observe them, which we refer to as the "graduate degree sample". 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, which we call the "full sample", contains 858,130 observations, and includes 195,540 individuals who are observed more than once. The sample used for FE-cg contains 297,530 observations and includes 8,170 pre advanced degree observations on 4,810 individuals.[14]

Definitions and descriptive statistics for the key control variables that appear in our regression models are in Table A1.

2.2 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 estimate the start date by subtracting an assumed typical number of years required to obtain the degree for a full time student. Earnings are treated as prior to graduate school if they are prior to the estimated start date.[15] 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 A2 reports the mean, and 10th, 25th, 50th, 75th, and 90th quantiles of the number of years from BA completion

mix of surveys that contribute observations. The pooled sample weights for earnings account for the fact that some interviews contribute earnings observations for two years. We trim the adjusted weights using 1/10 and 10 times of the median of the weights of all observations in the combined data.

[11] The regression controls include a cubic in age interacted with gender, race\Hispanic interacted with gender, and dummies for whether or not the person has a master's degree, a professional degree, and PhD. Unfortunately, the ACS does not report field of advanced degree.

[12] We code BA based on the primary field of the first BA obtained. Thus, we do not account for a second major, or a minor. One could extend the FE-cg approach to treat BA combinations as an additional type of BA, but we have not done so. We drop individuals who obtain multiple BA degrees in different years. Because of concerns about choice based sampling, we also exclude the follow up observations of individuals who do not have degrees in S&E fields but are SESTAT-eligible only because of their occupation choices in their first observation (0.523% of the person year observations in the pooled sample).

[13] We code an individual as full-time if she reported working full-time or if she worked at least 41 weeks per year and at least 35 hours per week. We used 41 weeks to accommodate the employment arrangements of many teachers. With the exception of the 1989 annual earnings measure, we assume that full-time status in the prior year is the same as the survey year when the earnings measure refers to the year before the survey. We do so because we lack data on full time status in the prior year.

[14] We round all observation counts to the nearest 10. The mean, 1st percentile, median, and 99th percentile number of observations per person in the full sample for earnings are 3.72, 1, 3, and 9. The corresponding values in the graduate degree sample are 3.88, 1, 3, and 9.

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

for earnings observations that precede graduate school enrollment. All statistics in the table are unweighted. The 10th, 50th, and 90th quantiles are 1 (the minimum), 4, and 12. More than 82% of pre graduate school earnings observations occur between 1 (the minimum) and 5 years before completion of the advanced degree (column 2). Column 3 reports that the 10th, 50th, and 90th quantiles of time from advanced degree completion to post advanced degree earnings observations are 2, 9, and 24. The corresponding values are much lower for individuals with earnings observations both before and after the advanced degree (column 5). 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. 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 the availability of a pre advanced observation. The 10th, median and 90th quantiles are 2, 5, and 12.

Table A3 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, 38, and 53. The 10th, median and 90th quantiles of the age distribution of the 8,170 pre advanced degree observations of people with a graduate degree by the last interview are 24, 28, and 38 (column 3). The mean is 29.4. These individuals are younger and have a more condensed distribution than those who only have a BA when last observed (column 2). The fourth column reports the age distribution of the 289,360 post advanced degree earnings observations from the graduate degree sample. The 10th, 50th, and 90th percentiles are 28, 39, and 53. The observations are fairly evenly distributed across calendar years.[16]

3 Facts about Earnings Differences across Graduate Fields

Table 1 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. Differences across fields are large. 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 mean for the graduate degree sample. 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 1.36 (0.09).

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 equation (3) using the disaggregated BA and advanced degree categories.[17] Figure 3 graphs average earnings by advanced degree against the BA premiums. There is a positive relationship, with a slope coefficient of 1.77 (0.34). 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

[16] See Table B5. For the graduate degree sample, the 10th, 50th, and 90th percentiles of year are 1993, 2003, and 2014. The percentiles of the distribution of years for earnings observations that are post graduate degree are the same. For pre graduate school earnings observations the 10th, 50th, and 90th percentile values are 1990, 2002 and 2009, with a mean of 1999.8.

[17] The BA premiums are reported in Table B2.

heavily from biology and other life science majors, which are not especially high paying.

Figure B1 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 0.22, while the gender gaps in the occupational premium are centered around 0.05. The slope of the relationship is 0.54 (0.53). In the cases of biology and the arts, the earnings gaps are about 0.15, while the occupational earnings gap is very small. In the case of medicine, the overall gap is large (0.34) even though 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.[18]

Figure B2 plots the gender 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. 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 1.19 (0.97), but the gender gaps in average BA premiums within graduate fields are relatively small.

4 Links among BA Fields, Graduate Fields and Occupations

Here we document three facts about links among education fields and occupation and then look at case studies of occupation before and after graduate school for engineering and education majors. The evidence indicates that both specificity of knowledge and heterogeneity of preferences influence education and occupation paths. The patterns suggest that comparisons of earnings of those with and without a graduate degree will be misleading, even controlling for undergraduate field.

The first fact is that the link between undergraduate field and graduate field varies dramatically across graduate fields. Table 4 of Altonji et al. (2016b) 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. In reality, the table shows that particular undergraduate majors are heavily overrepresented in certain graduate programs. For example, the relative share of undergraduate engineering majors among those with 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 types. 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, which have many prerequisites.

The second fact is that both undergraduate field and occupation before graduate school have strong connections to 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 degree. Separate F tests indicate that both the undergraduate field indicators and the occupation dummies are highly significant predictors of graduate field.

Third, the effect of graduate field on post graduate occupation is about twice as large as the effect of BA field. To establish this, we regress estimates of the probability of working in occupation j conditional on

[18] See Sasser (2005), Bertrand et al. (2010), Goldin and Katz (2011) and Goldin and Katz (2016) for analyses of the gender gaps in various professional occupations, including pharmacist and doctor, and for MBA holders.

having *both* a BA in c and an advanced degree in g on a constant, the probability of working in occupation j given c and the probability of working in j given g. The coefficient on the probability of $j|c$ is 0.437 (0.033) while the coefficient on the probability of $j|g$ is (0.874 (0.017)).[19]

4.1 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 2 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 instances. In Table 2 as well as Table 3, we only report results for occupation categories containing at least 10 cases, and in some instances we aggregate occupations. For comparison, the top panel of Table 2 lists the five most common occupations for engineering graduates who have not obtained an advanced degree by age 35.[20] For this group, 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 three panels of the table examine 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 6.2%. Post MBA, managerial occupations are the first, fourth and fifth most common.

Few engineers get a master's in education, 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 11% 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 account for 72.1% 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 3 provides similar information 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 (4.0%) and top-level managers (2.7%). The number of pre MBA education majors is too small to break out occupations 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. Interestingly, top level manager is the third most common post master's occupation, with 8.01% 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.[21]

[19] We restrict the sample of j, c, g combination to the 1,137 cases with at least 50 observations on c, at least 50 on g, and at least 15 on occupation for the c, g pair. The results are not very sensitive to lowering or raising these restrictions.

[20] 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.

[21] The SESTAT top level manager category includes presidents and provosts. (See note 2 of Table B3). 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.

These examples show that the pre graduate school career paths of individuals 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. Calculations for physical and related sciences show a similar pattern (not shown). They are consistent with the regression analysis of the link between occupation after graduate school and undergraduate major and graduate field discussed above. For undergraduate engineering majors, we have used 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 (Table B6). Not surprisingly, occupation prior to graduate school is related to the reason for working in an unrelated job, and so is average pay. Engineering majors who were working in an unrelated job are less likely to get an engineering master's and more likely to pursue a business degree.

Overall, the evidence in section 4 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 a strategy of comparing earnings before and after graduate school for those who eventually obtain a specific graduate degree is likely to be superior to simple OLS.

5 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 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.

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

First, some notation. Let i denote the individual and for now let t 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. We only consider people who already have a college degree. We use the terms "major," "field," and "degree type" synonymously. The index j, $j = 1, \cdots, \mathcal{J}$, denotes occupation.

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.[22] 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

[22] Altonji et al. (2016b) briefly discuss the evidence on interactions between occupation and college major in earnings equations, which is limited. 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.

bias from Ashenfelter's dip (Ashenfelter (1978)) prior to graduate school.[23] 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 the combination of j, c and g. However, the 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 conditional on c. 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 earnings. Some elements of A_{it} also influence preferences for g and j. We define A_{it} and Q_{it} so that the influence of c and g on occupation specific earnings and nonpecuniary preferences are captured by $w_{jcgt}(A_{it})$ and the occupation choice probabilities introduced below. This definition makes it easier to distinguish between the causal effects of c and g on $w_{jcgt}(A_{it})$ 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 include demographic controls. We abstract from the quality and selectivity of the college and graduate programs, which we do not observe.[24] We suppress the i subscript when i is not needed for clarity.

We focus on TT_{cgt}, the average treatment effect of g for c majors who eventually go on to obtain g. Let $\overline{w}_{c0t}|G_{gt}$ be the mean of what these individuals would have earned had they *not* gone to graduate school. Let $\overline{w}_{cgt}|G_{gt}$ be the mean of actual earnings in t for c majors with a g degree. Let $p_{cgt}(j|A_t, Q_t)$ be the probability of choosing j in t given A_t, Q_t, c and g. Let $dF_t(A_t, Q_t|c, G_{gt})$ denote the conditional density of A and Q, which reflects selection based on choice of c and g, as discussed in Appendix B.1. Then

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

The treatment on the treated effect is

$$TT_{cgt} = \overline{w}_{cgt}|G_{gt} - \overline{w}_{c0t}|G_{gt}.$$

Comparing the expressions for $\overline{w}_{cgt}|G_{gt}$ and $\overline{w}_{c0t}|G_{gt}$ in (1) reveals that g affects earnings 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 $\overline{w}_{c0t}|G_{gt}$, which is the counterfactual earnings in t of those who chose c, g. The FE and FE-cg approaches, detailed in section 5.2, 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 $\overline{w}_{c0t-\tau}|G_{gt}$ after adjusting for age and time effects, where $t-\tau$ is prior to graduate school.

[23] 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. They do not find evidence of an earnings dip prior to entering an MBA. Nor do earnings rise for those who previously said that they expect to enroll in an MBA program but do not do so. However, it is possible that the issue is important for some of the other graduate degrees that we consider. We lack sufficient panel data to assess it.

[24] 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. One could also condition on other information such as undergraduate records and test scores if it were available.

Consideration of a randomized controlled trial provides insights into the challenge of identifying the causal effect of graduate education when multiple fields are available, even for those who work before graduate school. Suppose at the end of the pre-graduate school period (t_1 below), 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 on earnings is identified, and one could identify such effects for each value of pre-graduate school occupation (j_{t1} below). But these effects mix gains from an MBA relative to no advanced degree with gains relative to alternative graduate degrees. The counterfactual for the TT 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.[25] Consequently, while we will point out serious limitations of the FE-cg and FE approaches, they have the big advantage of providing a way to control for alternative graduate school options.

5.2 What Do Alternative Estimators of TT_{cg} 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 earnings discussed above. We consider 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). We consider the three period case. 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. We consider the 15 percent of individuals who go directly from college to graduate school in section 7.1.12. 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.

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

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

TT_{cgt3}^{OLS} is a biased estimator of TT_{cgt3} because both education and occupation choice depend on A and Q. This 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_{cgt3}^{OLS} 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 average earnings to differ for a given occupation. Second, A and Q influence occupation choice, and occupation matters for earnings.[26] Intuitively, an English major who 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.

[25] 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 exploits the fact that in some countries, university admission is centralized and in on the basis of test scores with program specific cutoffs. See also Hastings et al. (2013).

[26] 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.

5.2.2 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.[27] 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

$$\begin{aligned} TT^{FE}_{cgt3} &= E\left[w_{icgjt3} - w_{ic0jt_1}|c, G_{git3}\right] \qquad (2) \\ &= \sum_j \int_{A,Q} p_{cgt3}\left(j|A_{t3}, Q_{t3}\right) w_{cgjt3}\left(A_{t3}\right) dF_{t3}\left(A_{t3}, Q_{t3}|c, G_{gt3}\right) \\ &\quad -\sum_j \int_{A,Q} p_{c0t1}\left(j|A_{t1}, Q_{t1}\right) w_{c0jt1}\left(A_{t1}\right) dF_{t1}\left(A_{t1}, Q_{t1}|c, G_{gt3}\right). \end{aligned}$$

Comparing the above equation with (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 $TT^{FE}_{cgt3} = TT_{cgt3}$ if the distribution of A and Q does not change between t_1 and t_3. 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. However, other factors may lead to changes in A and Q (or updating of beliefs about A and Q) in the years after college.

To see the implications, consider a change in Q that would induce individuals both to move toward higher paying occupations and to get a degree g, say an MBA. Then $\overline{w}_{cgt_1}|G_{gt3}$ 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 were not to pursue an MBA. Her newly found 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.

Assumption A1 *(Constant ability and preferences)*:

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

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.

5.2.3 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, which we refer to as A2a-A2c.

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

A2a concerns the effects of new information about A and Q. New information arriving between t_2 and t_3 could still lead $dF_{t1}(A_{t1}, Q_{t1}|c, G_{gt3})$ and $dF_{t3}(A_{t3}, Q_{t3}|c, G_{gt3})$ to differ even if $dF_{t1}(A_{t1}, Q_{t1}|c, G_{gt3}) = dF_{t2}(A_{t2}, Q_{t2}|c, G_{gt3})$. The new information will induce a change in earnings, as individuals optimize across occupations. We assume that on average the earnings change from new information about A and Q would have been the same in the counterfactual case in which the person did not attend g.

Assumption A2b is that earnings growth within occupation is the same for all occupations conditional on college major and ability. Assumption A2c concerns the earnings growth from predictable shifts in occupation with experience. We assume that 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. In appendix B.2, we provide mathematical statements of the three assumptions.

The upshot of the three assumptions about experience effects is that c majors 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 do report some estimates that allow the experience profile to depend on graduate degree based on the specification in 6.1.

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

Our main econometric approach is closely related to the person fixed effects approach but allows us to use data on people who only are observed through t_2 or are only observed in t_3. Either way, we know whether they obtained g by the time they exited the sample. We make an additional assumption, A3, which is that the distributions $dF_{t3}(A_{t3}, Q_{t3}|c, G_{gt3})$ and $dF_{t1}(A_{t1}, Q_{t1}|c, G_{0t3})$ of A and Q do not depend on whether we observe an individual in t_1 only, t_3 only, or both $t_1$and t_3.

Consider the estimator

$$TT_{cgt3}^{\text{FEcg}} = \overline{w}_{cgt3}|G_{0t1}, G_{gt3} - \overline{w}_{c0t1}|G_{0t1}, G_{gt3},$$

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 and thus have the degree in t_3. Under assumptions A1, A3, and the parallel age trend assumptions mentioned in section 5.2.3, $TT_{cgt3}^{FEcg} = TT_{cgt3}$. We call this estimator 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_{cgt}^{FEcg} other than by helping to identify effects of control variables, including age profiles. In our main specification, we exclude them from the sample.

5.2.5 Occupation-Major Specific Treatment Effects

The earnings model assumes that early occupation does not have g specific or j_{t3} specific effects on future earnings.[28] We are also implicitly ruling out any effect of j_{t1} on the nonpecuniary costs of graduate school. 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 the 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 considering a PhD in Economics. Such individuals sometimes work as a research assistant for a year or two, in part

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

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 violations of separability are likely to be the strongest for PhD studies, which we do not consider in this paper. But it may be important for an MD degree and is unlikely to hold perfectly. Violations may lead to an overstatement of returns to some fields.

One could modify FE to estimate a separate TT effect for each c, g, j_{t1} combination. One could also modify FE-cg to estimate the c, g, j_{t1} specific treatment effect by 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}.[29] In practice, sample size considerations and lack of information about occupation prior to graduate school for those who are only surveyed after graduate school limits our ability to condition 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. We leave this to future research.

6 Econometric Specification

We work with a specification in which the effects of college and graduate school are additive and a specification in which the return to graduate school depends upon the undergraduate major. The additive specification is

$$w_{it} = a_1 + \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{g=1}^{\mathcal{G}} \gamma_g G_{g(i)t} + X_{it}\beta + u_{it}. \tag{3}$$

Here t denotes the year, $\alpha_0^c + \alpha_{age_{it}}^c$ is the return to c at age_{it} relative to the reference major (education), and $C_{c(i)}$ is a dummy variable for whether i majored in c. We specify $\alpha_{age_{it}}^c$ to be a major specific cubic polynomial in age_{it} and α_0^c to be a constant. Similarly, γ_g is the premium for graduate degree g relative to no graduate degree and $G_{g(i)t}$ is the associated indicator for whether i holds a g degree in t. The control vector X_{it} consists of the full set of interactions between gender and race\Hispanic indicators, a gender specific cubic in age_{it}, which we measure relative to age 35, and year dummies.[30]

The error term u_{it} may be written as $u_{it} = e_i + \varepsilon_{it}$. 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,

$$e_i = \sum_{c=1}^{\mathcal{C}} \sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)} + v_i \tag{4}$$

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 (3) and applies OLS to

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

[30] The year dummies in combination with age will control for cohort effects that are linear in birth year and partially control for nonlinear birth year effects. We observe undergraduate GPA for about 28 percent of the people in our sample. In preliminary work, controlling for GPA did not alter our results very much.

$$w_{it} = a_1 + \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{g=1}^{\mathcal{G}} \gamma_g G_{g(i)t} + X_{it}\beta + \sum_{c=1}^{\mathcal{C}}\sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)} + v_i + \varepsilon_{it} \tag{5}$$

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.[31]

The interactive specification is

$$w_{it} = a_1 + \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{c=1}^{\mathcal{C}}\sum_{g=1}^{\mathcal{G}} \gamma_{cg} C_{c(i)} G_{g(i)t} + X_{it}\beta + e_i + \varepsilon_{it}. \tag{6}$$

Here 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

$$w_{it} = a_1 + \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{c=1}^{\mathcal{C}}\sum_{g=1}^{\mathcal{G}} \gamma_{cg} C_{c(i)} G_{g(i)t} + X_{it}\beta + \sum_{c=1}^{\mathcal{C}}\sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)} + v_i + \varepsilon_{it}. \tag{7}$$

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 between e_i and BA major and graduate degree.

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 $c(i) = c$ is observed after graduate school and at least one person who eventually obtains g ($G_{g(i)} = 1$) is observed before graduate school. The before and after observations can be for different people.

A numerical example clarifies how observations contribute to the FE and FE-cg estimates. We abstract from age and time effects and other covariates. Table 4 presents earnings data for three individuals who obtained a 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.

6.1 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

$$\begin{aligned} w_{it} = a_1 &+ \sum_{c=2}^{\mathcal{C}} \left(\alpha_0^c + \alpha_{age_{it}}^c\right) C_{c(i)} + \sum_{g=1}^{\mathcal{G}} \gamma_{gx_{it}} G_{g(i)t} \\ &+ X_{it}\beta + \sum_{c=1}^{\mathcal{C}}\sum_{g=0}^{\mathcal{G}} b_{cg} C_{c(i)} G_{g(i)} + v_i + \varepsilon_{it}, \end{aligned} \tag{8}$$

[31] 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.

where x_{it} is years since i obtained the advanced degree. The variable x_{it} is 0 for those without an advanced degree in t. The return to g at x years after graduate school completion is given by $\gamma_{gx} = \gamma_{g0} + \gamma_{g1}x + \gamma_{g2}x^2$. In the OLS case, we exclude the term $\sum_{c=1}^{\mathcal{C}}\sum_{g=0}^{\mathcal{G}} b_{cg}C_{c(i)}G_{g(i)}$. We add experience interactions to the models with cg interactions using the parsimonious specification[32]

$$\gamma_{cgx} = \gamma_{gc0} + \gamma_{g1}x + \gamma_{g2}x^2. \tag{9}$$

If the return to g varies with time since graduate school, then the estimates of γ_g based on equations (3) and (5) 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 5 we report γ_g based on (3) and (5). 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 (8) with or without the $C_{c(i)}G_{g(i)}$ controls.[33] 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.

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 use the full sample, which includes 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 (5)) we use the graduate degree sample. We exclude college only individuals because the parameter of interest is treatment on the treated. However, when we allow for x_{it} interactions using equation (8), we use the full sample and assume that the age-earnings profile (but not the intercepts) for c majors who never go to graduate school is the counterfactual profile for c majors who do. 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. This could lead to upward bias if those who do not go to graduate school have flatter age profiles or different time trends than the counterfactual profiles of those who do. Using the full sample instead of the graduate degree sample usually leads to larger FE-cg estimates of γ_g that are usually closer to the OLS estimates. However, constraining graduate returns to be constant if they in fact rise with x_{it} might lead to upward bias in the age profiles, because $age_{it}$and x_{it} are correlated. This would lead to downward bias in γ_g as an estimate of the average return to g when equation (5)) is used.

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 the 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.

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

[33] 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.

7.1 Results Using the Additive Specification

Columns 1 and 2 of Table 5 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 (5). We use 19 aggregated BA categories and 19 aggregated graduate categories in most of our analyses. Column 1 uses the graduate degree sample. It is our preferred sample for FE-cg. Column 2 uses the full sample, which also includes the college only subsample. Columns 3-6 also use the full sample. Column 3 presents the corresponding OLS estimates based on equation (3).

Columns 4 and 5 present FE-cg and OLS estimates of γ_{g1_28} based on equation (8) 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 1, 2 and 3, column 6 presents the average of $\hat{\gamma}_{gx_{it}}$ over the distribution of x_{it} in the graduate degree 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 skewed somewhat to the left. Thus $\widehat{\gamma}_g$ places more weight on lower values, although it also places some weight on post graduate experience values above 28, while $\widehat{\gamma}_{g1\_28}$ does not.[34] Columns 7-11 correspond to columns 1-5 but are for the occupational component of earnings.

Before turning to Table 5, we note that Tables B1 and B2 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 small 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.[35] 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. Regressing the FE-cg estimates for the 19 graduate categories on the corresponding OLS estimates yields a slope of 0.607 (0.100) and a constant of 0.068 (0.026). Thus the FE-cg estimate tends to be small relative to the OLS estimate when OLS is large, and vice versa.[36] 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.[37] 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 0.549 (0.072) and the OLS estimate is 0.687 (0.016). The FE-cg estimate rises to 0.597 when the full sample is used (column 2). This points to the fact that part of

[34]Tables B7 and B8 report more detailed information about the experience profile of graduate school effects.

[35]For example, for engineering the estimates of $\hat{\gamma}_g$ range from -0.002 (0.034) for agricultural engineering to 0.249 (0.015) for computer and system engineering.

[36]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.

[37]The coefficient relating the gap to the g-specific average of the BA premiums is -0.603 (0.223).

the difference between OLS and FE-cg is the use of college only cases to estimate the counterfactual.

Columns 4 and 5 we report $\hat{\gamma}_{g1\_28}$ using the specification with g-specific experience profiles. The FE-cg estimate is 0.658 and the OLS estimate is 0.738. The FE-cg estimate of the return is only 0.072 (0.089) at one year, but rises to 0.659 (0.085) at 10 years and 0.867 (0.086) at 20 before declining to 0.606 (0.094) at 30 years (Tables B7 and B8). The college only observations in column 4 accounts for part of the difference between columns 1 and 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).[38] Consequently, the specification of the quadratic functional form for γ_{gx} as well as the choice of sample contribute to differences among the FE-cg estimates.

Columns 7-11 present a corresponding set of results for the occupational component of earnings. The FE-cg estimate is 0.492 (0.053) and the OLS estimate is 0.478 (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 (not controlling for degree type) are paid less on average than doctors.

Table B9 reports individual fixed effects estimates of γ_g. For the log of earnings, the FE point estimate is actually negative: -0.054 (0.107). 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 0.577 (0.092) 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 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 in future work.

