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ABSTRACT

As the workforce has become more educated, educational decisions are no longer just about whether to acquire more, but rather what type of education to pursue. In college, individuals somewhat specialize through their choice of college major. Further specialization occurs in graduate school. This chapter investigates how majors and graduate school affect labor market outcomes as well as how the individuals make these potentially important decisions. To do so, we develop a dynamic model of educational decision-making. In light of the model, we examine the estimation issues associated with obtaining causal effects of educational choices on earnings. We then examine ways that authors have overcome the selection problem as well as the approaches authors have taken to estimate the process by which these educational decisions are made.

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1 Introduction

The literature on the returns to education often focuses on the returns to years of schooling (Card, 1999), treating education as unidimensional. This may be a reasonable approach when there is relatively little specialization in school, as for example in secondary education in the United States.[1] But as the workforce has become more educated, educational decisions are about the type of education to pursue as well as about the quantity. While a liberal arts education is supposed to provide a broad background in many areas, there is nonetheless some specialization as individuals choose college majors that have different emphases in their coursework. Graduate education leads to even more specialization. An additional year of schooling in a Master's in Education program is quite different from that of engineering.

Wage difference across college majors are large. Using data from the 2009 American Community Survey, Altonji et al. (2012) show that the log wage gap between male electrical engineers and male general education majors is within two percentage points of the gap between college and high school graduates. And Altonji et al. (2014*b*) and Gemici & Wiswall (2014) show that these differentials have been significantly increasing over time. With increases in the returns to skill, the incentives to obtain graduate degree have also increased, with the share of individuals getting a Master's degree more than doubling between 1985 and 2010.

From an aggregate viewpoint, the distribution of college majors is an important input to the skill composition of tomorrow's workforce. In 2010, there were 209 federal programs designed to increase knowledge of STEM fields and attainment of STEM degrees with overall spending of more than three billion dollars (Scott, 2013). The governor of Florida has proposed freezing tuition for STEM majors (Alvarez, 2012), and the state of New York is offering free tuition for high performing students who enroll in public institutions and are STEM majors, conditional on working in the state for at least five years (Chapman, 2014).

[1] Even in secondary education in U.S., there is a great deal of heterogeneity in the mix of courses that students take–both with high schools and across high schools. See Altonji et al. (2012) for a survey the literature on the choice of high school curriculum and the labor market effects of high school curriculum.

The raw wage differences across majors may, however, reflect a number of factors besides differential accumulation of human capital across majors. One obvious issue is selection. Perhaps those who major in the more apparently lucrative fields would also have earned more in other majors. Perhaps those who choose less lucrative majors would have earned even less in the better paying majors because their skills are a poor match with the work required. These issues become even more complicated given the importance of occupations in the labor market, to the degree that individuals are heterogeneous in their preferences for occupations, and to the degree that majors have heterogeneous effects on both the pecuniary and non-pecuniary returns to different occupations.

But even if some majors have a larger causal effect on productivity than others, the high paying majors may be less attractive for students on other dimensions. For example, they may involve heavier university workloads or lead to less pleasant or fulfilling jobs. Initial interest in STEM majors at the undergraduate level, for example, is quite high. However, 48% switch out of STEM majors, with half dropping out and half switching to another major.

Universities may place less weight on student labor market prospects when deciding how much priority to give to increasing the number of STEM majors. For example, they may prefer a distribution of students across majors that is in line with the distribution of faculty members in their various departments. Princeton explicitly pushes students to consider departments with fewer students per instructor. And institutions may understate tradeoffs between non-pecuniary considerations and labor market prospects when counseling students. For example, the introduction to *Major Choices vol. II*, available on Princeton's website, states that its

> "purpose is to encourage undergraduates to follow their intellectual passions and study what they love, with confidence in the fulfilling lives that lie ahead and the knowledge that in no way will their choice of major limit the career choices they may wish to make in the future."[2]

[2] http://www.princeton.edu/pr/pub/mc/v2/home/index.htm

As a result of this push, departments with the largest percentage increases were classics, Slavic languages and literature, comparative literature, and religion.[3] But while we do not present evidence for samples drawn exclusively from elite universities, the evidence for a broad set of schools suggests strongly that choice of major does limit career choice.

In this chapter, we investigate how majors and graduate school impact labor market outcomes as well as how individuals make these potentially important decisions. In particular, we:

1. Document the trends in the number and earnings of different undergraduate majors and graduate programs (Section 2).

2. Develop a model for how to think about the various factors that influence major choice (Section 3).

3. In light of the model, examine the estimation issues associated with obtaining causal effects of educational choices on earnings and discuss the progress to date on addressing these issues (Section 4).

4. Review research on how individuals make postsecondary decisions regarding choice of major and graduate school, paying attention both to choices by the student as well as how choices by universities make particular fields of study more attractive (Subsections 5.1 and 5.2).

5. Discuss work using subjective expectations data to get at student beliefs regarding the benefits of choosing particular educational paths (Subsection 5.3).

We cover some of the same ground as the recent survey by Altonji et al. (2012). However, we give much more emphasis to graduate education. As we document, graduate school attendance has grown rapidly over the past two decades. Now is a good time to pull together the existing literature on the demand for and return to graduate school, although it is still relatively sparse. We also give more emphasis to how students make choices and to the role

[3] http://www.princeton.edu/main/news/archive/S11/45/32K06/index.xml

that universities play in influencing them. And we highlight papers that collect subjective expectations as a way of eliciting student beliefs about the monetary and nonmonetary value of various fields of study and the career paths that they will lead to. These beliefs play a central role in models of education choice.

2 Descriptives

We begin this chapter by providing descriptive evidence on the allocation of students across undergraduate majors and graduate degrees, together with the wage premia associated with the various combinations of undergraduate and graduate degrees. In Section 2.1 we examine the distribution of undergraduate majors among all individuals with a Bachelor's degree, discuss its evolution over time and report the mean wages associated with each major. In Section 2.2 we turn to graduate degrees and discuss the trends in the number of individuals graduating with different types of advanced degrees, in particular Master's, Ph.D., M.D., J.D. and Dental degrees. Finally, Section 2.3 focuses on the joint distribution of undergraduate and graduate degrees, and further presents descriptive results about the wage returns to different pairs of undergraduate and graduate degrees.

2.1 Undergraduate Degrees

Table 1 below reports the distribution of majors among individuals with a Bachelor's degree between the age of 27 and 58, using data from the 2013 American Community Survey. The five most common fields of study are Business (22.5%, includes Business Management, Accounting and General Business), Education (10.1%), Engineering (8.2%), Social Sciences (7.3%, includes Economics, Sociology, Anthropology and Archeology, Political Science and Government), and Medical and Health Services (7.2%). More than half of college graduates have a Bachelor's degree in one of those areas. We also report in this table the average hourly wage for each major. There are very large differences across majors in this dimension. For instance, individuals with an Engineering degree earn on average close to 80% as much as individuals who obtained a degree in Education. Interestingly though, and consistent with non-pecuniary factors playing an important role when choosing a college major, Education majors account for a larger share of Bachelor's degrees than Engineering majors. In addition to Engineering, other high-paying college majors (with mean wages above $40 per hour) include Biology, Computer and Information Systems, Physical Sciences, Mathematics and Transportation Sciences. On average, individuals who earned a Bachelor's degree in any of those fields of study earn at least 50% more than college graduates who obtained their Bachelor's degree in fields of study such as Education, Fine Arts, Public Administration, Family and Consumer Sciences, Theology, and Cosmetology and Culinary Arts. From the outset, it is important to keep in mind that those stark differences across majors are clearly partly driven by the fact that students with different productivity levels tend to choose different majors. Accounting for endogenous sorting of students across majors is crucial in order to estimate the causal effect of college majors on wages. We will discuss this issue thoroughly in Section 4.

While the dramatic increase in college graduation rates in the last four decades has been the object of much attention, relatively little is known about the change in the distribution of undergraduate majors over time. Figure 1 reports the evolution from 1981 to 2013 of the proportions of students graduating with a Bachelor's degree in Business, Life Sciences, Social Sciences, Engineering, Mathematics and Physical Sciences, Health, Education, Humanities, Fine Arts and other fields, among all students receiving a Bachelor's degree in any given year.[4] Those shares are computed using data from the Higher Education General Information Survey (HEGIS) through 1985-86, and the Integrated Postsecondary Education Data System (IPEDS) from 1986-87 to 2012-13. Majors in Business, Social Sciences, Humanities and Fine Arts, along with the majors included in the Other fields category, have been accounting for the highest share of Bachelor's degrees since the late eighties. As of 2013, these majors

[4]Other fields includes fields such as Communication and Journalism, Homeland Security, Law Enforcement and Firefighting, Park, Recreation, Leisure and Fitness Studies, Agriculture and Natural Resources, Public Administration and Social Services, as well as Family and Consumer Sciences.

accounted for as much as 68% of college graduates, up from 63% in 1981. Health majors have become more popular in the last ten years. Those majors account for 9.8% of the Bachelor's degrees awarded in 2013, which is about twice as much as in 2003. On the other hand, majors in Education, and, to a lesser extent, majors in Engineering, Math and Physical Sciences have become less popular over time. In particular, the fraction of Bachelors' degrees awarded in Education dropped from 12% in 1981 to 6% only in 2013. As of 2013, Life Sciences (the least popular field of study throughout this period) accounted for only 5% of the total number of Bachelor's degrees awarded during that year.

2.2 Graduate Degrees

The share of individuals receiving an advanced degree has increased very substantially in the last thirty years. Figure 2 reports the evolution of the number of individuals graduating with a Master's degree in the U.S. (restricted to permanent residents and U.S. citizens) over the period 1985 to 2013, computed as a fraction of the total resident population of 24 year olds.[5] The share of individuals getting a Master's degree within each cohort has increased by 240% between 1985 and 2013, likely reflecting an increase in the demand as well as in the supply of those types of advanced degrees. It is worth noting that this trend is steeper than the growth in the number of Bachelor's degrees awarded each year (+86% over the period 1985 to 2013, see Figure 3), reflecting a large increase in the rate at which college graduates go on to a Master's program. While the share of individuals getting a Master's degree has increased significantly for all fields over that period, the growth has been particularly dramatic for Health and, to a lesser extent, Business (see Figure 4).

Figure 5 reports the proportions of students who graduated with a Master's degree in Business, Education, Health Professions, Other STEM and Other Non-STEM fields, among all students (again restricted to permanent residents and U.S. citizens) receiving a Master's degree in any given year from 1985 to 2013.[6] Education and Business together account for

[5] The number of degrees awarded each year, used in Figures 2 to 7, are obtained from the HEGIS (1985-86) and IPEDS (1986-87 through 2012-13).

[6] Other STEM fields includes Computer and Information Sciences, Engineering, Mathematics, Physical

around 50% of the Master's degrees awarded throughout this period. Education was, by a substantial margin, the most popular field until 2007, then followed in the most recent years by a steady decline in the proportion of Master's degrees awarded in this field. As of 2013, Education and Business accounted for pretty much the same share of Master's degrees awarded in that year. It will be interesting to see whether the decline in the popularity of Education is confirmed in the next couple of years.
On the other side of the spectrum, Master's degrees in Health and STEM are, throughout the period, the least popular fields. Notably, in 2013, about 10% of the Master's degrees were received in STEM fields, which represents less than half of the share of Master's degrees awarded in Business or Education.

Ph.D. degrees have also become more prevalent over this period, while still accounting for only a small share of each cohort. Figure 6 below reports the evolution of the number of permanent residents and U.S. citizens graduating with a Ph.D. degree in the U.S., as a fraction of the total resident population of 28 year olds. The share of individuals receiving a Ph.D. degree has fluctuated between 0.6% and 1.1% over the period 1985 to 2013, with the number of Ph.D. degrees awarded in 2013, as a share of 28 year-old U.S. residents, being 70% higher in 2013 relative to 1985. Figure 7 reports for each year the share of students who earned a Ph.D. degree in STEM, Social Sciences, Humanities, Business, Education and Other fields, among all students receiving receiving a Ph.D. degree in that year.[7] Throughout this period, Business (and Others) are the least popular fields, while STEM fields account for the highest fraction of Ph.D. degrees. It is worth noting that, although the flow of new

Sciences and Social Sciences. Other Non-STEM fields includes fields such as Visual and Performing Arts, Theology, Public Administration and Social Services, English and Literature, Communication and Journalism, Architecture as well as Homeland Security, Law Enforcement and Firefighting.

[7]STEM includes Biological and Medical Sciences, Mathematics and Statistics, Physical Sciences, Computer and Information Sciences, and Engineering. Social Sciences includes Economics, Sociology, Political Science, Psychology, Public Administration and Social Services. Humanities includes Visual and Performing Arts, Foreign Languages, Literatures and Linguistics, English and Literature, and Theology. Finally, Other fields includes Agriculture and Natural Resources, Architecture, Multi/interdisciplinary Studies, Park, Recreation, Leisure and Fitness Studies, and Homeland Security, Law Enforcement and Firefighting.

PhD degrees awarded each year has substantially increased over time, the distribution of fields within those types of degrees is pretty similar in 2013 to what it was close to three decades ago. The most noticeable change occurs for Education, with a decrease in the share of Ph.D.'s in that field from 24.9% to 21.5%.

Turning to professional degrees, Figure 8 plots the evolution of the number of individuals graduating with a M.D., J.D. or a Dental degree, as a fraction of the total resident population of 28 years olds. The share of individuals graduating with a Dental degree or with a M.D. degree has been remarkably stable over the last 30 years, hovering around 0.1% and 0.4%, respectively. The share of J.D. degrees is somewhat more volatile but remains of similar order of magnitude in the most recent years as 30 years ago (around 1%). Those patterns contrast sharply with the large increase in the share of individuals graduating with a Master's or a Ph.D. degree over the same period.

Interestingly, Figures 9 and 10 show that the number of applications to M.D. and J.D. programs fluctuate significantly more over the last fifteen years than the number of matriculants and first-year enrollments, respectively.[8] These patterns are consistent with the demand for those types of advanced degrees being constrained by the supply side. Figure 9 further points to a significant increase over this period in the selectivity of M.D. programs, while Figure 10 shows that rejection rates from J.D. programs are in fact slightly lower in 2012 than in 2000.

2.3 The Distribution of Undergraduate and Graduate Degrees

In this section we provide basic facts about the joint distribution of undergraduate and graduate degrees. The source of the information is the 2010 sample of the National Survey of College Graduates (NSCG10). We report results for persons between the ages of 27 and 59, inclusive. The NSCG10 information provides facts about the stock of college graduates

[8]The numbers reported for M in Figure 9 also include the number of applicants, matriculants and first-year enrollments to Doctor of Osteopathic Medicine (D.O.) programs.

at a point in time.[9] It complements the IPEDS and HEGIS, which we use to summarize trends in college and advanced degrees.[10]

Table 2 reports on the proportions of male and female college graduates with advanced degree, by broad graduate degree type. The fractions of men and women with at least one advanced degree are almost identical: 0.353 and 0.344, respectively. However, the distribution is different, with the women much more likely to have a master's in education or psychology, and less likely to have a master's in a business related field, an MBA, a master's in computer and mathematical sciences, engineering, or a medical degree. The gender differences in graduate degrees in part reflects gender differences in undergraduate field. For example, the proportions of men and women with a bachelor's degree in education are 0.053 and 0.151 respectively while the corresponding proportions in engineering are 0.132 and 0.023.[11]

Table 3 reports on graduate degree attainment by field of undergraduate study. Column 1 provides the unweighted sample size for each major. Column 2 reports the fraction of college graduates with a bachelor's degree in the specified field. Column 3 reports the fraction of college graduates in each field who obtain at least one advanced degree.[12] The remaining columns of each row report the fraction of persons in the specified undergraduate field who obtained the graduate degree listed in the column heading. Consider engineering.

[9]The sample size does not permit a cohort analysis at the level of disaggregation by field that we use. One could use earlier waves of the NSCG to examine trends, but we have not done so.

[10] The IPEDS and HEGIS lack information on the interrelationship between undergraduate field and graduate degree type.

[11]See Appendix Table 1, which is also based on NSCG10 but includes ages 24 through 59. All summary statistics and regression results based on the NSCG10 use sample weights.

[12]About 19.4 percent of the sample report a second undergraduate field, although this also includes minors. For persons with a second undergraduate field, we use the first major specified. Altonji & Zhong (2015) provide evidence that to a first approximation, the earnings and occupations of double majors are a weighted average of the earnings and occupation distribution associated with the separate fields, but with more of the weight on the first. Presumably, the presence of double majors in the sample will blur to some degree the connection between the specified undergraduate major and graduate degree type. Note also that some sample members report more than one graduate degree and are counted as having a graduate degree in more than one column of the table.

In the NSCG sample, 7.4% of undergraduates obtained an engineering degree (column 2). Of these 39.5% obtained at least one graduate degree. 18.2% obtained master's in engineering and 3.6% in computer science and mathematical sciences. 7.7% obtained an MBA and 2.2% obtained a master's in a business related field.[13] The fractions are much lower for other non-science related graduate degrees.

The table supports the following generalizations. First, and not surprisingly, there is a strong link between the undergraduate major and graduate degree type.[14] The large fraction of engineers who obtain a Masters in engineering is echoed in the fact that 36.0% of education majors get an education-related Masters degree, 9.5% of biology/agricultural/environmental life sciences majors get a Masters in a life-sciences field and 18.5% of these majors get a Medical degree. Similarly, 14.1% of business majors get master's degrees in a business related field or an MBA. 15.7% of nurses obtain a Masters in nursing, while only 0.6% of all undergraduates obtained a Masters in nursing.

Second, aggregating across groups of majors within the same broad field obscures the links. Consider the social sciences. The percentage of economics majors who obtain an MBA or a business-related Masters degree is 15.5%. The percentage who obtain a law degree is 9.0%. In contrast, the corresponding values for political science are 6.4% for business and 26.3% for law. The differences with psychology are also very large.

Third, the degree of concentration in particular advanced degrees varies across undergraduate majors. One can see this by noting that the relative values of the row entries vary more for some majors than others. Table 4 makes this point more directly. Each row of Table 4 reports the ratio of the share of the advanced degree specified in the column accounted for by the specified undergraduate major to the share of that major among all

[13]The MBA category consists of master's in business administration and management, in business and managerial economics, in business, general and other business management/administrative services. The category Masters in a business related field consists of accounting, marketing, and financial management.

[14]Black et al. (2003) analyze the role of graduate degree attainment in earnings difference across undergraduate degrees using the 1993 National Survey of College Graduates. For a small set of majors, they present evidence on the distribution of graduate degrees by type of undergraduate degree.

college graduates (column 2). If majors were equally represented in each graduate degree, all the cell values would be 1 (aside from sampling error). In the case of nursing, the value is 27.0 for a Masters degree in nursing. That is, a person with a Masters degree in nursing is *27.0 times* more likely to have majored in nursing than undergraduates as a whole. Undergraduate nursing majors are also substantially overrepresented in Health Services Administration, but are underrepresented in all other broad graduate programs. On the other hand, economics majors are overrepresented in several graduate degree types but are not massively overrepresented in any.

Finally, the extent to which particular advanced degrees draw from a broad set of majors varies considerably. Graduate Nursing draws almost entirely from undergraduate nursing majors, with biologists also slightly overrepresented. This point is made most directly in table 5. Each column of table 5 reports the shares of the specified graduate degree that are contributed by the various undergraduate majors. MBA programs draw from a number of undergraduate majors, while nursing draws almost entirely from undergraduate nursing majors. The columns of table 4 also provide information on the same point. Again, the entries show the relative odds that a person in the major specified in the row has received a graduate degree of the type indicated in the column. These are the shares of a major in a graduate degree normalized by the size of the undergraduate major. One can see that the values are much more tightly concentrated around 1 for an MBA degree or a Masters degree in a business related field than for fields such as nursing or engineering. In nursing and engineering, field specific preparation at the undergraduate level may be critical.

2.3.1 Facts About Earnings

In Table 6 we provide descriptive evidence on the relative return to various undergraduate and graduate degrees based on 1993 and 2010 NSCG surveys. The table reports coefficients from the regression of log earnings on 19 mutually exclusive indicators for undergraduate field of study and on 20 mutually exclusive indicators for advanced degree type. The model includes controls for gender, race/ethnicity interacted with gender, and a cubic in age interacted with gender. We control for mother's education category and father's education category but lack data on test scores and high school curriculum. The sample is restricted to full-time workers between the age of 24 and 59, inclusive.[15] The sample only includes people with at least a bachelor's degree. The returns are relative to a bachelor's in education. Column 1 reports coefficients on undergraduate major, with education as the excluded category. Column 2 reports coefficients on advanced degrees. Both columns come from the same regression.

The estimates show that the highest returns are in engineering, the physical sciences, computer and mathematical sciences, accounting, and nursing. The highest-paid major is which pays 0.392 log points more than education. The next four highest-paid fields are accounting (.327), computer and mathematical sciences (0.327), economics (0.313), and nursing (.312). Political science majors earn a 0.176 premium over teachers. English, Languages and Literature, other humanities (which includes History), other social sciences, and psychology majors earn a small premium over education. The life sciences pay less than the physical sciences. The patterns are consistent with evidence from many other data sets for the U.S., as we discuss in more detail in section 4. Fine and Performing Arts is the lowest paid major among the set broken out in the table followed by education being the second lowest, with other humanities a close third. Altonji et al. (2012) and other studies that report results for more disaggregated categories find a number of majors that pay less than education.

The results show a premium for a master's in education of 0.124 (.01). The returns to master's degrees in the sciences range from 0.053 (.02) for biology/agricultural/environmental life sciences, to 0.229 (.02) for computer and mathematical sciences The return is only .081 (.01) for psychology/social work but 0.166 (.02) for the other social sciences. It is .068 (.01) for a miscellaneous category of fields outside of science and engineering and is negative for

[15] Altonji et al. (2012) report the results of a similar regression using the log hourly wage rate as the dependent variable and a much larger set of degree categories. They lack information on parental education. Their data are from the 2009 ACS. The ACS is much larger, but it does not provide information on the field of study of graduate degrees.

the humanities (-.106). The ranking of the returns for an MBA, Law and MD match the ranking of the number of years of study these degrees typically require.