7.1.2 Law

The FE-cg estimate of γ_g for a law degree is 0.416 (0.059). It is slightly below the OLS estimate. The estimate of γ_{g1_28} is 0.469 (0.056) in the case of FE-cg. Both approaches indicate that the return rises with time since graduation, as is documented in Table B7. The FE-cg estimates rise from 0.280 (0.060) one year after law school to 0.542 (0.058) 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 0.117 (0.058), although the FE results indicate that occupational upgrading is important and are in line with the other approaches. Given the partnership system and the importance of on the job training in law, one might expect the short time between law school and the earnings observations in the effective sample for FE to lead it to understate the earnings effect of a law degree while capturing the occupation related component.

Overall, the evidence indicates that the TT effect of a law degree is large – about 0.15 per year for a 3 year degree. Of course these estimates do not account for tuition costs, which are substantial especially at private universities.[39]

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

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

7.1.3 MBA and Other Business Related Master's Degrees

Row 4 of Table 5 reports estimates of the return to an MBA. The FE-cg estimate of γ_g is 0.110 (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: 0.181 and 0.308 respectively, reflecting the fact that the return rises with time since graduate school and that γ_g places more weight on the earlier years. 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 0.016 over the first 28 years. The comparable OLS estimate is 0.096. We believe that selection on ability and occupational preferences leads to substantial 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 who obtain an MBA.

The business related master's degree category consists of financial management (48.1%), business marketing and business management (24.8%), accounting (18.7%), agricultural economics (3.7%), marketing research (3.4%), other agricultural business and production (0.9%), 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 0.206 (0.044). This is a healthy return assuming that these programs take one or even two years if pursued full time. Occupation accounts for about 0.028 (0.013) of the return. The OLS estimate of γ_g is again much larger than FE-cg: 0.342 (0.012). Of this 0.107 (0.004) is through occupation alone. Like the MBA case, the gap between FE-cg and OLS is narrower for γ_{g1_28}. Most of the relative increase in the FE-cg estimate is due to the switch to the full sample.

7.1.4 MA in 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 0.273 (0.091). The OLS estimate is similar: 0.302 (0.026). Occupational returns account for 25% and 42% (respectively) of these effects. The FE-cg and OLS estimates of γ_g for public administration are about two thirds as large — 0.193 (0.052) and 0.212 (0.020), respectively. About half of the return is through occupation.

7.1.5 MA in Nursing

The FE-cg and OLS estimates of γ_g are 0.235 (0.041) and 0.313 (0.014) respectively, a large difference. The FE-cg estimate of γ_{g1_28} is 0.163 (0.038), which is 55 percent of the corresponding OLS estimate. FE-cg and OLS show similar occupation premiums of 0.02 and 0.03. 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 (26.9%), audiology and speech pathology (19.8%), public health (18.9%), other health/medical sciences (18.5%), pharmacy (9.1%), and health/medical assistant (4.2%). Both FE-cg and OLS show a return of about 0.22, with little variation with x_{it}. The FE-cg estimate suggests that 0.098 (0.022) 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 0.147 (0.005). For computer science and math, the FE-cg and OLS estimates are 0.179 (0.033) versus 0.204 (0.009). 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 B7 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 0.089 (0.057). The OLS estimate is 0.115 (0.013). 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 0.231 (0.045). The estimate for the physical sciences is 0.158 (0.054), which is also substantial. The estimates of γ_{g1_28} are about 0.10 and 0.13 higher. Most of these returns are within occupation. In sharp contrast, the corresponding OLS estimates are only 0.015 (0.011) and 0.053 (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.[40] 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 masters facilitates movement into higher paying administrative or specialized teaching positions. The FE-cg estimate of γ_g is 0.163 (0.019), of which 0.028 (0.007) 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 15.7% of the education category, and it pays better (Table B1). When we add the college only

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

observations and allow the return to depend on x_{it}, the effect rises from 0.109 (0.019) when $x_{it} = 1$ to 0.261 (0.019) when $x_{it} = 20$. The increase seems implausibly large.

In contrast, the OLS estimate is 0.102 (0.006), and it is only 0.045 (0.007) five years after the degree. OLS shows a substantial *negative* effect on occupational pay of -0.064 (0.003). 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 $\hat{\gamma}_{cg}$. 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.

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 is 0.202 (0.029), while the OLS value is only 0.056 (0.009). About 0.087 of the gap is because FE-cg implies a 0.025 (0.017) occupational return while OLS implies a *loss* of -0.062 (0.004).

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 0.018 (0.062). The small return is associated with an estimate of -0.076 (0.025) for occupational earnings. One interpretation of this finding is 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 -0.145 (0.014) and is driven by a huge -0.202 (0.008) 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 (13.2%), library science (39.3%), criminal justice/protective services (13.9%), and journalism (8.2%). The FE-cg estimate is 0.117 (0.056) while the OLS estimate is 0.064 (0.014). About 0.02 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.[41]

7.1.12 Returns for Individuals Who Go Directly to Graduate School

In our data 15% of those with graduate degrees when we last observe them went directly to graduate school after college. The fraction varies from 1.9% in Health administration to 62.1% for Medicine (Table B10). It would be useful to know whether our TT estimates also apply to degrees obtained directly after college. Relevant to the answer is whether those who go directly to graduate school are very different from those who do not. Table B10 reports that direct goers are 9.65 percentage points more likely to have a college educated father than those who delay, on a base of 40.54%. We also used the earnings regression coefficients on the race\Hispanic indicators to form a race\Hispanic earnings index for men and for women. The mean of the index is 0.004 higher for men who go direct and 0.001 higher for women who go direct. For most graduate fields, those who go direct have slightly higher grades (Table B10). The mean advantage is 0.067

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

on a 4.0 scale.[42] Overall, these results suggest those who go directly to graduate school are academically and economically advantaged relative to those who do not, but the differences seem small.[43]

Second, we also estimated equation (5) on a sample that includes those who went directly to graduate school, with an indicator for "go direct" added. The coefficient on "go direct" is 0.077 (0.008). The value falls to 0.043 (0.008) when we use the model with experience interactions (equation 8, suggesting that part of the gap is because direct goers have more post graduate school experience. Table B11 reports estimates of equation (5) with a full set of interactions between the G_{gt} indicators and "go direct" added. We do not have space to discuss the estimates but they are typically positive and are substantial for some degrees. For example, the value is only 0.004 for an MBA but 0.107 (0.019) for law and 0.081 (0.013) for engineering. The values fall when we include experience interactions. Caution is warranted, because the coefficients on the "go direct" interactions combine the difference in the return to a particular graduate degree for those who go direct and those who delay with differences between the two groups in the b_{cg} heterogeneity terms. A different identification strategy, perhaps based on a rich control set for family background, undergraduate achievement, and preferences, will be required to identify TT effects for those who go direct to graduate school.

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

Table 6 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 degrees 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 (National Center for Education Statistics (2019)). 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\Hispanic 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.[44] The PDV and counterfactual PDVs vary a great

[42] We control for BA field, advanced field, and year of college degree. The standard deviation of GPA is 0.41.

[43] Oyer (2006), Kahn (2010) and other studies find that leaving school during a recession has substantial effects on early earnings that persist. Labor market conditions also affect the decision to attend graduate school, an issue that is relevant to the discussion of Ashenfelter's dip. However, the empirical evidence is mixed (Altonji et al. (2016b)). College graduation year dummies explain only 0.004 of the variation in the "go direct" indicator, controlling for a cubic in graduation year (not shown). This indicates that going direct is only weakly related to labor market conditions at college graduation. Consequently, the effects of labor market conditions on the timing of graduate school and on pre graduate school earnings seem unlikely to matter much for our estimates.

[44] 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

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

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

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

deal across graduate degrees.

For medicine, the percentage gain in PDV (with tuition accounted for) is 41.6%. It is a 4 year degree, and $\hat{\rho}_g$ is 0.160. For law, the values are 28.7% and 0.148, while the percentage gain for an MBA is 1.1% and $\hat{\rho}_g$ is 0.059. 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. Using average private tuition lowers $\hat{\rho}_g$ to about 0.13 for medicine, and about 0.13 for law (not reported). It leads to a reduction of about 0.01 or 0.02 for the other fields. Table B12 uses the model (7) with experience interactions and reports values of $\hat{\rho}_g$ that are often lower even though γ_{1-28} is often higher, presumably because later career earnings are discounted. The values are 0.128 for medicine, 0.131 for law, 0.083 for an MBA, and 0.150 for engineering.

7.3 Returns by Gender

Tables B13 and B14 report summary statistics about earnings for men and women, by graduate field. Table 7 reports 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 5. 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 0.513 (0.187).[45] The female - male difference in the simple averages of coefficients is 0.042, but when one weights the coefficients using the shares of the advanced degrees in the pooled sample of men and women, the difference is only 0.003. It is interesting to note that women obtain a larger return to an MBA than men do: 0.156 (0.039) versus 0.091 (0.024), 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. In Table B15 we report results for 31 degree combinations with pre advanced observations on at least 31 individuals, but due to space constraints only consider a subset in the text and Table 8. Columns 1 and 2 of Table 8 report FE-cg and OLS estimates of the treatment effect for earnings. For completeness, columns 3 and 4 report the FE-cg estimates of γ_{cg} and γ_{cg1_28} using the full sample, which includes the college only observations. In column 4 the effect of x_{it} on earnings after graduate school depends on g but not c, as given in equation (9). We do not discuss these estimates, but they are typically larger than the FE-cg estimate of $\hat{\gamma}_{cg}$ when the college only observations are excluded (column 1). They are probably upward biased, while the sample weighted γ_{cg} parameter estimates in column 1 probably underestimate 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.

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.

[45] See footnote 36. The correction factor is 1.395.

7.4.1 MBA and Business Related Master's Degrees

The first 8 rows of Table 8 report the returns to an MBA for various undergraduate fields. For business majors the FE-cg estimate is 0.157 (0.065), while the OLS estimate is 0.239 (0.016). For economics majors the FE-cg estimate is 0.098 (0.070) and the OLS estimate is 0.280 (0.036). One might have expected the return to 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 0.065, but FE-cg does not.

Next we consider STEM majors. The FE-cg estimate of the return to an MBA for biological, agricultural, and environmental sciences majors is -0.107 (0.087). The value for engineering is only 0.083 (0.024). In contrast, the OLS estimates range from 0.221 (0.013) for engineering to a whopping 0.335 (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 0.153 (0.076) and 0.140 (0.102) for other social sciences and psychology. The corresponding OLS estimates are much larger—0.403 (0.049) and 0.399 (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, although sampling error is likely part of the story. The pattern suggests that for some undergraduate fields an MBA can provide the skills needed to facilitate a transition into a higher level business career.

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 8 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 masters is common. FE-cg indicates a return of 0.153 (0.028), of which 0.017 (0.009) is an occupational premium. The corresponding OLS estimate is even larger: 0.204 (0.008). 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 an 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. This is not the case for education majors, which may be why FE-CG and OLS are similar for them.

7.4.3 Other Master's Degrees

The return to a master's in engineering for engineering majors is 0.119 (0.021), of which 0.015 (0.012) is occupational upgrading. In this case, the OLS estimates are similar. We obtain a healthy return of 0.147 (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 about 0.14 in both cases.

For psychology or social work the FE-cg estimates of γ_{cg} are about 0.235 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.

7.4.4 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 premiums. We estimate a series of weighted regressions of the FE-cg estimate of $\hat{\gamma}_{cg}$ on the OLS estimate for the 113 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).[46] The OLS estimates are probably biased as estimates of causal effects, but they do capture differences across fields in the conditional mean of earnings.

When only $\hat{\gamma}_c$ is included, the coefficient is -0.204 (0.071), When both $\hat{\gamma}_c$ and $\hat{\gamma}_g$ are included, they enter with coefficients of -0.333 (0.095) and 0.480 (0.114) 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 $\hat{\gamma}_g$ 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 term is only 0.107. When the FE-cg estimates of γ_{cg}^{occ} for the occupation premium are used in place of $\hat{\gamma}_{cg}$, the estimates again indicate that the effect of g is smaller for those with high paying undergraduate degrees, especially for graduate degrees that pay well.

8 Concluding Remarks

Information about the labor market value of alternative graduate degrees is both critical to education decisions and in short supply. The biggest challenge, in addition to data, 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.

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 31 estimates of returns to graduate fields that are for specific undergraduate majors. The 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.

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

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. For most fields annual returns appear to rise with post graduate school experience. However, we suspect that the experience specific estimates may be biased because they require the use of data on people who never attend graduate school to identify the counterfactual experience profile. Third, estimates of internal rates of return, which account for tuition and program length, vary less across fields. They are also less sensitive to including experience interactions.

Fourth, the return to a given graduate field, such as an MBA, depends on the college major. Fifth, 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 as 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 experience adjusted 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.[47]

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 on institutions that are collected in the NSCG and NSRCG were made available to researchers. We also stressed that our results are for people who work before going to graduate school. The returns in some fields could be 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.

Despite these limitations 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.

[47]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

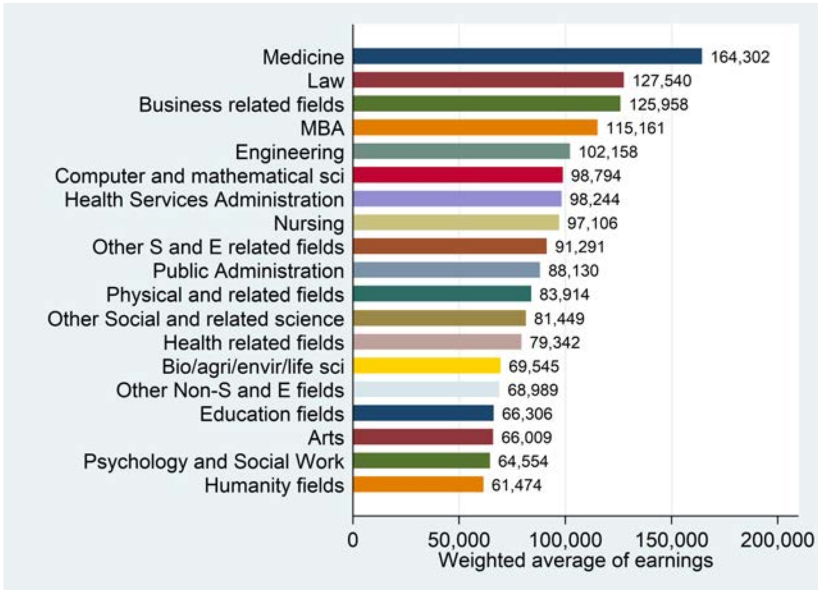

Figure 1: Average earnings by advanced field

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.

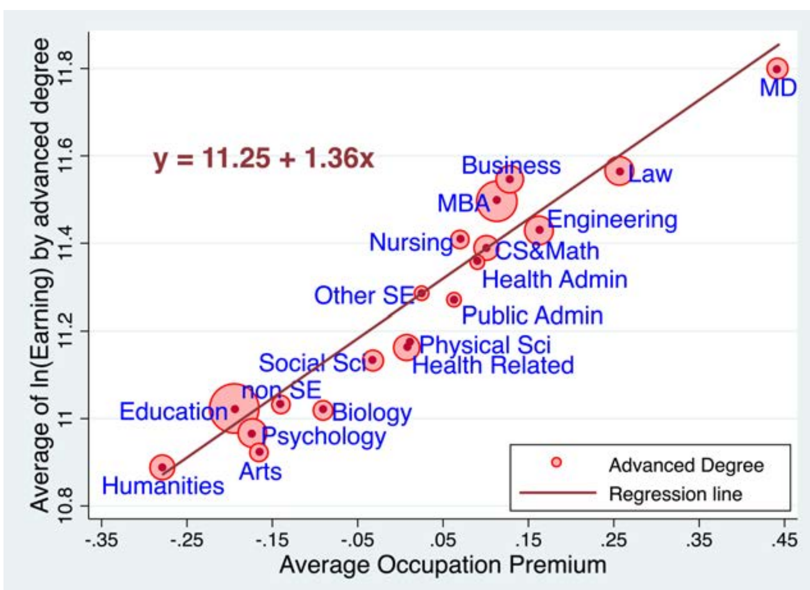

Figure 2: Average ln(earnings) of advanced fields by average occupation premium

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.

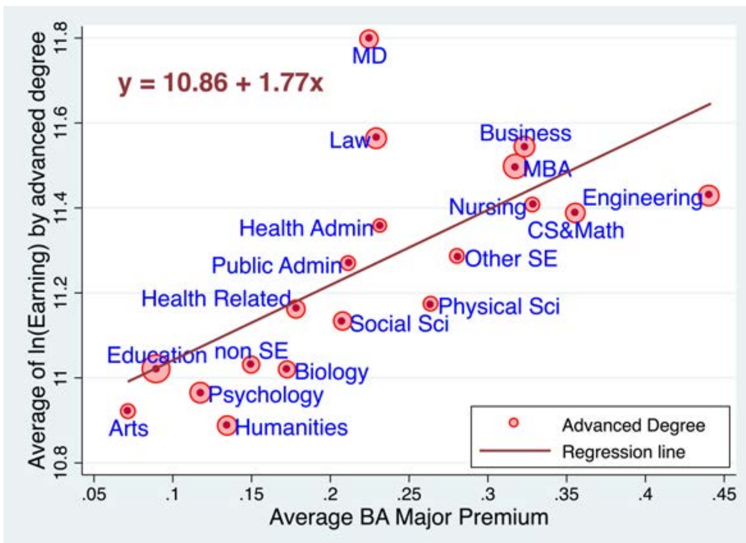

Figure 3: Average ln(earnings) of advanced fields by average BA major premium

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 0.34. 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.

Tables

Table 1: 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	164,317 [104,585]	11.797 [0.695]	0.443 [0.181]	0.225 [0.101]	8,470	3.717
Law	128,813 [90,921]	11.563 [0.652]	0.258 [0.140]	0.230 [0.113]	9,950	6.949
Master's in Business related fields	122,957 [85,639]	11.543 [0.591]	0.130 [0.192]	0.324 [0.124]	11,240	6.563
MBA	113,177 [67,599]	11.495 [0.542]	0.114 [0.215]	0.318 [0.132]	30,140	13.714
Master's in Engineering	101,916 [51,287]	11.428 [0.471]	0.164 [0.140]	0.441 [0.087]	63,560	7.000
Master's in Computer and mathematical sciences	98,898 [50,789]	11.386 [0.500]	0.102 [0.176]	0.356 [0.130]	26,510	5.259
Master's in Health Services Admin.	97,979 [57,931]	11.356 [0.520]	0.091 [0.227]	0.232 [0.107]	2,430	1.088
Master's in Nursing	97,553 [43,653]	11.406 [0.408]	0.071 [0.163]	0.329 [0.049]	4,440	1.767
Master's in Other Science and Engineering related fields	90,477 [53,875]	11.284 [0.513]	0.026 [0.219]	0.281 [0.118]	4,430	1.640
Master's in Public Administration	88,437 [44,286]	11.268 [0.517]	0.064 [0.254]	0.212 [0.103]	3,460	1.781
Master's in Physical and related sciences	83,227 [46,735]	11.172 [0.595]	0.013 [0.191]	0.264 [0.092]	14,700	1.667
Master's in Other Social and related sciences	81,130 [56,708]	11.131 [0.585]	-0.031 [0.255]	0.208 [0.125]	17,190	3.628
Master's in Health related fields	79,264 [45,515]	11.161 [0.488]	0.009 [0.219]	0.179 [0.125]	11,320	3.995
Master's in Biological / agricultural / environmental / life sciences	69,445 [39,952]	11.018 [0.518]	-0.089 [0.208]	0.173 [0.094]	18,160	3.038
Master's in Other Non-Science and Engineering fields	69,023 [38,552]	11.030 [0.472]	-0.139 [0.239]	0.150 [0.098]	4,000	2.869
Master's in Education fields	66,174 [29,774]	11.020 [0.403]	-0.193 [0.205]	0.090 [0.104]	29,390	21.751
Master's in Arts	65,212 [48,187]	10.920 [0.571]	-0.164 [0.207]	0.072 [0.095]	2,330	1.804
Master's in Psychology and Social Work	64,541 [34,381]	10.964 [0.471]	-0.172 [0.236]	0.118 [0.082]	20,970	6.860
Master's in Humanity fields	61,536 [39,599]	10.887 [0.525]	-0.278 [0.272]	0.135 [0.110]	6,660	4.909

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. Column 5 presents the unweighted cell counts, rounded to the nearest 10, of the regression sample excluding the constructed occupation observations for 1988. Column 6 presents the weighted percentages of each advanced field of the regression sample using the regression weights.

Table 2: 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	15.16	67,837
	2	Electrical engineer	12.38	70,696
	3	Civil engineers	12.24	65,031
	4	Not-elsewhere-classified engineers	8.97	67,518
	5	Computer software developers	6.24	73,822
Have an MBA by last observation		Pre Adv Occupation before age 45		
	1	Mechanical engineers	15.25	69,839
	2	Electrical engineer	14.55	73,585
	3	Not-elsewhere-classified engineers	10.45	76,191
	4	Industrial engineers	9.21	69,919
	5	Top-level managers, executives, administrators	6.19	96,982
		Post Adv Occupation before age 59		
	1	Top-level managers, executives, administrators	17.27	151,210
	2	Mechanical engineers	9.29	96,330
	3	Electrical engineer	9.04	95,666
	4	Other management related occupations	7.06	120,469
	5	Managers and administrators, n.e.c.	6.82	132,180
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	46.49	65,805
	2	Postsecondary Teachers	10.70	72,512
	3	Top-level managers, executives, administrators	5.17	83,531
	4	Other management related occupations	4.80	85,472
	5	Managers in education and related fields	3.32	74,616
Have a Master's in Engineering		Pre Adv Occupation before age 45		
	1	Electrical engineer	22.85	67,798
	2	Mechanical engineers	16.54	66,747
	3	Not-elsewhere-classified engineers	11.96	64,654
	4	Aeronautical/aerospace/astronautical engineers	11.71	65,358
	5	Civil engineers	9.01	64,756
		Post Adv Occupation before age 59		
	1	Electrical engineer	16.21	94,987
	2	Mechanical engineers	13.57	88,893
	3	Civil engineers	12.51	87,868
	4	Not-elsewhere-classified engineers	10.58	94,738
	5	Computer software developers	7.86	96,650

Note: Tables 2-3 report occupation distributions and average earnings by BA field and advanced degree field and status. All statistics are weighted. The sample excludes observations based on the annual earnings in the previous year. 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 report 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 2 focuses on people with a BA in Engineering.

Table 3: Occupation choices of individuals with BA in Education by advanced degree choice

Educational background	Rank	Occupation before age 35	%	Average earnings
No advanced degree	1	Secondary school teachers	26.32	42,720
	2	Primary school teachers	25.89	40,812
	3	Kindergarten and earlier school teachers	5.21	36,359
	4	Secretaries	3.99	37,331
	5	Top-level managers, executives, administrators	2.73	57,770
Have an MBA		Pre Adv Occupation before age 45		
		Not teachers		
		Post Adv Occupation before age 59		
	1	Top-level managers, executives, administrators	12.87	129,247
	2	Other management related occupations	8.04	68,075
	3	Computer systems analysts and computer scientists	7.77	85,146
	4	Accountants, auditors, and other financial specialists	7.24	69,521
	5	Personnel, training, and labor relations specialists	6.7	90,492
Have a Master's in Education		Pre Adv Occupation before age 45		
	1	Secondary school teachers	40.98	42,961
	2	Primary school teachers	36.08	43,581
	3	Postsecondary Teachers	5.67	58,166
	4	Kindergarten and earlier school teachers	3.35	30,082
	5	Vocational and educational counselors	2.32	42,652
		Post Adv Occupation before age 59		
	1	Secondary school teachers	31.06	61,917
	2	Primary school teachers	26.08	59,601
	3	Top-level managers, executives, administrators	8.01	83,162
	4	Vocational and educational counselors	7.22	61,624
	5	Postsecondary Teachers	4.89	61,625

Note: This table repeats the case study presented in Table 2, but focusing on people with a BA in Education.