The above model assumes that the return to undergraduate and graduate degrees are additively separable in a log specification. What about complementarity between undergraduate and graduate degrees in the labor market? Much of the complementarity presumably operates through preparation for graduate school. An individual's skill set upon completion of an engineering master's depends upon having a base in science and engineering to build on. Application decisions and admissions decisions will both reflect this dependence. The undergraduate English major who is studying for a master's in engineering is unusual. On the other hand, some graduate degrees, such as law and MBA programs, do not have strong prerequisites. The degree of complementarity is likely to differ across degree pairs.

Table 7 reports estimates of the return to various combinations of undergraduate and graduate degrees relative to an undergraduate degree in education with no graduate degree. The table was constructed from a regression that includes the main effects of the undergraduate degree categories with education omitted, and interactions between the undergraduate categories (including education) and the aggregated graduate degree categories shown in the table. The row label specifies the undergraduate field and the column label indicates highest degree. The table also reports the number of observations underlying the main effects of the majors and the interaction terms. We have suppressed entries based on fewer than 15 observations.

Estimates of the return to undergraduate major relative to education are reported in the first column. They echo the results in table 4, although the values differ to some extent. Some graduate degrees narrow differences across undergraduate fields, while others preserve or widen them. A Master's in education narrows differentials substantially. For example, engineering majors with a Masters in education earn about the same amount as an education major with a Masters degree, despite the fact that an engineer without a graduate degree Masters earns 0.46 more than an education major without a graduate degree. If one regresses the returns to the undergraduate field/Masters in education combinations that are reported in column 2 on the returns to undergraduate major in column one, the intercept and slope are 0.196 (.04) and 0.0172 (.16).[16] Proceeding on to graduate school education has a leveling effect across undergraduate degree types, presumably because many of those who pursue master degrees in the education field work as teachers and school administrators within a relatively narrow pay band.

In the case of terminal master's degrees outside education, the corresponding regression yields an intercept of 0.0526 and a slope of 1.19 (0.172). That is, master's degrees raise the earnings of undergraduates by an amount that increases more than 1 for 1 with the relative return to the undergraduate major. For an MBA the intercept and slope are 0.421 (.04) and 0.476 (0.13), respectively. This indicates that getting an MBA narrows the gap in earnings between low and high paying majors, although .48% of that gap is preserved. In the case of law, the intercept and the slope are 0.627 (0.04) and 0.305 (0.17). The point estimates suggests that in percentage terms the payoff to law is higher on average for those coming from a lower paying undergraduate degree. Medicine follows the same pattern, although the coefficient is very imprecise

These estimates are undoubtedly affected in complicated ways by selection bias, and are imprecise.[17] Nevertheless, they suggest that the relative return to different fields of graduate study varies sharply across undergraduate majors. We return to this question when discussing the relatively limited evidence on return to graduate education in section 4.6.

Math Test Scores, Course Content and Earnings Differential Across Fields A number of papers, including Paglin & Rufolo (1990), Weinberger (1999), Arcidiacono (2004), and Altonji et al. (2012) show that average scores on math and verbal tests differ substantially across undergraduate majors. Paglin & Rufolo (1990) show that the average Math GRE score for the major (toward the end or after college) explains 82 percent of the variance across fields

[16]This regression and those described in the next paragraph are limited to undergraduate majors with at least 20 cases for the specified graduate degree.

[17]The slope coefficients are also biased toward zero by sampling error in the estimates coefficient on the undergraduate major in column 1 of Table 7. However, the variance of the coefficient estimates is large relative to sampling error variances, so this bias is small.

of study in entry level wages. Using the 2009 ACS, Altonji et al. (2012) find that average SAT math and SAT verbal test scores (taken before college) account for about 58 percent varaince in the major specific earnings coefficients. However, they point out that part of this reflects the association between the average scores and the major specific averages of other unobserved student characteristics that matter for wage rates. These characteristics may influence wage rates regardless of major and occupation, and they may also influence wage rates by influencing occupational preferences. As we discuss in section 4, controlling for an individual's test scores usually reduces the variance of major specific earnings differences, but by less than controlling for the major specific averages does.[18] Some of the empirical studies that we discuss below examine the link between test scores and grades and major choice. Some examine the extent to which return to a major depends on them.

Occupation Choice and Earnings Differentials Across Fields Black et al. (2003), Ransom & Phipps (2010), Altonji et al. (2012) and Altonji et al. (2014*a*) present evidence on the degree to which undergraduate majors are concentrated in particular occupations. Arcidiacono et al. (2014) also present evidence on this question using data from Duke students. Altonji et al. (2012, Figure 3) displays the distribution of the major specific proportions of graduates who work in the ten most common 3 digit occupations for the major. It is based on the 2009 ACS. The mode of the distribution is about .43. The occupational concentration is larger for younger workers. They also report evidence on the proportion of workers in each occupation that is accounted for by the three most popular majors in that occupation. The fraction varies widely across occupations, in ways that generally coincide with conceptions about how specific the skill requirements of the occupations are. For example, nursing, psychology, and multi-disciplinary or general science majors account for 82.9% of all registered nurses between the age of 40 and 44. Accounting, business management and administration, and finance majors together account for 72.1% of all accountants and auditors in the same age range. On the other hand, the top three majors account for only

[18]Noise in the student level test scores may be part of the reason why the major specific averages are more important.

30.7% of first-line supervisors/managers and sales workers and only 32.1% of marketing and sales managers. Differences across majors in the strength of the link between preferences for fields of study and preferences for the mix of tasks associated with particular occupations is one reason why the strength of the links between particular occupations and fields of study varies. Differences in the degree to which occupational tasks require knowledge that is specific to particular fields of study are a second reason. Note that the connection between undergraduate field of study and occupation is also presumably affected by the connection between undergraduate field of study and graduate degree, and between graduate degree and occupation. We do not have quantitative evidence on this.

3 Model

In this section we present a series of models that highlight a number of key factors in the decisions individuals make about what type of education to get, how much to get, and where to get it. The most important of these are the fact that individuals are uncertain about their ability and labor market returns as they relate to specific fields of study and occupations. What they learn about these variables over time depends on prior education choices. The second is that past choices about type of education condition future education and labor market opportunities. We begin with a simple three period model that highlights the role of uncertainty about ability, with only two field choices. In Section 3.2 we expand the number of majors, incorporate choice of institution, add uncertainty about meeting graduation requirements, and add graduate school. In Section 3.3 we add occupation choice, giving special emphasis to the fact that treatment effects of a major on wage rates depend on effects of wages in a given occupation and effects on occupation choice through non-pecuniary benefits and search frictions. Section 3.4 discusses in more detail the role of learning about ability in the return to a specific field of study, the decision to change majors, and decision to obtain additional education. Section 3.5 briefly discusses the role of the supply side of education–the implications of the fact that institutions set admissions requirements, the pecuniary and non-pecuniary costs of particular fields of study, and the costs of changing majors.

3.1 A Simple Model of Dynamic Major Choice

We begin by specifying a three-period model in the spirit of Altonji (1993) to illustrate how uncertainty about one's abilities affects the dynamics of major choice. To save notation and words, we allow abilities to influence both pecuniary and non-pecuniary costs and benefits of schooling and labor market choices rather than separately introduce tastes.[19] In period 1 individuals choose between two majors, m or h, or choose not to attend college, n. Denote d_{ijt} as an indicator for whether individual i chose option j at time t. For the moment we treat the decision not to attend college as terminal. In period 2, those individuals who chose one of the college options update their beliefs about their abilities and then choose again among the different schooling options and not attending college. In period 3, all agents work, reaping the benefits of their past educational decisions. Since no additional decisions are made in period 3, we collapse the period 3 payoffs into those for period 2.

In period 1, payoffs for each of the choices depend on the individual's abilities—abilities that, at least for the schooling choices, are uncertain. An individual's ability in major j, denoted by A_{ij}^{tot}, is given by the sum of two terms: A_{ij}, which is known in period 1, and ζ_{ij} which is initially unknown and only realized if the individual chooses j in either period 1 or 2. ζ_{ij} is i.i.d. $N(0, \sigma_j)$.[20] We normalize the utility payoff to not attending college at all to zero. For simplicity, we also make the stark assumption that the post school utility flow if a person leaves school after one period is the same as the flow if the person never attends school, and thus is also zero. Relative to not attending college, the first period of school offers a one period utility flow (which could be negative) but also the option value of completing school.

Denote A_{ij1} as the beliefs of the individual regarding his ability in option j in the first

[19] This modeling assumption is also consistent with most of the empirical literature dealing with schooling choices in the presence of imperfect information on the part of the students.

[20] We relax this assumption by allowing for correlated learning across majors in Section 3.4.

period, so that $A_{ij1} = A_{ij}$. Beliefs in period 2 depend on the choices made in periods 1 and are given by:

$$A_{ij2} = \begin{cases} A_{ij1} + \zeta_{ij} & \text{if } d_{ij1} = 1 \text{for } j \neq n \\ A_{ij1} & \text{otherwise.} \end{cases}$$

Expected flow payoffs for each of the options depend on the individual's beliefs regarding their abilities. In addition, if the individual changes his schooling decision in period 2 the individual incurs a switching cost. We specify expected flow payoffs while in school in each period as the following linear functions ($j \in \{m, h\}$):

$$\begin{aligned} U_{ij1} &= \alpha_{0j} + \alpha_{1j} A_{ij1} \\ U_{ij2} &= \alpha_{0j} + \alpha_{1j} A_{ij2} - \alpha_{2j} I(d_{ij1} \neq 1). \end{aligned}$$

In the third period, when everyone is working, the expected utility is

$$U_{3ij} = (\gamma_{0j} + \gamma_{1j} A_{ij2})(d_{ih2} + d_{im2}).$$

In the equation for U_{ij2}, $I(\cdot)$ is the indicator function, implying α_{2j} is the cost of switching to major j. The α_j terms represent expected utility while in school, while the γ_j terms give the expected utility in the final period as a function of A_{ij2} for those who complete college. Note that $U_{3ij} = 0$ if the person did not attend school or left school after 1 period.

Denoting the discount factor by β, individuals choose their educational decisions to sequentially maximize the discounted sum of their payoffs:

$$E \left\{ \sum_{t=1}^{3} \sum_{j \in \{h,m,n\}} \beta^{t-1} d_{ijt} \left(U_{ijt} + \varepsilon_{ijt} \right) \right\}$$

where the ε_{ijt}, $j \in \{h, m, n\}$, $t \in \{1, 2, 3\}$ are idiosyncratic shocks. Note that the schooling options d_{ih2} and d_{im2} when $t = 2$ are not available if i chose the labor market option d_{in1} when $t = 1$. This simple model produces a number of implications for the dynamics of major choice:

1. *All else equal, individuals in the first period will choose the major with the higher variance on the unknown ability.*

Analogous to the occupational choice model of Miller (1984), high variance majors should be sampled first. If the fit with the major is bad, then the individual can always choose a different major. Even if switching to another major is prohibitively costly, the option to drop out still works to insure against bad information draws.

2. *All else equal, individuals in the first period will choose the major that is most difficult to switch into.*

   Majors that have high switching costs due to, for example, the course material building on past material will also be more attractive in period 1 all else equal (e.g. Engineering versus History).

3. *The timing of information revelation matters.*

   Better prior information reduces the option value of high switching cost majors and of college in general. Better posterior information increases the option value associated with the high switching cost majors and for college in general. Dropping out in this model is rational as individuals respond to the new information they receive.

4. *Ability sorting may be driven either by the payoffs in school or in the labor market.*

   Ability could matter only in the labor market ($\gamma_{1j} > 0$, $\alpha_{1j} = 0$) or only in school ($\gamma_{1j} = 0$, $\alpha_{1j} > 0$). In the former case, the school provides information about the individual's abilities which influence labor market productivity and the non-pecuniary value of work, but do not affect the utility received in school. In the latter case, it may be that everyone receives higher returns in one major over another, but low ability individuals do not choose that major because of the difficulty of the subject matter in school.

5. *Changes in returns to particular majors elicit larger long run supply responses than short run responses, particularly for high switching cost majors.*

   Suppose the baseline returns to the different education options, the γ_{0j}'s, evolved stochastically. Because i) switching majors is costly and ii) schooling takes two periods, the response to changes in labor market returns is gradual. If switching costs in major j are high, fewer individuals will find it optimal to switch to major j in response to a positive shock to γ_{0j} after the first period. Asymmetries in response to shocks to major-specific labor market returns then arise due to differences in switching costs.

3.2 Heterogeneity in Schooling Options

3.2.1 Expanding the Choice Set

We now consider a model that expands the number of majors from 2 to J, allows C institutions of higher education, incorporates uncertainty for graduation, and incorporates graduate school. We again treat the decision not to go to college as an absorbing state. Before obtaining a bachelor's degree, individuals decide to begin schooling in one of the J majors at one of the C institutions. Not all the institutions grant bachelors degrees, incorporating the case of 2-year colleges. Individuals in college have a positive probability of graduating. If they do so, they then have the option of attending graduate school in one of J^g subjects.

Schools influence the choice of major—and in turn the choice of occupation—in part through the flow payoffs individuals receive. We generalize the within-school flow payoffs as follows:

$$U_{ijct} = \alpha_{0jc} + \alpha_{1jc}A_{ijt} + \alpha_{2jc}I(d_{ijt-1} \neq 1) + \alpha_{3jc}I(d_{ict-1} \neq 1) + \epsilon_{ijct} \tag{1}$$

The specification above allows schools to differ along four dimensions: the intercept for major j (α_{0jc}), the return on ability for major j (α_{1jc}), the cost of switching to major j (α_{2jc}), and the cost of switching to school c (α_{3jc}).

6. *Consider two schools c and c' where $\alpha_{0jc} < \alpha_{0jc'}$ and $\alpha_{1jc} > \alpha_{1jc'}$. Then all else equal there is a cutoff A_{ijt} such that those above A_{ijt} would prefer school c and those below would prefer c'.*

   Schools with higher endowments may have higher payoffs, either through the effect of these resources on human capital or through the effect on the college experience. These effects, however, may differ by both major and academic preparation. For example, schools could tailor their curriculum to the preparation levels of their students. An introductory math course at one university may require more math background and proceed at a faster pace than the same course at another university. The effects can differ across majors because preparation may matter more for some majors than others.

7. *The cost of switching majors (α_{2jc}) may vary by school and the set of majors offered may vary as well, limiting responses to changes in the labor market.*

   When a major is not offered at a particular school, this is equivalent to $\alpha_{0jc} = -\infty$. Some schools in the United States specialize in particular majors such as engineering. Others do not offer engineering. In many countries, students are accepted into a particular major and switching majors entails starting the college application process over. When only a subset of majors are offered or when students must pre-commit to a major, the short-run response to an increase in the returns to another major will be limited, similar to implication 5.

Up until now we have treated the cost of switching as operating through the utility function. But there may be other costs associated with switching majors such as an increase in graduation times. Denote C_{ijct} as an indicator for whether i has completed a degree in major j at school c by time t. Denote H_{it} as the history of educational choices and outcomes up until time t. Think of H_{it} as a vector of credits and grades in various courses. We treat graduation as a stochastic process that depends on A_{it} and H_{it} so that the individual's perceived probability of graduating is:

$$Pr(C_{ijct} = 1) = f_{jt}\left(A_{it}, H_{it}\right) \tag{2}$$

where $f_{jt}(\cdot)$ maps $\{A_{it}, H_{it}\}$ into the unit interval.

8. *Switching may delay graduation more in some majors than in others. Later switches may delay graduation more than earlier switches.*

   Some courses of study may require that courses be taken in sequence or require more specific courses than other majors. The cost of delaying graduation may be particularly acute for those with limited finances for whom paying for an additional year of college could be especially burdensome.

Should the individual graduate, the choice set changes. The person now must decide whether to enter the labor market or attend graduate school. Let n indicate as before the choice to enter the labor market. Denote g as an indicator for the highest level of educational attainment which, if the individual has graduated with a bachelor's or a post-bachelor's degree, includes their school and major for their last degree. Extending the baseline payoff for working to incorporate the expanded educational options, the payoff for working at time t is:

$$U_{ingt} = \gamma_{0g} + \gamma_{1g} A_{ig} + \epsilon_{ingt}$$

9. *All else equal, those who chose less-lucrative schooling options will be more likely to attend graduate school. Further, graduate school serves as insurance against changes in demand for particular majors.*

   By attending graduate school, the individual can partly erase the earnings dependence from the previous schooling choice. If for idiosyncratic reasons similar individuals chose different majors, then persons choosing the lower-paying major should be more likely to pursue graduate work. However, this assumes that majors do not prepare students differently for graduate work, and ignores complementarities between undergraduate major and graduate degree type. In Subsection 2.3.1 we presented descriptive evidence that such complementarities differ substantially across graduate degree types. In this case, U_{ingt} would also depend on the undergraduate field j. Note also that if the earnings premium for a school-major combination falls, then individuals in those school-major combinations may find graduate school attractive, particularly if the change in the earnings premium is seen as persistent.

3.3 Heterogeneity in Occupations

We now extend the baseline model discussed in Section 3.1 by allowing for $K > 1$ occupations in the workforce. distinguish the expected flow payoffs in school from the expected flow payoffs for working, we denote the expected flow payoff for i working in occupation k after graduating from major j as U_{ikj}. We specify this flow payoff as the sum of two parts: pecuniary and non-pecuniary. Both the pecuniary aspects (given by the expected wage) and the non-pecuniary aspects are functions of the individual's abilities (A_i) given by $w_{kj}(A_i)$ and $np_{kj}(A_i)$ respectively so:

$$U_{ikj} = np_{kj}(A_i) + \gamma_1 w_{kj}(A_i) \tag{3}$$

with $\gamma_1 \geq 0$.

In this framework, individuals make their schooling and occupational choices to sequentially maximize the discounted sum of their payoffs:

$$E\left\{\sum_{t=1}^{2}\sum_{j}\beta^{t-1}d_{ijt}\left(U_{ijt}+\varepsilon_{ijt}\right)+\sum_{j}\sum_{k}\beta^{2}d_{ij2}d_{ik3}\left(U_{ikj}+e_{ikj}\right)\right\}$$

where $(\varepsilon_{ijt}, e_{ikj})_{k,j,t}$ is a vector of idiosyncratic shocks. Note that individuals now choose their occupation upon entering the labor market in period 3.

10. *The treatment effect of a major on wages operates through both the choice of occupation and through the effects on wages in each occupation. These effects may be of opposite sign if majors affect the non-pecuniary benefits of occupations.*

    Note that since individuals value more than just the wage on the job, they may prefer a major j over a major j' even though the treatment effect of major j relative to j' on future earnings is negative. Furthermore, the treatment effect of graduating from college with a given major j (relative to high school) on future earnings can also be negative even if the effects on earnings are positive within each occupation. Consider someone who chooses to complete a degree in education. Completing a degree in education may increase earnings in all occupations relative to not having a college degree. But if it also raises the non-pecuniary returns to working in an education occupation and working in education pays less than other occupations, then the unconditional effect of majoring in education (relative to no college degree) on earnings could be negative.

Even if some majors do not affect the non-pecuniary benefits of occupations, the unconditional effect on earnings may still be ambiguous. Namely, if the pecuniary returns for a particular major are larger in low-paying but high non-pecuniary benefits occupations, the probability of choosing a low paying occupation may increase, leading to an overall negative effect on earnings.

In practice, individuals from different demographic subgroups may attach different values to the non-pecuniary aspects of the occupations. For instance, workplace flexibility is likely to be more important for women than men. Denoting by X_i a set of demographic characteristics for individual i, we can extend our framework by writing the non-pecuniary part of the flow payoff for occupation k as $np_{kj}(A_i, X_i)$.

11. *Treatment effects of major on wages may vary across individuals with identical wages in all occupations.*

    The treatment effect of graduating from college with any given major j may be lower for those individuals who place a greater emphasis on non-pecuniary job benefits, and are more likely to prefer relatively low-paying but high non-pecuniary benefits occupations.

3.3.1 Accounting for Search Frictions

We have implicitly assumed so far that, after graduating from college, individuals can always choose across all possible occupations. We now relax this assumption by allowing workers who graduated from major j to receive λ_{jk} job offers within each occupation l, where λ_{jk} may be zero for certain (major,occupation)-pairs.

12. *Individuals choose their college major by taking into account the occupation-specific effects of majors on wages, job offer arrival rates and non-pecuniary benefits.*

    For instance, completing a college degree in Science (relative to Humanities) may lead to an increase in wages in science occupations, as well as in the job offer arrival rates and non-pecuniary returns to these occupations. Individuals take into account those three effects when deciding whether to major in Science.

3.3.2 The Effect of Labor Market Conditions

This framework can be extended to incorporate aggregate labor market conditions. Specifically, define U_{ikj}^S to be the expected flow payoff for individual i working in occupation k when the economy is in state $S \in \{R, E\}$ (recession or expansion, respectively) after graduating from major j. Wages within each occupation and major vary across the business cycle, resulting in the following expected flow payoff:

$$U_{ikj}^S = np_{kj}(A_i) + \gamma_1 w_{kj}^S(A_i) \tag{4}$$

13. *The effect of aggregate labor market conditions on wages may vary across majors, through both i) the choice of occupation and ii) the effect on wages within each occupation.*

    For instance, i) jobs in Education are likely to benefit less from good economic conditions than other occupations such as Science, while ii) workers with a Science degree working in Science are likely to be less affected by a recession relative to those who work in Science and graduated from another major.

    It follows that the allocation of students across majors may vary across the business cycle. Although this stylized framework abstracts from these considerations, it is worth noting that, in practice, the effect of labor market conditions on the decision to enroll in a given major will also depend on how persistent students anticipate the labor market conditions to be.

3.4 Evolution of Beliefs

Individuals have innate abilities in each of the J majors and K occupations with a population distribution that is multivariate normal. Let Σ denote the $(J + K) \times (J + K)$ population covariance matrix of the abilities. Abilities may be correlated across majors and occupations, resulting in a generally non-diagonal matrix Σ. Individual i's expectations of these abilities at time t are given by A_{it}, a $J + K$ vector, where A_{ijt} gives expected ability in major j and

A_{ikt} gives expected ability in occupation k.[21]

These expectations evolve with the signals received across different choice paths. Specifically, consider the case in which individuals who attend college learn about their academic ability through their schooling performance, as measured by their GPA by the end of the year. Any discrepancy between the actual and expected GPA leads the individuals to update their belief in a Bayesian fashion. Since Σ is non-diagonal, GPA in a given college major j also provides some information about the abilities in other majors $j' \neq j$ as well as about the abilities in all occupations k. Similarly, those who enter the labor market and work in occupation k update their beliefs about their abilities in all occupations and all majors using their log-wage as a signal. Hereafter we relax the assumption that labor market is absorbing by allowing for college re-entry, which arises here as a natural consequence of learning about ability.[22]

Formally, denoting by $\Sigma_t(A_i)$ the posterior ability covariance matrix at the end of period t, ability beliefs are updated as follows:

$$A_{it} = [(\Sigma_{t-1}(A_i))^{-1} + \Omega_{it}]^{-1}[(\Sigma_{t-1}(A_i))^{-1}A_{it-1} + \Omega_{it}S_{it}] \tag{5}$$

$$\Sigma_t(A_i) = [(\Sigma_{t-1}(A_i))^{-1} + \Omega_{it}]^{-1} \tag{6}$$

where Ω_{it} is a $(J+K)\times(J+K)$ matrix with zeros everywhere except for the diagonal element corresponding to the major or occupation of individual i in period t. The nonzero diagonal element is inverse of the variance of the idiosyncratic shock affecting the GPA received in that major or the wage received in that occupation, respectively. S_{it} denotes a $J+K$ vector with zeros everywhere except for the element corresponding to the major or occupation of

[21] The model discussed in this subsection shares the same features as the correlated learning model estimated in Arcidiacono et al. (2015). In that model, individuals are uncertain about their abilities in two-year colleges, in four-year colleges as STEM majors, in four-year colleges as non-STEM majors. They are also uncertain about their ability in the skilled and unskilled sectors of the labor market. We discuss other work that emphasizes learning about preferences and ability in Section 5.1.2.

[22] Of course, students receive other signals about their academic ability. They also learn about their preferences for non-pecuniary aspects of a field of study and the occupations related to it through the experience of taking classes in the field.

individual i in period t. That element is the ability signal received in t, i.e. GPA if individual i is enrolled in college and the log-wage otherwise.

This updating rule, which follows from the assumption that ability is normally distributed, boils down to the standard "signal-to-noise ratio times the signal plus noise-to-signal ratio times the prior belief" updating formula in the unidimensional case. As individuals accumulate signals, the prior ability variance shrinks towards zero, thus giving more weight to the prior about ability and less to the new signals when updating the ability beliefs.

14. *Treatment effects of majors on wages partly operate through learning about ability.*

    Suppose it is the case that individuals who enroll in a Science major acquire a better sense of their comparative advantage, both in terms of major-specific and occupation-specific abilities, than those who enroll in the Humanities. Then this informational edge would lead Science graduates to make better decisions in the labor market (from an ex-post optimality viewpoint). All else equal, this should result in higher wages.

15. *Individuals who do not perform as well as expected revise their major-specific ability downward and may, as a result, find it optimal to switch major.*

16. *Individuals who leave college before graduating may decide to subsequently re-enroll in the same or a different major as they update their beliefs about the wage returns to graduation and the wage returns to the different majors.*

    Some of the individuals who left college and realize that they earn less than expected in the high-school sector may decide to re-enroll and get a Bachelor's degree. Depending on the correlation patterns across the different occupation and major-specific abilities, those individuals may either re-enroll in their initial major, or enroll in a new major.

3.5 Supply side

Until now we have focused on how individuals make their educational decisions taking the environment as given. Yet the production of degrees in various fields is also affected by institutions of higher education. Consider the recent work by Hastings et al. (2013) and Kirkebøen et al. (2015), who analyze school and major choices in Chile and Norway respectively. In these countries, individuals apply to school-major combinations and switching majors is very costly. Admissions into school-major combinations is determined by test scores, with programs taking those with the highest test scores admitted into the program until all the spots are filled. This introduces discontinuities that can be used in the identification of the treatment effects of different majors on outcomes such as earnings. But the fact that these discontinuities exist suggest that, at least for some programs, the number of majors is not determined by demand but by supply. A clear next step in this research is to understand how schools are choosing the size of their programs.

Even when individuals are allowed to change their major, the school may make it more or less attractive to do so. Returning to the baseline model, schools influence the cost of effort and switching majors through the workload they require; α_{0j}, α_{1j}, and α_{2j} are in part choice variables of the universities. Universities affect these parameters through the allocation of resources across departments. To the extent that a department has low (high) demand relative to the funding provided by the university, the department may have incentives to make their major more (less) attractive through the assignment of workload or grading standards. As pointed out earlier, many individuals begin in STEM fields but switch out, with those switching out tending to have lower test scores. This might be indicative of STEM departments facing high demand given their teaching resources relative to non-STEM departments.

4 Estimating the Return to College Majors

In this section we provide an overview of the literature on the returns to specific fields of study. We begin by highlighting the key sources of endogeneity that have to be addressed, focussing on the largely neglected problem posed by the fact that people choose occupations. We then discuss the methods and estimates.

4.1 Sources of Bias in Estimating the Return to College Majors

Estimating the return to specific college majors is a formidable task. Two main issues have been broadly recognized in the empirical literature. First, the absolute advantage of workers may differ across college majors for a number of reasons. For example, general labor market ability may be related to non-pecuniary preferences for particular majors. It also may affect the ability of students to complete more difficult ones, and the amount of study time they need to do so. Second, students may have occupation specific talents that alter the relative payoffs of different majors. A student may be good at engineering and poor at teaching, and as a consequence have a relatively high return to engineering compared to teaching. As long as students choose their college major partly based on the labor market returns, this type of sorting on comparative advantage will typically result in biased OLS estimates of the returns to majors. Sorting based on comparative advantage is of course a pervasive issue in economics, and the subject of a vast econometrics literature on heterogenous treatment effects and essential heterogeneity.[23] The potential selection bias arising from absolute advantage is also common to many discrete choice problems.

A third source of bias is more subtle. As we discussed in Section 3.3, with heterogeneity in preferences across occupations, the treatment effect of a major on *observed* wages operates through both the choice of occupation and through effects on wages in each occupation. The particular field that a college student chooses alters the distribution of wage rates and employment opportunities that the student will experience in each of the occupations in the economy. For example, a computer science degree presumably has a larger positive effect on the wage offer distribution for computer programming jobs than for social worker positions. If graduates simply maximize income, then they would choose the highest paying occupation given their majors. In this case, the treatment effect on actual wages rates, abstracting from occupation, would be a natural summary of how field of study affects productivity. However,

[23]See, for example, Heckman et al. (2006). See also the seminal work of Roy (1951) on sorting based on comparative advantage, and subsequent empirical analyses by, among others, Heckman & Sedlacek (1985), Heckman & Honore (1990) in the context of the Roy's model, and more recent work by Eisenhauer et al. (2015) and D'Haultfoeuille & Maurel (2013) dealing with the empirical analysis of extensions of Roy's model.

with occupation specific preferences, the utility maximizing choice of occupation will depend on an individual's preferences for non-pecuniary characteristics of occupation. The observed wage rate of a computer science graduate will be affected by both the size of the treatment effects on potential wages in various occupations and by what occupation the graduate chooses to pursue given both pecuniary and non-pecuniary considerations. Consequently, pre-existing differences across majors in occupation preferences, and the treatment effect of field of study on occupation preferences both influence the treatment effect of a major on wage rates.

To better see the implications, consider what one could learn from an experiment in which individuals are forced to choose a major that is selected at random, and then forced to pursue a career in an occupation that is also chosen at random. This experiment would identify differences across fields in the vector of average treatment effects on potential wage rates in various occupations. Next consider an alternative experiment in which individuals are forced to choose a major that is selected at random but are then allowed to choose jobs freely. The alternative experiment would identify average treatment effects of majors on observed wages rates and on occupational choices. However, identifying the effect of majors on wages in an occupation is more complicated as the observed wage response depends on both the effects on occupation-specific potential wages and the distribution of occupational preferences. This poses a formidable estimation problem.

Consider an instrumental variables estimation strategy that relies on a vector of instruments that do not affect occupation specific potential wages but influence choice of field of study by altering the non-pecuniary benefits of particular occupations. Such an IV strategy will not identify the $LATE$ for majors on realized wage rates, because variation in the instrument will be associated with variation in the types of jobs that individuals choose conditional on major. On the other hand, suppose that the instruments influence the monetary and/or non-pecuniary benefits during college to a particular field of study but do not influence the monetary returns or the non-pecuniary benefits of particular occupations. Then IV could identify the $LATE$ of major choice on realized (not occupation-specific) wage rates.

To help frame the discussion, consider the following equation for the log wage rate of an individual i who majored in field j and is working in occupation k in period t.

$$\ln w_{ijkt} = \gamma_{00} + \gamma_{jk} + \gamma_A A_i + \gamma_{jA} A_i + \gamma_{kA} A_i + \gamma_{jkA} A_i + Q'_{c(i)} \gamma_{jQ} + X'_{it} \gamma_{jkX} + v_{ijkt} \tag{7}$$

In (7), γ_{jk} is the average treatment effect of being assigned to field j and occupation k. We normalize the γ_{jk} to be relative to an excluded field-occupation combination. All other variables are deviations from population averages. A_i is a vector valued measure of the student's ability. The coefficient γ_A is the influence of A_i on wages in all occupation/field combinations. It captures the effect of ability on absolute advantage. The coefficient γ_{jA} is the effect of A_i on comparative advantage in j. It reflects the interaction between j and A_i in the production of general human capital that is valued in all jobs. It also reflects complementarity between A_i and the skills taught in j. Similarly, the coefficient γ_{kA} corresponds to the effect of A_i on comparative advantage in occupation k. The coefficientγ_{jkA} is the differential effect of A_i on the wages of those who study j and work in k. It arises from complementarity between the task requirements of k and field j, and captures the effect of A_i on comparative advantage in the field/occupation pair j, k. Since γ_A is defined to be the average effect of A_i over all field/occupation combinations, the γ_{jA} sum to 0 over j, γ_{kA} sum to 0 over k, and γ_{jkA} sum to 0 over j, k.

The vector $Q_{c(i)}$ is a vector of measures of the quality/selectivity of the college c that i attends. demographic characteristics and labor market experience. The effects of these variables may depend on j and k. The error term captures random factors that influence wages in j, k at a particular point in time.

As noted in the theoretical discussion of choice of major in Section 3, students choose j in part based upon the labor market payoffs in the various occupations given their beliefs about A_i and X_{it}, and in part based upon non-pecuniary factors associated with alternative majors and associated occupations. Conditional on the major j, and absent search frictions, individuals would then choose to work in occupations k that yield the highest utility given the wage equation (7). In practice though, search frictions imply that individuals may only get to choose among a subset of all possible occupations. the observed choice of k and the associated wage rate depends upon j, A_i, non-pecuniary factors, and labor market frictions. Fully modeling the selection rule that leads i to a field j, occupation k pair would be quite complicated. However, it will be difficult to estimate complementarities between fields of study and occupational wage rates without understanding the selection process.

Empirical evidence on interactions between occupation and major in earnings equations is very limited. Some studies include occupation fixed effects as an informal way to assess the extent to which the return to major operates within occupations rather than across occupations. Arcidiacono et al. (2014) obtain data from a sample of Duke University students on beliefs about potential earnings by occupation for both chosen major and for alternative majors. The data indicate that students believe that the monetary returns to particular majors vary substantially across occupations, consistent with the existence of complementarities between majors and occupations. Expected earnings for any given major-occupation pair are also found to be highly heterogenous across individuals. Lemieux (2014) is one of the few papers in the literature that uses multiple regression to estimate the system of potential wage equations for j, k pairs given by (7). Robst (2007), Nordin et al. (2010), Yuen (2010), Kinsler & Pavan (forthcoming), Lemieux (2014), Lindley & McIntosh (forthcoming) and Altonji et al. (2014*a*) show that college graduates receive a larger earnings premium when individuals report that the skill requirements of their occupation is a good match for their college major or when their occupation is typical for their major.

The wage equation used by most studies is

$$\ln w_{ijt} = \gamma_0 + \bar{\gamma}_j + \bar{\gamma}_A A_i + \bar{\gamma}_{jA} A_i + Q_{c(i)} \gamma_{jQ} + X_{it}' \bar{\gamma}_{jX} + v_{ijt} \tag{8}$$

In the above equation $\bar{\gamma}_j$ is the average treatment effect of major j relative to the reference major. It is a weighted average of the γ_{jk}. The parameter $\bar{\gamma}_A$ is the sum of γ_A and a weighted average of the γ_{kA}. sum of γ_{jA}, a weighted average of the γ_{jkA}, and a term that reflects differences by j in weighted average of the γ_{kA}. Thus all of the parameters reflect differences by major in occupation choice.

We now discuss the alternative approaches that have been taken to estimate of variants of (8).

4.2 Multiple Regression with Controls for A_i

Most studies in the literature have used multiple regression to estimated variants of (8). Table 8 summarizes the results from a few studies. The studies differ primarily in the choice of control variables. Most include basic demographic variables such as race. Almost all either control for gender or estimate separate equations for men and women. Some include parental background measures such as parental income and education. Most include prior test scores and/or high school grades. Webber (2014) controls for personality traits that are associated with labor market success. A few papers, including James et al. (1989) and Altonji (1993) control for high school curriculum. A few studies, such as Rumberger & Thomas (1993) and Loury & Garman (1995) control for college quality or selectivity. Failure to control for college quality could lead to biased estimates if college quality directly affects wage rates and is correlated with major choice.

Much of what leads to different (true) returns to different major is likely reflected in the different courses taken. Hamermesh & Donald (2008) is one of the few studies to explore the degree to which earnings effects depend on the course content of the major by adding counts of course credits in various subjects. They find that adding the course credits account for part of the difference across fields, with math and science courses entering positively. College grades also enter positively in a log specification. This implies that differences across fields in the level (as opposed to the log) of earnings are larger for those with high grades.

The content of the coursework will also vary with how easy it is to switch majors. In much of Europe, individuals pre-commit to majors, allowing for more specialization at the cost of perhaps worse matches.

Some studies use hourly wage rates rather than earnings as the compensation measure, while some report results for both, and comment on the degree to which earnings effects operate through hours rather than wage rates. Most studies find larger differences across fields in earnings effects than in wage effects, although the correlation between the two is high. Most studies condition on positive earnings.[24] Some studies condition on full-time work.

We now turn to the estimates, which are reported in the last columns of the table.[25] For each set of estimates we identify the reference category. When possible, we have expressed the coefficients as relative to education. In some cases, the estimates are relative to high school.

Most studies find that the return to engineering is substantially larger than the return to education. In U.S studies, the differential is typically about 0.4 even when family background and prior test scores are included. There is also a substantial premium to business, although the estimate is typically below that of engineering. Social studies majors also earn more than education majors.

Controlling for occupation compresses the earnings differences across fields of study, as illustrated by the estimates from James et al. (1989) in the table, or the estimates in Altonji et al. (2012) mentioned earlier. One would expect this if complementarity between field of study and occupation specific tasks that are highly valued in the labor market is key to differences in the payoffs to fields of study. But it also may be due in part to differences in compensating differentials for non-pecuniary characteristics of occupations, to unobserved heterogeneity in general labor market ability that is correlated with choice of field and occupation and to the fact that conditioning on occupation in an earnings regression is to some degree conditioning on the dependent variable.

Most studies find that controlling for prior test scores, family background, and/or high

[24] Hamermesh & Donald (2008) is the only paper we are aware of that corrects for selection into employment. They find that doing so reduces earnings differentials by between 10 and 20%.

[25] A few entries in the table are taken from a similar table in Altonji et al. (2012). We have included a number of more recent studies, including the handful that attempt to address bias from unobserved heterogeneity. We have converted estimates that are expressed as a percentage effect or in terms of actual earnings to log points.

school curriculum reduces estimates of the differences, but the changes are not always large. For example, Hamermesh & Donald (2008) obtain very similar estimates when they add high school class rank and SAT scores to their basic model.[26] In Table 9, we use the NLSY79 to explore how the returns change as we add additional controls to a model with fairly detailed field of study categories. The estimation sample is constructed by pooling across survey waves (1981 to 2012) the observations of individuals with at least a high school degree, who are 24 years old or older, and work 30 hours or more per week. In all four regressions we include dummy variables indicating whether individuals have a high school degree or some college education only. To make the results easier to assess, we have ordered the majors from the highest return to lowest return based on the specification with only controls for gender, race/ethnicity and age, which we report in the first column. The returns to the various majors are computed here relative to Education. Columns (2) to (4) report the estimated returns as we add the following controls to the baseline specification, namely (2) father's and mother's highest grade completed, (3) six components of the ASVAB test (Arithmetic Reasoning, Numerical Operation, Coding Speed, Mathematics Knowledge, Paragraph Comprehension, and Word Knowledge), and finally (4) measures of personality traits (Rosenberg Self-Esteem and Rotter Locus of Control Scales). Overall, the estimated returns do change somewhat as we add these different sets of controls, but for most majors these changes are pretty small. There are a few exceptions though, with the returns to a major in military sciences or general studies exhibiting sizable changes as we go from specification (1) to specification (4) (0.256 to 0.185 log-points and 0.083 to 0.039 log-points, respectively). In most cases the estimated returns (relative to Education) fall as we control for differences in parental education, cognitive ability and personality traits. When interpreting these results, it is important to keep in mind that the ASVAB scores as well as the Rotter and Rosenberg scales are noisy and incomplete measures of cognitive and non-cognitive ability. It follows that, even in the specification with the most comprehensive set of controls (Column (4)),

[26] The fact that their sample is from only one university may affect class rank and SAT scores and other student characteristics, given the rank and SAT scores are used in determining admission at U. of Texas and also influence the decision to attend that school rather than somewhere else.

the estimated returns to the various majors are likely to biased upward. The size of the bias from selection on unobservables is a key empirical question. We discuss papers that address selection on unobservables when estimating the returns to majors in Sections 4.3-4.5.

4.2.1 OLS Evidence on Heterogeneity in the Returns

For a few studies we present estimates separately for men and women. Grogger & Eide (1995) is a good example. The relative returns are positively correlated, and there is no clear pattern in the differences. Brown & Corcoran (1997) report estimates using the 1984 SIPP panel for a sample of college graduates, but use field of highest degree (15 categories) rather field of undergraduate degree with controls for graduate education. Gender differences in the returns to major are relatively small. Altonji (1993, Appendix Table A1) reports separate estimates for men and women in a regression that includes dummies for less than 2 years of college, more than 2 years but no degree, and 16 mutually exclusive indicators for highest degree consisting of 10 undergraduate and 6 graduate degree categories. Relative to no college, women receive a higher payoff to nontechnical fields than men do, and about the same return in technical fields. But relative to education and other nontechnical fields, men tend to receive a higher premium in business and STEM fields.[27] Using the ACS 2009 with minimal controls, Altonji et al.(2012, Supplemental Table 3) report estimates by gender of the effects of college major on log wages, with a degree in education as the reference category. They use 171 major categories. The effects relative to education are larger for men than women in most fields. However, the correlation in the estimates is large. The results suggest that the gender gap for those obtaining a degree in education is smaller than in most other fields. Chevalier (2011) finds that for women education pays well relative to most other majors, while for men most other fields pay better, with physical science being an odd exception. The correlation in the relative returns to the degrees is fairly strong at

[27]Brown and Corcoran include controls for high school curriculum. Altonji includes controls for high school curriculum, SAT Math and Verbal scores, high school grades, and the student's self assessment of whether or not he is college material.

0.597, especially given that this value is downward biased by sampling error in the regression coefficients.

Several studies examine the effects of ability measures on the relative returns to field of undergraduate degree. Altonji (1993, Table A3) finds that the gap between the return to a technical major and a nontechnical major is substantially larger for those with higher values of a set of ability measures. Webber's (2014) evidence based on NLSY79 is less clear. We discuss other evidence on this issue in the next section.

4.2.2 Estimation Using Selection on Observables as a Guide to Selection on Unobservables

Webber (2014) estimates the effects of some college and a college degree in STEM, Business, Social Sciences, and Arts and Humanities on log earnings using the NLSY79. In line with several prior studies, he measures the effects of bias from selection on observables by examining how the coefficients on the college degree parameters change when the AFQT test, mother's education, the Rotter score measure of self control and the Rosenberg Self-Esteem scale are added to the controls. In addition, he also examines the effects of selection on unobservables using the methodology proposed by Altonji et al. (2005). Altonji et al. provide a set of assumptions under which the strength of the relationship between selection into various education outcomes and the observed explanatory variables in the earnings model are informative about the degree of selection based upon unobserved characteristics. Webber reports the fraction of the premium (over high school) associated with the different degrees that is due to selection on unobservables under the assumption that the degree of selection on unobservables is the same as the degree of selection on the observables. The fractions are large, but the assumption that selection on unobservables is as strong as selection on the observables is extreme in a study of the effects of field choice on earnings.[28] Using a simulation

[28]This is because much of the variance in earnings at a point in time is due to measurement error or permanent and transitory shocks that occur after college decisions have been made. These components of measured earnings are not related to education choices and thus are not a source of selection bias.

methodology that involves the use of the American Community Survey as well as estimates of selection bias parameters that are based upon the NLSY79, Webber provides estimates of the effects of the majors on lifetime earnings under alternative assumptions about the degree of selection on unobservables relative to observables. When test scores and personality measures are excluded, the estimates indicate that STEM graduates earn 39.1% more than Arts/Humanities majors. The corresponding values for Business and Social Science Majors are 34.1% and 21.6%. Correcting for observable ability measures changes these percentages to 37.4%, 77.6% and 16.4%. degree of selection on unobservables is half as large as selection on observables, the STEM, Business and Social Science premiums over Arts/Humanities are reduced to a relatively modest 11%, 10.9% and 4.9% respectively.[29] As we note below, most of the other approaches to accounting for selection on unobservables show larger differences across fields in returns.