Table 4: 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 5: Returns to graduate education, additive specification

Dependent variable:	ln(earnings)						Occupational Premium				
				w/ post Adv exp. interaction						w/ post Adv exp. interaction	
	FE-cg†	FE-cg full	OLS	FE-cg 1∼28 yrs*	OLS 1∼28 yrs*	FE-cg all years#	FE-cg†	FE-cg full	OLS	FE-cg 1∼28 yrs*	OLS 1∼28 yrs*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Medicine	0.549	0.597	0.687	0.658	0.738	0.619	0.492	0.482	0.478	0.478	0.475
	(0.072)	(0.083)	(0.016)	(0.084)	(0.016)	(0.084)	(0.053)	(0.057)	(0.005)	(0.057)	(0.005)
Law	0.416	0.438	0.457	0.469	0.474	0.462	0.319	0.307	0.291	0.307	0.289
	(0.059)	(0.056)	(0.015)	(0.056)	(0.015)	(0.056)	(0.033)	(0.033)	(0.004)	(0.033)	(0.004)
Master's in Business related fields	0.206	0.238	0.342	0.265	0.358	0.248	0.028	0.031	0.107	0.036	0.112
	(0.044)	(0.044)	(0.012)	(0.044)	(0.013)	(0.044)	(0.013)	(0.013)	(0.004)	(0.013)	(0.004)
MBA	0.11	0.142	0.282	0.181	0.308	0.162	0.010	0.012	0.092	0.016	0.096
	(0.021)	(0.021)	(0.008)	(0.021)	(0.009)	(0.020)	(0.007)	(0.007)	(0.003)	(0.008)	(0.004)
Master's in Engineering	0.103	0.146	0.147	0.198	0.184	0.165	0.017	0.024	0.063	0.027	0.067
	(0.018)	(0.019)	(0.005)	(0.019)	(0.007)	(0.019)	(0.010)	(0.011)	(0.002)	(0.011)	(0.002)
Master's in Computer and mathematical sciences	0.179	0.192	0.204	0.228	0.232	0.202	0.011	0.010	0.064	0.009	0.064
	(0.033)	(0.033)	(0.009)	(0.034)	(0.011)	(0.033)	(0.010)	(0.010)	(0.003)	(0.010)	(0.004)
Master's in Health Services Administration	0.273	0.259	0.302	0.300	0.342	0.268	0.069	0.059	0.127	0.074	0.144
	(0.091)	(0.088)	(0.026)	(0.091)	(0.031)	(0.088)	(0.028)	(0.030)	(0.010)	(0.032)	(0.012)
Master's in Nursing	0.235	0.181	0.313	0.163	0.294	0.181	0.023	0.010	0.032	0.006	0.024
	(0.041)	(0.036)	(0.014)	(0.038)	(0.018)	(0.036)	(0.010)	(0.009)	(0.006)	(0.010)	(0.008)
Master's in Other Science and Engineering related fields	-0.018	-0.002	0.097	0.024	0.106	0.002	0.025	0.015	0.016	0.017	0.018
	(0.058)	(0.056)	(0.019)	(0.056)	(0.019)	(0.056)	(0.040)	(0.040)	(0.009)	(0.040)	(0.009)
Master's in Public Administration	0.193	0.214	0.212	0.263	0.246	0.229	0.104	0.104	0.111	0.122	0.126
	(0.052)	(0.052)	(0.020)	(0.053)	(0.020)	(0.052)	(0.034)	(0.034)	(0.009)	(0.034)	(0.009)
Master's in Physical and related sciences	0.158	0.224	0.053	0.285	0.094	0.245	-0.018	-0.022	0.010	-0.025	0.008
	(0.054)	(0.052)	(0.015)	(0.053)	(0.016)	(0.052)	(0.018)	(0.018)	(0.006)	(0.019)	(0.007)
Master's in Other Social and related sciences	0.089	0.118	0.115	0.164	0.144	0.134	0.027	0.019	0.029	0.027	0.036
	(0.057)	(0.056)	(0.013)	(0.057)	(0.017)	(0.056)	(0.023)	(0.022)	(0.006)	(0.023)	(0.007)
Master's in Health related fields	0.227	0.232	0.219	0.246	0.214	0.240	0.098	0.084	0.078	0.077	0.069
	(0.053)	(0.052)	(0.012)	(0.054)	(0.015)	(0.053)	(0.022)	(0.021)	(0.005)	(0.022)	(0.007)
Master's in Bio/agricultural/ environmental/life sciences	0.231	0.276	0.015	0.331	0.049	0.298	0.029	0.032	-0.021	0.040	-0.015
	(0.045)	(0.046)	(0.011)	(0.046)	(0.012)	(0.045)	(0.014)	(0.014)	(0.005)	(0.015)	(0.006)
Master's in Other Non-Science and Engineering fields	0.117	0.148	0.064	0.187	0.085	0.173	-0.034	-0.031	-0.053	-0.030	-0.054
	(0.056)	(0.055)	(0.014)	(0.056)	(0.015)	(0.056)	(0.025)	(0.025)	(0.008)	(0.026)	(0.008)
Master's in Education fields	0.162	0.188	0.102	0.218	0.118	0.210	0.028	0.025	-0.064	0.032	-0.059
	(0.019)	(0.018)	(0.006)	(0.018)	(0.006)	(0.018)	(0.007)	(0.007)	(0.003)	(0.007)	(0.003)
Master's in Arts	-0.025	-0.022	-0.001	0.021	0.018	0.003	0.027	0.024	-0.051	0.026	-0.051
	(0.099)	(0.103)	(0.023)	(0.103)	(0.023)	(0.103)	(0.039)	(0.040)	(0.009)	(0.040)	(0.009)
Master's in Psychology and Social Work	0.202	0.200	0.056	0.254	0.091	0.218	0.025	0.011	-0.062	0.023	-0.054
	(0.029)	(0.029)	(0.009)	(0.030)	(0.010)	(0.029)	(0.017)	(0.017)	(0.004)	(0.017)	(0.005)
Master's in Humanity fields	0.018	0.037	-0.145	0.063	-0.138	0.060	-0.076	-0.079	-0.202	-0.076	-0.201
	(0.062)	(0.060)	(0.014)	(0.060)	(0.014)	(0.060)	(0.025)	(0.024)	(0.008)	(0.025)	(0.008)

(† graduate degree sample, which only includes people who have an advanced degree when they are last observed; * γ_{g1-28}; # sample mean over x of γ_{gx})

Note: The table reports estimates of returns to advanced degrees for a set of additive regression specifications. Sample weights are used. Standard errors are clustered by person. The dependent variable is log earnings in col. 1-6 and the occupation premium in col. 7-11. The regressions include dummies for each BA field (OLS only) and each advanced degree, as well as parental education, the year, interactions between a cubic in age and gender, a cubic in age and BA field, and between race\Hispanic and gender. The age polynomials and the year dummies control for linear birth cohort trend and partially control for nonlinear birth cohort effects. Col. 1 and 7 report FE-cg estimates of γ_g on the graduate degree sample using equation (10). Cell counts for this sample for earnings range from 2,410 for an MA Arts to 64,810 for an MA in Engineering. Columns 2-6 and 8-11 use the full sample. Col. 2 and 8 report FE-cg estimates of γ_g using (10). Col. 3 and 9 report OLS estimates of γ_g using (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 attainment. They are based on (13), with degree combination fixed effects excluded in the OLS case. Col. 6 is the same as col. 4 but reports the mean of γ_{gx} over sample distribution of x; see the notes to Table B7 for details. The graduate (full) sample has 297,530 (858,130) observations for earnings and 195,540 (581,280) for occupation.

Table 6: 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	1,810,100	1,277,127	41.565	0.160
Law	3	16,697	1,497,405	1,162,502	28.700	0.148
Master's in Business related fields	2	6,736	1,600,132	1,430,585	11.815	0.130
MBA	2	9,311	1,498,869	1,482,262	1.069	0.059
Master's in Engineering	1	8,131	1,603,010	1,515,778	5.746	0.128
Master's in Computer and mathematical sciences	1	8,131	1,486,989	1,306,222	13.809	0.213
Master's in Health Services Administration	2	6,736	1,317,210	1,110,126	18.573	0.161
Master's in Nursing	2	8,131	1,772,490	1,579,679	12.230	0.123
Master's in Other Science and Engineering related fields	1	8,131	1,176,934	1,258,478	-6.513	Negative
Master's in Public Administration	2	6,736	1,326,570	1,204,609	10.053	0.117
Master's in Physical and related sciences	1	8,131	1,149,323	1,026,048	11.992	0.196
Master's in Other Social and related sciences	1	6,736	1,089,713	1,046,047	4.135	0.107
Master's in Health related fields	2	8,131	1,169,304	1,033,358	13.034	0.130
Master's in Bio/agricultural/ environmental/life sciences	1	8,131	1,019,034	848,672	20.050	0.266
Master's in Other Non-Science and Engineering fields	1	6,736	1,009,283	943,427	6.953	0.138
Master's in Education fields	1	6,736	968,676	867,243	11.668	0.184
Master's in Arts	2	6,736	875,820	995,711	-12.132	Negative
Master's in Psychology and Social Work	2	6,736	891,215	807,823	10.240	0.114
Master's in Humanity fields	1	6,736	846,302	873,830	-3.176	Negative

Note: The statistics are calculated from regression coefficients underlying the FE-cg estimates reported in Table 5, 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\Hispanic indicators to non-Hispanic white. For each graduate degree we calculate the population weighted average of predicted earnings at each age over the distribution of gender and of undergraduate major for that graduate degree. We subtract the tuition of the graduate degree from 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 the 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 7: 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 1∼28 yrs	FE-cg†	OLS	FE-cg 1∼28 yrs	FE-cg†	OLS	FE-cg 1∼28 yrs	FE-cg†	OLS	FE-cg 1∼28 yrs
Medicine	0.452	0.640	0.548	0.552	0.518	0.513	0.514	0.703	0.730	0.456	0.460	0.465
	(0.132)	(0.030)	(0.161)	(0.097)	(0.008)	(0.115)	(0.096)	(0.020)	(0.083)	(0.049)	(0.006)	(0.050)
Law	0.439	0.518	0.527	0.345	0.346	0.335	0.405	0.422	0.470	0.316	0.265	0.310
	(0.070)	(0.023)	(0.067)	(0.042)	(0.006)	(0.043)	(0.095)	(0.018)	(0.092)	(0.051)	(0.004)	(0.050)
Master's in Business related fields	0.240	0.375	0.313	0.022	0.135	0.045	0.177	0.327	0.242	0.033	0.098	0.038
	(0.079)	(0.024)	(0.082)	(0.025)	(0.009)	(0.026)	(0.052)	(0.014)	(0.052)	(0.015)	(0.005)	(0.015)
MBA	0.156	0.354	0.243	0.022	0.124	0.030	0.091	0.250	0.170	0.005	0.079	0.012
	(0.039)	(0.016)	(0.041)	(0.015)	(0.006)	(0.016)	(0.024)	(0.009)	(0.024)	(0.008)	(0.004)	(0.008)
Master's in Engineering	0.044	0.182	0.190	-0.002	0.081	0.002	0.117	0.138	0.207	0.020	0.059	0.029
	(0.041)	(0.014)	(0.046)	(0.020)	(0.005)	(0.022)	(0.021)	(0.006)	(0.022)	(0.012)	(0.002)	(0.013)
Master's in Computer and mathematical sciences	0.241	0.231	0.288	0.017	0.083	0.017	0.149	0.191	0.199	0.007	0.056	0.005
	(0.066)	(0.018)	(0.067)	(0.019)	(0.007)	(0.020)	(0.036)	(0.010)	(0.037)	(0.012)	(0.004)	(0.012)
Master's in Health Services Administration	0.279	0.294	0.316	0.048	0.108	0.047	0.092	0.323	0.170	0.109	0.156	0.111
	(0.100)	(0.029)	(0.102)	(0.030)	(0.012)	(0.034)	(0.128)	(0.045)	(0.133)	(0.060)	(0.018)	(0.061)
Master's in Nursing	0.190	0.275	0.120	0.022	0.028	0.001	0.567	0.576	0.574	0.028	0.069	0.074
	(0.043)	(0.015)	(0.038)	(0.011)	(0.006)	(0.011)	(0.113)	(0.039)	(0.136)	(0.032)	(0.013)	(0.034)
Master's in Other Science and Engineering related fields	0.074	0.134	0.166	0.116	0.039	0.126	-0.072	0.079	-0.027	-0.013	0.008	-0.020
	(0.106)	(0.042)	(0.110)	(0.075)	(0.016)	(0.070)	(0.058)	(0.022)	(0.055)	(0.042)	(0.010)	(0.043)
Master's in Public Administration	0.172	0.273	0.245	0.082	0.108	0.088	0.219	0.170	0.289	0.125	0.113	0.147
	(0.061)	(0.032)	(0.066)	(0.048)	(0.016)	(0.048)	(0.077)	(0.025)	(0.078)	(0.045)	(0.011)	(0.044)
Master's in Physical and related sciences	0.032	0.087	0.191	0.007	0.015	-0.006	0.203	0.038	0.330	-0.027	0.007	-0.034
	(0.073)	(0.027)	(0.084)	(0.027)	(0.011)	(0.029)	(0.066)	(0.018)	(0.062)	(0.022)	(0.007)	(0.023)
Master's in Other Social and related sciences	0.147	0.168	0.235	0.039	0.044	0.040	0.033	0.072	0.124	0.023	0.017	0.028
	(0.080)	(0.017)	(0.081)	(0.027)	(0.008)	(0.026)	(0.077)	(0.020)	(0.079)	(0.040)	(0.008)	(0.039)
Master's in Health related fields	0.327	0.220	0.302	0.102	0.076	0.065	0.012	0.232	0.101	0.100	0.090	0.103
	(0.063)	(0.013)	(0.065)	(0.023)	(0.006)	(0.023)	(0.073)	(0.023)	(0.077)	(0.050)	(0.011)	(0.051)
Master's in Bio/agricultural/ environmental/life sciences	0.232	0.077	0.301	0.021	0.002	0.029	0.219	-0.035	0.378	0.033	-0.039	0.044
	(0.069)	(0.015)	(0.070)	(0.022)	(0.007)	(0.022)	(0.062)	(0.016)	(0.060)	(0.020)	(0.007)	(0.020)
Master's in Other Non-Sci and Engineering fields	0.154	0.100	0.224	-0.072	-0.069	-0.070	0.094	0.024	0.159	0.020	-0.031	0.025
	(0.072)	(0.018)	(0.075)	(0.037)	(0.009)	(0.038)	(0.092)	(0.024)	(0.089)	(0.032)	(0.013)	(0.033)
Master's in Education fields	0.196	0.154	0.253	0.016	-0.055	0.021	0.087	0.016	0.151	0.049	-0.075	0.057
	(0.023)	(0.007)	(0.022)	(0.009)	(0.003)	(0.009)	(0.034)	(0.010)	(0.034)	(0.011)	(0.005)	(0.011)
Master's in Arts	0.024	0.027	0.089	0.035	-0.027	0.026	-0.091	-0.024	-0.064	0.000	-0.070	0.025
	(0.119)	(0.032)	(0.122)	(0.055)	(0.013)	(0.055)	(0.159)	(0.033)	(0.165)	(0.052)	(0.013)	(0.057)
Master's in Psychology and Social Work	0.205	0.101	0.264	0.016	-0.055	0.007	0.201	-0.021	0.262	0.056	-0.067	0.060
	(0.033)	(0.010)	(0.033)	(0.018)	(0.005)	(0.018)	(0.065)	(0.017)	(0.062)	(0.038)	(0.009)	(0.038)
Master's in Humanity fields	0.163	0.019	0.232	-0.054	-0.091	-0.051	-0.049	-0.247	0.005	-0.087	-0.263	-0.084
	(0.061)	(0.019)	(0.059)	(0.030)	(0.010)	(0.030)	(0.097)	(0.018)	(0.095)	(0.032)	(0.010)	(0.032)

(† graduate degree sample, which only includes people who have an advanced degree when they are last observed)

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\Hispanic 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 an FE-cg regression on the graduate degree sample. The specification is equation (10). Cell counts for this FE-cg regression specification are identical to the cell counts reported in Table B13 and Table B14. 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 the simple average of return to each advanced degree between 1 and 28 years after degree obtainment. The specification is equation (13) and the full sample. A detailed explanation for the construction of these averages is provided in the notes for Table B7.

Table 8: Returns to graduate education by undergraduate fields

Advanced field	Undergraduate field	ln(earnings)				Occupation premium		Earnings	# of pre Adv obs
		FE-cg†	FE-cg full	OLS	γ_{g1-28}*	FE-cg†	OLS	Mean [SD]	person-yr [person]
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) **MBA**	Bio/agricultural/environmental sci.	-0.107	-0.049	0.335	0.005	0.114	0.162	104,487	140
		(0.087)	(0.089)	(0.038)	(0.089)	(0.036)	(0.015)	[71,152]	[70]
	Business	0.157	0.185	0.239	0.215	0.008	0.062	106,338	110
		(0.065)	(0.062)	(0.016)	(0.063)	(0.016)	(0.006)	[63,644]	[90]
	Computer and mathematical sci.	0.093	0.086	0.244	0.127	0.007	0.051	111,408	220
		(0.053)	(0.053)	(0.026)	(0.053)	(0.018)	(0.010)	[63,853]	[120]
	Economics	0.098	0.171	0.280	0.200	-0.006	0.069	124,810	100
		(0.070)	(0.057)	(0.036)	(0.058)	(0.028)	(0.013)	[79,541]	[60]
	Engineering	0.083	0.127	0.221	0.165	0.002	0.037	125,730	870
		(0.024)	(0.023)	(0.013)	(0.024)	(0.010)	(0.005)	[68,201]	[460]
	Other Social and related sci.	0.153	0.200	0.403	0.238	0.052	0.188	103,004	80
		(0.076)	(0.075)	(0.049)	(0.075)	(0.041)	(0.018)	[70,458]	[40]
	Physical and related sci.	0.131	0.159	0.292	0.211	0.063	0.104	116,660	60
		(0.123)	(0.119)	(0.049)	(0.119)	(0.042)	(0.020)	[64,735]	[40]
	Psychology or Social Work	0.140	0.133	0.399	0.184	0.043	0.194	98,845	80
		(0.102)	(0.100)	(0.042)	(0.100)	(0.037)	(0.019)	[59,509]	[50]
(2) **Master's in Business related fields**	Business	0.271	0.305	0.277	0.328	0.030	0.081	113,906	70
		(0.090)	(0.092)	(0.020)	(0.092)	(0.019)	(0.006)	[81,716]	[60]
	Economics	0.039	0.117	0.361	0.133	-0.011	0.100	141,223	70
		(0.105)	(0.092)	(0.045)	(0.092)	(0.025)	(0.015)	[103,505]	[40]
	Engineering	0.084	0.138	0.269	0.163	0.014	0.030	137,198	150
		(0.051)	(0.050)	(0.030)	(0.050)	(0.023)	(0.009)	[80,653]	[70]
(3) **Master's in Education**	Bio/agricultural/environmental sci.	0.093	0.163	0.035	0.208	0.026	-0.079	66,709	160
		(0.061)	(0.060)	(0.025)	(0.060)	(0.019)	(0.013)	[37,250]	[80]
	Computer and mathematical sci.	0.175	0.153	-0.147	0.175	0.072	-0.191	69,224	180
		(0.066)	(0.066)	(0.026)	(0.066)	(0.029)	(0.017)	[30,063]	[100]
	Education	0.153	0.185	0.204	0.209	0.017	-0.009	64,584	230
		(0.028)	(0.025)	(0.008)	(0.025)	(0.009)	(0.004)	[27,230]	[180]
	Other Social and related sci.	0.174	0.230	0.110	0.254	0.022	-0.064	65,574	170
		(0.047)	(0.048)	(0.024)	(0.048)	(0.023)	(0.012)	[31,374]	[90]
	Physical and related sci.	0.172	0.233	-0.128	0.281	0.064	-0.214	66,977	90
		(0.078)	(0.075)	(0.045)	(0.076)	(0.048)	(0.019)	[27,996]	[50]
	Political science	0.035	0.024	-0.056	0.058	0.039	-0.119	73,058	80
		(0.095)	(0.095)	(0.049)	(0.095)	(0.043)	(0.022)	[38,120]	[40]
	Psychology or Social Work	0.243	0.226	0.089	0.266	0.037	-0.074	61,028	190
		(0.043)	(0.043)	(0.018)	(0.043)	(0.021)	(0.010)	[28,240]	[120]
(4) **Master's in Engineering**	Engineering	0.119	0.170	0.110	0.220	0.015	0.038	101,372	1,070
		(0.021)	(0.021)	(0.006)	(0.022)	(0.012)	(0.002)	[50,854]	[630]
	Physical and related sci.	0.080	0.137	0.248	0.197	0.044	0.143	99,008	60
		(0.085)	(0.082)	(0.022)	(0.082)	(0.040)	(0.006)	[46,062]	[40]
(5) **Master's in Computer and math sci.**	Computer and mathematical sci.	0.147	0.137	0.142	0.173	0.002	0.023	95,083	330
		(0.055)	(0.053)	(0.012)	(0.054)	(0.015)	(0.005)	[46,515]	[180]
	Engineering	0.056	0.093	0.133	0.136	0.000	0.034	102,825	150
		(0.050)	(0.047)	(0.015)	(0.047)	(0.013)	(0.004)	[50,290]	[80]
(10) **Master's in Psychology and Social Work**	Other Social and related sci.	0.232	0.262	0.101	0.292	0.037	-0.074	63,118	90
		(0.065)	(0.067)	(0.019)	(0.066)	(0.030)	(0.011)	[28,577]	[50]
	Psychology or Social Work	0.238	0.208	0.090	0.272	0.024	-0.045	62,264	290
		(0.035)	(0.033)	(0.012)	(0.034)	(0.020)	(0.007)	[36,053]	[180]

(† graduate degree sample, which only includes people who have an advanced degree when they are last observed; * FE-cg with experience profile, averaged over 1∼28 years)

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 estimates 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 on the full sample. 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 B7. Column 7 presents the mean and [standard deviation] of the annualized basic salary of the principal job in 2013 dollars for people with each combination of undergraduate and graduate field. Column 8 presents the individual-level cell count and [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. The individual-level cell count counts multiple observations of one individual as one. Unweighted cell counts are rounded to the nearest 10. A complete set of estimates of degree combinations with at least 30 individuals is provided in Table B15.

Appendix A

Table A1: Summary statistics of the control variables

Gender		
	Percentage	Frequency
	(1)	(2)
Female	41.90	315,550
Male	58.10	542,580
Total	100	858,130
Gender and Race		
Asian, Female	2.74	36,520
Asian, Male	3.75	64,000
Black Hispanic, Female	0.11	1,400
Black Hispanic, Male	0.09	1,320
Black Non-hispanics, Female	3.69	39,360
Black Non-hispanics, Male	2.73	32,190
Native American, Female	0.31	4,150
Native American, Male	0.33	5,410
Other race, Female	0.66	8,400
Other race, Male	0.69	10,010
White Hispanic, Female	2.08	27,040
White Hispanic, Male	2.30	35,380
White Non-hispanic, Female	32.32	198,690
White Non-hispanic, Male	48.21	394,260
Father's education attainment		
Less than high school	15.15	123,300
High school diploma	28.01	223,740
Some college, vocational, trade school, 2-year college	18.66	156,550
College Degree	20.46	189,120
Master's degree (including MBA)	6.11	61,090
Professional degree (e.g. JD, LLB, MD, DDS, etc.)	9.75	84,010
Doctorate (e.g. PhD, DSc, EdD, etc.)	1.86	20,310
Mother's education attainment		
Less than high school	12.30	112,040
High school diploma	38.00	300,110
Some college, vocational, trade school, 2-year college	22.13	184,320
College Degree	17.81	165,090
Master's degree (including MBA)	4.99	51,750
Professional degree (e.g. JD, LLB, MD, DDS, etc.)	4.19	38,190
Doctorate (e.g. PhD, DSc, EdD, etc.)	0.50	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.