4.3 Control Function Approaches To Controlling for Selection on Unobservables

The OLS approaches assume that the control variables are sufficient to address the problem of unobserved variation in ability, family background, and high school preparation that may alter the estimated returns to specific fields of study. A few studies have attempted to address selection on unobservables based on absolute advantage and/or comparative advantage. Drawing on Heckman (1979) and Lee (1983), Berger (1988) deals with selection by constructing a control function based on a reduced form multinomial logit model of the choice among five fields—Education, Liberal Arts, Business, Science, and Engineering. The data are the NLS Young Men panel, which included men aged 14 to 24 in 1966. The sample is restricted to college graduates who do not get an advanced degree. The logit model includes

[29] Webber also reports that selection into college and into STEM and Business majors is less strongly related to ability measures in the NLSY97 cohort than in the NLS79 cohort. Part of the discrepancy may be due to differences in the test instruments used and to the fact that the test was administered to the NLSY97 cohort at younger ages.

variables that belong in A_i and X_{it} plus a set of additional variables that are assumed to alter major choice by shifting the non-pecuniary preferences for field of study but not to directly affect wage rates. These variables include father's occupation, an indicator for whether both parents were present in the household when the respondent was 14, mother's and father's education, college prep high school curriculum, and ethnic origin. Given the literature on intergenerational links, there is reason to believe that some of these variables have a direct effect on wages. Furthermore, to the extent that variables such as father's occupation affect occupation choice conditional on field of study, they would affect the weighting that defines the parameters in (8).

Berger finds substantial differences in the average payoff to major that are in line with many other studies in the literature (see Table 8). The pattern of the coefficients on the sample selection terms varies across fields of study. They are only statistically significant in the wage rate equations for Education majors and Liberal Arts majors. The coefficients indicate positive selection into these majors. The sign on the ability measures (IQ and Knowledge of the World of Work) are mixed across equations. The experience profiles of wages vary across majors but also depend on the birth cohort, so it is hard to draw strong conclusions about whether they differ by field.

Even though the use of a reduced form model of major choice is a straightforward way to address selection on unobservables when estimating (8), Berger is the only study we know of that has employed it. The lack of obvious choices for variables that influence choice of major but not wages may partially explain the lack of use.

4.4 Structural Modeling of Major Choice and Wages

Arcidiacono (2004) estimates the monetary return to fields of study as a piece of a full dynamic discrete choice model. The model considers the decisions of whether to remain in college (conditional on having applied), where to attend college, and field of study. A key purpose of the paper is to shed light on why students sort by ability across schools and majors, not simply to estimate wage equations. But modeling the education decision making process is also the most natural way to get a handle on effects of heterogeneity in ability and on dynamic selection that is induced by the arrival of information about talent, tastes, and field specific wages.

Students may transfer, and optimal choice depends on field of study and ability. The monetary payoff to college depends on college quality with a field specific coefficient. The non-pecuniary costs of attending college and of effort depend on college quality as well as the match between the student and the college.[30]

The basic set up is as follows. The analysis is restricted to students those who were admitted to at least one 4 year college. The college application decision and the set of colleges to which a student is admitted are treated as exogenous. These individuals presumably have at least some interest in college and the opportunity to attend. As in Altonji's (1993) stylized model, individuals are forward looking but uncertain about preferences, ability, and labor market opportunities. In the first period, an individual chooses a major and a college from the set she was admitted to, or she makes an irreversible decision to enter the labor market. After making these choices, college students get new information about ability from grades, and about preferences for particular programs of study.

In Period 2, those who were college students in the first period once again choose a major and choose a college from the set they were originally admitted to.[31] Alternatively, they may leave school and enter the labor market. After period 2, those who had remained in college get additional information about their ability and preferences and enter the labor market.

For present purposes, the key equation of the model is the wage equation. Ability has three components. The first two are proxied by the SAT math and SAT verbal scores. These are assumed to be known at the start of college. The second is proxied by cumulative grades. In the model, as college progresses, agents learn about their general ability and subject spe-

[30]The effort level and associated utility cost to i of attending a college of a given quality $Q_{c(i)}$ depends on a major specific term that depends on Q. It also depends on a term that is increasing in the mismatch between a student of ability A_i and $Q_{c(i)}$.

[31]Arcidiacono's results imply that ability sorting across majors is primarily due to heterogeneity in preferences for major and the workplace.

cific abilities only through grades. The flow of information affects choices about college major and whether to remain in school, but cumulative grades and test scores are assumed to fully summarize the agent's ability. Cumulative grades and test scores are included in the wage equation. Thus, in Arcidiacono's basic specification, all components of ability that influence wage rates are assumed to be observed by the econometrician. The wage equation of the model can be estimated consistently by ordinary least squares. However, Arcidiacono also estimates a second specification that includes fixed person specific unobserved heterogeneity. The unobserved heterogeneity influences both the returns to each major as well as preferences. In the wage equation this amounts to replacing the parameters $\bar{\gamma}_j$ with $\bar{\gamma}_{r(i)j}$ where $r(i)$ is $i's$ type. He allows for two types. Thus the wages take the form

$$\ln w_{ijt} = \bar{\gamma}_{r(i)j} + [SATM_i, SATV_i, Grades_i]'\bar{\gamma}_{Aj} + [SATM_{c(i)}, SATV_{c(i)}]'\gamma_{jQ} + X_{it}'\bar{\gamma}_{jX} + v_{ijt} \quad (9)$$

The equation must be estimated jointly with the other equations of the model. Identification of the type parameters comes from the correlation between the various outcomes. For example, someone may have a high unobservable preference for engineering. This preference may be correlated with grades and with wages in ways that are not accounted for by observables.

The results are as follows. In the two-type model, the premium relative to no college is highest in the natural sciences (which include engineering) followed by business. Social sciences/humanities have a 5% return, and education is slightly negative for males and has a return of 6% for women.[32]

The parameters on average test scores for the school and for the individual are constrained to be greater than or equal to zero. $SATM_i$ and $SATM_{c(i)}$ are typically positive and statistically significant for all majors except for education. $SATM_i$ also substantially increases the return to the "no college" option, so the net positive effect on the return to college is small. A 100 point increase in SAT math has little effect on the premiums for

[32]Similar findings with the same data are found in Arcidiacono (2005) who does not model the dynamics of major choice but does model the college application decision and the decisions by colleges as to who to admit.

the various majors relative to the return to no college. It increases the return to natural sciences and business relative to education by about 2.5%. The non-negativity constraint binds in many cases for $SATV_i$ and $SATV_{c(i)}$. Indeed, a number of studies have noted that verbal test scores sometimes appear with a negative sign in regression models that include math test scores.[33] Since verbal skills will almost certainly raise productivity across a broad array of jobs rather than lower it, a natural explanation for the negative coefficients is that conditional on grades and $SATM$, $SATV$ is associated with preferences for occupations that pay less for non-pecuniary reasons. However, Sanders (2015) does not find much support for this interpretation. He finds that the negative return is concentrated in occupations for which interpersonal contact is important. He speculates that reading scores may proxy for introversion conditional on math scores. This is an interesting area for future research.

What about school quality? The results indicate that attending a school with a one-hundred-point higher average math SAT score raises the return to natural sciences degree by 2.8% and a social sciences degree by 6%. These numbers are small compared to the differences in returns across majors.

A few other papers have taken a structural approach. Beffy et al. (2012) estimate a sequential model in which university entrants choose a field, and then decide on the (initially uncertain) level of education before entering the labor market. The model is estimated using data from two cohorts of students in France, where there is evidence that a large fraction of students complete a level of education which differs from the level they aspired to when starting college. The choice of field of study, which is the main focus of the paper, is based on both monetary and nonmonetary factors. The earnings equation allows the effects of field (Sciences, Humanities and Social Sciences, and Law, Economics and Management) to interact with the level (5 levels from dropout to graduate school) and to vary across cohorts. The equation includes controls for gender, foreign birth and whether the parents are immigrants, but test scores and secondary school grades are not observed in the data. Unobserved

[33] See Kinsler & Pavan (forthcoming) and Seki (2013), who use SAT math and verbal scores and study a sample of college graduates. Sanders (2015) finds a negative effect of verbal test scores using five different data sets.

heterogeneity is accounted for through the use of vectors of heterogeneity parameters that allow for correlation between earnings, field choice and degree level (3 heterogeneity types). Estimation results show that, for both cohorts (students entering the labor market in 1992 or 1998) and most of the levels of education, majoring in Science leads to the highest earnings, followed by Law, Economics and Management and Humanities and Social Sciences. The returns to field of study are highly heterogeneous across cohorts and levels of education. Notably, for those graduating in 1992, receiving a *Maitrise* (four year of college) in Science is associated with a 15.2% premium over a degree in Humanities and Social Sciences. The premium goes up to 27.3% for the individuals graduating in 1998. The returns to Science relative to Humanities and Social Sciences also tend to increase with the level of education.

Kinsler & Pavan (forthcoming) also develop and estimate a structural model of field of study and labor market outcomes. Individuals first choose what to study and then choose a job type. They are endowed with two types of human capital, math and verbal, but are imperfectly informed about them when they are deciding what to study. Human capital accumulation depends upon choice of major. Individuals find out their true human capital when they finish school. They choose which sector to work in based upon wage rates, non-pecuniary factors, and random variation in the opportunities available to them.

Kinsler & Pavan estimate the model using the 1993 cohort of Baccalaureate and Beyond. They complement the structural analysis by providing descriptive information on test scores and grades, subject matter by field of study, on the occupation distribution. They also present regression evidence on the interplay between wage rates, field of study, and on employment in a job that is related to their field of study.

Kinsler & Pavan report average treatment effects of the return to business and science relative to an "Other" category. They obtain estimates of 0.145 for business and 0.184 for science. These are below the corresponding OLS estimates of 0.204 and 0.229 in the base specification and 0.185 and 0.214 when SAT math and verbal scores and Major GPA are controlled for. Thus OLS overstates the difference in returns even with controls, in part because the controls are noisy measures of ability and human capital. Kinsler & Pavan also use the model to show that the monetary return to science does not vary much across the population. The returns to business are actually a bit smaller for those who choose business. Finally, the paper presents both descriptive evidence and evidence from the model that the payoff to science and to the "Other" major category strongly depend on working in a job related to the major. In the case of Science, the difference is almost 30%. The payoff to business does not depend much on this, although the estimates are somewhat noisy.[34]

4.5 Using Variation in Access to Fields of Study to Identify Returns

4.5.1 Methods

The use of exogenous variation in access to fields of study is an alternative approach to identifying returns. In many universities, the access to some fields of study, such as business or computer science, is restricted. When well-defined, measurable student characteristics are used to determine admission, and the admissions criteria are known or can be easily estimated, then the possibility of using variation in the probability of admission to particular programs of study arises. In the United States, one could in principle use grade point average cutoffs along with other criteria to identify the return to selective programs. This would require assembling information on the cutoffs at a few universities. One would also need detailed information on the college transcripts of students. Multiple states, including Florida, Texas, and North Carolina, have invested in student record systems that could in principle be used for this purpose. Variation over time in the field specific admissions cutoffs would also be very helpful.

The research possibilities are greater in the many countries where public provision of higher education dominates, admission is to a specific college program, and the criterion is an index of test scores or secondary school grades. Bertrand, Hanna & Mullainathan

[34] Across a full set of 50 majors, Altonji et al. (2014*a*) find that earnings are 29% higher for those who work in a occupation that is among the top 5 most common one for the major.

(2010), Hastings et al. (2013) (hereafter, HNZ) study for Chile and Kirkebøen et al.'s (2015) (hereafter KLM) study for Norway show the potential as well as the challenges.[35] As we mentioned previously, in both countries admission is to a school/field combination. Students provide a ranked list of their preferred programs. They are generally admitted to the most preferred program for which they exceed the admissions cut off.[36] The cost of changing programs is very high, so new crossing the admissions threshold has a very large, discontinuous effect on the odds that a student will matriculate in a particular program. This provides the potential for a fuzzy RD design. At first glance, this seems straightforward. However, the appropriate use and interpretation of IV estimators, including those based on fuzzy RD designs, to estimate the effects of multiple unordered categorical choices raises very difficult issues that are still being sorted out. HNZ and KLM are an important start of what we expect to become a very active area of research.

To illustrate the regression discontinuity approach, consider a simple case where there are three fields and only one school. Let s_i denote i's test score. Denote s^j as the test score cutoff for field j. Order the fields according to their test score cutoffs: $s^2 > s^1 > s^0$ and, for ease of exposition, assume that the cutoff for field 0 never binds.

We can obtain the effect of crossing the threshold in field j on earnings by examining those who were near the threshold for field j. Let $\bar{t}_{i1}$ ($\underline{t}_{i1}$) equal one if i (a) listed field 1 ahead of field 0 and (b) had a test score slightly above (below) s^1, and equal zero otherwise. For now, assume that admission is perfectly determined by the student's score and field ranking (strict RD design). The average treatment effect for crossing the threshold for field 1 for those for whom $\bar{t}_{i1} = 1$ or $\underline{t}_{i1} = 1$ is given by:

[35] Bertrand, Hanna & Mullainathan (2010) use an RD approach to study the returns to engineering colleges in India. They use variation across castes in admissions cutoff scores. We do not discuss their study in detail, because their estimates of earnings effects are too noisy to draw strong conclusions. Other countries that use indices based on grades and/or test scores heavily in the admissions process include Turkey and Columbia.

[36] Students are permitted to rank up to 8 school/field combinations in Chile and up to 15 in Norway. In the absence of these restrictions (which do not bind for most students), students have an incentive to rank schools in accordance with their preference and without regard to admissions chances.

$$\Delta_1 = E(Y_i|\bar{t}_{i1} = 1) - E(Y_i|\underline{t}_{i1} = 1) \tag{10}$$

where Y_i is some measure of earnings. This treatment effect has a clear interpretation. It gives the expected earning from being assigned to field 1 ahead of field 0 for this subset of individuals.

The corresponding effect for crossing the threshold for field 2 is not as straightforward to interpret. Let $\bar{t}_{i2}$ ($\underline{t}_{i2}$) equal one if i (a) listed field 2 first and (b) had a test score slightly above (below) s^2, and equal zero otherwise.The average treatment effect for crossing the threshold for field 2 for those for whom $\bar{t}_{i2} = 1$ or $\underline{t}_{i2} = 1$ is given by:

$$\Delta_2 = E(Y_i|\bar{t}_{i2} = 1) - E(Y_i|\underline{t}_{i2} = 1). \tag{11}$$

The second term is now a mixture of earnings from those rejected by 2 who choose field 1 and others who choose field 0. Letting d_{ij} indicate being assigned to field j, the second term can be decomposed as:

$$E(Y_i|\underline{t}_{i2} = 1) \quad = \quad E(d_{i0}|\underline{t}_{i2} = 1)E(Y_i|\underline{t}_{i2} = 1, d_{i0} = 1) + E(d_{i1}|\underline{t}_{i2} = 1)E(Y_i|\underline{t}_{i2} = 1, d_{i1} = 1)$$

In order to recover the treatment effect of assignment to field 2 relative to 1, either more data is needed or more structure needs to be placed on the problem. HNZ take the latter approach, writing earnings as:

$$Y_i = \theta_i + (\gamma_0 + \phi_{i0})d_{i0} + (\gamma_1 + \phi_{i1})d_{i1} + (\gamma_2 + \phi_{i2})d_{i2} \tag{12}$$

The first term gives the absolute advantage across all fields. A major advantage of the RD design over OLS is that it eliminates bias from the unobserved components of the absolute advantage term θ_i. The coefficients on the field of admission dummies d_{ij} include comparative advantage terms ϕ_{ij}. HNZ express the comparative advantage terms as depending on a function of observables, X_i, and unobservables, ν_{ij}:

$$\phi_{ij} = X_i\phi_j + \nu_{ij} \tag{13}$$

Let ν_i be the vector of comparative advantage terms of which ν_{ij} is an element. HNZ assume no selection into fields based on unobservables that affect earnings for those near the cutoff:

$$E(d_{ij}|\underline{t}_{i2} + \bar{t}_{i2} = 1, \theta_i, X_i, \nu_i) = E(d_{ij}|\underline{t}_{i2} + \bar{t}_{i2} = 1, X_i) \tag{14}$$

Given enough data, we could then calculate the field-specific premia for those near the threshold and holding particular values of X_i. Namely, the premium for field 2 over field 1 is:

$$\Delta_{21}(X_i) = E(Y_i|\bar{t}_{i2} = 1, X_i) - E(Y_i|\underline{t}_{i2} = 1, d_{i1} = 1, X_i) \tag{15}$$

HNZ note that the assumption of no selection on ν_i might be a reasonable approximation if students are unaware of individual heterogeneity in returns and/or are not very responsive to earnings differentials when choosing majors. They provide some evidence supporting these assumptions in the Chilean context.[37] As HNZ point out, even under these conditions, the ν_{ij} could lead to bias if they are correlated with non-pecuniary preferences for fields that influence rankings and affect comparative advantage. For example, suppose that students who enjoy engineering and science courses are more likely to be good engineers. Or suppose that they are more likely to pursue occupations for which an engineering degree adds value. Then occupation or major-specific abilities will be correlated with field rankings. Indeed, Arcidiacono's (2004) model assumes that the effects of ability on relative returns and on preferences are strongly related. The empirical significance of this issue is still an important research question.

KLM provide weaker conditions for identifying treatment effects when data on the next-best alternative, defined as the alternative that would have been chosen if the preferred alternative is not part of the choice set, is available. Identification is conditional on the

[37]For example, HNZ report that males, students from higher-SES schools, and students who are strong at math are not more likely to apply to programs for which returns are estimated to be high for these subgroups. Hastings, Neilson, Ramirez and Zimmerman (2015a, b) provide evidence for Chile that applicants are poorly informed about the earnings and education costs of different college programs. This is particularly true for low-SES students. See Section 5.3 for a discussion of evidence on the role of expectations and learning in major choice.

standard IV/LATE assumptions, plus an assumption that they refer to as the "irrelevance and next-best alternative" condition. This condition states that if crossing the admissions threshold to field 1 does not induce i to choose 1, then crossing the threshold does not induce her to choose 2 either. Similarly, it states that if crossing the admissions threshold to field 2 does not induce her to choose 2, then it does not induce her to choose field 1 either. In this case, we compare differences in earnings for those who are either just above or below the threshold *and* who have the same next-best alternative. Let d_{i2k} denote whether i listed field k immediately after field 2. Under their assumption, in the strict RD case we can calculate the local average treatment effect of being admitted to 2 over the next-best alternative k using

$$\Delta^*_{2k} = E(Y_i|\bar{t}_{i2} = 1, d_{i2k} = 1) - E(Y_i|\underline{t}_{i2} = 1, d_{i2k} = 1). \tag{16}$$

This is an important result that shows the value of information about next-best alternatives in this context.[38]

KLM, however, focus on degree completion rather than admission. They also report reduced form estimates for predicted admission based on crossing the admissions threshold. We would often rather obtain the effects of completing a field than being assigned to a field, so the degree completion results are of great interest. But, from a more general methodological viewpoint, it also raises the question of the conditions under which exogenous variation in *field assignment* can be used to identify the treatment effect of *field completion*. It is possible that the irrelevance condition may not hold for field completion even when it holds for admission.

Let g_{ij} indicate whether i completes a degree in field j. Assume for the moment that individuals only complete degrees in the fields for which they are initially assigned. KLM's estimate of the treatment effect for completing a degree in field 2 relative to field j would

[38]In practice, KLM use a fuzzy RD design as admission to the preferred field is not a deterministic function of the application score. They extend the previous result to a fuzzy RD setting by showing that these assumptions are sufficient to identify the LATE of being admitted to field 2 over the next-best alternative k.

then be given by

$$\Delta_{2j}^{c} = E(Y_i|\bar{t}_{i2} = 1, d_{i2j} = 1, g_{i2} = 1) - E(Y_i|\underline{t}_{i2} = 1, d_{i2j} = 1, g_{ij} = 1), \tag{17}$$

where the superscript c indicates completion.

In their baseline specification for effects of degree completion, KLM select their sample by restricting to individuals who have obtained a post-secondary degree. For the discontinuity in admissions to be used to recover the completion premium for field 2 relative to next-best alternative j, one needs to be in a scenario where this restriction does not lead to a sample selection bias. In particular, this empirical strategy leads to consistent estimates of the premium of interest if either of the following scenarios holds:

1. Degree completion is unrelated to factors that affect earnings, implying that expected earning in the degree completion state is the same for actual completers as well as non-completers.

2. Crossing the admission threshold does not affect degree completion. Formally, for any individual i, $d_0^i(\bar{t}_{i2} = 1) = d_0^i(\underline{t}_{i2} = 0)$ where $d_0^i(\bar{t}_{i2} = 1)$ and $d_0^i(\underline{t}_{i2} = 0)$ respectively denote the potential degree completion status for test scores above the admission cutoff for field 2 and below the admissions threshold for 2.

The first scenario is clear. The second scenario is more subtle. To see why this condition is needed if the first scenario does not hold, we turn back to HNZ's decomposition. Suppose completing a degree depends on θ_i but a higher θ_i is needed to complete a degree in field 2 than j. Then those who cross the admission threshold for field 2 and then graduate will be positively selected relative to those who do not cross the threshold, biasing upward the estimated treatment effect of completion. This condition is implied by what KLM refer to as the irrelevance condition.