Table A2: 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)
10th quantile	1	1	2	2	1	4
25th quantile	2	2	4	3	1	5
Mean	5.45	3.11	10.92	5.98	2.18	8.36
Median	4	3	9	5	2	7
75th quantile	8	4	17	8	3	11
90th quantile	12	5	24	12	4	15
count	8,170	8,120	289,360	297,480	7,400	15,520

Note: Unweighted summary statistics of the time gaps reported for the regression sample. Columns 3-4 are estimated from the graduate degree sample. Columns 1, 2, 5, and 6 are estimated from a more-restricted subsample in which the individuals are observed working full time before they obtain the advanced degree. Our sample selection rules impose a minimum of 1 for the time gap variables in columns 1-5. Column 2 excludes about 50 pre advanced earnings observations on individuals for whom we dropped post advanced observations because they were reinterviewed only because of occupation. See footnote 13. Unweighted cell counts are rounded to the nearest 10.

Table A3: 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)
10th quantile	26	25	24	28
25th quantile	30	29	25	32
Mean	38.70	38.25	29.40	39.83
Median	38	37	28	39
75th quantile	47	46	33	47
90th quantile	53	53	38	53
Count	858,130	560,600	8,170	289,360

Note: Unweighted 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 are both included. Column 4 is estimated from the graduate degree sample. Column 3 is estimated from the more restricted subsample of individuals who are observed working full time before they obtain an advanced degree. Unweighted cell counts are rounded to the nearest 10.

Appendix B

B.1 The Distribution of Ability and Preferences Conditional on College Major and Graduate Education Choice

In this appendix we use a three period model of education and occupation choice to study how selection influences the relationship between $dF_{t1}(A_{t1}, Q_{t1}|c, G_{gt3})$ and $dF_{t3}(A_t, Q_t|c, G_{gt3})$. 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 skills 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. At the end of the appendix, we discuss how occupation specific experience alters the pattern of selection. In keeping with the analysis in section 5.2, 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. 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.

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. 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 5.2.5.

People are indifferent to the timing of consumption and income and are risk neutral.[48]

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

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

The individual chooses the occupation j_{t3} with the highest flow value, which we denote by $V_{cgt3}\left(A_{t3},Q_{t3},\xi_{t3}\right)$. The occupation choice probabilities $p_{cgt_3}\left(j_{t3}|A_{t3},Q_{t3}\right)$ 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 $nu^{grad}_{cg}\left(A_{t2},Q_{t2},v_{t2}\right)$ minus the monetary cost $COST_g\left(A_{t2},z_{t2}\right)$. 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.

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

$$V_{cgt2}\left(A_{t2},Q_{t2},v_{t2},z_{t2}\right)>V_{cg't2}\left(A_{t2},Q_{t2},v_{t2},z_{t2}\right),\ g'=1,\cdots,\mathcal{G}\text{ and }g'\neq g \tag{10}$$

[48]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.

and

$$V_{cgt2}\left(A_{t2},Q_{t2},v_{t2},z_{t2}\right)>V_{c0t2}\left(A_{t2},Q_{t2},\xi_{t2}\right). \tag{11}$$

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 (10, 11) and the 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 discussion of identification in 5.2.

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

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

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 $p_{c0t1}(j_{t1}|A_{t1},Q_{t1})$.

B.2 Mathematical Statement of Assumptions About the Age Profile of Earnings

A2a concerns the effects of new information about A and Q.

Assumption A2a (*Neutral contribution of updating about A_t,Q_t to earnings trends*):

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

The occupation probability function and 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 is that earnings growth within occupation is the same for all occupations conditional on college major and ability.

Assumption A2b *(Earnings trends do not depend on occupation)*: $w_{cgjt}\left(A_t\right)$ *and* $w_{c0jt}\left(A_t\right)$ *follow parallel trends that depend on* A_{t1} *but not the occupation. That is,*

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

where $a_c\left(\cdot,\cdot\right)$ is some college major specific function.

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

Assumption A2c (*Occupational earnings progression*): *Evaluated at $dF_{t1}\left(A,Q|c,G^g_{t3}\right)$, 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,*

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

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

B.3 Data Appendix

B.3.1 Construction of the panel data

As described in section 2, we pool all waves of NSCG (1993 to 2015) and NSRCG (1993 to 2010) to build the panel data set for empirical analyses. Each raw data set we use is based on a separate survey , so they unavoidably have various inconsistencies in variable names and values across waves, and across multiple observations of the same person. We start assembling the panel data from a set of 10 NSCG data files and 8 NSRCG data files, and append and clean the panel data in the following steps.

Step 1. We modify the variable names in each separate data file to unify key variable names.

Step 2. We assign values to categorical variables using crosswalks modified from the codebook of each separate data source to ensure consistent classifications. These variables include parental education, marital status, race, type of each postsecondary degree, major and minor field of each degree with three different levels of disaggregation ("best code" includes 144 categories, "minor group" includes 33, and "major group" includes 7), occupation with three different levels of disaggregation ("best code" includes 144 categories, "minor group" includes 31, "major group" includes 7). Table B2 is the crosswalk for BA fields, and table B1 is the crosswalk for advanced fields. In both tables, column (1) is the aggregated classification we define and use in most of the empirical analysis. Table B3 is the crosswalk for occupation, in which column (1) and (2) present an aggregated (19 categories) and a disaggregated (66 categories) classification that we construct to incorporate the NSCG/NSRCG and 1990 Census occupation codes. We also merge in the BA premiums and occupational premiums estimated from the ACS through crosswalks between BA field and occupation classifications in the ACS and the NSCG/NSRCG data.

Step 3. We hard code a number of cases to ensure the value of time invariant variables are consistent across multiple cases of the same person in the panel data. These variables include birth year, parental education, primary and secondary fields and the graduation year of the first BA.

Step 4. We re-organize the degree information. The raw data organize the advanced fields in the time order of completion. It also records two fields of the same degree (i.e. with the same degree type and graduation year) as multiple degrees. We re-order the degrees so that they are in time order, and multiple records of the same degree are collapsed.

Step 5. We drop people whose educational background implies odd time order. For example, a few people completed their advanced degree before they have a BA degree.

Step 6. We make use of the question about the person's total income in the previous year to expand the panel data. From each existing observation, we generate an observation of the same person from a year before the survey. For the prior year observation, we remove any degree that is completed in the year of the survey, and modify other age and calendar year. We also drop observations that are prior to the graduation year of the first BA.

Step 7. We define the regression sample by imposing the following restrictions. First, people have to work full time. This is indicated by either the dummy variable for working full time in the raw data, or jointly by working at least 35 hours a week and at least 40 weeks a year. We do not have information about hours worked or a direct question about full time status for the calendar year prior to the survey. Consequently, we assume that full time status in the year prior to the NSCG and NSRCG survey is the same as full time status at the time of the survey. The full time status indicator for the 1989 earnings observation and the 1990 occupation variables is based on 1990 Census questions about usual hours worked per week and number of weeks worked in 1989.

Second, people have to be aged between 23 and 59. Third, we drop people with a PhD by the last time we observe them and drop observations of people who are currently enrolled in an educational program.[49] We also drop people who hold a BA degree before 18 years old and drop people who obtained their first advanced degree before age 23 or after age 49. We also drop people who did not work between BA completion and being enrolled in graduate school. Section 7.1.12 provides a detailed discussion of the last restriction. Lastly, we drop the follow up observations of people who became SESTAT-eligible solely because of occupation.[50]

Step 8. We deflate all the nominal earnings to 2013 US dollars.

Step 9, We define the weights as described in section B.3.2.

Step 10. We rescale the occupation premiums based on the ACS (see below) to have a coefficient of 1. We let $\gamma_{occ}^{rescale} = \hat{\beta}\gamma_{occ}$, in which $\hat{\beta}$ is the estimated coefficient from $w = \alpha + \beta\gamma_{occ}$. The value is of $\hat{\beta}$ is 0.934.

B.3.2 Construction of Sample Weights

Overview of construction of weights We aim to study the labor market returns to advanced degrees that represent the population of people who have a college degree in any field who are between 23 and 59 years old who live in the U.S.. The target populations of the 1993, 2003, 2010, 2013 NSCG are individuals with at least a BA degree. We use the survey weights for each of these samples produced by the National Center for Science and Engineering Statistics (NCSES) to estimate the distribution college graduates across combinations of BA field and graduate field (including no graduate degree) over the four years combined. The NSRCG and the other waves of the NSCG prior to 2010 are restricted to the SESTAT eligible population. Thus individuals with STEM eligible occupations and advanced degrees are overrepresented when we pool all of the data. Furthermore, and the NCSES weights for these waves weight to the SESTAT population.

We adjust the NCSES weights for all waves of the NSRCG and NSCG so that the weighted distribution of c, g pairs in the pooled sample matches the distribution of c, g pairs that we estimated using the 1993, 2003, 2010, and 2013 NSCG. Separate weights are constructed for the earnings regressions and the occupational premium regressions that reflect the mix of surveys that contribute observations. The pooled sample weights for earnings account for the fact that some interviews contribute earnings observations for two years. We trim the adjusted weights using 1/10 and 10 times of the median of the weights of all observations in the combined data.

[49] Enrollment is inferred by completion time of the degree. We assume all master degrees, MBA, and other professional degrees take 2 years, Law takes 3 years, and Medicine takes 4 years. Surveys are conducted in April prior to 2000, and October after.

[50] If a person does not hold a BA or an advanced degree in a S&E field, but is included in the database and has follow up interviews, we say this person becomes SESTAT-eligible because of an S&E occupation choice.

Details Let $weight_{is}$ denote that survey weights provided by NCSES, where i denotes the person and s denotes a specific wave of a survey, such as the NSCG 2003.

Step 1. Standardize weights across NSCG and NSCRG waves. First, we want to preserve the relative weights within each survey while accounting for varying sample sizes across surveys. We divide the survey weight by the sum of weights of all observations from the survey and then multiply by the number of observations.

$$weight_{is}^{surv-adj} = \frac{weight_{it}}{\sum_{i=1}^{N_s} weight_{is}} \times N_s$$

.

Step 2: Estimate the population probabilities of each college major and graduate degree combination.

In the second step, we estimate the fraction p_{cg}^{base} of college graduates in each c, g cell over the period of full sample, where no advance degree ($g = 0$) form a separate cell for each major c. To do so, we use the NSCG 1993, 2003, 2010, and 2013. Each is a stratified random sample of the population of college graduates to estimate at the time of observation. For these waves of the NSCG, the weights provided by the NCSES weight the samples to the population of college graduates who have had a BA for 3 or more years.[51] The NSCG 2015 is also a stratified random sample of the population of college graduates but we chose not to use it to avoid giving excessive weight to the distribution of college graduates from 2010 on when estimating p_{cg}^{base}. The formula is

$$p_{cg}^{base} = \frac{\sum\limits_{s \in \{1993,2003,2010,2013\}} \left(\sum_{i=1}^{N_s} weight_{is}^{surv-adj} \times 1\left\{C_{is} = c, G_{is} = g\right\} \right)}{\sum\limits_{s \in \{1993,2003,2010,2013\}} \left(\sum_{i=1}^{N_s} weight_{is}^{surv-adj} \right)}$$

.

Step 3: Adjust weights for the pooled NSCG and NSRCG samples so that the weighted fractions of observations in cell c,g in combined sample match p_{cg}^{base} for all c,g combinations.

First, we compute the fractions in the pooled sample implied by the unadjusted weights:

$$p_{cg}^{pooled} = \frac{\sum_s \sum_{i=1}^{N_s} weight_{is}^{surv-adj} \times 1\left\{C_{is} = c, G_{is} = g\right\}}{\sum_s \sum_{i=1}^{N_s} weight_{is}^{surv-adj}}$$

Then we multiply the normalized weights from Step 1 for individuals for whom $C_{is} = c, G_{is} = g$ by $p_{cg}^{base}./p_{cg}^{pooled}$:

$$weight_{is}^{surv,edu-adj} = \sum_{c,g} \left[1\left\{C_{is} = c, G_{is} = g\right\} \frac{p_{cg}^{base}}{p_{cg}^{pooled}} \right] \times weight_{is}^{surv-adj} \quad \text{for all } i, s.$$

In the empirical analysis the mix of observations depends on the dependent variable in the regression. In the case of earnings, in many cases a given survey wave contributes an observation on current earnings and an observation on past earnings. We compute p_{cg}^{base} using only the current earnings observation. However, when p_{cg}^{pooled}, we include two observations for i, s — one for the current observation and one for earnings last years' earnings. We assign the same value of $weight_{is}^{surv-adj}$, but in a small number of cases the education cell is different because the individual obtained a degree in the current year.

[51] We are ignoring the possibility that the mix of degrees across fields is different for people who received their college degree more recently.

We construct separate values for the occupation regression sample using observations for which occupation is available. In section 7 and the notes of figures and tables, we state the sample frame of the analysis without reiterating that the weights are adjusted for the relevant sample frame.

Finally, we want to avoid the case in which the importance of one single observation is too small or too large. We trim the adjusted weights $weight_{is}^{surv,edu-adj}$ using 1/10 and 10 times of the median of the weights of all observations in the combined data.

$$weight_{it}^{*} = \begin{cases} med\{weight_{it}^{surv,edu-adj}\}/10 & if\ weight_{it}^{surv,edu-adj} < med\{weight_{it}^{surv,edu-adj}\}/10 \\ weight_{it}^{surv,edu-adj} & if\ med\{weight_{it}^{surv,edu-adj}\}/10 < weight_{it}^{surv,edu-adj} \\ & < med\{weight_{it}^{surv,edu-adj}\} \times 10 \\ med\{weight_{it}^{surv,edu-adj}\}/10 & if\ med\{weight_{it}^{surv,edu-adj}\} \times 10 < weight_{it}^{surv,edu-adj} \end{cases}$$

B.3.3 Earnings premium of BA fields from ACS

We pool the 2009 - 2014 American Community Survey to construct a large cross sectional data. We apply sample restrictions to only include people who are between 24 and 59 years old, working full time, and earn at least $5,000 a year. We regress the log of annual earnings on dummies for 172 college majors, a cubic of age interacted with gender, race\Hispanic interacted with gender, and three dummies for having a master's degree, PhD, and professional degree, subject to the ACS survey weights. The coefficients on the disaggregated college major categories are the BA major earnings premium from the ACS. We also extract the population distribution of BA fields from the regression sample. Then we use a crosswalk between BA field classification of the ACS and the SESTAT database to merge the premium into the SESTAT data. When multiple majors in ACS are mapped to a single major in SESTAT, we calculate the population weighted average of the major premium.

B.3.4 Occupation premium from ACS

We estimate the occupation premiums using ACS data and an approach that is similar to the one used to estimate the BA major earnings premiums. The regression has the same set of control variables, except that we now include the 331 occupation dummies instead of college major dummies. We construct an occupation crosswalk among ACS, SESTAT and the 1990 Census. Section 2.1 describes the use of 1990 Census occupation in the empirical analysis.

Appendix figures

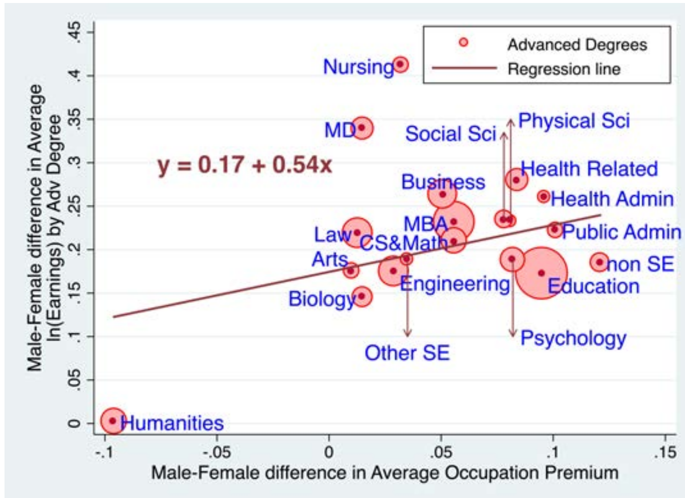

Figure B1: Gender differences in average ln(earnings) by differences in the average occupation premiums of advanced fields

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 0.53. 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.

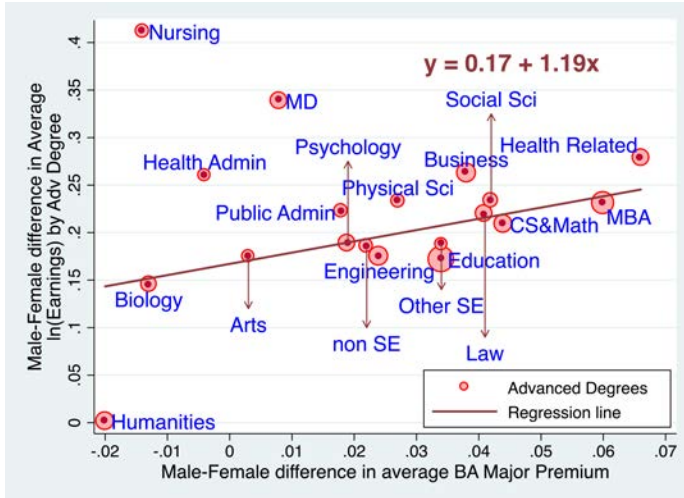

Figure B2: Gender differences in average ln(earnings) by differences in the average BA major premiums of advanced fields

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 0.97. 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.

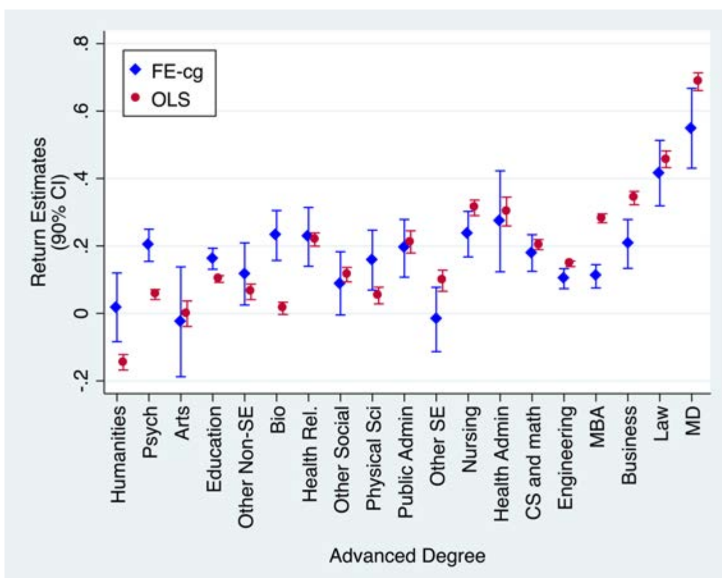

Figure B3: FE-cg and OLS estimates of the Advanced degree premiums

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).

Appendix tables

Table B1: Aggregation of advanced fields and degree type and disaggregated earnings statistics

Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occupational premium		OLS Earnings premium		% of sample	Freq.
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Law	Law/prelaw/legal studies	Master	105,202	72,430	-0.482	0.287	0.257	0.168	0.111	160
	Law/prelaw/legal studies	Prof	129,198	91,144	-0.313	0.139	0.454	0.014	6.837	9,800
MBA	Business, general	Master	122,688	72,023	-0.457	0.231	0.356	0.022	1.993	4,630
	Business administration and management	Master	113,929	68,271	-0.450	0.213	0.274	0.009	9.662	21,030
	Business and managerial economics	Master	120,945	85,184	-0.482	0.238	0.256	0.051	0.217	510
	Other business management/admin services	Master	97,921	52,658	-0.498	0.223	0.209	0.019	1.814	3,940
Medicine	Medicine[1]	Master	102,845	62,510	-0.416	0.257	0.221	0.110	0.103	290
	Medicine[1]	Prof	166,066	105,014	-0.122	0.176	0.682	0.017	3.614	8,180
Master's in Arts	Dramatic arts	Master	66,386	36,273	-0.682	0.209	0.068	0.053	0.244	330
	Fine arts, all fields	Master	61,697	37,282	-0.730	0.206	-0.071	0.037	0.667	830
	Music, all fields	Master	60,427	32,910	-0.779	0.211	0.031	0.034	0.586	700
	Other visual and performing arts	Master	80,921	85,443	-0.716	0.194	0.120	0.070	0.301	450
Master's in Biological/ Agricultural/ Environmental/ Life Sciences	Animal sciences	Master	59,289	37,505	-0.692	0.251	0.036	0.075	0.076	520
	Biochemistry and biophysics	Master	79,335	58,369	-0.657	0.217	0.077	0.064	0.117	850
	Biology, general	Master	66,155	31,980	-0.713	0.186	-0.019	0.022	0.595	3,190
	Botany	Master	56,521	23,504	-0.703	0.191	-0.073	0.052	0.081	450
	Cell and molecular biology	Master	71,332	51,272	-0.684	0.194	0.020	0.046	0.121	840
	Ecology	Master	64,680	31,178	-0.685	0.185	-0.101	0.045	0.189	1,140
	Environmental science or studies	Master	74,070	36,512	-0.607	0.193	0.104	0.032	0.311	1,890
	Food sciences and technology	Master	78,724	38,726	-0.608	0.201	0.156	0.045	0.101	690
	Forestry sciences	Master	71,480	34,106	-0.704	0.242	-0.056	0.082	0.113	680
	Genetics, animal and plant	Master	70,007	38,129	-0.682	0.185	0.038	0.058	0.051	310
	Microbiological sciences and immunology	Master	76,755	44,657	-0.651	0.196	0.051	0.048	0.157	1,070
	Nutritional sciences	Master	67,112	40,243	-0.564	0.174	0.138	0.042	0.158	780
	Other agricultural sciences	Master	64,629	24,497	-0.657	0.244	-0.020	0.045	0.124	720
	Other biological sciences	Master	73,623	61,272	-0.651	0.231	0.056	0.029	0.253	1,670
	Other conservation and natural resources	Master	71,643	35,157	-0.636	0.187	0.007	0.042	0.135	720
	Pharmacology, human and animal	Master	89,019	38,292	-0.623	0.194	0.144	0.081	0.034	230
	Physiology and pathology, human and animal	Master	74,716	40,548	-0.578	0.219	0.103	0.049	0.108	590
	Plant sciences	Master	60,825	30,983	-0.706	0.197	-0.043	0.044	0.174	1,020
	Zoology, general	Master	64,923	33,899	-0.671	0.199	-0.092	0.041	0.137	790

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occupational premium		OLS Earnings premium		% of sample	Freq.
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Master's in Business related fields	Accounting	Master	110,561	75,745	-0.446	0.185	0.228	0.031	1.223	1,660
	Actuarial science	Master	138,848	127,744	-0.180	0.221	0.387	0.158	0.024	70
	Agricultural economics	Master	100,771	65,004	-0.510	0.218	0.276	0.060	0.245	630
	Business marketing/marketing management	Master	118,355	75,609	-0.449	0.212	0.314	0.026	1.622	3,000
	Financial management	Master	133,233	94,901	-0.428	0.185	0.385	0.016	3.143	5,380
	Marketing research	Master	112,879	66,870	-0.429	0.148	0.318	0.058	0.223	340
	Other agricultural business and production	Master	74,722	43,486	-0.684	0.268	0.044	0.132	0.058	130
Master's in Computer and Mathematical Sciences	Applied mathematics	Master	89,175	49,318	-0.481	0.209	0.137	0.039	0.123	900
	Computer and information sciences, general	Master	99,185	47,977	-0.466	0.166	0.223	0.022	0.734	3,250
	Computer programming	Master	95,840	48,945	-0.445	0.120	0.185	0.073	0.067	300
	Computer science	Master	101,759	46,697	-0.423	0.128	0.219	0.011	2.160	11,130
	Computer systems analysis	Master	109,293	45,663	-0.457	0.135	0.293	0.054	0.123	510
	Data processing	Master	110,374	46,270	-0.449	0.087	0.240	0.123	0.010	60
	Information services and systems	Master	101,763	54,086	-0.476	0.176	0.256	0.027	0.650	2,920
	Mathematics, general	Master	79,005	44,533	-0.617	0.240	0.004	0.024	0.621	3,280
	Other computer and information sciences	Master	112,048	81,085	-0.478	0.168	0.286	0.057	0.219	1,030
	Other mathematics	Master	84,671	41,432	-0.547	0.206	0.092	0.065	0.052	290
	Operations research	Master	108,181	50,083	-0.458	0.182	0.207	0.033	0.286	1,170
	Statistics	Master	95,699	56,526	-0.481	0.171	0.211	0.047	0.212	1,660
Master's in Education fields	Computer teacher education	Master	66,336	19,417	-0.764	0.160	0.094	0.046	0.220	370
	Counselor education and guidance	Master	64,189	33,368	-0.812	0.198	0.078	0.014	1.965	3,330
	Education administration	Master	75,754	32,076	-0.657	0.231	0.175	0.013	3.417	4,390
	Educational psychology	Master	67,757	31,928	-0.751	0.207	0.144	0.025	1.097	2,100
	Elementary teacher education	Master	62,691	30,146	-0.837	0.146	0.145	0.012	3.980	3,760
	Mathematics teacher education	Master	68,248	29,446	-0.774	0.181	0.038	0.034	0.622	1,280
	Other education	Master	64,361	26,111	-0.767	0.195	0.084	0.011	4.292	5,770
	Physical education and coaching	Master	65,002	27,837	-0.759	0.184	0.034	0.025	0.652	730
	Pre-school/kindergarten/early childhood teacher education	Master	57,832	20,199	-0.897	0.220	0.100	0.033	0.391	460
	Science teacher education	Master	65,037	28,627	-0.797	0.144	0.017	0.041	0.470	1,160
	Secondary teacher education	Master	64,301	28,431	-0.778	0.171	0.032	0.015	2.088	2,980
	Social science teacher education	Master	68,230	27,461	-0.799	0.180	0.020	0.037	0.219	370
	Special education	Master	64,846	27,392	-0.791	0.169	0.137	0.015	2.299	2,640

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occupational premium		OLS Earnings premium		% of sample	Freq.
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Master's in Engineering	Aerospace, aeronautical, astronautical/space engineering	Master	103,845	48,129	-0.425	0.184	0.153	0.031	0.276	3,510
	Agricultural engineering	Master	80,853	32,363	-0.500	0.205	-0.002	0.046	0.044	320
	Architectural engineering	Master	94,784	65,428	-0.524	0.158	0.053	0.061	0.055	330
	Bioengineering and biomedical engineering	Master	88,730	61,222	-0.576	0.217	0.055	0.051	0.108	1,140
	Chemical engineering	Master	104,890	52,568	-0.343	0.161	0.086	0.025	0.331	4,050
	Civil engineering	Master	93,649	43,704	-0.411	0.131	0.086	0.012	0.925	8,780
	Computer and systems engineering	Master	112,213	59,232	-0.402	0.116	0.249	0.015	0.624	4,710
	Electrical, electronics & communication eng.	Master	107,549	55,170	-0.380	0.111	0.185	0.010	1.890	15,150
	Engineering, general	Master	106,889	62,748	-0.406	0.177	0.172	0.056	0.116	950
	Engineering sciences, mechanics and physics	Master	106,161	59,253	-0.414	0.124	0.153	0.038	0.104	790
	Environmental engineering	Master	96,342	41,933	-0.392	0.131	0.129	0.020	0.271	2,290
	Geophysical and geological engineering	Master	102,917	58,728	-0.416	0.191	0.131	0.060	0.021	220
	Industrial and manufacturing engineering	Master	96,409	50,219	-0.448	0.147	0.159	0.017	0.427	4,870
	Materials eng., incl. ceramic and textile sci.	Master	94,784	39,126	-0.427	0.135	0.133	0.029	0.170	1,480
	Mechanical engineering	Master	98,708	48,334	-0.430	0.127	0.108	0.012	1.062	10,390
	Metallurgical engineering	Master	101,133	37,411	-0.413	0.122	0.125	0.080	0.055	420
	Mining and minerals engineering	Master	101,566	30,280	-0.259	0.281	0.142	0.098	0.020	110
	Naval architecture and marine engineering	Master	101,181	44,625	-0.407	0.124	0.038	0.091	0.020	160
	Nuclear engineering	Master	105,983	42,801	-0.402	0.122	0.124	0.037	0.069	540
	Other engineering	Master	97,250	38,570	-0.426	0.142	0.141	0.015	0.375	3,080
	Petroleum engineering	Master	123,686	65,289	-0.174	0.264	0.244	0.067	0.036	290
Master's in Health Serv. Admin.	Health services administration	Master	97,990	57,941	-0.482	0.231	0.305	0.026	1.087	2,430
Master's in Health related fields	Audiology and speech pathology	Master	64,964	24,209	-0.584	0.189	0.249	0.027	0.788	1,820
	Health/medical assistants	Master	91,810	27,164	-0.510	0.195	0.475	0.064	0.167	430
	Health/medical technologies	Master	93,689	77,068	-0.608	0.214	0.226	0.066	0.052	240
	Health/medical technologies	Prof	97,134	69,006	-0.395	0.334	0.330	0.188	0.008	30
	Medical preparatory programs[2]	Master	138,530	95,514	-0.504	0.357	0.533	0.212	0.005	30
	Medical preparatory programs[2]	Prof	170,943	76,922	-0.107	0.173	0.771	0.064	0.040	150
	Other health/medical sciences	Master	79,325	56,450	-0.623	0.236	0.205	0.028	0.675	1,960
	Other health/medical sciences	Prof	151,881	108,648	-0.165	0.182	0.580	0.083	0.062	160
	Pharmacy	Master	103,885	47,918	-0.514	0.212	0.150	0.090	0.066	280
	Pharmacy	Prof	119,708	36,556	-0.501	0.121	0.569	0.030	0.295	830
	Physical therapy and other rehabilitation/ therapeutic services	Master	70,843	30,035	-0.586	0.184	0.178	0.020	1.010	2,480
	Physical therapy and other rehabilitation/ therapeutic services	Prof	81,710	52,269	-0.454	0.166	0.442	0.040	0.063	120
	Public health (including environmental health and epidemiology)	Master	72,052	37,026	-0.592	0.207	0.143	0.026	0.755	2,780

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occupational premium		OLS Earnings premium		% of sample	Freq.
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Master's in Humanity fields	English Language, literature and letters	Master	65,404	45,832	-0.754	0.202	-0.025	0.026	0.983	1,390
	History, other	Master	69,223	47,775	-0.723	0.243	-0.041	0.034	0.669	930
	Liberal arts/general studies	Master	72,957	36,450	-0.721	0.230	0.115	0.056	0.264	410
	Linguistics	Master	60,610	24,301	-0.776	0.179	0.015	0.041	0.239	480
	Other foreign languages and literature	Master	68,682	51,804	-0.730	0.206	0.006	0.047	0.360	620
	Other philosophy, religion, theology	Master	55,200	30,245	-0.951	0.276	-0.242	0.021	2.172	2,600
	Other philosophy, religion, theology	Prof	55,830	35,782	-0.967	0.273	-0.308	0.068	0.210	210
Master's in Other Non-Science and Engineering fields	Communications, general	Master	77,388	46,563	-0.598	0.235	0.115	0.051	0.375	580
	Criminal justice/protective services	Master	72,796	35,771	-0.656	0.271	0.114	0.039	0.393	730
	Journalism	Master	73,140	37,932	-0.683	0.161	0.086	0.051	0.232	310
	Library science	Master	61,382	22,630	-0.829	0.189	0.038	0.019	1.115	1,270
	Other communication	Master	75,445	38,793	-0.589	0.237	0.124	0.041	0.341	530
	Parks, recreation, leisure, and fitness studies	Master	63,807	27,732	-0.668	0.226	-0.016	0.032	0.378	550
Master's in Nursing	Nursing (4 years or longer program)	Master	97,580	43,604	-0.497	0.160	0.310	0.014	1.761	4,420
Master's in Physical and related sciences	Astronomy and astrophysics	Master	76,841	66,085	-0.521	0.198	-0.100	0.109	0.029	310
	Atmospheric sciences and meteorology	Master	84,414	39,998	-0.464	0.135	0.109	0.047	0.073	740
	Chemistry, except biochemistry	Master	78,480	42,777	-0.594	0.180	0.002	0.032	0.539	4,920
	Earth sciences	Master	75,623	30,621	-0.677	0.175	0.085	0.037	0.060	440
	Geological sciences, other	Master	84,125	49,799	-0.554	0.162	0.120	0.055	0.105	950
	Geology	Master	88,967	50,269	-0.552	0.177	0.140	0.028	0.340	3,040
	Other physical sciences	Master	77,832	35,081	-0.599	0.218	0.090	0.045	0.059	440
	Oceanography	Master	69,253	36,117	-0.531	0.183	-0.048	0.077	0.039	320
	Physics, except biophysics	Master	90,224	51,549	-0.496	0.188	0.042	0.028	0.367	3,320
	Science, unclassified	Master	72,035	37,243	-0.684	0.211	0.007	0.061	0.056	220
Master's in Psychology and Social Work	Clinical psychology	Master	63,205	41,447	-0.711	0.223	0.010	0.030	0.550	1,990
	Clinical psychology	Prof	83,371	39,581	-0.734	0.133	0.259	0.080	0.011	70
	Counseling psychology	Master	60,631	30,622	-0.774	0.234	0.003	0.014	2.080	6,450
	Experimental psychology	Master	75,988	54,790	-0.666	0.255	0.008	0.120	0.089	330
	General psychology	Master	66,436	38,568	-0.681	0.229	0.083	0.025	0.589	1,900
	General psychology	Prof	87,277	43,936	-0.600	0.309	0.212	0.230	0.023	40
	Industrial/Organizational psychology	Master	85,080	50,556	-0.575	0.203	0.266	0.047	0.245	780
	Other psychology	Master	65,227	33,495	-0.720	0.212	0.069	0.034	0.542	1,990
	Social Work	Master	64,243	30,094	-0.779	0.229	0.100	0.012	2.649	7,190
	Social psychology	Master	70,795	39,624	-0.688	0.284	0.056	0.092	0.051	190
Master's in Public Admin	Other public affairs	Master	73,667	40,665	-0.631	0.290	0.104	0.068	0.113	280
	Public administration	Master	89,440	44,348	-0.504	0.257	0.220	0.021	1.668	3,190

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Aggregated advanced degrees	Disaggregated advanced degree field	Adv.deg. type	Earnings		Occupational premium		OLS Earnings premium		% of sample	Freq.
			Mean	SD	Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Master's in Other Science and Engineering related fields	Architecture/environmental design	Master	87,258	50,704	-0.561	0.209	0.106	0.024	1.184	2,780
	Electrical and electronics technologies	Master	102,294	47,102	-0.417	0.150	0.173	0.094	0.100	410
	Industrial production technologies	Master	83,343	39,522	-0.578	0.295	-0.016	0.059	0.103	320
	Mechanical engineering-related technologies	Master	105,103	40,134	-0.497	0.260	0.099	0.108	0.074	280
	Other engineering-related technologies	Master	105,277	82,203	-0.501	0.204	0.203	0.043	0.166	600
Master's in Other Social and Related Sciences	Anthropology and archaeology	Master	58,124	33,100	-0.689	0.225	-0.059	0.045	0.182	1,180
	Area and ethnic studies	Master	66,078	36,109	-0.714	0.230	0.014	0.056	0.206	1,030
	Criminology	Master	68,783	32,991	-0.719	0.258	0.066	0.059	0.088	500
	Economics	Master	105,543	75,831	-0.474	0.220	0.205	0.032	0.563	3,050
	Geography	Master	76,084	42,931	-0.610	0.227	0.086	0.050	0.246	1,090
	History of science	Master	66,304	29,327	-0.679	0.199	-0.183	0.138	0.022	40
	Home Economics	Master	59,901	26,707	-0.723	0.253	0.069	0.048	0.140	390
	International relations	Master	97,854	69,609	-0.539	0.246	0.286	0.043	0.455	1,980
	Other social sciences	Master	63,727	30,073	-0.661	0.248	0.013	0.028	0.466	2,010
	Philosophy of science	Master	50,447	27,031	-0.768	0.245	-0.300	0.130	0.024	60
	Political science and government	Master	77,622	47,870	-0.616	0.257	0.003	0.034	0.489	1,830
	Public policy studies	Master	101,283	75,027	-0.515	0.235	0.328	0.035	0.340	1,940
	Sociology	Master	69,505	37,245	-0.664	0.256	0.077	0.034	0.406	2,110

Note: Column 1 presents 19 aggregated advanced degree fields that are constructed from 168 disaggregated advanced degrees. For each disaggregated advanced degree, columns 2-11 present its field, type (Master or Professional Degree), mean and standard deviation of earnings, mean and standard deviation of occupation premiums, its coefficient and standard error from a disaggregated additive earnings regression, percentage of the sample, and cell count rounded to the nearest 10. The full regression sample is used, but disaggregated advanced degrees with less than 10 observations are removed from the table. The specification is Table 5 column (3), with disaggregated BA and advanced fields. Sample weights are used for all statistics except cell count. 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: Aggregation of BA fields and disaggregated earnings statistics

Aggregated BA major	Disaggregated BA major	Earnings		BA earnings prem.		% of sample	Freq.
		Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Biological/ Agricultural/ Environmental Sciences	Animal sciences	62,806	43,934	0.020	-0.023	0.419	4,950
	Biochemistry and biophysics	88,181	75,649	0.265	-0.028	0.294	4,300
	Biology, general	79,620	63,967	0.181	-0.014	2.939	35,660
	Botany	65,369	42,522	0.008	-0.051	0.068	840
	Cell and molecular biology	89,098	86,890	0.290	-0.046	0.114	1,670
	Ecology	70,675	57,826	0.142	-0.045	0.145	2,170
	Environmental science or studies	62,961	41,413	0.129	-0.022	0.351	5,920
	Food sciences and technology	77,619	45,014	0.270	-0.046	0.101	1,530
	Forestry sciences	73,551	46,255	0.109	-0.030	0.206	3,190
	Genetics, animal and plant	72,097	55,168	0.136	-0.058	0.034	500
	Microbiological sciences and immunology	76,676	62,416	0.193	-0.025	0.287	4,130
	Nutritional sciences	63,911	42,787	0.165	-0.030	0.142	1,740
	Other agricultural sciences	64,587	36,361	0.075	-0.029	0.193	2,390
	Other biological sciences	65,749	55,669	0.141	-0.023	0.308	4,050
	Other conservation and natural resources	67,677	33,563	0.088	-0.033	0.122	1,980
	Pharmacology, human and animal	83,469	35,184	0.337	-0.074	0.017	230
	Physiology and pathology, human and animal	86,081	59,735	0.260	-0.032	0.091	990
	Plant sciences	64,380	41,842	0.044	-0.027	0.286	3,780
	Zoology, general	88,888	71,059	0.164	-0.026	0.315	3,680
Business	Accounting	93,321	65,467	0.415	-0.013	4.472	13,850
	Actuarial science	104,809	72,046	0.619	-0.067	0.081	440
	Agricultural economics	81,926	55,519	0.247	-0.030	0.764	2,480
	Business, general	84,714	60,120	0.272	-0.017	1.870	6,810
	Business administration and management	82,202	56,846	0.280	-0.012	6.670	25,550
	Business and managerial economics	94,691	80,465	0.364	-0.024	0.548	2,330
	Financial management	97,808	76,583	0.411	-0.017	1.673	5,790
	Other agricultural business and production	65,963	45,361	0.027	-0.033	0.281	1,170
	Other business management/admin services	81,077	57,721	0.306	-0.018	1.364	5,860
Communications/ Journalism	Communications, general	69,073	48,364	0.214	-0.020	1.318	4,660
	Journalism	72,908	51,007	0.233	-0.020	0.923	3,100
	Other communication	69,323	48,863	0.208	-0.023	0.799	2,860
Computer and Mathematical Sciences	Applied mathematics	92,966	61,064	0.382	-0.027	0.283	4,030
	Computer and information sciences, general	82,855	43,553	0.402	-0.017	0.654	8,630
	Computer science	90,138	50,269	0.463	-0.013	2.149	32,580
	Computer systems analysis	85,660	42,261	0.416	-0.031	0.115	1,600
	Information services and systems	79,842	45,251	0.372	-0.017	0.631	8,420
	Mathematics, general	84,575	55,762	0.301	-0.016	1.662	22,870
	Other computer and information sciences	67,244	39,418	0.235	-0.031	0.162	1,810
	Other mathematics	86,193	55,054	0.358	-0.039	0.118	1,650
	Operations research	87,616	45,550	0.411	-0.043	0.063	790
	Statistics	90,329	54,625	0.403	-0.038	0.089	1,570
Economics	Economics	99,065	78,429	0.424	-0.020	2.478	23,620
Education	Computer teacher education	73,395	28,357	0.158	-0.058	0.015	100
	Counselor education and guidance	59,352	47,126	0.044	-0.059	0.027	140
	Education administration	67,103	33,103	0.079	-0.045	0.066	270
	Educational psychology	63,446	33,626	0.052	-0.035	0.326	1,250
	Elementary teacher education	54,536	26,975	0.000	0.000	4.005	11,870
	Mathematics teacher education	62,190	33,601	0.030	-0.022	0.415	2,320
	Other education	63,008	41,225	0.035	-0.012	1.574	6,110
	Physical education and coaching	64,992	42,854	0.050	-0.015	1.145	3,930
	Pre-school/kindergarten/early childhood teacher education	48,917	22,602	-0.071	-0.024	0.360	1,000
	Science teacher education	64,136	31,041	0.023	-0.031	0.309	1,580
	Secondary teacher education	62,575	37,320	0.037	-0.013	1.318	5,050
	Social science teacher education	66,758	46,397	0.011	-0.032	0.392	1,630
	Special education	58,748	32,300	0.068	-0.018	0.607	2,040

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Aggregated BA major	Disaggregated BA major	Earnings		BA earnings prem.		% of sample	Freq.
		Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Engineering	Aerospace, aeronautical, astronautical/ space engineering	96,734	51,320	0.439	-0.019	0.425	11,690
	Agricultural engineering	82,656	41,570	0.309	-0.034	0.097	1,750
	Architectural engineering	88,338	55,145	0.376	-0.030	0.167	2,800
	Bioengineering and biomedical engineering	93,217	78,309	0.416	-0.033	0.084	2,170
	Chemical engineering	105,915	56,474	0.549	-0.014	0.830	21,980
	Civil engineering	92,902	52,216	0.430	-0.012	1.536	35,630
	Computer and systems engineering	99,868	50,898	0.561	-0.017	0.526	10,280
	Electrical, electronics & communication eng.	99,985	50,901	0.490	-0.012	2.902	62,550
	Engineering, general	98,580	57,579	0.403	-0.024	0.189	2,990
	Engineering sciences, mechanics and physics	95,539	51,822	0.385	-0.034	0.148	2,790
	Environmental engineering	87,038	44,628	0.399	-0.030	0.079	1,760
	Geophysical and geological engineering	103,194	92,392	0.415	-0.056	0.020	450
	Industrial and manufacturing engineering	96,965	59,247	0.434	-0.017	0.636	14,290
	Materials eng., incl. ceramic and textile sci.	84,466	38,845	0.371	-0.028	0.125	2,900
	Mechanical engineering	96,580	52,185	0.463	-0.012	2.376	54,190
	Metallurgical engineering	102,952	56,173	0.419	-0.037	0.090	1,740
	Mining and minerals engineering	96,717	46,315	0.368	-0.051	0.044	780
	Naval architecture and marine engineering	97,234	50,374	0.416	-0.041	0.069	1,270
	Nuclear engineering	106,421	53,578	0.539	-0.033	0.046	960
	Other engineering	102,526	63,879	0.444	-0.026	0.227	3,790
	Petroleum engineering	112,905	67,436	0.587	-0.050	0.079	1,540
English/ Languages/ Literature	English Language, literature and letters	73,062	53,022	0.169	-0.018	2.473	9,760
	Linguistics	59,086	36,703	0.055	-0.050	0.215	940
	Other foreign languages and literature	70,319	46,634	0.155	-0.022	0.867	4,240
Fine/ Performing Arts	Dramatic arts	61,147	48,211	0.010	-0.034	0.330	1,230
	Fine arts, all fields	62,306	47,197	0.070	-0.021	1.242	4,570
	Music, all fields	58,739	36,400	-0.013	-0.026	0.710	2,610
	Other visual and performing arts	64,322	44,504	0.116	-0.024	0.846	2,790
Health related fields	Audiology and speech pathology	59,560	25,423	0.063	-0.029	0.323	2,220
	Health/medical assistants	79,479	59,271	0.353	-0.063	0.039	260
	Health/medical technologies	71,163	42,663	0.268	-0.022	0.492	4,270
	Medical preparatory programs[2]	127,099	117,319	0.296	-0.049	0.188	1,390
	Medicine[1]	128,452	109,212	0.436	-0.057	0.180	1,360
	Other health/medical sciences	67,863	45,891	0.199	-0.024	0.486	3,090
	Pharmacy	106,997	45,002	0.571	-0.022	0.527	3,390
	Physical therapy and other rehabilitation/ therapeutic services	70,451	43,693	0.254	-0.022	0.701	3,560
	Public health (including environmental health and epidemiology)	62,011	36,053	0.092	-0.031	0.210	1,580
Marketing	Business marketing/marketing management	86,438	65,819	0.350	-0.017	2.346	7,680
	Marketing research	77,662	61,670	0.262	-0.034	0.275	860
Nursing	Nursing (4 years or longer program)	74,238	36,288	0.341	-0.014	3.209	16,590
Other Humanities	History, other	80,302	64,129	0.168	-0.019	2.017	7,990
	Liberal arts/general studies	76,998	59,180	0.188	-0.022	1.070	4,660
	Other philosophy, religion, theology	61,804	50,514	-0.035	-0.024	0.925	3,370
Other Non-S and E fields	Criminal justice/protective services	65,057	35,967	0.112	-0.023	0.914	3,840
	Health services administration	69,545	45,647	0.208	-0.033	0.403	2,100
	Library science	54,970	23,660	0.029	-0.056	0.031	140
	Non-Science and Enginnering Group	96,426	64,765	0.354	-0.096	0.012	90
	Parks, recreation, leisure, and fitness studies	58,374	37,773	0.024	-0.023	0.528	2,110

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Aggregated BA major	Disaggregated BA major	Earnings		BA earnings prem.		% of sample	Freq.
		Mean	SD	Coef	SE		
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Other Science and Engineering-related fields	Architecture/environmental design	85,881	57,170	0.297	-0.021	0.940	6,440
	Computer programming	85,317	38,492	0.430	-0.027	0.251	2,410
	Data processing	84,417	30,106	0.408	-0.055	0.031	330
	Electrical and electronics technologies	86,607	40,264	0.389	-0.022	0.427	5,100
	Industrial production technologies	83,706	44,807	0.277	-0.031	0.404	3,100
	Mechanical engineering-related technologies	89,066	41,486	0.383	-0.026	0.281	3,120
	Other engineering-related technologies	87,997	48,416	0.349	-0.028	0.320	2,760
	Suppressed-All Science & Engineering Major	102,422	27,672	0.354	-0.120	0.003	30
Other Social and Related Sciences	Anthropology and archaeology	60,732	46,956	0.059	-0.022	0.512	5,100
	Area and ethnic studies	65,280	49,978	0.164	-0.029	0.341	3,870
	Criminology	60,478	31,244	0.103	-0.025	0.281	2,250
	Geography	66,977	47,031	0.104	-0.022	0.463	4,430
	History of science	77,201	46,282	0.168	-0.065	0.058	380
	Home Economics	57,533	32,746	0.066	-0.025	0.357	2,950
	International relations	79,790	61,409	0.298	-0.024	0.459	4,460
	Other social sciences	65,084	43,991	0.113	-0.020	0.859	6,900
	Philosophy of science	90,081	67,829	0.229	-0.053	0.089	580
	Public policy studies	82,619	89,735	0.246	-0.078	0.058	670
	Sociology	63,440	43,041	0.118	-0.014	2.816	23,730
Physical and Related Sciences	Astronomy and astrophysics	66,081	47,546	0.157	-0.084	0.018	510
	Atmospheric sciences and meteorology	74,059	42,787	0.227	-0.039	0.067	1,860
	Chemistry, except biochemistry	88,570	62,226	0.294	-0.017	1.226	24,630
	Earth sciences	66,022	38,846	0.105	-0.039	0.093	1,900
	Geological sciences, other	78,506	45,287	0.284	-0.041	0.040	1,200
	Geology	82,645	53,234	0.216	-0.023	0.450	10,090
	Other physical sciences	79,809	50,933	0.165	-0.038	0.137	2,040
	Oceanography	65,837	33,667	0.075	-0.086	0.026	440
	Physics, except biophysics	90,579	55,126	0.321	-0.021	0.516	12,560
	Science, unclassified	78,764	47,143	0.244	-0.039	0.084	1,050
Political Science	Law/prelaw/legal studies	75,065	54,414	0.123	-0.040	0.166	1,320
	Other public affairs	68,448	46,681	0.107	-0.069	0.057	360
	Political science and government	85,973	67,174	0.262	-0.017	3.393	27,520
	Public administration	75,468	42,062	0.190	-0.043	0.076	700
Psychology or Social Work	Clinical psychology	76,679	57,403	0.161	-0.034	0.305	2,880
	Counseling psychology	60,641	35,447	0.069	-0.024	0.308	2,790
	Experimental psychology	86,226	62,091	0.207	-0.046	0.142	1,280
	General psychology	60,781	45,541	0.102	-0.013	4.229	35,150
	Industrial/Organizational psychology	79,966	49,200	0.276	-0.038	0.159	1,340
	Other psychology	68,456	45,698	0.135	-0.020	0.461	4,010
	Social Work	54,321	26,671	0.007	-0.019	0.498	5,050
	Social psychology	66,967	38,831	0.139	-0.031	0.191	1,730

Note: Column 1 presents 19 aggregated BA fields that are constructed from 144 disaggregated BA fields. For each disaggregated field, columns 2-8 present its field name, mean and standard deviation of earnings, its coefficient and standard error from a disaggregated additive earnings regression, percentage of the sample, and cell count rounded to the nearest 10. Disaggregated BA fields with less than 10 observations are removed from the table. See notes for Table B1.