KLM consider whether their results are sensitive to conditioning on degree completion. First, they show that, averaging across preferred and next-best alternative pairs, crossing the admissions cutoff for the preferred field has a negligible effect on the graduation rate. Second, they estimate models that include all individuals, not just college completers, and show that their estimates change very little. This is true even when they add a dummy for completing post-secondary education as an additional endogenous outcome. These findings provide reassurance that differential selection by field in who graduates conditional on admission to field j is a second order issue for their analysis. While in the Norwegian context the second condition above appears to hold, it is possible that both conditions are violated in other contexts. These are important questions for future research.

4.5.2 Discontinuities in Practice

In practice, the data are not as clean as what we described above. Both HNZ and KLM see many individuals who either (i) cross the cutoff but do not attend their supposedly best available option or (ii) do not cross the cutoff but later are found to have attended that program. The first could result from students changing their minds and the second from individuals deciding to wait for another admissions cycle in the hopes of enrolling in their first-choice program. Furthermore, in KLM's analyses of effects of degree completion, some enroll in a program may end up graduating in a different program or not graduating with a degree. There are also differences in college quality and many more majors than three. Some aggregation of majors is then necessary to obtain statistical precision, particularly if a small window around the test threshold is used.

HNZ consider combinations of schools and majors which they refer to as degree programs. Each of these programs is characterized by an admission cutoff that varies in an arguably unpredictable way from one year to another. HNZ first estimate the effects of crossing the various program-specific admission cutoffs on future earnings, for students whose test scores lie in the neighborhood of the admission cutoffs. They also examine how these effects vary across program selectivity, major and socioeconomic background. As discussed above though, these effects are complicated to interpret in a structural fashion as different "untreated" individuals who are just below the admission cutoff may end up enrolling in different degrees. HNZ address this issue by imposing the restriction that individuals do not choose their program based on their unobserved (to the econometrician) program-specific comparative advantage. Under this assumption, they are able to estimate the effects on future earnings of being admitted to the different programs relative to not being admitted to any selective program. Specifically, they rely on the following specification of the earnings equation, for the set of individuals applying to the program p:

$$Y_{ip} \quad = \quad f_p(s_{ip}) + \sum_{r=1}^{P}(\theta_r + X_i\psi_r)d_{ir} + \epsilon_{ip} \tag{18}$$

where P denotes the total number of programs, d_{ir} is a dummy for admission into program r and $f_p(s_{ip})$ is a smooth (program-specific) function of the difference between individual i's test score and the admission cutoff for program p. The authors then estimate (18) by instrumenting for the admission dummies d_{ir} and their interactions with the $X_i's$ using the threshold-crossing dummies $\bar{t}_{ir}$. Note that absent the assumption that individuals do not choose their program based on their unobserved comparative advantage, one would need to estimate instead a correlated random coefficient model in order to recover the payoffs to being admitted to each program.

KLM focuses on graduation rather than admission. Letting X_i now denote the set of observed characteristics such as gender, age, and the running variable, KLM use the following specifications for every next-best field k:

$$Y_i \quad = \quad \sum_{j \neq k} \beta_{jk} g_{ij} + X_i\gamma_k + \lambda_{jk} + \epsilon_i \tag{19}$$

$$g_{ij} \quad = \quad \sum_{j \neq k} \pi_{jk} \bar{t}_{ij} + X_i\psi_{jk} + \eta_{jk} + \zeta_i \qquad \forall j \neq k \tag{20}$$

where the first subscript refers to the preferred field and the second to the next-best alternative. Graduation in field j, g_{ij}, is then instrumented for with whether the individual crossed the test score threshold. To gain precision, they estimate the first stage for all next-best alternatives at once and then the second stage returns for all next-best alternatives at once, imposing a more restricted version where $\lambda_{jk} = \mu_k + \theta_j$ and $\eta_{jk} = \tau_k + \sigma_j$. They then show that their results are robust to including all interactions between preferred and next-best alternatives. They also show that their results are robust to including more flexible functions of the running variable.

In practice, the field specific grade cutoffs vary across universities and over time within universities. That is, at a given point in time, s^2 might exceed s^1 at one school while s^1 exceeds s^2 at another. And at a given university, the ranking of the cutoffs change over time in some cases. Both KLM and HNZ take advantage of such variation. Cutoff reversals are particularly important in order to separately identify the returns to field j relative to field k, and the returns to field k relative to field j. KLM find little evidence of complementarities between school quality and fields of study in the Norweigan data. As a result, in their main analysis KLM assume that the effect of school quality on earnings is the same for all fields. With this additive separable specification, one is justified in using variation across schools and the relative values of the admissions cutoffs to identify the β_{jk}. This increases the number of β_{jk} parameters that are identified.

4.5.3 Results Using the Fuzzy RD Approach

HNZ provide estimates of effects of admission to a program relative to the outside option of not being admitted to any selective program, which are not directly comparable to estimates of degree completion effects. One would expect them to lie below the effects of degree completion.[39] In any event, they find earnings effects of 25.6% (of the average sample earnings) of being admitted to a health degree, 16.1% for social science degree, 11.9% for a science/technology degree, 15.1% for a law degree, and 10.1% for a business degree. The effect of education is 4.2%, while the effects of art/architecture and humanities are essentially zero. The relative returns are broadly consistent with the literature that takes field choice as exogenous conditional on a rich control set. HNZ also estimate the effect of program selectivity on future earnings. They find that being admitted to a program in the bottom selectivity quartile, relative to not being admitted to any selective program, raises earnings by 4.7%. The effect is much larger for the highly selective programs (24.2% for the top quartile). The relative returns to fields of study depend upon the selectivity of the degree program j. For example, the return to admission to law and social science programs are

[39]They do not have information about college completion rates that one might use to do a rough adjustment of these estimates.

primarily associated with admission to high selectivity degree programs. Here one should keep in mind that variation in selectivity arises from both variation in selectivity of the institution and variation in the selectivity of the specific program within the broad categories, e.g. nursing versus physician in the health category. Interestingly, HNZ find that students from high SES backgrounds receive large gains (30.7%) from admission to highly selective business programs, while the return for low SES students is close to zero. On the other hand, the return to highly selective health programs is large and positive for both groups.

Table 4 of KLM reports the estimates of the returns to different fields (j) relative to next-best alternatives (k) parameters for almost all pairs of 10 fields. Here we emphasize two main findings.[40] First, there are large differences in the returns across fields.[41] For example, relative to the teaching degree, returns are large and positive in all fields except the humanities and social sciences. For engineers the *gain* over teaching is US $75,240, which is very large relative to the average of $46,150 for teachers. Second, the pattern of the gains to j over k is broadly consistent with what we would expect given the difference in the average earnings of those who complete a degree in j and the average earnings of those who complete a degree in k. One can reject, however, the restriction that the estimates of the relative gains are equal to the corresponding differences among 10 return parameters, one for each field, as opposed to the series of pairs. HNZ's basic specification in the homogeneous returns case implies this restriction.[42]

Overall, recent work employing RD designs to establish the earnings effects of particular fields of study as well as the quality of an institution is a major step forward. There is scope

[40]In addition to estimating relative returns, KLM also provide a rich analysis of how relative returns influence preferences, and provide evidence that students rank majors in part based upon them.

[41]Under the KLM's baseline specification, there are no college quality effects. KLM show that specifications which do add the effects of institutions indicate field of study is much more important than college quality, at least in Norway. Further, controlling for institution effects has little impact on the premiums associated with particular fields.

[42]KLM also provide OLS estimates of a reduced form model of the earnings effects of a predicted offer of admission to preferred field j for each preferred/next best combination. The prediction is based on the threshold crossing instrument. See their Table A4.

for much more work. We would highlight two areas. The first is to build directly on the work of Bertrand, Hanna & Mullainathan (2010), HNZ, and KLM. Further work is required on how best to balance between the restrictiveness of the samples used to identify relative returns to particular pairs of fields, how best to handle unobserved heterogeneity in returns, and how best to address complementarity between the quality/selectivity of an institution in particular fields of study. It would also be valuable to make richer use of measures of socioeconomic background and high school preparation in studying heterogeneity in returns.

The second area is to combine the use of discontinuities in admissions with explicit modeling of how students rank schools and fields of study. One could start with a reduced form approach that relates student rankings of school/field programs to observed variables and unobserved variables that are influenced by the pecuniary and non-pecuniary returns to particular fields of study and occupations. A more ambitious approach is to work with a structural model of field and school choice.

4.6 Returns to Graduate Degrees

As noted in the previous section, one of the primary barriers to estimating the returns to college majors is the selection problem: those who are in high-paying majors may have also received high labor market returns in other majors. This issue is partly mitigated when estimating the returns to an MBA because MBA programs often require work experience before entry.[43] Seeing earnings absent the MBA degree makes it possible to control for individual fixed effects in the wage equation. Note that it is not obvious *a priori* that fixed effects will produce the correct estimate as selection may be occurring into the MBA program based on wage residuals. Those who have temporarily low wages may be more likely to enroll in MBA programs due to the lower opportunity cost. This is similar to estimating the effects of training programs where wages often dip immediately before enrollment, which is known as the "Ashenfelter dip" (Ashenfelter, 1978).

[43] Arcidiacono et al. (2008) show that over 90% of MBA students entered their MBA programs with at least two years of work experience.

Arcidiacono et al. (2008) use panel data from those who registered to take the Graduate Management Admissions Test (GMAT) in 1990 to estimate the returns to different MBA programs. Four surveys were administered with the latest data coming in 1998. Note that this is already a selected sample in that the individual must have already been considering enrollment in an MBA program to take the test. Controlling for observed covariates such as GMAT scores, undergraduate grades, demographics, and other advanced degrees shows virtually no return for males unless they were attending a program in the top-25.[44] Top 10 (11-25) programs were associated with earnings that were 25% (20%) higher than those who did not obtain an MBA.

Controlling for individual fixed effects, however, substantially changes the results, reducing the importance of quality of the program. The returns to a top-10 MBA program fall to 19% while the returns to attending a program outside the top-25 increase to 9%. The first finding is to be expected: those who attend the most selective MBA programs are likely those who have the highest unobserved abilities. That the return increases for those outside the top-25 is unexpected, particularly given that these students have significantly higher test scores and undergraduate grades than those who do not enter an MBA program. The authors show that the increase in returns is not being driven by the Ashenfelter dip. Rather, there is a component of skills that individuals who enter these programs are weaker on. Namely, individuals were asked about their perceptions of how the MBA program would help them. Individuals who enroll perceive that the MBA would improve their skills on in areas not measured by test scores, suggesting the possibility that these students are "book smart" but not "people smart".

Specialization within MBA tracks also affects future earnings. Using the same data set and identification strategy as Arcidiacono et al. (2008), Grove & Hussey (2011) examine

[44]The regression estimate based on the NCES in Table 6 is 0.284 for obtaining any MBA. The NCES covers a much broader population and does not have information on test scores and grades. The data in Arcidiacono et al. (2008) includes only individuals who registered for the GMAT and so were at least considering obtaining an MBA. This suggests that those who are considering an MBA have stronger labor market skills the general population conditional on the same degree attainment.

the returns to specialties within MBA programs. Concentrating in finance or management information systems yields returns of 6% and 8% respectively above an MBA degree in another concentration. Returns to finance classes within an MBA program has also been shown in a study of University of Chicago MBA's by Bertrand, Goldin & Katz (2010), who attribute part of the differences in the returns to an MBA between men and women to the share of courses in finance. This finding is consistent with Grove & Hussey (2011) who show that women are significantly less likely to choose a finance concentration.

Specialization is even more important in medical school. For example, the average surgeon earned $269,000 compared to $131,200 for family practice doctors (Bhattacharya, 2005). Bhattacharya (2005) considers a number of factors for the large income disparities across specialities. First, high-income specialities often require more hours, implying that the wage gap across specialties is not as large as the corresponding income gap. Second, although the time to graduation does not vary across specialties, physicians have a period where they serve as residents before they can become "board certified" and this period varies substantially across specialties. High-income specialties often have longer residency programs. For example, pediatrics residency programs typically take three years while surgical residency programs take at least five. Finally, the returns to skills may be higher for specialists and this induces high-skilled medical students to sort into these residency programs.

To assess the role each of these explanations play in explaining the differences in labor market outcomes across specialties, Bhattacharya (2005) estimates a model of physician specialty choice and labor market earnings where unobserved factors (such as ability) influence both specialty choice and earnings via discrete factors. Using data from the 1991 Survey of Young Physicians, he shows that just moving from salaries to hourly wages reduces the surgery premium from 55% to 46% over family practitioners. Selection on observed and unobserved abilities reduces the premium to 41%, and accounting for differences in training program length reduces the premium to 31%. This is still a substantial "unexplained" gap, with two clear sources remaining. First, there may be a compensating differential for working as a specialist. Second, not all medical school graduates are able to work as surgeons due to limits on the number of residency slots. With the number of entering surgeons restricted, wages for surgeons (and other specialties where the residency caps bind) are high due to low supply.

Long residency programs and work hours may make the high-income specialties unattractive for those with family concerns, who are disproportionately female. Taking time away or reducing hours when one has a family limits the time medical school graduates have to recoup their investments. Chen & Chevalier (2012) suggest that female family practitioners would actually have higher lifetime earnings have they instead become physician assistants. Becoming a physician assistant requires two year of post-baccalaureate work (as opposed to four for medical school) with no residency programs. Using data from the Robert Wood John Community Tracking Physician Survey of 2004-05 and the American Academy of of Physician Assistant's annual survey for 2005, they show that, not surprisingly, medical school graduates are stronger on such factors like undergraduate grade point average than those who graduate as physician assistants. Yet, given the (uncorrected for selection) wages for female physician assistants and the hours worked by female family practitioners, the net present value from working as a physician assistant would be on average higher than the net present value for female family practitioners. These results are driven by the extended time in medical school and low wages during residency programs coupled with female family practitioners working less hours than their male counterparts. Indeed, male family practitioners see higher lifetime earnings (again uncorrected for selection) as family practitioners than as physician assistants because they work more hours at the high post-residency wage.

Whether individuals are able to recoup their investments also depends on the returns to hours worked and the penalties associated with time away. Bronson (2015) provides evidence that the wage penalties associated with taking time off in occupations such as engineering are higher than in other majors and provides a partial explanation for why women may find the sciences unattractive. Goldin (2014) shows that in some occupations the returns to hours worked is linear with low penalties for taking time off, but in other occupations the last hour worked has a much higher return than the first hour and the penalties for taking time off are high. This latter group includes occupations associated with obtaining an MBA or a law degree. Goldin (2014) finds no gender gap between male and female MBA and law school graduates one year after graduation but a substantial gap emerges later in life, in large part due to differences in labor supply decisions. In contrast, the returns to hours are linear in pharmacy, there is no part time penalty. Bertrand, Goldin & Katz (2010)'s regression analysis of MBAs from the University of Chicago indicates that the fact that men work more hours per week and have fewer spells of nonemployment leads to a substantial male advantage in earnings growth in the first 10 years after MBA completion. Using the GMAT registrant data employed by Arcidiacono et al. (2008), Gicheva (2013) estimates a regression model relating wage growth to a nonlinear function of weekly hours in the previous period. She finds that a substantial effect of long work hours on hourly wage growth for MBAs. The point estimate is larger for MBAs than for persons who registered for the GMAT but did not receive an MBA. Her estimates are quite consistent with Bertrand, Goldin & Katz (2010)'s results on the link between weekly hours and wage growth.

Black et al. (2003) use the 1993 National Survey of College Graduates to see how the returns to graduate school may vary by undergraduate major. Recall from the theoretical model that those with low paying undergraduate majors may have a greater incentive to go to graduate school if by doing so they erase some of the earnings disadvantage associated with their undergraduate major. However, it may be the case that graduate school builds on past human capital accumulation. Black et al. (2003) show results suggesting that the premium associated with being an economics major over majors like history and English are just as high if one gets an MBA or a law degree as it is without an advanced degree, suggesting the additional treatment effect of having an MBA or a law degree is the same across these undergraduate majors. An important caveat is that the estimates are calculated based on matching on demographics; there are no controls for things like test scores or for selection into graduate school. Furthermore, Black et al. (2003)'s finding are somewhat at odds with the evidence in Table 7, which we discussed earlier. Table 7 shows for a broader set of majors using the 1993 and 2010 National Survey of College Graduates that in percentage terms the gain from an MBA or a law degree is larger for individuals from low paying majors than high paying majors. Additional work on complementarity between undergraduate and graduate degrees is needed.

As is the case for undergraduates, excellent data are available on entry to graduate programs in other countries, expanding the possible identification strategies. A good example of this is Ketel et al. (forthcoming) who examine the choice to enter medical school in the Netherlands.[45] Weighted lotteries determine whether an interested individual can enroll in medical school. Higher high school grades and exam scores are associated with higher probabilities of admittance, but even those with very low scores may be admitted at the expense of higher-achieving classmates.

Ketel et al. (forthcoming) use winning the medical school lottery as an instrument for medical school completion in a log earnings regression.[46] They do this for many years, making it possible to trace out the effects over time. Ketel et al. (forthcoming) show substantially higher earnings for medical school completers in all years after graduation, with earnings differences of almost 40% twenty-two years after high school.

Instrumenting for medical school completion–as opposed to assignment–raises two of the same issues that were discussed in Section 4.5.1. First, as pointed out by HNZ and KLM, what is the treatment effect relative to? Lottery losers are likely to pursue a degree in some other field and so the estimated effects are relative to some combination of earnings in different fields. Ketel et al. acknowledge this difficulty of interpretation. They shed some light on this question by documenting the distribution of fields of study chosen by the lottery losers. Second, winning the lottery may affect future earnings irrespective of whether individuals end up graduating from medical school, thus leading to a violation

[45] While entering medical school in the Netherlands, like many countries outside of the United States, takes place immediately after high school, the amount of training required places medical school under graduate education.

[46] Some students who won the lottery chose not to attend while others who lost chose to enter the lottery the following year. Ketel et al. (forthcoming) use the outcome of the lottery the first time the individual enters as their instrument.

of the exclusion restriction required to identify the LATE. In the context of Ketel et al. (forthcoming) where a large share (82%) of the lottery winners end up graduating from medical school, this potential threat is most likely of second order importance.

In other contexts where non-completion rates are higher, this could be a serious problem. Consider an extreme example where only half of those who win the lottery complete medical school with the other half dropping out and entering the labor market. Further assume that those who lose the lottery enter business school and graduate with probability one. In this case, the IV estimates will not give the return to completing medical school relative to completing business school, or relative to not completing any education. In fact, even if medical school completers earn more than business school completers, the IV estimate could still be negative if business school completers earn sufficiently more than medical school dropouts. The problem in this specific example is that the exclusion restriction does not hold as the instrument (indicator for winning the lottery) affects earnings not only via the treatment status (medical school completion), but also through the potential earnings in the untreated state (earnings of medical school dropouts for lottery winners, and earnings of business graduates for lottery losers). Using the terminology of KLM, this is a situation where the irrelevance condition does not hold since the instrument affects completion of post-secondary education. In this example where the untreated state includes both dropping out from medical school and graduating from business, this, in turn, leads to a violation of the exclusion restriction. In this setting though, one can still produce a consistent estimate of the expected earnings gain from beginning medical school versus not, if one instruments for assignment to medical school in the earnings regression and as long as there is no effect of winning the lottery on the potential earnings in the untreated state (not assigned to medical school).

5 Choice of Major

As discussed in the previous section, the choice of college major has key implications in terms of future earnings and career prospects. In the last ten years, the empirical literature has paid increasing attention to the determinants of college major choice, and in particular to the relative importance of expected earnings versus non-monetary factors including abilities and preferences.

5.1 Demand Side

5.1.1 The Role of Expected Earnings

Although the results vary depending on the context and the methodology used, most of the recent evidence available points to a significant but quantitatively modest elasticity of college major choice to expected earnings. Beffy et al. (2012) use French data to estimate a sequential schooling decisions model where students choose their major by comparing the (rationally) expected earnings and non-monetary characteristics associated with each major. In this framework, in the spirit of Altonji (1993), the potential level of education that would be completed within each major is uncertain to the individual at the time of the choice. Beffy et al. use variation across the business cycle in the relative returns to the different majors to identify the earnings elasticity of college major choice. They find significant but quantitatively small elasticities of major choice to expected earnings, ranging between 0.09 and 0.14 for majors in Sciences and Humanities and Social Sciences, respectively.

Earlier work by Berger (1988) on this question uses a rational expectations framework where the utility for each major is also given by the sum of the present value of expected lifetime earnings in that major and a non-pecuniary major-specific component. Berger uses a sample drawn from the National Longitudinal Survey of Young Men (NLS), which is made up of individuals who entered the labor market from 1962 to 1977. Key to the identification of the earnings elasticity of college major choice is the assumption that college major choices vary over this period only through the monetary returns to majors. Consistent with the students being forward-looking when choosing their college major, Berger finds that expected lifetime earnings are a better predictor of the choice of college major than the earnings at the start of the career. In his model, students are only uncertain about the future earnings associated with each potential major. In particular, when forming their expectations over lifetime earnings, students implicitly assume that they would complete any of the potential majors.[47] This assumption comes in contrast with Altonji (1993) and subsequent work allowing for uncertainty regarding major completion. Montmarquette et al. (2002) estimate the effect of expected earnings on college major choice by allowing the completion probabilities to be smaller than one and to vary across individuals and majors. However, unlike Berger (1988) and Beffy et al. (2012), the major-specific expected earnings are estimated without controlling for selection into each major, thus implying that one needs to be cautious when interpreting the estimated choice elasticities.

Long et al. (2015) examines the effects of wages on major choice using U.S. survey data (IPEDS and CPS) combined with administrative data from Washington state over the period 1982-2012. Their estimate of the elasticity of major choice to the lagged major-specific wage premia is 0.67. This value is substantially larger than the ones obtained by Beffy et al. (2012) and by Wiswall & Zafar (forthcoming) (discussed in Subsection 5.3). However, the analysis of Long et al. is descriptive in nature, and as a result this discrepancy is likely to partly reflect the fact that those elasticity parameters have different interpretations.