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

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

Table B3: Aggregation of occupations

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)
Biological Scientist	Agricultural and food scientists	Agricultural and food scientists	Census	59,650	23,833	-0.730	0.122	180
		Agricultural and food scientists	SESTAT	59,249	29,087	-0.730	0.128	2,270
	Biological scientists	Biochemists and biophysicists	SESTAT	51,216	27,342	-0.757	0.075	1,760
		Biological scientists	Census	55,615	19,922	-0.757	0.286	430
		Biological scientists (e.g., botanists, ecologists, zoologists)	SESTAT	53,968	29,809	-0.757	0.195	4,080
		Other biological and life scientists	SESTAT	63,264	32,982	-0.757	0.084	1,750
	Foresters and conservation scientists	Foresters and conservation scientists	Census	61,162	28,212	-0.764	0.170	260
		Forestry and conservation scientists	SESTAT	59,689	21,938	-0.764	0.074	1,510
	Medical scientists	Medical scientists	Census	74,770	85,341	-0.649	0.097	150
		Medical scientists (excluding practitioners)	SESTAT	62,526	42,489	-0.649	0.136	2,270
Blue Collar	Construction and extraction occupations	Carpenters	Census	44,002	18,251	-1.216	0.030	50
		Construction and extraction occupations	SESTAT	66,173	38,211	-1.008	0.532	3,230
		Construction trades, n.e.c.	Census					
		Drillers of oil wells	Census					
		Electric power installers and repairers	Census					
		Electricians	Census					
		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	76,791	49,214	-0.603	0.175	260
	Installation, maintenance, and repair occupations	Aircraft mechanics	Census					
		Auto body repairers	Census					
		Automobile mechanics	Census					
		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	62,210	26,513	-0.864	0.022	30
		Installation, maintenance, and repair occupations	SESTAT	55,770	27,536	-0.888	0.344	2,110

....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)	Locksmiths and safe repairers	Census					
		Machinery maintenance occupations	Census					
		Mechanics and repairers, n.e.c.	Census	55,848	26,593	-0.963	0.021	30
		Millwrights	Census					
		Precision makers, repairers, and smiths	Census					
		Repairers of data processing equipment	Census	62,707	17,161	-0.865	0.025	40
		Repairers of electrical equipment, n.e.c.	Census					
		Repairers of household appliances and power tools	Census					
		Repairers of industrial electrical equipment	Census	58,435	32,379	-0.903	0.050	80
		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	47,988	24,934	-1.195	0.031	50
		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, and 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	48,032	27,450	-1.029	0.025	40
		Machinists	Census					
		Metal platers	Census					
		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					

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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)
Blue Collar (continued)	Precision/production occupations (e.g., metal workers, woodworkers, butchers, bakers, assemblers, printing occupations, tailors, shoemakers, photographic process) (continued)	Patternmakers and model makers	Census					
		Photographic process workers	Census					
		Plant and system operators, stationary engineers	Census	77,956	28,442	-0.620	0.079	120
		Power plant operators	Census					
		Precision/production occupations (e.g., metal workers, woodworkers, butchers, bakers, assemblers, printing occupations, tailors, shoemakers, photographic process)	SESTAT	53,575	33,404	-0.891	0.455	2,770
		Pressing machine operators (clothing)	Census					
		Printing machine operators, n.e.c.	Census	47,553	29,091	-1.268	0.020	30
		Production supervisors or foremen	Census	85,223	73,500	-0.553	0.214	320
		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	82,770	91,799	-0.570	0.049	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	69,406	21,190	-0.547	0.037	60
		Guards, watchmen, doorkeepers	Census	49,834	24,425	-1.027	0.075	110
		Other law enforcement: sheriffs, bailiffs, correctional institution officers	Census	62,589	24,084	-0.785	0.031	50
		Police, detectives, and private investigators	Census	69,565	24,363	-0.502	0.183	280
		Protective services, n.e.c.	Census					
		Protective services (e.g., fire fighters, police, guards, wardens, park rangers)	SESTAT	63,361	29,505	-0.620	0.812	4,470
		Supervisors of guards	Census					
	Transportation and material moving occupations	Bus drivers	Census					
		Construction laborers	Census	64,577	41,083	-1.140	0.027	40
		Crane, derrick, winch, and hoist operators	Census					
		Excavating and loading machine operators	Census					
		Freight, stock, and materials handlers	Census					
		Garage and service station related occupations	Census					
		Gharbage and recyclable material collectors	Census					
		Helpers, constructions	Census					
		Helpers, surveyors	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)	Laborers outside construction	Census	42,077	20,957	-1.253	0.027	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					
		Ship crews and marine engineers	Census					
		Supervisors of motor vehicle transportation	Census					
		Taxi cab drivers and chauffeurs	Census					
		Transportation and material moving occupations	SESTAT	71,268	50,506	-1.111	0.511	3,230
		Truck, delivery, and tractor drivers	Census	52,636	20,393	-1.134	0.071	110
		Vehicle washers and equipment cleaners	Census					
Business related occupations	Accountants, auditors, and other financial specialists	Accountants, auditors & other financial specialists	SESTAT	83,266	49,820	-0.460	4.149	18,890
		Accountants and auditors	Census	68,276	45,815	-0.504	1.365	2,050
		Other financial specialists	Census	80,949	73,892	-0.348	0.402	600
	Actuaries	Actuaries	Census	102,133	45,671	-0.021	0.029	40
		Actuaries	SESTAT	105,810	70,554	-0.021	0.084	750
	Insurance, securities, real estate and business services	Advertising and related sales jobs	Census	76,125	55,704	-0.456	0.073	110
		Financial services sales occupations	Census	134,128	163,482	-0.075	0.168	250
		Insurance, securities, real estate and business services	SESTAT	90,705	64,672	-0.438	2.328	10,810
		Insurance sales occupations	Census	87,815	73,643	-0.547	0.280	420
		Real estate sales occupations	Census	88,257	86,343	-0.665	0.241	360
	Personnel, training, and labor relations specialists	Personnel, HR, training & labor relations specialists	Census	59,446	31,873	-0.548	0.313	470
		Personnel, training, and labor relations specialists	SESTAT	70,584	39,913	-0.548	1.071	6,550
Clerical occupations	Bookkeepers, accounting & auditing clerks	Accounting clerks and bookkeepers	SESTAT	43,726	25,009	-0.925	0.542	2,680
		Bookkeepers, accounting & auditing clerks	Census	42,382	22,251	-0.925	0.169	250
	Legal assistants	Legal assistants, paralegals, legal support, etc	Census	50,875	27,718	-0.721	0.088	130
	Secretaries	Other admin. (e.g. record clerks, telephone operators)	SESTAT	45,213	22,856	-0.961	1.954	12,050
		Secretaries	Census	37,242	13,215	-0.961	0.306	460
		Secretaries, receptionists, typists	SESTAT	38,997	18,795	-0.961	0.794	4,000

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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)
Computer Scientist	Computer software developers	Computer programmers (business, scientific, process control)	SESTAT	77,677	31,735	-0.347	0.805	10,080
		Computer software developers	Census	66,864	25,773	-0.347	1.580	2,370
		Computer system analysts	SESTAT	95,182	35,907	-0.347	1.140	19,310
	Computer systems analysts and computer scientists	Computer system analysts	SESTAT	82,129	38,259	-0.497	1.510	18,850
		Computer systems analysts and computer scientists	Census	75,645	28,718	-0.498	2.068	3,110
		Other computer information science occupations	SESTAT	80,334	36,682	-0.497	0.556	5,460
	Operations and systems researchers and analysts	Computer system analysts	SESTAT	84,658	34,572	-0.495	0.534	6,360
		Other computer information science occupations	SESTAT	82,121	34,435	-0.490	0.930	10,960
		Operations and systems researchers & analysts	Census	71,213	31,218	-0.488	0.872	1,310
Doctor	Diagnosing/treating practitioners[1]	Dentists	Census	119,418	78,485	-0.166	0.021	30
		Diagnosing/treating practitioners[1]	SESTAT	146,338	89,398	-0.075	0.781	6,810
		Optometrists	Census					
		Physicians	Census	163,841	160,189	-0.007	0.501	750
		Podiatrists	Census					
		Veterinarians	Census	77,544	40,817	-0.588	0.031	50
Engineer	Aeronautical/aerospace/astronautical engineers	Aeronautical/aerospace/astronautical engineers	SESTAT	92,300	31,093	-0.368	0.243	7,310
		Aerospace engineer	Census	85,627	26,466	-0.291	0.725	1,090
	Architects	Architects	Census	78,767	59,187	-0.596	0.400	600
		Architects	SESTAT	78,727	37,023	-0.596	0.390	3,280
	Chemical engineers	Chemical engineers	Census	86,844	29,124	-0.240	0.336	510
		Chemical engineers	SESTAT	90,207	35,361	-0.240	0.219	6,730
	Civil engineers	Civil, including architectural/sanitary engineers	SESTAT	77,830	30,790	-0.403	0.646	16,270
		Civil engineers	Census	82,141	50,508	-0.403	1.233	1,850
	Electrical engineer	Electrical and electronics engineers	SESTAT	88,864	31,353	-0.346	0.949	21,,670
		Electrical engineer	Census	83,573	29,135	-0.346	2.243	3,370
	Industrial engineers	Industrial engineers	Census	75,197	25,322	-0.446	0.659	990
		Industrial engineers	SESTAT	76,667	26,352	-0.446	0.286	6,320
	Mechanical engineers	Mechanical engineers	Census	81,080	28,711	-0.430	0.806	1,210
		Mechanical engineers	SESTAT	83,101	30,121	-0.430	0.876	21,150
	Metallurgical and materials engineers, variously phrased	Materials and metallurgical engineers	SESTAT	79,418	29,678	-0.421	0.093	2,510
		Metallurgical and materials engineers, variously phrased	Census	76,669	21,897	-0.421	0.088	130
	Not-elsewhere-classified engineers	Agricultural engineers	SESTAT	70,848	26,307	-0.730	0.015	280
		Bioengineers or biomedical engineers	SESTAT	70,930	34,727	-0.757	0.046	1,120
		Computer engineer - hardware	SESTAT	90,814	36,939	-0.368	0.169	3,130
		Environmental engineers	SESTAT	77,208	29,818	-0.368	0.220	4,750
		Marine engineers and naval architects	SESTAT	88,791	33,002	-0.368	0.023	540
		Not-elsewhere-classified engineers	Census	82,506	48,836	-0.368	1.492	2,240
		Nuclear engineers	SESTAT	92,938	34,781	-0.368	0.054	1,150
		Other engineers	SESTAT	87,563	31,245	-0.368	0.239	5,260

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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)
Engineer (continued)	Petroleum, mining, and geological engineers	Mining and geological engineers	SESTAT	79,649	31,085	0.003	0.020	430
		Petroleum, mining, and geological engineers	Census	100,671	38,321	0.003	0.131	200
		Petroleum engineers	SESTAT	105,165	43,590	0.003	0.055	1,240
	Sales engineers	Sales engineers	Census	93,336	42,875	-0.267	0.178	270
		Sales engineers	SESTAT	95,609	46,320	-0.267	0.210	2,640
Farmers, Foresters and Fishermen	Farmers, Foresters and Fishermen	Animal caretakers except on farms	Census					
		Farm managers, except for horticultural farms	Census	51,910	26,079	-1.008	0.026	40
		Farm workers	Census					
		Farmers, Foresters and Fishermen	SESTAT	58,084	50,648	-1.060	0.331	2,370
		Farmers (owners and tenants)	Census					
		Gardeners and groundskeepers	Census	45,856	21,937	-1.297	0.021	30
		Supervisors of agricultural occupations	Census					
		Weighers, measurers, and checkers	Census					
Law related occupations	Lawyers, judges	Lawyers	Census	118,706	122,843	-0.275	0.361	540
		Lawyers, judges	SESTAT	124,854	78,445	-0.275	1.187	5,770
Manager	Managers and administrators, n.e.c.	Computer and information systems managers	SESTAT	129,166	47,104	-0.498	0.222	2,210
		Engineering managers	SESTAT	122,833	43,222	-0.343	0.205	4,070
		Financial managers	Census	93,568	79,829	-0.282	0.476	720
		Funeral directors	Census					
		Human resources and labor relations managers	Census	81,691	40,560	-0.371	0.168	250
		Managers and administrators, n.e.c.	Census	104,265	88,890	-0.343	2.632	3,950
		Managers and specialists in marketing, advertising, and public relations	Census	99,562	55,683	-0.314	0.446	670
		Managers of properties and real estate	Census	91,241	88,889	-0.582	0.114	170
		Managers of service organizations, n.e.c.	Census	59,189	29,813	-0.665	0.161	240
		Natural sciences managers	SESTAT	96,820	45,850	-0.343	0.020	530
		Supervisors and proprietors of sales jobs	Census	82,439	77,605	-0.600	0.962	1,450
	Managers in education and related fields	Education admin. (e.g. registrar, dean, principal)	SESTAT	86,873	28,908	-0.632	0.198	1,160
		Managers in education and related fields	Census	68,964	31,989	-0.632	0.445	670
		Managers of medicine and health occupations	Census	71,478	34,087	-0.431	0.131	200
		Medical and health services managers	SESTAT	104,799	54,422	-0.431	0.197	1,410

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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)
Manager (continued)	Other management related occupations	Business and promotion agents	Census					
		Buyers, wholesale and retail trade	Census	64,215	49,628	-0.654	0.056	80
		Construction inspectors	Census	56,656	18,167	-0.795	0.042	60
		Inspectors and compliance officers, outside construction	Census	58,098	24,249	-0.478	0.288	430
		Insurance underwriters	Census	56,692	20,945	-0.476	0.041	60
		Management analysts	Census	91,619	72,224	-0.357	0.414	620
		Management support occupations	Census	54,200	24,849	-0.554	0.092	140
		Other management related occupations	SESTAT	76,436	40,771	-0.487	2.995	20,870
		Purchasing agents and buyers, of farm products	Census					
		Purchasing managers, agents and buyers, n.e.c.	Census	60,705	38,306	-0.510	0.110	160
	Top-level managers, executives, administrators[2]	Chief executives and public administrators	Census					
		Top-level managers[2]	SESTAT	147,000	85,050	0.000	1.226	8,240
		Top mid-level managers, executives, admin	SESTAT	102,000	51,056	-0.343	6.102	34,940
Marketing	Retail sales clerks	Retail sales clerks	Census					
		Sales occupations - retail (e.g., furnishings, clothing, motor vehicles, cosmetics)	SESTAT	53,508	37,650	-0.859	1.330	6,410
	Salespersons, n.e.c.	Door-to-door sales, street sales, and news vendors	Census	61,679	34,114	-1.082	0.030	50
		Other marketing and sales occupations	SESTAT	77,709	49,304	-0.432	2.087	11,690
		Sales demonstrators/promoters/models	Census					
		Sales occupations - Commodities except retail (e.g., industrial machinery/equipment/supplies, medical and dental equip./supplies)	SESTAT	83,778	46,500	-0.432	1.593	8,080
		Salespersons, n.e.c.	Census	53,030	38,135	-0.432	0.153	230
Math Scientist	Mathematicians and mathematical scientists	Mathematicians	SESTAT	60,935	37,242	-0.460	0.009	180
		Mathematicians and mathematical scientists	Census	69,924	23,235	-0.460	0.023	40
		Other mathematical scientists	SESTAT	74,534	39,301	-0.460	0.012	150
		Statisticians	SESTAT	73,948	32,130	-0.460	0.064	1,380
Other health occupations	Health technologists and technicians, n.e.c.	Clinical laboratory technologies and technicians	Census	54,398	17,141	-0.736	0.501	750
		Dental hygenists	Census					
		Health record tech specialists	Census					
		Health technologists and technicians, n.e.c.	Census	52,318	30,869	-0.729	0.070	110
		Health technologists and technicians[3]	SESTAT	53,808	31,465	-0.727	0.708	6,380
		Licensed practical nurses	Census					
		Other health occupations	SESTAT	55,300	39,456	-0.729	0.613	4,590
		Radiologic tech specialists	Census	58,288	20,140	-0.618	0.045	70

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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)
Other health occupations (continued)	Registered nurses, pharmacists, dieticians, therapists, physician assistants, nurse practitioners	Dietitians and nutritionists	Census	48,297	15,663	-0.742	0.130	200
		Occupational therapists	Census	55,487	18,983	-0.567	0.031	50
		Pharmacists	Census	81,197	26,442	-0.210	0.158	240
		Physical therapists	Census	63,901	38,913	-0.594	0.061	90
		Registered nurses	Census	62,472	19,596	-0.488	0.713	1,070
		Registered nurses, pharmacists, dieticians, therapists, physician assistants, nurse practitioners	SESTAT	72,720	29,978	-0.502	2.941	15,990
		Respiratory therapists	Census					
		Speech therapists	Census	49,988	16,748	-0.684	0.031	50
		Therapists, n.e.c.	Census	43,173	13,534	-0.894	0.048	70
Other service occupations	Food preparation and service (e.g., cookes, waitresses, bartenders)	Cooks, variously defined	Census	39,442	30,429	-1.206	0.023	40
		Food preparation and service (e.g., cookes, waitresses, bartenders)	SESTAT	38,473	25,862	-1.270	0.399	2,320
		Kitchen workers	Census					
		Misc food prep workers	Census					
		Waiter's assistant	Census					
		Waiter/waitress	Census	30,696	14,335	-1.276	0.029	40
	Other service occupations, except health (e.g., prbation officers, human services workers)	Barbers	Census					
		Cashiers	Census	54,006	123,948	-1.312	0.061	90
		Hairdressers and cosmetologists	Census					
		Hotel clerks	Census					
		Other service occupations, except health (e.g., probation officers, human services workers)	SESTAT	48,070	30,216	-1.327	0.952	5,660
		Personal service occupations, nec	Census					
Other social service occupations	Clergy and religious workers	Clergy and Other religious workers	SESTAT	48,460	24,581	-1.119	0.517	2,030
		Clergy and religious workers	Census	41,458	20,576	-1.119	0.247	370
	Librarians, archivists, curators	Archivists and curators	Census	60,890	55,672	-0.880	0.041	60
		Librarians	Census	47,457	14,946	-0.909	0.102	150
		Librarians, archivists, curators	SESTAT	53,474	20,715	-0.909	0.300	1,420
		Library assistants	Census	35,583	11,995	-1.247	0.021	30
	Other teachers and instructors	Other teachers and instructors	SESTAT	50,158	30,323	-1.082	0.133	890
		Teachers , n.e.c.	Census	54,216	26,607	-1.082	0.187	280
	Social workers	Recreation workers	Census					
		Social Workers	SESTAT	47,207	21,452	-0.888	1.203	11,620
		Social workers	Census	48,127	19,267	-0.888	1.564	2,350
	Vocational and educational counselors	Counselors (Educational, vocational health, and substance abuse)	SESTAT	50,727	21,606	-0.925	0.774	6,690
		Vocational and educational counselors	Census	53,116	21,339	-0.925	0.398	600

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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)
Physical Scientist	Atmospheric and space scientists	Atmospheric and space scientists	Census	70,447	26,491	-0.455	0.031	50
		Atmospheric and space scientists	SESTAT	68,223	32,995	-0.455	0.028	940
	Chemists	Chemists	Census	66,646	24,890	-0.582	0.563	850
		Chemists, except biochemists	SESTAT	63,755	29,902	-0.582	0.271	7,410
	Geologists	Geologists	Census	76,093	48,295	-0.553	0.270	410
		Geologists, including earth scientists	SESTAT	75,852	39,880	-0.553	0.138	4,290
		Oceanographers	SESTAT	57,078	29,278	-0.553	0.007	170
	Physical scientists, n.e.c.	Other physical scientists	SESTAT	63,469	26,245	-0.642	0.073	1,780
		Physical scientists, n.e.c.	Census	62,430	22,161	-0.642	0.104	160
	Physicists and astronomers	Astronomers	SESTAT	36,444	19,491	-0.508	0.003	150
		Physicists, except biophysicists	SESTAT	60,597	40,274	-0.508	0.039	1,380
		Physicists and astronomers	Census	80,989	34,669	-0.508	0.085	130
Post-secondary Teachers	Postsecondary Teachers	Post-sec teachers - physical education	SESTAT	57,270	30,367	-0.807	0.043	240
		Postsecondary Teachers: Agriculture	SESTAT	57,389	18,646	-0.807	0.016	190
		Postsecondary Teachers: Art, Drama, and Music	SESTAT	53,491	22,380	-0.807	0.066	440
		Postsecondary Teachers: Biological Sciences	SESTAT	40,103	21,257	-0.807	0.030	540
		Postsecondary Teachers: Business Commerce and Marketing	SESTAT	60,771	24,267	-0.807	0.041	330
		Postsecondary Teachers: Chemistry	SESTAT	36,247	21,706	-0.807	0.017	360
		Postsecondary Teachers: Computer Science	SESTAT	62,532	32,381	-0.807	0.031	350
		Postsecondary Teachers: Earth, Environmental, and Marine Science	SESTAT	46,624	28,110	-0.807	0.010	180
		Postsecondary Teachers: Economics	SESTAT	61,073	48,267	-0.807	0.006	100
		Postsecondary Teachers: Education	SESTAT	54,962	33,762	-0.807	0.029	250
		Postsecondary Teachers: Engineering	SESTAT	56,409	30,755	-0.807	0.024	510
		Postsecondary Teachers: English	SESTAT	45,590	19,634	-0.807	0.059	440
		Postsecondary Teachers: Foreign Language	SESTAT	52,732	20,505	-0.807	0.018	180
		Postsecondary Teachers: Health and related sci.	SESTAT	72,834	49,884	-0.807	0.086	870
		Postsecondary Teachers: History	SESTAT	52,647	34,860	-0.807	0.012	100
		Postsecondary Teachers: Mathematics and Statistics	SESTAT	46,493	19,855	-0.807	0.042	820
		Postsecondary Teachers: Other Natural Sciences	SESTAT	83,264	55,018	-0.807	0.014	170
		Postsecondary Teachers: Other Postsecondary fields	SESTAT	59,950	27,252	-0.807	0.156	1,240
		Postsecondary Teachers: Other Social Sciences	SESTAT	54,214	32,158	-0.807	0.012	180
		Postsecondary Teachers: Physics	SESTAT	41,541	24,306	-0.807	0.008	260
		Postsecondary Teachers: Political Science	SESTAT	54,999	35,630	-0.807	0.008	90
		Postsecondary Teachers: Psychology	SESTAT	42,221	25,306	-0.807	0.014	180
		Postsecondary Teachers: Sociology	SESTAT	54,046	22,241	-0.807	0.007	110
		Subject instructors (HS/college)	Census	56,364	33,102	-0.807	0.409	610

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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)
Primary and secondary teachers	Kindergarten and earlier school teachers	Kindergarten and earlier school teachers	Census	33,058	17,467	-1.108	0.036	50
		Teachers: Pre-kindergarten and kindergarten	SESTAT	45,012	23,590	-1.108	0.522	2,000
	Primary school teachers	Primary school teachers	Census	51,125	20,363	-0.847	1.338	2,010
		Special education teachers	Census	46,737	18,944	-0.854	0.027	40
		Teachers: Elementary	SESTAT	53,433	23,332	-0.847	2.601	9,680
	Secondary school teachers	Secondary school teachers	Census	53,510	18,798	-0.831	0.643	970
		Teachers: Other precollegiate area	SESTAT	51,416	25,826	-0.831	0.275	1,630
		Teachers: Secondary - computer, math or sciences	SESTAT	54,663	19,352	-0.831	1.022	9,220
		Teachers: Secondary - Other subjects	SESTAT	55,752	20,619	-0.831	1.298	6,130
		Teachers: Secondary - social sciences	SESTAT	54,770	18,540	-0.831	0.417	2,460
		Teachers: Special education - primary and secondary	SESTAT	53,649	20,075	-0.831	0.752	3,270
Social Scientist	Economists, market researchers, and survey researchers	Economists	SESTAT	82,107	50,421	-0.372	0.080	1,370
		Economists, market researchers, and survey researchers	Census	83,373	51,690	-0.372	0.591	890
	Psychologists	Psychologists	Census	53,377	47,630	-0.763	0.380	570
		Psychologists, including clinical	SESTAT	53,306	27,960	-0.763	0.306	3,830
	Social scientists, n.e.c.	Anthropologists	SESTAT	43,083	21,142	-0.724	0.020	460
		Historian, science and technology	SESTAT					
		Historians	SESTAT	54,257	22,724	-0.724	0.008	120
		Other social scientists	SESTAT	74,152	39,670	-0.724	0.160	1,890
		Political scientists	SESTAT	64,287	35,679	-0.724	0.041	520
		Social scientists, n.e.c.	Census	65,312	71,082	-0.724	0.094	140
		Sociologists	SESTAT	48,886	24,583	-0.724	0.019	310
		Urban and regional planners	Census	66,082	27,226	-0.608	0.021	30
Technician	Biological technicians	Biological technicians	Census	53,284	24,249	-0.841	0.045	70
		Technologists and technicians in the bio/life sciences	SESTAT	45,746	21,071	-0.841	0.223	3,200
	Drafters	Drafters	Census	57,805	25,113	-0.803	0.220	330
		Drafting occupations, including computer drafting	SESTAT	59,017	25,307	-0.803	0.086	950
	Engineering technicians, n.e.c.	Electrical, electronic, industrial, and mechanical technicians	SESTAT	66,431	29,348	-0.779	0.292	3,750
		Engineering technicians, n.e.c.	Census	66,235	17,829	-0.779	0.027	40
		Other engineering technologists and technicians	SESTAT	70,321	30,756	-0.779	0.161	2,420
	Other science technicians	Air traffic controllers	Census					
		Airplane pilots and navigators	Census	94,320	55,848	-0.273	0.282	420
		Broadcast equipment operators	Census					
		Chemical technicians	Census	61,303	24,879	-0.734	0.073	110
		Other science technicians	Census	57,953	28,582	-0.526	0.055	80
		Programmers of numerically controlled machine tools	Census					
		Technologists and technicians in the math sciences	SESTAT	65,090	44,731	-0.526	0.003	50
		Technologists and technicians in the physical sciences	SESTAT	52,549	24,942	-0.526	0.087	1,380

....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)
Technician (continued)	Surveyors, cartographers, mapping scientists and technicians	Surveying and mapping technicians	SESTAT	52,682	22,051	-0.783	0.034	440
		Surveyors, cartographers, mapping scientists and technicians	Census	54,147	18,817	-0.783	0.046	70
		Surveyors, cartographers, photogrammetrists	SESTAT	60,635	23,985	-0.783	0.040	480
Writers and Artists	Writers, editors, public relations specialists, artists, entertaininers, broadcasters	Actors, directors, producers	Census	81,671	116,903	-0.565	0.053	80
		Announcers	Census					
		Art/entertainment performers and related	Census					
		Art makers: painters, sculptors, craft-artists, and print-makers	Census	49,296	28,239	-0.703	0.035	50
		Athletes, sports instructors, and officials	Census					
		Dancers	Census					
		Designers	Census	64,287	60,593	-0.706	0.212	320
		Editors and reporters	Census	56,452	30,718	-0.703	0.190	290
		Musician or composer	Census	46,572	31,303	-1.054	0.034	50
		Photographers	Census	57,770	55,605	-1.050	0.031	50
		Technical writers	Census	65,722	41,993	-0.611	0.143	210
		Writers, editors, public relations specialists, artists, entertaininers, broadcasters	SESTAT	65,828	44,028	-0.722	1.618	6,850
		Writers and authors	Census	61,177	40,761	-0.680	0.033	50

Note: Column 1 presents 20 aggregated occupation categories that are constructed from 66 disaggregated occupations that are available in both Census 1990 (source of our earnings and occupation observation for 1990), and the NSCG and NSRCG observations (SESTAT) for 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 data source (Census 1990 or either the NSCG or NSRCG (SESTAT)) of each most detailed-level occupation. For each detailed occupation, Col. 7 reports the occupational premium we imported from an earnings regression in ACS 2009-2014. Columns 5, 6, 8 and 9 refer to the "full" earnings regression sample. For each occupation, they present the weighted mean and standard deviation of earnings, the unweighted percentage of the sample, and the number of cases. 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] Diagnosing/treating practitioners include dentists, optometrists, physicians, podiatrists, surgeons, veterinarians.

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

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

Table B4: Return to graduate education on current and previous earnings subsamples

Advanced degree	Current year earnings (1)	Previous year earnings (2)	Pooled sample (3)	t-statistics for the diffeence between (1) and (2) (4)
Medicine	0.498 (0.064)	0.641 (0.113)	0.549 (0.072)	-1.100
Law	0.396 (0.050)	0.466 (0.126)	0.416 (0.059)	-0.520
Master's in Business related fields	0.180 (0.033)	0.260 (0.093)	0.206 (0.044)	-0.813
MBA	0.115 (0.020)	0.088 (0.035)	0.110 (0.021)	0.656
Master's in Engineering	0.110 (0.019)	0.087 (0.028)	0.103 (0.018)	0.696
Master's in Computer and mathematical sciences	0.201 (0.032)	0.160 (0.047)	0.179 (0.033)	0.709
Master's in Health Services Administration	0.272 (0.080)	0.264 (0.117)	0.273 (0.091)	0.054
Master's in Nursing	0.232 (0.038)	0.243 (0.057)	0.235 (0.041)	-0.160
Master's in Other Science and Engineering related fields	-0.006 (0.060)	-0.034 (0.077)	-0.018 (0.058)	0.287
Master's in Public Administration	0.235 (0.057)	0.112 (0.062)	0.193 (0.052)	1.466
Master's in Physical and related sciences	0.132 (0.053)	0.206 (0.084)	0.158 (0.054)	-0.744
Master's in Other Social and related sciences	0.115 (0.066)	0.054 (0.071)	0.089 (0.057)	0.627
Master's in Health related fields	0.274 (0.045)	0.165 (0.098)	0.227 (0.053)	1.008
Master's in Biology/agricultural/ environmental/life sciences	0.265 (0.049)	0.161 (0.059)	0.231 (0.045)	1.359
Master's in Other Non-Science and Engineering fields	0.037 (0.059)	0.241 (0.093)	0.117 (0.056)	-1.857
Master's in Education fields	0.161 (0.019)	0.169 (0.030)	0.162 (0.019)	-0.230
Master's in Arts	0.040 (0.093)	-0.318 (0.178)	-0.025 (0.099)	1.779
Master's in Psychology and Social Work	0.203 (0.030)	0.207 (0.042)	0.202 (0.029)	-0.064
Master's in Humanity fields	-0.003 (0.050)	0.047 (0.102)	0.018 (0.062)	-0.439
Observations	178,540	119,000	297,540	

Note: The table reports estimates of returns to advanced degrees for additive FE-cg regression specification. The same regression is estimated on three samples: Column 1 presents the regression estimates on current year earnings measures only. Column 2 presents the estimates on the previous year earnings measure only. Column 3 repeats Table 5 column 1 to show the estimates on the union set of sample for columns 1 and 2. Column 4 reports the two-sample t-statistics for the difference between coefficients in columns 1 and 2.

Table B5: Distribution of the full earnings regression sample by year

Year (1)	Percentage (2)	Frequency (3)
1990	10.445	62,850
1993	15.436	92,950
1994	2.780	28,940
1995	3.685	39,060
1996	2.806	29,450
1997	3.437	36,560
1998	2.340	24,960
1999	2.919	31,560
2001	0.546	6,140
2002	8.664	52,470
2003	8.838	54,310
2005	3.618	34,010
2006	3.788	35,990
2007	3.620	33,660
2008	3.821	35,820
2009	3.398	37,620
2010	3.580	39,730
2012	4.433	47,850
2013	4.397	48,040
2014	3.730	43,020
2015	3.722	43,140
Total	100	858,130

Note: Tabulation of the year of earnings for the full earnings regression sample (Table 5, col. 3). Percentages are weighted. Unweighted cell counts are rounded to the nearest 10.

Table B6: 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	2,930	84.4	2,830	72,204	30,120	2,180	96,700	38,323
If not closely related:								
Pay and promotion opportunities	120	3.93	110	93,304	38,757	90	113,615	38,896
Working conditions	40	1.64	40	66,341	35,370	30	91,721	48,120
Job location	30	0.65	30	77,219	29,460	20	100,080	26,216
Change in career/prof. interests	120	5.18	110	59,577	21,836	60	87,427	35,716
Family-related reasons	20	0.7	10	58,972	13,664	10	68,443	24,702
Job in BA field not available	60	1.3	60	57,552	34,647	60	87,029	35,703
Other reasons	50	2.2	40	64,104	16,852	30	57,400	25,506

Panel B: Pre adv occupation

Closely related	Freq.	%	Not Closely related	Freq.	%
Engineer	1,030	74.12	Engineer	610	56.77
Computer scientist	130	8.63	Computer scientist	150	14.83
Manager	70	5.66	Manager	110	10.59

Panel C: Advanced field choice

Advanced field	Closely related		Not closely related	
	Freq.	%	Freq.	%
Master's in Engineering	980	26.60	370	17.43
MBA	740	50.52	680	57.16
Master's in Computer and mathematical sciences	90	4.59	50	3.31
Master's in Business related fields	80	6.98	120	9.49
Law	40	2.96		

Panel D: Pre adv average earnings by advanced field

Advanced field	Closely related			Not closely related		
	count	mean	sd	count	mean	sd
Master's in Engineering	1,140	61,248	29,193	530	65,628	30,154
MBA	870	82,347	27,267	830	82,367	34,103
Master's in Computer and mathematical sciences	130	70,829	28,382	80	73,707	22,740
Master's in Business related fields	80	90,799	40,458	130	84,833	70,035
Law	40	80,808	32,661			

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. Weighted percentages and the weighted mean and standard deviations of earnings statistics are presented. Unweighted cell counts are rounded to the nearest 10.

Table B7: Return to advanced degrees by years of post adv experience, FE-cg

	Averages			Return to advanced degree by years of post Adv experience				
	γ_{gx} 1∼28 years, sample weighted	$\bar{\gamma_{gx}}$ 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	0.627	0.619	0.658	0.072	0.380	0.659	0.867	0.606
	(0.084)	(0.084)	(0.084)	(0.089)	(0.085)	(0.085)	(0.086)	(0.094)
Law	0.451	0.462	0.469	0.280	0.353	0.431	0.542	0.595
	(0.056)	(0.056)	(0.056)	(0.060)	(0.057)	(0.058)	(0.058)	(0.071)
Master's in Business related fields	0.245	0.248	0.265	0.109	0.180	0.249	0.323	0.311
	(0.044)	(0.044)	(0.044)	(0.047)	(0.044)	(0.045)	(0.047)	(0.057)
MBA	0.157	0.162	0.181	0.098	0.120	0.150	0.216	0.289
	(0.020)	(0.020)	(0.021)	(0.023)	(0.020)	(0.022)	(0.023)	(0.039)
Master's in Engineering	0.161	0.165	0.198	0.046	0.113	0.179	0.256	0.258
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.021)	(0.027)
Master's in Computer and mathematical sciences	0.202	0.202	0.228	0.106	0.170	0.228	0.272	0.219
	(0.033)	(0.033)	(0.034)	(0.033)	(0.032)	(0.034)	(0.035)	(0.046)
Master's in Health Services Administration	0.269	0.268	0.300	0.159	0.238	0.308	0.349	0.259
	(0.088)	(0.088)	(0.091)	(0.089)	(0.086)	(0.091)	(0.097)	(0.139)
Master's in Nursing	0.186	0.181	0.163	0.183	0.204	0.209	0.149	-0.003
	(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	-0.013	0.002	0.024	-0.188	-0.120	-0.040	0.110	0.243
	(0.056)	(0.056)	(0.056)	(0.064)	(0.057)	(0.057)	(0.059)	(0.070)
Master's in Public Administration	0.228	0.229	0.263	0.030	0.143	0.249	0.348	0.295
	(0.052)	(0.052)	(0.053)	(0.061)	(0.053)	(0.055)	(0.058)	(0.085)
Master's in Physical and related sciences	0.238	0.245	0.285	0.032	0.147	0.259	0.380	0.362
	(0.052)	(0.052)	(0.053)	(0.052)	(0.052)	(0.054)	(0.055)	(0.066)
Master's in Other Social and related sciences	0.125	0.134	0.164	0.019	0.070	0.128	0.221	0.287
	(0.056)	(0.056)	(0.057)	(0.055)	(0.055)	(0.058)	(0.060)	(0.066)
Master's in Health Related Fields	0.241	0.240	0.246	0.221	0.238	0.252	0.254	0.221
	(0.053)	(0.053)	(0.054)	(0.053)	(0.052)	(0.054)	(0.057)	(0.071)
Master's in Biological/agricultural/ environmental/life sciences	0.295	0.298	0.331	0.149	0.236	0.318	0.397	0.362
	(0.045)	(0.045)	(0.046)	(0.046)	(0.045)	(0.047)	(0.048)	(0.058)
Master's in Other Non-Science and Engineering fields	0.169	0.173	0.187	0.059	0.112	0.166	0.236	0.254
	(0.056)	(0.056)	(0.056)	(0.059)	(0.056)	(0.057)	(0.059)	(0.072)
Master's in Education fields	0.205	0.210	0.218	0.109	0.151	0.196	0.261	0.293
	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)	(0.019)	(0.019)	(0.024)
Master's in Arts	-0.002	0.003	0.021	-0.152	-0.077	-0.001	0.086	0.089
	(0.103)	(0.103)	(0.103)	(0.109)	(0.103)	(0.104)	(0.107)	(0.122)
Master's in Psychology and Social Work	0.215	0.218	0.254	0.070	0.153	0.233	0.323	0.315
	(0.029)	(0.029)	(0.030)	(0.029)	(0.029)	(0.030)	(0.032)	(0.040)
Master's in Humanity fields	0.050	0.060	0.063	0.010	0.012	0.025	0.088	0.201
	(0.060)	(0.060)	(0.060)	(0.062)	(0.060)	(0.061)	(0.063)	(0.070)

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 (8) on the full sample. 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 1 to 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 B8: 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	0.707	0.699	0.738	0.147	0.457	0.738	0.949	0.690
	(0.016)	(0.016)	(0.016)	(0.033)	(0.020)	(0.020)	(0.024)	(0.043)
Law	0.457	0.467	0.474	0.292	0.363	0.438	0.545	0.594
	(0.015)	(0.015)	(0.015)	(0.028)	(0.017)	(0.019)	(0.022)	(0.048)
Master's in Business related fields	0.338	0.341	0.358	0.200	0.272	0.342	0.418	0.405
	(0.012)	(0.012)	(0.013)	(0.025)	(0.015)	(0.015)	(0.019)	(0.039)
MBA	0.283	0.288	0.308	0.220	0.245	0.277	0.344	0.412
	(0.008)	(0.008)	(0.009)	(0.015)	(0.009)	(0.010)	(0.013)	(0.034)
Master's in Engineering	0.145	0.149	0.184	0.025	0.096	0.166	0.243	0.239
	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.007)	(0.009)	(0.019)
Master's in Computer and mathematical sciences	0.204	0.203	0.232	0.095	0.171	0.238	0.281	0.203
	(0.009)	(0.009)	(0.011)	(0.012)	(0.009)	(0.012)	(0.015)	(0.034)
Master's in Health Services Administration	0.304	0.304	0.342	0.178	0.267	0.347	0.400	0.311
	(0.025)	(0.025)	(0.031)	(0.035)	(0.027)	(0.037)	(0.044)	(0.104)
Master's in Nursing	0.316	0.312	0.294	0.311	0.334	0.341	0.281	0.120
	(0.014)	(0.014)	(0.018)	(0.020)	(0.015)	(0.020)	(0.025)	(0.062)
Master's in Other Science and Engineering related fields	0.069	0.083	0.106	-0.111	-0.038	0.046	0.192	0.307
	(0.018)	(0.018)	(0.019)	(0.039)	(0.023)	(0.023)	(0.027)	(0.048)
Master's in Public Administration	0.211	0.212	0.246	0.008	0.124	0.234	0.333	0.273
	(0.020)	(0.020)	(0.020)	(0.045)	(0.027)	(0.024)	(0.028)	(0.072)
Master's in Physical and related sciences	0.044	0.052	0.094	-0.169	-0.051	0.066	0.192	0.176
	(0.014)	(0.014)	(0.016)	(0.020)	(0.015)	(0.019)	(0.022)	(0.042)
Master's in Other Social and related sciences	0.105	0.115	0.144	0.000	0.050	0.107	0.202	0.272
	(0.013)	(0.013)	(0.017)	(0.015)	(0.012)	(0.020)	(0.024)	(0.037)
Master's in Health Related Fields	0.214	0.213	0.214	0.206	0.215	0.221	0.217	0.190
	(0.012)	(0.012)	(0.015)	(0.017)	(0.013)	(0.018)	(0.021)	(0.048)
Master's in Biological/agricultural/ environmental/ life sciences	0.012	0.015	0.049	-0.137	-0.049	0.035	0.117	0.083
	(0.011)	(0.011)	(0.012)	(0.015)	(0.011)	(0.015)	(0.017)	(0.038)
Master's in Other Non-Science and Engineering fields	0.066	0.070	0.085	-0.050	0.007	0.064	0.136	0.150
	(0.014)	(0.014)	(0.015)	(0.031)	(0.019)	(0.018)	(0.020)	(0.050)
Master's in Education fields	0.104	0.109	0.118	-0.001	0.045	0.094	0.164	0.195
	(0.006)	(0.006)	(0.006)	(0.010)	(0.007)	(0.007)	(0.008)	(0.017)
Master's in Arts	-0.008	-0.001	0.018	-0.173	-0.091	-0.009	0.090	0.101
	(0.023)	(0.023)	(0.023)	(0.052)	(0.032)	(0.027)	(0.032)	(0.069)
Master's in Psychology and Social Work	0.053	0.057	0.091	-0.086	-0.007	0.071	0.157	0.151
	(0.009)	(0.009)	(0.010)	(0.012)	(0.008)	(0.011)	(0.014)	(0.029)
Master's in Humanity fields	-0.152	-0.141	-0.138	-0.193	-0.191	-0.178	-0.113	0.002
	(0.014)	(0.014)	(0.014)	(0.026)	(0.016)	(0.017)	(0.020)	(0.039)

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 B7 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 (8) on the full sample, with degree combination fixed effects excluded. See the notes for Table B7.

Table B9: FE estimates of the returns to graduate education

Dependent variable:	ln(earnings) (1)	Occupational Premium (2)
Medicine	-0.054	0.577
	(0.107)	(0.092)
Law	0.117	0.288
	(0.058)	(0.045)
Master's in Business related fields	0.058	0.008
	(0.024)	(0.011)
MBA	0.058	-0.010
	(0.018)	(0.009)
Master's in Engineering	0.032	-0.002
	(0.021)	(0.007)
Master's in Computer and mathematical sciences	0.083	-0.008
	(0.031)	(0.010)
Master's in Health Services Administration	0.079	0.007
	(0.048)	(0.026)
Master's in Nursing	0.070	-0.024
	(0.044)	(0.019)
Master's in Other Science and Engineering related fields	-0.143	-0.001
	(0.054)	(0.061)
Master's in Public Administration	0.117	0.086
	(0.042)	(0.034)
Master's in Physical and related sciences	-0.010	0.006
	(0.036)	(0.024)
Master's in Other Social and related sciences	0.016	0.026
	(0.069)	(0.033)
Master's in Health related fields	0.123	0.019
	(0.058)	(0.021)
Master's in Biology/agricultural/ environmental/life sciences	0.137	-0.005
	(0.046)	(0.017)
Master's in Other Non-Science and Engineering fields	0.157	0.014
	(0.045)	(0.027)
Master's in Education fields	0.029	0.006
	(0.020)	(0.008)
Master's in Arts	0.005	0.015
	(0.096)	(0.048)
Master's in Psychology and Social Work	0.075	-0.009
	(0.031)	(0.016)
Master's in Humanity fields	-0.055	-0.080
	(0.036)	(0.031)

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 5 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. The estimates are for the full sample. Estimates for the graduate sample tend to be smaller for earnings and similar for the occupation premium.