Blom (2012) uses ACS data on major choice for cohorts of college graduates who were 20 years old between 1976 to 2006. She uses the occupational composition of majors to construct region specific time series of major-specific wage premia based on region/occupation/year specific wage data from the CPS. For the combined period, she finds the elasticity of major share with respect to the major-specific wage is only .0166 for men and .0646 for women, estimates that are broadly consistent with Beffy et al. (2012) and Wiswall & Zafar (forthcoming). Neither value is statistically significant. However, Blom also finds that the elasticities are positive and substantial for the early cohorts but negative and substantial for the later cohorts. The negative estimates are puzzling, and so caution is called for.[48] Long et al.

[47]Berger also assumes independence from irrelevant alternatives, which is unlikely to hold in the context of college major choice.

[48]Blom (2012) and Blom et al. (2015) use similar data to examine how general economic conditions influence major choice. They show that the aggregate unemployment rate at the age when college students are choosing their majors has a substantial positive effect on the probability that students choose a high paying field. The shift toward higher paying majors induced by a 3 point in rise the unemployment rate

(2015) find that the major choice elasticities display a large degree of heterogeneity across individuals and majors. In particular, their results suggest that enrollments are more sensitive to changes in earnings for those majors which are tightly associated with particular occupations, such as nursing.

5.1.2 Ability Sorting and Learning

The literature has also examined the effect of perceived ability on college major choice. As we discussed above, Arcidiacono (2004) estimates a dynamic model of college and major decisions where students are uncertain about their abilities. In this model, it may be optimal for students to dropout, switch majors or switch colleges after observing their grades and updating their ability beliefs accordingly. Estimation results indicate that ability is an important factor in explaining the decision to enroll in a given major. Interestingly, Math ability is found to play a much more important role in major choice than verbal ability. Arcidiacono also finds that learning about ability is an important factor in the decision to switch majors or drop out of college. Finally, most of the ability sorting across majors appears to be driven by the heterogeneity across abilities in major-specific preferences

Recent work by Arcidiacono et al. (2015) also examines how students update their ability beliefs as they receive new information, and the extent to which this learning process accounts for the observed transitions between college and work, as well as between STEM and non-STEM majors. To do so, Arcidiacono et al. use data from the NLSY97 to estimate dynamic model where students decide at each period whether to attend college, either in a two- or four-year institution (in a STEM or non-STEM major), work part-time or full-time, or engage in home production. Unlike Arcidiacono (2004) and the other papers discussed below, their framework allows for correlated ability learning through college grades (in the different types of colleges and majors) and wages, as in the model discussed in Section 3.4. Arcidiacono et al. find that the ability components which are revealed over time account for a sizable

leads to an increase in 1.5% increase in average wage rates for the cohort. Since these effects are permanent, they are large enough to offset a substantial part of the losses of students who graduate in a recession found by Kahn (2010), Oreopoulos et al. (2012), Altonji et al. (2014*a*) and others.

share of the dispersion in grades and wages, with the abilities in STEM and non-STEM majors being highly, though not perfectly, correlated. However, grades earned in college, both in STEM and non-STEM majors, reveal little about future labor market performance. Inasmuch as college education should help prepare students for the labor market, the latter finding suggests that the screening mechanisms in place in college perform poorly. Overall, estimation results show that college exit and re-entry decisions as well as major switching are all affected by learning about ability.

Fricke et al. (2015) provides interesting evidence on the impact of exposure to a given field of study on college major choice. Specifically, Fricke et al. make use of a natural experiment at the University of St. Gallen (Switzerland) where first-year students, who have not chosen a major yet, have to write a research paper in business, economics or law. Excess demand for business leads the university to assign the field of the paper randomly for the students who expressed a preference for business, thus making it possible to identify for those students the effect on major choice of exposure to economics and law. Having to write a paper in economics is found to increase by 2.7 percentage points the probability of majoring in economics, which is significant and large in comparison with the share of economics majors within this group (5.9%). Note that the mechanism at work here combines the exposure to additional information on the economics field along with the accumulation of skills in that field.

Using administrative data from the University of Toulouse, Pistolesi (2014) focuses on the effects of providing information to high-school students about their probability of graduating from college in a given field. Pistolesi uses a fuzzy RDD approach to identify the impact of receiving a negative or positive (as opposed to neutral) signal about future graduation prospects on enrollment in each field. While receiving a positive signal has virtually no effect on enrollment, receiving a negative signal has a strong negative effect (-14 pp.) on the enrollment probability.

Should Higher Education Systems Require Students to Specialize Early? The evidence that students are learning about field-specific wage rates and their preferences and talents while proceeding through school raises an important question about the optimal design of higher education systems: When should students specialize? Some jurisdiction, including England, France, Chile, and Norway, require students to choose a school and a field as part of the college admissions process. The cost of switching later are quite high. Others, such as Scotland, the US, and Canada either require or permit students students to choose a field later. In such "late choice" systems students typically take fewer field specific courses. Malamud(2010, 2011) provides a simple model that highlights some of the tradeoffs. Students who specialize early can take more courses in their chosen field. This is a benefit if depth in that field area is valued in the labor market. It is a negative if more broad education is valued. The labor market value of depth versus breadth likely varies across fields of study and across individuals. Students who specialize earlier must do so with less information about the costs and benefits of pursuing particular fields of study. Consequently, early specializers may be more likely to pursue a field of study that they regret. Whether or not they will be more likely to switch away from the occupation that their chosen major prepared them for depends upon the degree of mismatch relative to the return feel specific preparation in the occupation. Malamud shows that students in the English university system are more likely to switch to occupations that are different from those associated with their field of study than students in the Scottish system. However, Malamud (2011) shows that the consequences for wages are relatively small.

In an ambitious paper, Bordon & Fu (forthcoming) estimate the equilibrium effects, in the presence of individual uncertainty about major-specific match quality, of switching from a college-major specific admission system (as in Chile and many other countries) to a system where students choose their major after entering college (as in the U.S. and Canada). Bordon & Fu find that this would result in a 1% increase in average student welfare, which would disproportionally benefit females as well as low-income and low-ability students. However, the authors do not have data on college grades or other direct measures of the flow of information to the student about ability and preferences. They do observe dropout decisions, but because transfers across majors are very difficult and thus rare, the researchers do not have access to the information about transfer costs and learning about talent and preferences that observing them would provide. Consequently model specification appears to play an important role in identifying features that are key to assessing the gains from allowing students to delay specialization.

Bridet & Leighton (2015) address similar questions using panel data on college graduates from U.S. from Baccalaureate and Beyond: 1993-2003. They specify a structural model of course selection and specialization with the following features. A particular program of study influences both the types of human capital acquired and what the student learns about her abilities and preferences. Changing fields while in college or after entering the labor market is costly. In the model, students enter college with prior beliefs about their type (say engineering versus business). If they do not specialize initially, they acquire skills in both fields, and also obtain signals about their true type. Engineering courses raise productivity in engineering occupations more than in business occupations. The opposite is true of business courses. After specialization, students accumulate human capital in the chosen field. They do not acquire any more information about their type until they enter the labor market, at which point type is revealed. A student's choice of when to specialize is a key endogenous variable in the model. She does so when she is confident enough about her type given that the opportunity costs of additional time in school are rising and taking account of the size of the labor market gains from more depth in the field under consideration. Using information on test scores, course taking, grades, time to specialization, occupation, and wage rates, Bridet and Leighton estimate model parameters governing the rate at which students learn about type, the labor market return to field specific knowledge when used in one's chosen field and when used in the alternatives, and the fixed cost of switching fields after graduation. The estimates suggest that a person working in her field of comparative advantage earns up to 20 percent more than a student in the same field who is poorly matched. This paper offers a number of original insights about the trade-offs. Simulations indicate the changing the U.S. system to require that students specialize at college entry would increase the share who end up working outside their field of comparative advantage by 7%. Expected earnings would fall by 1.5%.

In summary, the work to date suggests that on net, allowing students to specialize later leads to modest gains in earnings and student welfare. However, much more work is needed to understand information flows and human capital production by fields. In addition, a full analysis must account for the effects of timing of specialization on higher education costs, and how early specialization influences student behavior in secondary school.[49]

5.1.3 Other determinants

Gender-Specific Preferences Rather than attempt to provide a comprehensive survey of the literature on gender differences in college major choice, we simply highlight a few recent studies.[50] Gemici & Wiswall (2014) examine the determinants of the gender gap in college major choice as well as its evolution over time. Their analysis is based on a dynamic model of human capital investments, both in terms of numbers of years of schooling and field of study, and labor supply, where agents are assumed to form rational expectations about future outcomes. The authors estimate this model combining data from the National Survey of College Graduates (NSCG) with the Census and the CPS. Similar to Zafar (2013) (discussed in Subsection 5.3), their results provide evidence that differences in preferences for majors are the main driving force behind the gender gap in college major choice. Gender differences in the distribution of major-specific skills, while significant, are far less important

[49] Timing of specialization may also matter in terms of peer effects on college major choice. The role played by students' peers on the decision to enroll in a given college major is an important question, which has not been the object of much attention in this literature. Notable exceptions include Sacerdote (2001) and De Giorgi et al. (2010). Using data from Dartmouth college and exploiting the random assignment of roommates among Freshmen, Sacerdote (2001) finds no evidence of peer effects on college major choice. This finding contrasts with De Giorgi et al. (2010) who use data from Bocconi University and a different identification strategy based on the existence of partially overlapping peer groups. They conclude that peers have a significant influence on major choice.

[50] Older papers include Daymont and Andrissani (1984), who make use of measures of the importance the individual places on particular job characteristics, and Blackemore and Low (1984), who provide evidence that women choose majors with lower skill depreciation rates.

in explaining the gender gap. Estimation results also show that males were more responsive than females to the increase of the relative prices of science and business skills during the 80's and 90's, leading to a widening of the college major gender gap during this period.

Earlier analysis on this question by Turner & Bowen (1999) also finds that differences in skills across males and females, as measured by SAT Math and Verbal scores, only account for less than half of the overall gender gap in major choice. Turner & Bowen conclude that other factors, in particular gender-specific preferences for majors, play a dominant role in explaining the significant gender differences in major choice. [51]

Parental Influence: A couple of papers have examined the role played by parents on the choice of college major. Notably, Zafar (2012, 2013) addresses this question using subjective expectations data collected from a sample of sophomores from Northwestern University. Zafar finds that getting approval of parents is one of the most important factors underlying the choice of majors. According to the students, the probability of the parents approving a given major increases with the social status as well as the wage returns associated with the major.

[51] Dickson (2010) uses administrative data from three public universities in Texas to show that women are less likely than men to begin college intending to major in engineering and computer science relative to the social sciences conditional on SAT scores and high school class rank. Women are more likely to intend to major in the humanites and relative to the social sciences. Dickson also shows that they are also less likely to graduate in engineering and computer science and more likely to graduate in the humanities and other majors conditional on initial field choice. Morgan et al. (2013) analyze gender differences in initial interest in STEM related occupations and early college major using the ELS 2002-2006 panel data survey. The ELS panel follows students who were in 10th grade in 2002 for four years. They find that high school preparation and work-family orientation explain only a modest portion of the gender gap in college major choice. Gender differences in occupational plans play a strong role. See also Weinberger (2004), who surveyed women in a set of female dominated majors and in economics and business about importance of course preferences, course difficulty, classroom atmosphere, taste for occupations, and labor market prospects in their decisions not to choose each of a set of alternative majors.

Risk Aversion: Several papers have also examined the influence of risk aversion on college major choice. Assuming that individuals have constant relative risk aversion preferences, Wiswall & Zafar (forthcoming) find that students tend to exhibit a high degree of relative risk aversion (around 5). The authors further show that ignoring risk aversion in this context would result in overestimating substantially the earnings elasticity of college major choice. Nielsen & Vissing-Jorgensen (2005) investigate the role played by risk aversion on the choice of post-secondary curriculum in Danemark and estimate a high degree of relative risk aversion of similar magnitude as in Wiswall & Zafar (forthcoming). Saks & Shore (2005) also examine the impact of risk, as measured by the volatility of wages associated with different types of careers, on college major choice. Consistent with decreasing absolute risk aversion preferences, they find that students from wealthier background tend to choose riskier majors such as business.

5.2 Supply Side

That ability sorting occurs is partly a result of differences in expectations of the instructors across fields. Grading differences and workloads differ substantially across fields in ways that suggest competition for students. Dickson (1984) shows that fields that have low student to faculty ratios give higher grades and Freeman (1999) shows that fields that pay less also give higher grades. The fields that are typically associated with low student to faculty ratios and low pay are courses in the the humanities and social sciences, excluding economics. The differences in grading standards can be so dramatic as to swamp any comparative advantage students in particular fields. For example, Johnson (2003) shows that students at Duke University who major in biology actually receive higher grades in the classes they take in all other departments, with the exception of chemistry and math classes. If grading standards were uniform across departments, we would expect students to have higher grades in courses in their own major due to sorting on comparative advantage.

When student demand for a course is low, perhaps due to poor labor market conditions in the field, faculty may have incentives to provide higher grades as a way of inducing more demand for their courses. Sabot & Wakeman-Linn (1991) and Johnson (2003) provide evidence that suggests students do respond to differences in grading standards. But perhaps the most compelling evidence is Butcher et al. (2014), who examine a policy at Wellesley College which required introductory (100 level) and intermediate (200 level) courses with at least ten students to have average grades that did not exceed a B+. Average grades in STEM classes and economics were below this cutoff while on average courses in other disciplines were above it. Predictably, grades fell in the non-STEM or economics courses, by 0.17 points. But enrollments in these courses fell as well, falling by almost 19%, with majors in these fields falling a remarkable 30%. The drops in enrollment occurred despite grades also falling in courses in non-treated departments (STEM and economics) by 0.09 points. Grades might fall in a non-treated department because the cap was binding for some classes in that department even if the departmental average grade across all classes was below the cap. But it also could be an equilibrium response to increased demand for its courses.

Instructors have more tools to induce demand for their courses besides grades. Arcidiacono, Aucejo & Spenner (2012) provide multiple pieces of evidence from Duke University suggesting that STEM and economics classes are on average more demanding than their humanities and social science counterparts. First, their results suggest that freshmen students study fifty percent more in STEM and economics classes than in humanities and social science classes. Second, students were fifty percent more likely to list a STEM or economics course as their most challenging class compared to random assignment. Finally, students were significantly more likely to report they were switching majors due to lack of pre-college academic preparation or academic difficulty of the subject matter if their initial major was in STEM or economics.

The differences in grading standards and workloads differentially affect persistence in the major. Giving lower grades affects those at the bottom of the distribution more than those at the top due to both censoring at the top grade as well as the risks of failing out. The effect of Wellesley's anti-grade-inflation policy on black students in non-STEM and economics courses was over twice as large as the overall effect, resulting in average grade drops for black students in these courses of 0.36 points (Butcher et al., 2014). That the effect was larger for black students is due to blacks being significantly more likely to be toward the bottom of the grade distribution as a result of facing a worse pre-college educational environment. Data from Duke University showed 76.7% of African American males declaring an initial interest in a major in STEM or economics yet only 35% obtain a degree in one of these majors. The corresponding numbers for white males are 68.7% and 63.6% (Arcidiacono, Aucejo & Spenner, 2012). So while African American males came in just as interested as white males in STEM or economics, white males finished at a much higher rate. Arcidiacono, Aucejo & Spenner (2012) show that these cross-racial differences can be accounted for by controlling for differences in academic background, either as manifested in SAT scores and Duke's measures of application quality or in first year performance. Similarly, African American were much more likely to switch fields because of lack of academic preparation or course difficulty yet accounting for differences in pre-college preparation again eliminates the racial gap.

These findings suggest the possibility that a *relative* position in the academic preparation distribution of a school may have a positive effect on obtaining a STEM degree. A related possibility is that affirmative action policies, which result in under-represented minorities being more likely to be toward the bottom of the preparation distribution within a college, may work against minorities completing degrees in the sciences.[52] Arcidiacono et al. (forthcoming) provides evidence from the University of California system that this is the case. Using data for the three years preceding the implementation of Proposition 209,[53] Arcidiacono et al. (forthcoming) show that sorting out of STEM fields on the basis of low relative academic preparation happens at each school in the system. The effects are large enough that a student admitted under affirmative action at UC Berkeley would have a higher probability of graduating in the sciences at UC Riverside (but not necessarily a higher probability of graduating college overall). Smyth and McArdle (2004) do not directly address

[52] As noted by Arcidiacono & Lovenheim (forthcoming), the literature suggest affirmative action affects where individuals attend college, not whether they attend at all.

[53] Proposition 209 went into effect in 1998 and banned the use of racial preferences in admissions for public institutions.

the effects of affirmative action but do examine the effects of relative academic preparation on major choice. They use the selective and highly selective public and private institutions in the College and Beyond data set. They also find that a student's preparation relative to the school average positively affects the odds of attaining a STEM degree, controlling for the student's preparation. The findings of these two studies are at odds with Arcidiacono's (2004, 2005) results using NLS72 data and variants of the structural model discussed earlier. He finds that increases in college quality raise the probability of majoring in the sciences for all students. Arcidiacono (2015c) concludes that weight of the evidence is consistent with a positive relative preparation effect once the lowest quality institutions are excluded. More research is needed on this important topic.

While a number of papers have examined the role played by financial aid and tuition fees on college attendance, very little is known about their impact on college major choice. Two recent papers have addressed this question and reached different conclusions regarding the effect of differential pricing by major. Stange (2015) which analyzes the effect of differential pricing by major on the allocation of students across majors. Exploiting the fact that universities throughout the U.S. have adopted a differential pricing policy at different times, Stange shows that college major shares, in particular in engineering, do vary after the adoption of the policy. The author also provides some evidence that women and minorities are disproportionally affected by the introduction of higher tuitions for engineering. Related work by Evans (2013) uses administrative data from public institutions in Ohio to examine the effect of being eligible for a Science and Mathematics Access to Retain Talent (SMART) grant on majoring in STEM. SMART grants, which are attributed based on merit and financial need (students need to have received a Pell Grant), provide students in their junior and senior years with up to $4,000 per year conditional on majoring in STEM. Evans estimates the impact of being eligible for a SMART grant using a regression discontinuity design, and concludes that it had a negligibly small effect on the probability to major in STEM.

5.3 Subjective Expectations

Key to the dynamic models discussed in the previous section are the assumptions made about individual beliefs. These include beliefs about the availability of different schooling options, the difficulty of the course material, and the labor market returns associated with different educational paths. These dynamic models often assume that individuals, while not possessing perfect information, have beliefs that are at least right on average and are aware of how their abilities translate into future labor market success.

Yet there is evidence that individuals—and in particular those from poorer households—may be lacking important information when making their college decisions. Hoxby & Avery (2013) show that students from poor households with very high SAT scores apply to schools of much lower quality than those from wealthier households. This occurs despite the fact that it would often be less expensive for these students to attend elite institutions, given the generous financial aid policies. The importance of knowledge about potential financial aid and how to receive it is also evidenced in Bettinger et al. (2012), who show that students who received help filling out their FAFSA forms were significantly more likely to enroll in college.

Given the results in Hoxby & Avery (2013), Hoxby & Turner (2013) provided information to poor students with high SAT scores about their chances of getting into various types of schools as well as expected financial aid. Students who received this information were significantly more likely to apply and attend private institutions than the control group, though the overall rates of initial college attendance were unchanged. Informational issues are also studied in Pallais (2015) who examined how college application and enrollment decisions changed when the ACT increased the number of places scores are sent for free from 3 to 4. This small change increased both the quality of colleges that low income students applied to as well as the quality of the institution attended. This occurred even though the cost of submitting an extra score was only $6.

Lack of information may also be relevant once individuals enter college. Both Arcidiacono et al. (2011) and Stinebrickner & Stinebrickner (2014*a*) show that students substantially overestimate their first year grades for two very different schools (Duke and Berea). Indeed, Arcidiacono et al. (2011) show that Duke students have virtually no information regarding their abilities to perform well in the classroom that is not already known by the university. Given that Duke is a very selective university with students who have highly educated parents, we would expect informational concerns to be even more prevalent at less-selective institutions.

Information concerns may be particularly important in light of the substantial differences in grading policies and study hours across majors as well as the predictability of who is going to leave the low-grading/high study time majors. Stinebrickner & Stinebrickner (2014*b*) provide direct evidence on this point. Stinebrickner & Stinebrickner (2014*b*) show that the student over-optimism regarding performance at Berea is primarily driven by over-optimism about science grades.

As students take more classes, they generally revise their expected performance in the sciences downward. This holds true even for students who persist in the sciences. Those students expect their science grades to be about 0.3 points lower in their junior year than in their freshman year. Those who begin in the sciences but then switch out have much larger downward revisions. Their expected science grades drop by about 0.7 points between freshmen and junior year.

The over-optimism about performance in the sciences is also reflected in perceived versus actual probabilities of persisting in or switching to different majors. Stinebrickner & Stinebrickner (2014*b*) show that those who begin in the sciences are much less likely to persist in the science than they perceive, while those who begin in the humanities are much more likely to persist. Similarly, those who do not begin in the sciences expect to finish in the sciences at much higher rates than actually occurs.

Subjective expectations data have also been used to examine beliefs about earnings in both actual and counterfactual majors. These beliefs can then be used to see how expected earnings affects choices, providing another way to obtain wage elasticities. Zafar (2013) was the first to pursue such a strategy using subjective expectations data from students at

Northwestern. He found little evidence that expected future earnings are important to major choice. Rather, consistent with the literature using observational data, non-pecuniary components play a dominant role in major choice. Larger elasticities are found in Arcidiacono, Hotz & Kang (2012) who surveyed students at Duke University. The two main differences between Arcidiacono, Hotz & Kang (2012) and Zafar (2013) is that Arcidiacono, Hotz & Kang (2012) focus on males and also elicits information on occupations.[54] For each major (both actual and counterfactual), students were asked expected earnings and the probabilities of pursuing different occupations.[55]Due to attenuation bias, one might expect to find larger earnings elasticity estimates when using subjective expectations data than rational forecasts of earnings based on a statistical model if students do not have fully rational expectations. On the other hand, measurement error in student reports of their subjective expectations will lead to attenuation bias in estimates based on student reports. Wiswall & Zafar (forthcoming) find similar elasticities to Arcidiacono, Hotz & Kang (2012) for a sample of NYU students despite not asking about occupations when they use an estimation strategy similar to Arcidiacono, Hotz & Kang (2012).[56]

An important objective of Wiswall & Zafar (forthcoming) is to address the possibility that major choice elasticities are upward-biased because (unobserved) preferences for majors are correlated with the expected earnings for majors. To circumvent this issue as well as to study how students update their beliefs, Wiswall and Zafar provided their sample with information about average salaries by field for the U.S. population. Specifically, in the initial stage of the survey, for each of a set of majors, the NYU respondents were asked about

[54]There is some evidence in the literature (see, e.g., Montmarquette et al., 2002) that expected earnings play a more important for males than females in the context of college major choice. This might explain part of the discrepancy between those two studies.

[55]Focus groups suggested that students had an easier time thinking about expected earnings for different majors when they were tied to occupations. Using data from the same survey as Arcidiacono, Hotz & Kang (2012), Arcidiacono et al. (2014) examine the complementarities between majors and occupations in terms of expected earnings.

[56]Given the difference in results from Zafar (2013), this suggests the wording of the questions may be important for eliciting these beliefs.

the probability that they would graduate in that major and what they would earn if they did so. They were also asked about population averages of earnings for each major. In the intermediate stage, they were provided with the data on average earnings by major. In the final stage, the questions regarding probabilities of graduating with different majors and expected earnings by major were repeated. The authors essentially regress the change in major choice probabilities on the change in the vector of major specific earnings (relative to earnings in the humanities). Since the unobserved tastes likely did not changed in between the two times the question was asked, the authors get an estimate of the income elasticity with the taste factor differenced out. The estimated income elasticities shrink substantially and are on the order of those found with observational data. However, this shrinking of the elasticities likely reflects more than the correlation of the unobserved preference with earnings. The change in information is a shock. To the extent that individuals have already committed, or at least partially committed, to majors through their coursework, then the elasticity measured here is to the shocks in the labor market while in school. The long run responses for those who enter having not taken any coursework would likely be larger. More research is needed on this important question.

That students respond to information regarding average salaries suggests imperfect information regarding the market. Students in Wiswall & Zafar (forthcoming) tend to overestimate, sometimes quite substantially, the average wages in certain fields, including economics and business and the humanities and arts. They underestimate the average wages in some other fields including engineering and computer science. For instance, students overestimate on average by as much as 31.1% females' wages in engineering and computer science. There is, however, a fair amount of heterogeneity across students. For example, the median student underestimates males' wages in the natural sciences by 10.5%, but 10% of the students overestimate wages in the natural sciences by more than 37.7%.

Arcidiacono, Hotz & Kang (2012) examine how misinformation regarding labor market beliefs affects choices using a different approach than Wiswall & Zafar (forthcoming). Arcidiacono, Hotz & Kang (2012) asked students to report what the average Duke student would make in different occupation-major combinations. Then, under the assumption that Duke students are right on average about labor market returns, they forecast how choice of major would change if the expected returns were purged of errors regarding average labor market returns. Arcidiacono, Hotz & Kang (2012) findings suggest that 7.8% of students would have chosen different majors had they had correct measurements of population returns. Note that this number is not the response to new information (in which case the response would be intermingled with switching costs), but how choices would have differed from the status quo if students already had the correct information. There are likely conflicting biases present. First, the response may be biased upward for the reasons suggested by Wiswall & Zafar (forthcoming). But these responses may also be biased downward if students' forecasts of their future earnings have changed since they have committed to a major, the same issue faced by Wiswall & Zafar (forthcoming). This will lead to an underestimate of the coefficient on future earnings in the utility function, which would then translate to smaller responses to correct information.

In the Chilean context, Hastings et al. (2015) survey college applicants about earnings and as well as tuition costs associated with particular programs of study and conduct an information provision experiment.[57] And advantage of the study is that it include individuals from a wide range of backgrounds who are considering institutions across the quality spectrum. The applicants were asked to list up to the top 3 institution-major degree programs they planned to apply to. For each program they were then asked about expected earnings and the tuition costs they would experience if they enrolled in it. They were also asked about what the typical graduate in each program would earn. The results indicate that students overestimate earnings and have unbiased but highly variable beliefs about costs. Low-SES students are more poorly informed. They plan to choose degrees with lower net value (earnings net of costs) than other degrees that would be likely to be admitted to.

A randomly chosen treatment group of the applicants were then provided with data on the earnings and cost outcomes of past students who had pursued the respondents' planned

[57]See also Hastings et al. (forthcoming).

enrollment choices. The treatment group members were told whether they could obtain a higher net value by pursuing their first choice major at other institutions that they were likely to get into (given admissions test data), and what the expected net gain would be. They were also told whether they were competitive for other degree programs that offer higher net value but featured an alternative major in the same broad field as their first degree choice, and the size of the expected net gain. Finally, the treatment group students was given access to a data base application that could be used to help them find institutions (given a specified test score) that they could get into and that offer a high net value than their first choice major. They could also use it to find high net value majors in the same broad field as their chosen major. Hastings, Neilson and Zimmerman study the effects of the information treatment on enrollment in college and on degree program choice. They find that the effects are relatively small and are concentrated among low-SES students. The low-SES students become more likely to enroll in programs that lead to higher net returns. The results are qualitatively consist with Hoxby & Avery (2013) and Hoxby & Turner (2013)'s evidence of "undermatch". Ninety percent of the expected gain in expected earnings operates through major choice and 10% through institution choice. The overall increase in returns is large relative to the cost of the treatment.

Many papers in this literature find that preferences for non-monetary benefits of college majors play a key role in the decision to enroll in a given major. This is the case of Wiswall & Zafar (forthcoming), who find that tastes for each major are the most important determinant of college major choice. The authors also provide evidence of a substantial degree of individual heterogeneity in the preferences for each major. In particular, they find that males, Asians, and high-SAT Math students tend to exhibit stronger distastes for humanities. However, 80% of the variation in major-specific tastes remains unexplained by observable characteristics. Similarly, Zafar (2013) investigates the gender gap in college major choice using subjective expectations data collected from sophomore students at Northwestern University. He finds that gender differences in preferences for majors are, by far, the main determinants of the gender gap in college major choice. Gender differences in beliefs about ability and major-specific earnings, on the other hand, do not account for a significant share of the gender gap. Zafar also finds that differences in non-pecuniary outcomes across majors matter significantly more for females than for males. Note that the potential gains from providing students with better information about returns to field are limited to the degree that non-pecuniary factors dominate decisions about field.

5.4 Graduate School

now turn to the choice to attend graduate school. Given the many different options both in level (Master's, PhD) and educational content, and given limited data, this literature is relatively underdeveloped and few broad conclusions can be drawn. We highlight three areas where work has been undertaken: (i) how the business cycle affects graduate school enrollment, (ii) the factors that influence the decision to obtain an MBA and (iii) the determinants of specialty choice for medical students.

5.4.1 Demand for Graduate School and the Business Cycle

Bedard & Herman (2008) examine how the demand for post-baccalaureate degrees varies with the business cycle. Using five cohorts of the National Survey of Recent College Graduates (NSRCG),[58] Bedard and Herman estimate separate probit models for the decision to enter a PhD program, enter a professional program (JD, MD), or enter a Master's program. Consistent with the opportunity cost of schooling being low when the economy is poor, higher state unemployment rates[59] are associated with higher probabilities of entering a PhD program for men. Somewhat surprisingly, there is no effect of the state unemployment rate on enrollment in professional programs and the effect is actually negative and significant for

[58]The NSRCG data used comes from survey data taken every other year from 1993 to 2001. NSRCG focuses on those who have obtained a Bachelor of Science or a Master's degree in the past two years, with this paper focusing on those who obtained a bachelor of Science.

[59]Controls include state and year effects.

enrolling in a Master's program for men.[60] A possible explanation for Master's enrollment being pro-cyclical is that some Master's degrees in some fields (e.g. business) require work experience. When the economy is poor, students will have had less work experience and also may be reluctant to give up their current positions. Some support for this is found went Bedard and Herman interact the state unemployment rate with undergraduate major, finding that the pro-cyclical relationship is strongest among social science majors, arguably the group most likely to pursue an MBA.[61]

Johnson (2013) considers the same question as Bedard & Herman (2008) but uses data from the Current Population Survey (CPS). The advantage of doing so is two-fold. First, the analysis is not limited to those who obtained a Bachelor of Science, implying humanities majors are included as well. Second, many individuals wait to go to graduate school, with about half of individuals starting graduate school more than 18 months after they finish their undergraduate degree. Weighed against this is the lack of information on undergraduate majors, no measures of ability, and small sample sizes. Overall, Johnson (2013) finds that the state unemployment rate positively affects graduate school enrollment for women with no effect for men, with evidence that higher unemployment rates shift individuals into part-time programs conditional on enrollment. When the type of program is modeled (Master's, PhD or professional), the patterns become more similar to Bedard & Herman (2008) in that the reaction to changes in state unemployment rates for men and women with regard to Master's enrollment are opposite, with men being less likely to enroll in Master's programs when the unemployment rate is high. However, while the qualitative patterns are similar, the estimates are too noisy to say much at the program level.

[60] Results for women display a completely different pattern, with higher unemployment rates associated with increased professional school enrollment and no effect on PhD or Master's enrollment. To the extent that slots in professional programs are constrained, it may be the case that, when the unemployment rate is high, women crowd out some of the men who would otherwise be interested in entering a professional program. This might explain the lack of significant effects of the unemployment rate on professional program enrollment as a whole.

[61] The other undergraduate majors were classified as physical science, computer science and math, life science, and engineering.

5.4.2 Demand for MBA's

The only study we are aware of that examines the choice over which MBA program to attend is Montgomery (2002). Montgomery estimates a nested logit model where a set of MBA programs are in one nest, attending a part-time program is in another nest, with the final nest including the option to not attend at all. Montgomery estimates his model in two stages; first estimating the probability of choosing a particular full-time MBA program conditional on enrolling a full-time MBA program and second the probability of enrolling in a part-time or full-time MBA program or not enrolling at all.

Like Arcidiacono (2004, 2005), Montgomery needs to make assumptions regarding what MBA programs are in the individual's choice set. Montgomery's data contains information about whether the individual was admitted to their first choice school. Montgomery estimates a probit on the probability of being admitted to the first-choice school conditional on characteristics of the school and the individual; the coefficients of which are then used to form admissions probabilities for every MBA program. Next, Montgomery draws from a uniform distribution to see whether or not each of the schools is available to the individual. Note that assumes that, conditional on observables, admissions outcomes are independent. Montgomery then reduces the choice set further to keep computation feasible by assuming the choice set consists of the chosen school (for those who attended an MBA program) plus 14 schools randomly drawn from the set that first stage revealed that the individual would be admitted to.[62]

Conditional on attending graduate school, a number of measures of the quality of the program show up as important, including the ranking of the institution, and the average GMAT and undergraduate GPA of the student body. Conditional on these quality measures, higher tuition results in lower attendance. Average starting salaries of the graduates, however, shows up negative, likely indicative of the noisy measures of quality.

Turning to the decision to enroll in an MBA program, it is important to note that

[62] While this procedure may seem arbitrary, Montgomery notes that using 30 schools instead gave similar results.

substantial selection has already occurred as Montgomery's sample comes from students who took the GMAT and therefore at least had a passing interest in enrolling in an MBA program. This makes the results difficult to interpret. We do see, however, some evidence of positive selection on the basis of the student's GMAT scores, with factors such as currently being employed and positive expectations on the employer providing tuition assistance making attending a part-time program more likely.

Gicheva (2012) delves deeper into the decision to enroll in a full or part-time MBA program, though abstracting away from the choice of school. Her focus is on the specific incentives workers have to go either full or part-time and how employers influence this decision. Gicheva develops a search model where workers have heterogeneous costs of changing employers and where workers and firms bargain over wages. Workers with high adjustment costs have lower incentives to invest in human capital because the high adjustments costs lowers their threat point with their firm. But since these workers are more likely to stay at their current position, the firm has an incentive to encourage their investment as the firm benefits from the worker being more productive. In the model, these mobility costs effectively translate into whether the skills acquired are general or firm-specific. If the worker has extremely high mobility costs then the skills acquired through an MBA program will only be used at their current employer, implying that the worker has little bargaining power. The individual would be in a situation comparable to that of a worker who acquired firm-specific training.

Gicheva's model assumes that (i) full-time programs provide more networking opportunities than their part-time counterparts, so full-time graduates have higher offer arrival rates, and (ii) total cost of the program (tuition plus lost earnings) is lower for part-time programs. Firms then have a incentive to subsidize part-time programs over full-time programs for two reasons. First, they are more likely to see a return on their investment due to the lower offer arrival rates associated with part-time programs. Second, individuals with high mobility costs will underinvest from the firm's perspective due the reasons above.[63] Using the same

[63]See Acemoglu & Pischke (1998) for an analysis of why firms may pay for general training.

data as Montgomery (2002), Gicheva finds support for each of these predictions.

5.4.3 Demand for Medical School Specialties

The market for physicians is highly regulated. Individuals who graduate from medical school are generally required to enter a residency program that can last anywhere between 3 and 6 years depending on the speciality. But medical school graduates cannot enter any residency program they like. Rather, medical school graduates list their preferred residency programs, which is a combination of both a specialty (e.g. surgery, pediatrics, etc.) and a teaching hospital. Residency programs also list their preferences over medical students. For some specialities, such as surgery, there is an excess supply of graduates: many more graduates list their top choice as surgery than there are surgical residency positions.

Nicholson (2002) is the only paper that explicitly takes into account the probability of matching in a residency program when estimating a model of physician specialty choice. Nicholson estimates a conditional logit of specialty choice where the key coefficient is on the expected present value of lifetime earnings.[64] This earnings measure is constructed by multiplying the probability of matching in a specialty (which depends on the student's abilities as measured by test scores) by the earnings stream associated with the particular specialty. Those who do not match in their preferred speciality receive the income associated with the lowest paying specialty (family practice/pediatrics).

Two key assumptions are made. First, earnings in the different specialties only depend on gender and experience, not ability.[65] Second, ability does not affect preferences for particular specialities. This latter assumption is key to Nicholson's identification strategy. Namely,

[64] Agarwal (2015) studies the National Residency Matching Program. He estimates preferences for residency programs in family medicine, and hospital preferences for residences but does not examine choice of specialty.

[65] Support for this assumption is found in Nicholson & Souleles (2001) who show that subjective measures of expected income do not vary with MCAT scores once one conditions on specialty. However, their results are from one medical school. If sorting across medical schools is driven largely by ability, the variation in overall ability within a medical school may be small and test scores may be negatively correlated with other ability measures within schools even though if they are positively correlated across schools.

the lifetime earnings calculations depend on ability through the probability of matching in different residency programs. Hence to the extent that ability is related to choice of medical specialities, this is indicative of individuals responding to financial incentives.

In contrast with the literature on the responsiveness of the undergraduate major choice to earnings, Nicholson (2002) finds a substantial earnings elasticity. Since the model is both nonlinear and depends on the wage level, the average earnings elasticity varies by specialty despite the common coefficient estimate on the lifetime earnings measure, ranging from 1.0 to 2.2 across the specialities.

As with the literature on major choice, assumptions must be made about what individuals would earn in counterfactual specialties if observational data is used to obtain the earnings elasticities. Sivey et al. (2012) avoid these issues by presenting Australian medical students with different scenarios regarding compensation and job characteristics about two specialities and asking which specialty they would choose. By varying the compensation schemes and job characteristics in the hypotheticals it is then possible to measure the importance of these factors in specialty choice. Sivey et al. (2012) find large earnings elasticities, on the order of 0.95 for general practitioners. Their estimates also reveal that medical students have a strong preference to avoid having little control of their hours of work and being on call, with the estimates suggesting a marginal willingness to pay of over $70,000 to go from being on call one in four nights to one being on call one in ten nights.

Control of hours, average hours worked, and fraction female vary substantially across specialities. In 2014, residency applicants for surgery were 36% female while residency applicants for pediatrics were 71% female AAMC (2014). Goldin & Katz (2011) suggest that these differences are driven in part by workplace flexibility. They point to gastroenterology as a specialty that had very women but, as the job became more routine due to recommendations for routine colonoscopies, many more women entered the specialty. To our knowledge, however, there is no work in economics that seeks to decompose the gender gap in specialty choice into, for example, workplace flexibility, monetary renumeration, and tastes.

6 Conclusion

Choice of major is an important determinant of future earnings and is strongly associated with the type of jobs that people hold. The evidence suggests that much of the effect of major on earnings is causal, with STEM and business related majors leading the way. Indeed, even the choice of specialization within graduate programs has a large effect on earnings, be it choosing a more finance-related concentration in business school or choosing to be a surgeon in medical school. Further, although less clear, these positive effects appear to be present across the board: humanities majors would earn more had they majored in business. That they choose not to major in the more lucrative fields suggest compensating differentials in school or in the workplace, and an important role for heterogeneity in tastes for fields of study and the occupations they lead to.

One clear avenue for future research is to consider the ways universities affect major choice. For example, consider the regression discontinuity designs in Hastings et al. (2013) and Kirkebøen et al. (2015). Are the measures used to screen who gets access to particular slots the best measures for predicting performance in these fields, be it probabilities of persistence to graduation or future labor market earnings? Similarly, are the skills that translate into successful completion of STEM degrees in the U.S. the same skills that are rewarded in the labor market for these fields? If not, might there be more efficient ways to allocate university resources?

Another avenue is to consider the link between field of study and occupations. We summarized a small set of studies that indicate that particular majors may increase earnings in some occupations but not others. Much more research is needed. And differences in occupations in other dimensions, such as the penalty for time away from the workforce and the reward for long work hours may be useful for understanding why students make the choices they do. As occupations change, so too may the composition of the majors that feed those occupations. On the labor market side, more research is also needed to understand the determinants of the distributions of occupations within each field of study.

We have summarized some of the research on how degree completion by field and future earnings varies across schools, but more work is needed in this area. Here are some of the questions that are key to evaluating policies concerning student advising, admissions, and which schools and degree programs to support through loans or grants. Do some schools have absolute advantage for most students? To what extent do outcomes depend on the match among the student, the field of study, and the school? What characteristics of students and schools matter? To what extent would providing students with more information about admissions chances, degree completion probabilities and the earnings of past graduates by field and school lead to better choices? What is the role for admissions preference policies and financial aid policies that increase access of students from disadvantaged backgrounds to elite programs? What about graduate degree programs?

Research into the determinants and consequences of field choice in higher education has taken off in recent years. Indeed, many of the papers we discuss are still in working paper form or were published in the last two or three years. There is much left to do, and we hope that the questions raised in this chapter will stimulate further research on this fascinating topic.

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7 Tables

Table 1: Fraction of Bachelor's Graduates by Major

Major	Proportion (in %)	Mean Wage
Business	22.5	$35.86
Education	10.1	$25.23
Engineering	8.2	$45.20
Social Sciences	7.3	$37.57
Medical & Health Services	7.2	$35.93
Biology	4.8	$43.07
Psychology	4.7	$29.04
Communications	4.3	$30.18
Fine Arts	4.2	$25.15
Computer & Information Systems	3.9	$40.01
Physical Sciences	3.0	$41.33
English Language & Literature	2.9	$30.96
History	1.9	$34.63
Criminal Justice	1.9	$27.98
Liberal Arts & Humanities	1.4	$28.69
Public Administration	1.4	$25.15
Mathematics	1.3	$41.08
Agriculture	1.0	$28.77
Physical Fitness	0.9	$26.97
Linguistics	0.9	$30.29
Engineering Technologies	0.8	$36.89
Architecture	0.7	$31.93
Family & Consumer Sciences	0.7	$24.79
Interdisciplinary Studies	0.7	$29.41
Environmental Science	0.6	$29.73
Philosophy & Religion	0.6	$31.99
Theology	0.6	$22.43
Ethnic Studies	0.3	$33.78
Transportation Sciences	0.3	$40.37
Construction Services	0.2	$33.88
Court Reporting	0.2	$29.44
Communication Technologies	0.1	$26.73
Cosmetology & Culinary Arts	0.1	$20.61

Source: American Community Survey, 2013 1-year PUMS.

Proportions reported for all college graduates with a BA degree or higher, between the ages of 27 and 58. Mean wage is annual earnings, divided by average hours worked per week times weeks worked in the past year. Mean wages are censored to be larger than $5/hr. and less than $400/hr.