Table B10: Fraction of people who delay graduate education, and summary statistics related to delaying graduate education, by advanced degree

Advanced degree	% people who delay grad school	% college educated father		Race\Hispanic wage index (mean[sd])		Undergraduate GPA (mean[sd])	
		defer	go direct	defer	go direct	defer	go direct
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Medicine	0.379	0.568	0.591	-0.036 [0.037]	-0.034 [0.031]	3.450 [0.331]	0.113 [0.041]
Law	0.540	0.543	0.549	-0.031 [0.033]	-0.032 [0.030]	3.337 [0.389]	0.100 [0.041]
Master's in Business related fields	0.905	0.465	0.425	-0.034 [0.032]	-0.030 [0.029]	3.297 [0.418]	0.216 [0.074]
MBA	0.846	0.401	0.419	-0.035 [0.036]	-0.038 [0.039]	3.171 [0.379]	0.105 [0.056]
Master's in Engineering	0.885	0.539	0.545	-0.047 [0.036]	-0.043 [0.033]	3.370 [0.405]	0.055 [0.014]
Master's in Computer and mathematical sciences	0.942	0.515	0.566	-0.041 [0.041]	-0.042 [0.038]	3.402 [0.415]	-0.023 [0.045]
Master's in Health Services Administration	0.981	0.368	0.175	-0.026 [0.040]	-0.029 [0.054]	3.381 [0.366]	0.003 [0.139]
Master's in Nursing	0.975	0.321	0.327	-0.010 [0.027]	-0.008 [0.032]	3.547 [0.340]	-0.066 [0.169]
Master's in Other Science and Engineering related fields	0.945	0.536	0.520	-0.038 [0.037]	-0.048 [0.044]	3.245 [0.349]	0.285 [0.178]
Master's in Public Administration	0.960	0.341	0.320	-0.040 [0.048]	-0.055 [0.056]	3.314 [0.330]	-0.134 [0.154]
Master's in Physical and related sciences	0.956	0.487	0.575	-0.034 [0.033]	-0.035 [0.031]	3.363 [0.405]	0.090 [0.041]
Master's in Other Social and related sciences	0.937	0.509	0.485	-0.029 [0.040]	-0.028 [0.041]	3.361 [0.403]	0.094 [0.036]
Master's in Health related fields	0.904	0.457	0.374	-0.018 [0.036]	-0.007 [0.017]	3.454 [0.373]	0.085 [0.046]
Master's in Biology/agricultural/ environmental/life sciences	0.960	0.479	0.490	-0.026 [0.034]	-0.026 [0.031]	3.301 [0.399]	0.048 [0.048]
Master's in Other Non-Science and Engineering fields	0.891	0.385	0.346	-0.021 [0.035]	-0.021 [0.035]	3.203 [0.435]	-0.083 [0.159]
Master's in Education fields	0.946	0.286	0.339	-0.018 [0.032]	-0.018 [0.031]	3.295 [0.423]	0.069 [0.047]
Master's in Arts	0.938	0.481	0.388	-0.025 [0.033]	-0.025 [0.021]	3.352 [0.320]	
Master's in Psychology and Social Work	0.952	0.383	0.327	-0.020 [0.037]	-0.017 [0.031]	3.368 [0.409]	0.042 [0.048]
Master's in Humanity fields	0.951	0.374	0.420	-0.027 [0.033]	-0.026 [0.029]	3.418 [0.364]	0.104 [0.149]
All fields	0.849	0.405	0.501	-0.027 [0.036]	-0.031 [0.033]	3.373 [0.404]	0.067 [0.012]

Note: Weighted summary statistics and regression results reported for analysis about individuals who go directly to graduate school. We use the same set of sampling restrictions while relaxing the requirement that people defer going to graduate school. Column 1 presents the fraction of people who defer graduate school. Columns 2 and 3 present the fraction of people with college educated father by whether the individuals go directly to graduate school. Columns 4 and 5 present the mean and [standard deviation] of a race\Hispanic wage index by whether the individuals go directly to graduate school. The race\Hispanic wage index of each person is the coefficient of his/her race\Hispanic category in the FE-cg earnings regression, without restricting to people who defer graduate school. Column 6 presents the mean and [standard deviation] of GPA for people who defer graduate school. Column 7 presents the gap in GPA between people who go directly and people who defer graduate school, estimated from a regression that controls for advanced field, BA field, and year graduated from BA to account for GPA inflation. Since undergraduate GPA is only available for people who entered the SESTAT system through the Survey of Recent College Graduates, we have GPA for less than 30 individuals who go directly to get a master's in arts. We leave that cell blank.

Table B11: Return to graduate education by whether people go to graduate school directly

Advanced degree	FE-cg		FE-cg w/ post Adv exp. interaction	
	Baseline (1)	Adv×godirect (2)	Baseline* (3)	Adv×godirect (4)
Medicine	0.441 (0.072)	0.117 (0.019)	0.646 (0.085)	0.058 (0.019)
Law	0.384 (0.058)	0.107 (0.020)	0.471 (0.056)	0.083 (0.020)
Master's in Business related fields	0.185 (0.044)	0.054 (0.045)	0.268 (0.044)	0.025 (0.044)
MBA	0.094 (0.021)	0.004 (0.021)	0.187 (0.021)	-0.031 (0.020)
Master's in Engineering	0.097 (0.018)	0.081 (0.013)	0.200 (0.019)	0.049 (0.013)
Master's in Computer and mathematical sciences	0.173 (0.034)	0.115 (0.028)	0.231 (0.033)	0.104 (0.028)
Master's in Health Services Administration	0.264 (0.093)	-0.114 (0.092)	0.301 (0.091)	-0.110 (0.092)
Master's in Nursing	0.235 (0.041)	-0.117 (0.050)	0.164 (0.038)	-0.092 (0.050)
Master's in Other Science and Engineering related fields	-0.026 (0.056)	0.138 (0.062)	0.032 (0.056)	0.086 (0.059)
Master's in Public Administration	0.183 (0.053)	-0.007 (0.126)	0.268 (0.054)	-0.038 (0.115)
Master's in Physical and related sciences	0.123 (0.055)	0.122 (0.064)	0.289 (0.052)	0.083 (0.064)
Master's in Other Social and related sciences	0.079 (0.056)	0.090 (0.038)	0.167 (0.057)	0.069 (0.038)
Master's in Health related fields	0.203 (0.053)	0.024 (0.035)	0.242 (0.054)	0.032 (0.035)
Master's in Biology/agricultural/ environmental/life sciences	0.170 (0.045)	0.128 (0.044)	0.333 (0.046)	0.099 (0.046)
Master's in Other Non-Science and Engineering fields	0.099 (0.057)	0.075 (0.043)	0.187 (0.056)	0.040 (0.043)
Master's in Education fields	0.153 (0.019)	0.046 (0.018)	0.222 (0.018)	0.011 (0.018)
Master's in Arts	-0.039 (0.098)	0.066 (0.094)	0.020 (0.102)	0.016 (0.094)
Master's in Psychology and Social Work	0.195 (0.029)	0.066 (0.032)	0.256 (0.030)	0.049 (0.031)
Master's in Humanity fields	0.009 (0.062)	0.168 (0.058)	0.067 (0.060)	0.121 (0.058)

(* γ_{g1-28})

Note: The table reports estimates of returns to advanced degrees for two regressions. We use the same set of sampling restrictions while relaxing the requirement that people worked before going to graduate school. In both regressions we allow people who go directly to graduate school to have different returns than those who work before attending graduate school, by interacting the dummy for going directly with advanced field. Columns 1 and 2 use the same set of controls as the additive FE-cg regression (Table 5, column 1). Column 1 presents the return to advanced fields for people who delay graduate school, and column 2 presents the additional return for people who go directly to graduate school. Columns 3 and 4 use the same set of controls as the additive FE-cg regression with post advanced degree experience interactions (Table 5 column 4). Column 3 presents the equally weighted average return from 1 to 28 years after graduated school the advanced degree, i.e. γ_{g1-28}, for people who delay going to graduate school. Column 4 presents the additional return for people who go directly to graduate school.

Table B12: Internal rate of return to advanced degrees based on $\bar{\gamma}_{gx}$

Advanced field	Duration of the advanced degree (1)	Annual Tuition (public) (2)	Net PDV Actual (3)	PDV counterfactual (4)	Percentage gain from the advanced degree (5)	Internal rate of return (public) (6)	Annual Tuition (private) (7)	Internal rate of return (private) (8)
Medicine	4	13,317	1,749,356	1,195,320	46.073	0.128	31,807	0.110
Law	3	16,697	1,447,321	1,112,711	29.889	0.131	28,555	0.116
Master's in Business related fields	2	6,736	1,564,818	1,362,839	14.760	0.122	12,302	0.114
MBA	2	9,311	1,498,757	1,412,722	6.024	0.083	13,807	0.079
Master's in Engineering	1	8,131	1,597,105	1,410,017	13.245	0.150	14,058	0.142
Master's in Computer and mathematical sciences	1	8,131	1,489,751	1,271,668	17.100	0.193	14,058	0.181
Master's in Health Services Administration	2	6,736	1,318,574	1,110,790	18.559	0.140	12,302	0.131
Master's in Nursing	2	8,131	1,671,515	1,576,468	6.013	0.095	14,058	0.088
Master's in Other Science and Engineering related fields	1	8,131	1,134,376	1,200,232	-5.590	0.017	14,058	0.015
Master's in Public Administration	2	6,736	1,297,170	1,149,133	12.753	0.106	12,302	0.100
Master's in Physical and related sciences	1	8,131	1,169,990	953,526	22.629	0.182	14,058	0.170
Master's in Other Social and related sciences	1	6,736	1,453,844	1,326,920	9.503	0.121	12,302	0.115
Master's in Health related fields	2	8,131	1,146,890	1,002,601	14.281	0.134	14,058	0.121
Master's in Bio/agricultural/environmental/life sciences	1	8,131	1,011,181	785,955	28.580	0.242	14,058	0.221
Master's in Other Non-Science and Engineering fields	1	6,736	1,004,275	897,306	11.863	0.143	12,302	0.132
Master's in Education fields	1	6,736	967,050	836,826	15.503	0.173	12,302	0.158
Master's in Arts	2	6,736	859,923	963,971	-10.877	Negative	12,302	Negative
Master's in Psychology and Social Work	2	6,736	901,674	805,382	11.822	0.103	12,302	0.094
Master's in Humanity fields	1	6,736	844,386	843,110	0.115	0.051	12,302	0.046

Note: The statistics are calculated from regression coefficients underlying the FE-cg estimates with post-advanced degree experience specific effects reported in Table 5, column 4. For each advanced degree, we calculate the predicted value of actual income in levels (with graduate education) and counterfactual income (without graduate education) from age 27 to 59. When evaluating the log earnings model we set the earnings error term to 0, the parental education variables to their weighted sample means and the calendar year to 2012. We also set the race\ethnicity indicators to non-Hispanic white. For each graduate degree we calculate the population weighted average of predicted earnings at each age over the distribution of gender and of undergraduate major for that graduate degree. We subtract the tuition of the graduate degree from 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 the 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 at public institutions. The internal rate of return is the discount factor that equates actual and counterfactual lifetime net income. In column 7, we present the average tuition at private institutions in 2012 from the National Center of Education Statistics. In column 8, we report estimates of the internal rate of return of each advanced field at private institutions.

Table B13: 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	179,162	11.901	0.227	0.447	4.634	0.883
	[108,708]	[0.669]	[0.104]	[0.176]		
Law	138,966	11.636	0.244	0.262	8.332	0.918
	[97,718]	[0.662]	[0.115]	[0.133]		
Master's in Business related fields	131,611	11.611	0.334	0.142	8.742	0.892
	[90,494]	[0.593]	[0.122]	[0.188]		
MBA	120,089	11.559	0.335	0.129	17.775	0.907
	[71,042]	[0.530]	[0.129]	[0.212]		
Master's in Engineering	104,112	11.452	0.444	0.168	10.873	0.893
	[51,217]	[0.466]	[0.083]	[0.138]		
Master's in Computer and mathematical sciences	104,452	11.447	0.369	0.118	6.677	0.866
	[52,789]	[0.484]	[0.126]	[0.164]		
Master's in Health Services Administration	115,731	11.507	0.229	0.146	0.821	0.910
	[71,035]	[0.555]	[0.107]	[0.235]		
Master's in Nursing	139,359	11.766	0.316	0.099	0.408	0.874
	[58,539]	[0.409]	[0.064]	[0.119]		
Master's in Other Science and Engineering related fields	94,570	11.328	0.289	0.034	2.256	0.899
	[57,539]	[0.509]	[0.116]	[0.218]		
Master's in Public Administration	95,825	11.357	0.219	0.103	1.915	0.897
	[46,146]	[0.494]	[0.104]	[0.237]		
Master's in Physical and related sciences	88,163	11.232	0.271	0.034	2.223	0.812
	[48,463]	[0.594]	[0.089]	[0.189]		
Master's in Other Social and related sciences	91,206	11.236	0.227	0.003	3.595	0.807
	[65,066]	[0.610]	[0.129]	[0.253]		
Master's in Health related fields	100,243	11.360	0.226	0.068	2.047	0.847
	[63,802]	[0.564]	[0.140]	[0.249]		
Master's in Bio/agricultural/ environmental/life sciences	74,364	11.082	0.167	-0.083	3.047	0.821
	[43,550]	[0.527]	[0.092]	[0.216]		
Master's in Other Non-Science and Engineering fields	77,734	11.135	0.162	-0.071	2.228	0.856
	[44,125]	[0.507]	[0.100]	[0.244]		
Master's in Education fields	74,295	11.134	0.113	-0.133	13.285	0.742
	[34,914]	[0.404]	[0.112]	[0.229]		
Master's in Arts	71,597	11.002	0.073	-0.160	1.732	0.667
	[57,582]	[0.585]	[0.104]	[0.210]		
Master's in Psychology and Social Work	74,452	11.093	0.131	-0.117	3.920	0.818
	[39,684]	[0.510]	[0.093]	[0.265]		
Master's in Humanity fields	62,565	10.888	0.127	-0.312	5.490	0.779
	[43,649]	[0.549]	[0.122]	[0.287]		
Total	105,265	11.390	0.262	0.062	100	0.855
	[71,933]	[0.591]	[0.157]	[0.269]		

Note: Columns 1-4 repeat the statistics presented in Table 1 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 B14: 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	130,634 [85,508]	11.562 [0.694]	0.219 [0.094]	0.432 [0.193]	2.565	0.708
Law	108,433 [71,221]	11.417 [0.606]	0.203 [0.104]	0.249 [0.155]	5.212	0.748
Master's in Business related fields	98,129 [63,646]	11.348 [0.541]	0.296 [0.126]	0.091 [0.202]	3.826	0.715
MBA	95,271 [53,749]	11.328 [0.537]	0.275 [0.131]	0.073 [0.217]	8.615	0.751
Master's in Engineering	87,879 [49,485]	11.277 [0.474]	0.420 [0.107]	0.139 [0.153]	2.137	0.755
Master's in Computer and mathematical sciences	85,506 [42,739]	11.238 [0.507]	0.325 [0.135]	0.062 [0.197]	3.478	0.719
Master's in Health Services Administration	85,117 [41,719]	11.247 [0.463]	0.233 [0.106]	0.050 [0.212]	1.423	0.756
Master's in Nursing	91,394 [37,239]	11.354 [0.380]	0.330 [0.046]	0.067 [0.167]	3.475	0.665
Master's in Other Science and Engineering related fields	77,102 [36,561]	11.140 [0.500]	0.255 [0.121]	-0.001 [0.219]	0.867	0.721
Master's in Public Administration	77,428 [38,849]	11.135 [0.521]	0.201 [0.101]	0.002 [0.267]	1.614	0.770
Master's in Physical and related sciences	69,018 [37,935]	10.999 [0.563]	0.244 [0.098]	-0.047 [0.182]	0.970	0.678
Master's in Other Social and related sciences	68,728 [41,043]	11.002 [0.524]	0.185 [0.116]	-0.075 [0.250]	3.668	0.627
Master's in Health related fields	70,893 [32,073]	11.081 [0.429]	0.160 [0.114]	-0.016 [0.200]	6.442	0.600
Master's in Bio/agricultural/ environmental/life sciences	63,226 [33,870]	10.937 [0.493]	0.180 [0.096]	-0.098 [0.197]	3.027	0.666
Master's in Other Non-Science and Engineering fields	62,389 [32,159]	10.950 [0.427]	0.140 [0.095]	-0.192 [0.221]	3.674	0.639
Master's in Education fields	61,990 [25,764]	10.962 [0.389]	0.079 [0.098]	-0.228 [0.180]	32.382	0.584
Master's in Arts	57,886 [32,914]	10.827 [0.540]	0.070 [0.082]	-0.170 [0.204]	1.895	0.474
Master's in Psychology and Social Work	59,916 [30,524]	10.905 [0.439]	0.112 [0.076]	-0.199 [0.216]	10.552	0.648
Master's in Humanity fields	59,838 [31,746]	10.886 [0.481]	0.147 [0.085]	-0.216 [0.230]	4.179	0.550
Total	74,078 [44,595]	11.082 [0.506]	0.167 [0.137]	-0.082 [0.260]	100	0.641

Note: This table repeats the statistics presented in Table B13, but restricting the sample to women.

Table B15: Returns to graduate education by undergraduate fields

	Advanced field	Undergraduate field	ln(earnings)				Occupation premium		Earnings	# of pre Adv earnings obs
			FE-cg†	FE-cg full	OLS	FE-cg Avg 1∼28 years γ_{g1-28}	FE-cg†	OLS	Mean [SD]	person-year [person]
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1)	**MBA**	Bio/agricultural/environmental sci.	-0.107	-0.049	0.335	0.005	0.114	0.162	104,487	140
			(0.087)	(0.089)	(0.038)	(0.089)	(0.036)	(0.015)	[71,152]	[70]
		Business	0.157	0.185	0.239	0.215	0.008	0.062	106,338	110
			(0.065)	(0.062)	(0.016)	(0.063)	(0.016)	(0.006)	[63,644]	[90]
		Computer and mathematical sci.	0.093	0.086	0.244	0.127	0.007	0.051	111,408	220
			(0.053)	(0.053)	(0.026)	(0.053)	(0.018)	(0.010)	[63,853]	[120]
		Economics	0.098	0.171	0.280	0.200	-0.006	0.069	124,810	100
			(0.070)	(0.057)	(0.036)	(0.058)	(0.028)	(0.013)	[79,541]	[60]
		Engineering	0.083	0.127	0.221	0.165	0.002	0.037	125,730	870
			(0.024)	(0.023)	(0.013)	(0.024)	(0.010)	(0.005)	[68,201]	[460]
		Other Social and related sci.	0.153	0.200	0.403	0.238	0.052	0.188	103,004	80
			(0.076)	(0.075)	(0.049)	(0.075)	(0.041)	(0.018)	[70,458]	[40]
		Physical and related sci.	0.131	0.159	0.292	0.211	0.063	0.104	116,660	60
			(0.123)	(0.119)	(0.049)	(0.119)	(0.042)	(0.020)	[64,735]	[40]
		Psychology or Social Work	0.140	0.133	0.399	0.184	0.043	0.194	98,845	80
			(0.102)	(0.100)	(0.042)	(0.100)	(0.037)	(0.019)	[59,509]	[50]
(2)	**Master's in Business related fields**	Business	0.271	0.305	0.277	0.328	0.030	0.081	113,906	70
			(0.090)	(0.092)	(0.020)	(0.092)	(0.019)	(0.006)	[81,716]	[60]
		Economics	0.039	0.117	0.361	0.133	-0.011	0.100	141,223	70
			(0.105)	(0.092)	(0.045)	(0.092)	(0.025)	(0.015)	[103,505]	[40]
		Engineering	0.084	0.138	0.269	0.163	0.014	0.030	137,198	150
			(0.051)	(0.050)	(0.030)	(0.050)	(0.023)	(0.009)	[80,653]	[70]
(3)	**Master's in Education**	Bio/agricultural/environmental sci.	0.093	0.163	0.035	0.208	0.026	-0.079	66,709	160
			(0.061)	(0.060)	(0.025)	(0.060)	(0.019)	(0.013)	[37,250]	[80]
		Computer and mathematical sci.	0.175	0.153	-0.147	0.175	0.072	-0.191	69,224	180
			(0.066)	(0.066)	(0.026)	(0.066)	(0.029)	(0.017)	[30,063]	[100]
		Education	0.153	0.185	0.204	0.209	0.017	-0.009	64,584	230
			(0.028)	(0.025)	(0.008)	(0.025)	(0.009)	(0.004)	[27,230]	[180]
		Other Social and related sci.	0.174	0.230	0.110	0.254	0.022	-0.064	65,574	170
			(0.047)	(0.048)	(0.024)	(0.048)	(0.023)	(0.012)	[31,374]	[90]
		Physical and related sci.	0.172	0.233	-0.128	0.281	0.064	-0.214	66,977	90
			(0.078)	(0.075)	(0.045)	(0.076)	(0.048)	(0.019)	[27,996]	[50]
		Political science	0.035	0.024	-0.056	0.058	0.039	-0.119	73,058	80
			(0.095)	(0.095)	(0.049)	(0.095)	(0.043)	(0.022)	[38,120]	[40]
		Psychology or Social Work	0.243	0.226	0.089	0.266	0.037	-0.074	61,028	190
			(0.043)	(0.043)	(0.018)	(0.043)	(0.021)	(0.010)	[28,240]	[120]

...continued

	Advanced field	Undergraduate field	ln(earnings)				Occupation premium		Earnings	# of pre Adv earnings obs
			FE-cg†	FE-cg full	OLS	FE-cg Avg 1∼28 years γ_{g1-28}	FE-cg†	OLS	Mean [SD]	person-year [person]
			(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(4)	**Master's in Engineering**	Engineering	0.119	0.170	0.110	0.220	0.015	0.038	101,372	1,070
			(0.021)	(0.021)	(0.006)	(0.022)	(0.012)	(0.002)	[50,854]	[630]
		Physical and related sci.	0.080	0.137	0.248	0.197	0.044	0.143	99,008	60
			(0.085)	(0.082)	(0.022)	(0.082)	(0.040)	(0.006)	[46,062]	[40]
(5)	**Master's in Computer and mathematical sci.**	Computer and mathematical sci.	0.147	0.137	0.142	0.173	0.002	0.023	95,083	330
			(0.055)	(0.053)	(0.012)	(0.054)	(0.015)	(0.005)	[46,515]	[180]
		Engineering	0.056	0.093	0.133	0.136	0.000	0.034	102,825	150
			(0.050)	(0.047)	(0.015)	(0.047)	(0.013)	(0.004)	[50,290]	[80]
(6)	**Master's in Physical and related sci.**	Physical and related sci.	0.154	0.241	0.057	0.304	0.000	0.011	83,140	190
			(0.061)	(0.058)	(0.018)	(0.059)	(0.025)	(0.007)	[47,637]	[130]
(7)	**Master's in Bio/ agri/env/life sci.**	Bio/agricultural/environmental sci.	0.274	0.335	0.017	0.388	0.039	-0.015	66,208	190
			(0.054)	(0.054)	(0.013)	(0.054)	(0.017)	(0.006)	[39,591]	[120]
(8)	**Master's in Nursing**	Nursing	0.248	0.188	0.305	0.170	0.020	0.012	95,418	150
			(0.045)	(0.038)	(0.015)	(0.040)	(0.011)	(0.006)	[43,342]	[90]
(9)	**Master's in Health related fields**	Bio/agricultural/environmental sci.	0.331	0.365	0.431	0.376	0.198	0.170	84,859	90
			(0.049)	(0.049)	(0.022)	(0.050)	(0.027)	(0.010)	[45,510]	[50]
		Health related fields	0.058	0.045	0.109	0.057	0.052	0.042	77,600	70
			(0.132)	(0.130)	(0.020)	(0.131)	(0.042)	(0.009)	[47,330]	[40]
(10)	**Master's in Psychology and Social Work**	Other Social and related sci.	0.232	0.262	0.101	0.292	0.037	-0.074	63,118	90
			(0.065)	(0.067)	(0.019)	(0.066)	(0.030)	(0.011)	[28,577]	[50]
		Psychology or Social Work	0.238	0.208	0.090	0.272	0.024	-0.045	62,264	290
			(0.035)	(0.033)	(0.012)	(0.034)	(0.020)	(0.007)	[36,053]	[180]
(11)	**Master's in Other Social and related sci.**	Other Social and related sci.	0.151	0.196	0.138	0.236	0.075	0.041	70,954	60
			(0.083)	(0.081)	(0.020)	(0.081)	(0.036)	(0.009)	[39,081]	[40]
		Political science	0.036	0.027	0.079	0.070	0.105	0.018	82,602	40
			(0.146)	(0.132)	(0.035)	(0.130)	(0.065)	(0.015)	[58,283]	[30]

(† graduate degree sample, which only includes people who have an advanced degree when they are last observed; * FE-cg with experience profile, averaged over 1∼28 years)

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 on the full sample. 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 B7. 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.