Table 2: Proportion of Male and Female College Graduates with Advanced Degrees By Degree Type			
	All	Male	Female
	(1)	(2)	(3)
Masters-Education Field	0.077	0.042	0.108
Masters in Business related field	0.020	0.027	0.013
Masters in Public Administration	0.005	0.006	0.004
Masters in Arts field	0.006	0.005	0.007
Masters in Humanities field	0.015	0.016	0.014
Masters-Other Non-Science and Engineering Field	0.010	0.008	0.011
Masters in Psychology or Social Work	0.020	0.010	0.029
Masters-Other Social and related sciences	0.011	0.011	0.010
Masters in Health Services Administration	0.003	0.002	0.003
Masters in Nursing	0.006	0.001	0.010
Masters-Biological/agricultural/environmental life sciences	0.008	0.008	0.008
Masters-Computer and mathematical sciences	0.014	0.021	0.008
Masters-Engineering	0.017	0.029	0.006
Masters-Physical and related sciences	0.004	0.005	0.002
Masters-Other Science and Engineering related fields	0.018	0.011	0.023
MBA	0.046	0.060	0.034
Law	0.032	0.036	0.029
MD	0.023	0.031	0.015
PhD	0.029	0.038	0.020
Other professional degree	0.003	0.002	0.003
Has at least one advanced degree	**0.348**	**0.353**	**0.344**
N	56133	30367	25766

Source: AdvDegreeStats_v3.do. Data: National Survey of College Graduates 2010. The sample includes individuals aged 27 to 59. Estimates are weighted using sample weights

Table 3: The Fraction of Undergraduate Majors Who Obtain Graduate Degrees, by Major and Degree Type

	Raw Counts	Fraction of College Graduates	Fraction with Advanced Degrees	Masters-Education Field	Masters in Business related field	Masters in Public Administration	Masters in Arts field	Masters in Humanities field	Masters-Other Non-Science and Engineering Field	Masters in Psychology or Social Work	Masters-Other Social and related sciences	Masters in Health Services Administration	Masters in Nursing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Major													
Education	2138	0.108	0.425	0.360	0.002	0.000	0.004	0.007	0.007	0.014	0.003	0.001	0.001
English/Languages/Literature	891	0.039	0.447	0.121	0.007	0.010	0.005	0.102	0.029	0.009	0.020	0.000	0.000
Fine/Performing Arts	681	0.043	0.209	0.046	0.006	0.001	0.085	0.007	0.005	0.007	0.002	0.000	0.004
Other Humanities	1035	0.054	0.415	0.112	0.007	0.005	0.009	0.095	0.016	0.016	0.014	0.001	0.000
Communications/Journalism	648	0.043	0.182	0.058	0.006	0.001	0.005	0.007	0.039	0.004	0.009	0.000	0.001
Accounting	526	0.048	0.211	0.006	0.089	0.006	0.000	0.001	0.000	0.001	0.004	0.005	0.001
Business	2205	0.140	0.213	0.021	0.037	0.005	0.000	0.007	0.002	0.002	0.003	0.002	0.000
Marketing	446	0.031	0.216	0.018	0.082	0.000	0.000	0.000	0.015	0.001	0.002	0.000	0.000
Other Non-S and E Fields	326	0.021	0.228	0.060	0.001	0.020	0.006	0.000	0.042	0.006	0.004	0.001	0.000
Economics	1989	0.022	0.383	0.022	0.061	0.003	0.001	0.005	0.003	0.004	0.052	0.006	0.000
Political science	2571	0.034	0.521	0.041	0.011	0.048	0.001	0.014	0.012	0.008	0.047	0.001	0.001
Psychology or Social Work	4467	0.063	0.431	0.081	0.007	0.005	0.002	0.008	0.009	0.193	0.009	0.003	0.003
Other Social and related sciences	4303	0.057	0.377	0.084	0.008	0.009	0.005	0.018	0.021	0.049	0.055	0.001	0.002
Nursing	1596	0.030	0.232	0.004	0.002	0.001	0.000	0.001	0.002	0.003	0.001	0.014	0.157
Biological/agricultural/environmental science	6824	0.067	0.505	0.034	0.010	0.002	0.001	0.005	0.003	0.006	0.006	0.004	0.004
Computer and mathematical sciences	5271	0.048	0.315	0.031	0.016	0.003	0.000	0.005	0.003	0.001	0.003	0.001	0.000
Engineering	11907	0.074	0.395	0.004	0.022	0.001	0.003	0.002	0.004	0.000	0.003	0.000	0.000
Physical and related sciences	3874	0.023	0.574	0.029	0.009	0.001	0.000	0.006	0.006	0.001	0.007	0.003	0.001
Other S and E-Related Fields	4120	0.056	0.332	0.029	0.004	0.002	0.003	0.003	0.007	0.007	0.002	0.011	0.002
Total	55818	1											

				Masters-Biological/agricultural/environmental life sciences	Masters-Computer and mathematical sciences	Masters-Engineering	Masters-Physical and related sciences	Masters-Other Science and Engineering related fields	MBA	Law	MD	PhD	Other professional degree
				(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
Major													
Education				0.002	0.004	0.001	0.000	0.007	0.009	0.003	0.001	0.018	0.001
English/Languages/Literature				0.002	0.006	0.001	0.000	0.007	0.028	0.068	0.012	0.040	0.001
Fine/Performing Arts				0.000	0.009	0.001	0.000	0.014	0.002	0.010	0.001	0.013	0.000
Other Humanities				0.001	0.001	0.001	0.000	0.005	0.024	0.094	0.013	0.023	0.000
Communications/Journalism				0.001	0.002	0.001	0.000	0.003	0.014	0.030	0.001	0.008	0.000
Accounting				0.000	0.009	0.001	0.000	0.001	0.079	0.008	0.000	0.004	0.000
Business				0.000	0.009	0.001	0.000	0.002	0.104	0.017	0.002	0.002	0.000
Marketing				0.000	0.001	0.000	0.000	0.003	0.088	0.002	0.000	0.001	0.002
Other Non-S and E Fields				0.002	0.002	0.000	0.000	0.021	0.031	0.027	0.001	0.004	0.000
Economics				0.001	0.011	0.005	0.000	0.003	0.094	0.090	0.011	0.027	0.000
Political science				0.003	0.002	0.001	0.000	0.008	0.053	0.263	0.004	0.015	0.001
Psychology or Social Work				0.001	0.009	0.001	0.000	0.027	0.026	0.027	0.015	0.041	0.010
Other Social and related sciences				0.003	0.002	0.002	0.000	0.018	0.031	0.054	0.007	0.021	0.003
Nursing				0.001	0.000	0.000	0.000	0.017	0.014	0.005	0.002	0.008	0.000
Biological/agricultural/environmental science				0.095	0.005	0.004	0.003	0.036	0.030	0.014	0.185	0.077	0.009
Computer and mathematical sciences				0.004	0.129	0.018	0.001	0.009	0.050	0.010	0.009	0.033	0.001
Engineering				0.001	0.036	0.182	0.002	0.013	0.077	0.010	0.007	0.039	0.001
Physical and related sciences				0.013	0.020	0.045	0.126	0.012	0.032	0.017	0.088	0.181	0.007
Other S and E-Related Fields				0.006	0.008	0.006	0.000	0.128	0.030	0.006	0.060	0.020	0.010

Column 1 provides the unweighted sample size for each major. Column 2 reports the fraction of college graduates with a bachelor's degree in the specified field. Column 3 reports the fraction of college graduates who obtain at least one advanced degree, by undergraduate field. Columns 4 to 23 report the share of the advanced degree specified in the column accounted for by the undergraduate major listed in the row. Source: AdvDegreeStats_v3.do. Data: National Survey of College Graduates, 2010. The sample includes individuals aged 27 to 59. Estimates are weighted using sample weights.

Table 4: Ratio of the Fraction of Advanced Degree Receipients in College Major to the All College Graduates in that Major, by Advanced Degree type and College Major.

(Prob(major m | grad degree f))/Prob(major m|college graduate)

	Raw Counts	Fraction of College Graduates	Fraction with Advanced Degrees	Masters-Education Field	Masters in Business related field	Masters in Public Administration	Masters in Arts field	Masters in Humanities field	Masters-Other Non-Science and Engineering Field	Masters in Psychology or Social Work	Masters-Other Social and related sciences	Masters in Health Services Administration	Masters in Nursing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Major													
Education	2138	0.1081	0.425	4.65	0.10	0.01	0.73	0.49	0.75	0.69	0.27	0.54	0.25
English/Languages/Literature	891	0.039	0.447	1.56	0.38	1.95	0.74	6.91	2.97	0.46	1.95	0.06	0.05
Fine/Performing Arts	681	0.043	0.209	0.59	0.28	0.15	13.88	0.45	0.49	0.33	0.15	0.00	0.73
Other Humanities	1035	0.054	0.415	1.45	0.36	0.96	1.55	6.46	1.65	0.79	1.33	0.23	0.05
Communications/Journalism	648	0.043	0.182	0.74	0.31	0.19	0.77	0.46	4.02	0.19	0.81	0.00	0.21
Accounting	526	0.048	0.211	0.08	4.56	1.09	0.00	0.04	0.03	0.06	0.34	2.02	0.09
Business	2205	0.140	0.213	0.27	1.92	0.90	0.01	0.48	0.18	0.09	0.27	0.77	0.04
Marketing	446	0.031	0.216	0.24	4.21	0.03	0.02	0.03	1.54	0.05	0.15	0.16	0.00
Other Non-S and E Fields	326	0.021	0.228	0.77	0.06	3.90	0.97	0.00	4.33	0.28	0.38	0.42	0.00
Economics	1989	0.022	0.383	0.29	3.10	0.69	0.24	0.34	0.28	0.18	4.95	2.19	0.00
Political science	2571	0.034	0.521	0.52	0.58	9.44	0.10	0.96	1.25	0.38	4.47	0.55	0.12
Psychology or Social Work	4467	0.063	0.431	1.05	0.38	0.89	0.27	0.57	0.92	9.65	0.91	1.35	0.45
Other Social and related sciences	4303	0.057	0.377	1.08	0.40	1.79	0.87	1.20	2.10	2.48	5.24	0.46	0.32
Nursing	1596	0.030	0.232	0.05	0.11	0.23	0.04	0.10	0.21	0.13	0.13	5.30	26.96
Biological/agricultural/environmental science	6824	0.067	0.505	0.44	0.49	0.40	0.18	0.36	0.31	0.29	0.58	1.44	0.68
Computer and mathematical sciences	5271	0.048	0.315	0.40	0.84	0.59	0.06	0.33	0.34	0.05	0.28	0.38	0.00
Engineering	11907	0.074	0.395	0.05	1.13	0.16	0.49	0.12	0.37	0.01	0.25	0.00	0.00
Physical and related sciences	3874	0.023	0.574	0.37	0.45	0.21	0.07	0.43	0.64	0.03	0.67	1.05	0.21
Other S and E-Related Fields	4120	0.056	0.332	0.37	0.18	0.38	0.54	0.19	0.76	0.37	0.15	4.19	0.36
Total	55818	1											

	Masters-Biological/agricultural/environmental life sciences	Masters-Computer and mathematical sciences	Masters-Engineering	Masters-Physical and related sciences	Masters-Other Science and Engineering related fields	MBA	Law	MD	PhD	Other professional degree
	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
Major										
Education	0.19	0.25	0.07	0.10	0.39	0.19	0.09	0.06	0.68	0.23
English/Languages/Literature	0.21	0.41	0.06	0.02	0.40	0.61	2.14	0.52	1.51	0.36
Fine/Performing Arts	0.02	0.62	0.08	0.11	0.77	0.04	0.31	0.06	0.51	0.10
Other Humanities	0.11	0.11	0.03	0.07	0.29	0.53	2.95	0.59	0.87	0.15
Communications/Journalism	0.11	0.13	0.03	0.01	0.18	0.29	0.94	0.05	0.31	0.00
Accounting	0.01	0.65	0.05	0.03	0.04	1.72	0.26	0.02	0.16	0.00
Business	0.03	0.62	0.04	0.07	0.10	2.27	0.53	0.10	0.08	0.15
Marketing	0.02	0.06	0.02	0.02	0.19	1.92	0.05	0.00	0.04	0.87
Other Non-S and E Fields	0.23	0.17	0.01	0.00	1.19	0.68	0.85	0.06	0.15	0.00
Economics	0.07	0.80	0.32	0.03	0.18	2.04	2.83	0.49	1.03	0.05
Political science	0.36	0.12	0.03	0.03	0.44	1.14	8.26	0.18	0.56	0.23
Psychology or Social Work	0.15	0.64	0.04	0.09	1.51	0.56	0.86	0.68	1.57	3.91
Other Social and related sciences	0.38	0.17	0.10	0.13	1.04	0.67	1.69	0.33	0.80	1.25
Nursing	0.16	0.02	0.00	0.00	0.96	0.31	0.15	0.07	0.32	0.12
Biological/agricultural/environmental science	11.86	0.35	0.22	0.79	2.04	0.66	0.45	8.33	2.92	3.69
Computer and mathematical sciences	0.47	9.19	1.06	0.32	0.50	1.09	0.31	0.39	1.25	0.32
Engineering	0.16	2.57	10.96	0.70	0.73	1.69	0.31	0.31	1.49	0.23
Physical and related sciences	1.64	1.46	2.69	36.08	0.68	0.70	0.53	3.97	6.89	3.01
Other S and E-Related Fields	0.69	0.56	0.34	0.07	7.22	0.66	0.18	2.69	0.76	3.96

Column 1 provides the unweighted sample size for each major. Column 2 reports the fraction of college graduates with a bachelor's degree in the specified field. Column 3 reports the fraction of college graduates who obtain at least one advanced degree, by undergraduate field. Columns 4 to 23 report the ratio of the share of the advanced degree specified in the column accounted for by the undergraduate major listed in the row to the share of that major among all college graduates reported in column 2. Source: AdvDegreeStats_v3.do. Data: National Survey of College Graduates, 2010. The sample includes individuals aged 27 to 59. Estimates are weighted using sample weights.

Table 5: Fraction of Advanced Degree Recipients in College Major, by Advanced Degree Type and College Major

	Raw Counts	Fraction of College Graduates	Fraction with Advanced Degrees	Masters-Education Field	Masters in Business related field	Masters in Public Administration	Masters in Arts field	Masters in Humanities field	Masters-Other Non-Science and Engineering Field	Masters in Psychology or Social Work	Masters-Other Social and related sciences	Masters in Health Services Administration	Masters in Nursing
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Major													
Education	2138	0.1081	0.425	0.50	0.01	0.00	0.08	0.05	0.08	0.07	0.03	0.06	0.03
English/Languages/Literature	891	0.039	0.447	0.06	0.01	0.08	0.03	0.27	0.12	0.02	0.08	0.00	0.00
Fine/Performing Arts	681	0.043	0.209	0.03	0.01	0.01	0.59	0.02	0.02	0.01	0.01	0.00	0.03
Other Humanities	1035	0.054	0.415	0.08	0.02	0.05	0.08	0.35	0.09	0.04	0.07	0.01	0.00
Communications/Journalism	648	0.043	0.182	0.03	0.01	0.01	0.03	0.02	0.17	0.01	0.03	0.00	0.01
Accounting	526	0.048	0.211	0.00	0.22	0.05	0.00	0.00	0.00	0.00	0.02	0.10	0.00
Business	2205	0.140	0.213	0.04	0.27	0.13	0.00	0.07	0.03	0.01	0.04	0.11	0.01
Marketing	446	0.031	0.216	0.01	0.13	0.00	0.00	0.00	0.05	0.00	0.00	0.00	0.00
Other Non-S and E Fields	326	0.021	0.228	0.02	0.00	0.08	0.02	0.00	0.09	0.01	0.01	0.01	0.00
Economics	1989	0.022	0.383	0.01	0.07	0.02	0.01	0.01	0.01	0.00	0.11	0.05	0.00
Political science	2571	0.034	0.521	0.02	0.02	0.32	0.00	0.03	0.04	0.01	0.15	0.02	0.00
Psychology or Social Work	4467	0.063	0.431	0.07	0.02	0.06	0.02	0.04	0.06	0.61	0.06	0.09	0.03
Other Social and related sciences	4303	0.057	0.377	0.06	0.02	0.10	0.05	0.07	0.12	0.14	0.30	0.03	0.02
Nursing	1596	0.030	0.232	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.16	0.80
Biological/agricultural/environmental science	6824	0.067	0.505	0.03	0.03	0.03	0.01	0.02	0.02	0.02	0.04	0.10	0.05
Computer and mathematical sciences	5271	0.048	0.315	0.02	0.04	0.03	0.00	0.02	0.02	0.00	0.01	0.02	0.00
Engineering	11907	0.074	0.395	0.00	0.08	0.01	0.04	0.01	0.03	0.00	0.02	0.00	0.00
Physical and related sciences	3874	0.023	0.574	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.02	0.02	0.00
Other S and E-Related Fields	4120	0.056	0.332	0.02	0.01	0.02	0.03	0.01	0.04	0.02	0.01	0.24	0.02
Total	55818	1											

	Masters-Biological/agricultural/environmental life sciences	Masters-Computer and mathematical sciences	Masters-Engineering	Masters-Physical and related sciences	Masters-Other Science and Engineering related fields	MBA	Law	MD	PhD	Other professional degree
	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)
Major										
Education	0.02	0.03	0.01	0.01	0.04	0.02	0.01	0.01	0.07	0.02
English/Languages/Literature	0.01	0.02	0.00	0.00	0.02	0.02	0.08	0.02	0.06	0.01
Fine/Performing Arts	0.00	0.03	0.00	0.00	0.03	0.00	0.01	0.00	0.02	0.00
Other Humanities	0.01	0.01	0.00	0.00	0.02	0.03	0.16	0.03	0.05	0.01
Communications/Journalism	0.00	0.01	0.00	0.00	0.01	0.01	0.04	0.00	0.01	0.00
Accounting	0.00	0.03	0.00	0.00	0.00	0.08	0.01	0.00	0.01	0.00
Business	0.00	0.09	0.01	0.01	0.01	0.32	0.07	0.01	0.01	0.02
Marketing	0.00	0.00	0.00	0.00	0.01	0.06	0.00	0.00	0.00	0.03
Other Non-S and E Fields	0.00	0.00	0.00	0.00	0.03	0.01	0.02	0.00	0.00	0.00
Economics	0.00	0.02	0.01	0.00	0.00	0.04	0.06	0.01	0.02	0.00
Political science	0.01	0.00	0.00	0.00	0.02	0.04	0.28	0.01	0.02	0.01
Psychology or Social Work	0.01	0.04	0.00	0.01	0.10	0.04	0.05	0.04	0.10	0.25
Other Social and related sciences	0.02	0.01	0.01	0.01	0.06	0.04	0.10	0.02	0.05	0.07
Nursing	0.00	0.00	0.00	0.00	0.03	0.01	0.00	0.00	0.01	0.00
Biological/agricultural/environmental science	0.79	0.02	0.01	0.05	0.14	0.04	0.03	0.55	0.19	0.25
Computer and mathematical sciences	0.02	0.44	0.05	0.02	0.02	0.05	0.02	0.02	0.06	0.02
Engineering	0.01	0.19	0.81	0.05	0.05	0.12	0.02	0.02	0.11	0.02
Physical and related sciences	0.04	0.03	0.06	0.83	0.02	0.02	0.01	0.09	0.16	0.07
Other S and E-Related Fields	0.04	0.03	0.02	0.00	0.41	0.04	0.01	0.15	0.04	0.22

Column 1 provides the unweighted sample size for each major. Column 2 reports the fraction of college graduates with a bachelor's degree in the specified field. Column 3 reports the fraction of college graduates who obtain at least one advanced degree, by undergraduate field. Columns 4 to 23 report the share of the advanced degree specified in the column accounted for by the undergraduate major listed in the row. Source: AdvDegreeStats_v3.do. Data: National Survey of College Graduates, 2010. The sample includes individuals aged 27 to 59. Estimates are weighted using sample weights.

Table 6: The Return to Undergraduate and Graduate Degrees

	coef/se				coef/se
Education	0.000			Masters-Education Field	0.124
	.				(0.01)
English/Languages/Literature	0.105			MBA	0.263
	(0.02)				(0.02)
Fine/Performing Arts	-0.059			Law	0.503
	(0.02)				(0.02)
Other Humanities	0.013			MD	0.710
	(0.02)				(0.02)
Communications/Journalism	0.142			Other professional degree	0.328
	0.026				(0.03)
Accounting	0.328			PhD	0.208
	(0.02)				(0.01)
Business	0.184			Masters in Business related field	0.336
	(0.02)				(0.03)
Marketing	0.237			Masters in Public Administration	0.208
	(0.03)				(0.03)
Other Non-S and E Fields	0.142			Masters in Arts field	0.060
	(0.02)				(0.03)
Economics	0.313			Masters in Humanities field	-0.106
	(0.02)				(0.03)
Political science	0.176			Masters-Other Non-Science and Engineering Field	0.068
	(0.02)				(0.01)
Psychology or Social Work	0.079			Masters in Psychology or Social Work	0.081
	(0.01)				(0.01)
Other Social and related sciences	0.082			Masters-Other Social and related sciences	0.166
	(0.01)				(0.02)
Nursing	0.312			Masters in Health Services Administration	0.263
	(0.01)				(0.03)
Biological/agricultural/environmental science	0.125			Masters in Nursing	0.192
	(0.01)				(0.02)
Computer and mathematical sciences	0.327			Masters-Biological/agricultural/environmental life sciences	0.053
	(0.01)				(0.02)
Engineering	0.392			Masters-Computer and mathematical sciences	0.229
	(0.01)				(0.02)
Physical and related sciences	0.230			Masters-Engineering	0.196
	(0.01)				(0.01)
Other S and E-Related Fields	0.271			Masters-Physical and related sciences	(0.11)
	(0.02)				(0.02)
				Masters-Other Science and Engineering related fields	0.179
					(0.02)

This table reports coefficients from a regression of ln(earnings) a set of indicator variables for undergraduate major and a set of indicator variables for graduate degree type. A BA in education in the reference undergraduate major. The other control variables include a cubic in age interacted with gender, father's education (6 categories) mother's education (6 categories), gender interacted with race (6 categories), and Hispanic. The data are from The National Survey of College Graduates 1993 and 2010. The sample consists of persons with at least a BA/BS degree and is restricted to full-time workers between the ages of 24 and 59. The regression is weighted using survey weights. N=144635. R2 = .282. Source: AdvDegreeRegs_v3.do

Table 7: Returns to Combinations of Undergrad and Grad Degrees

Coefficient (Standard Error) [Unweighted Cell Count]

	Bachelors Only	Masters-Education Field	Non-MBA/Educ/Law Masters	MBA	Law	MD
Education	0 (0) [6877]	0.242 (0.01) [4768]	0.196 (0.03) [1007]	0.331 (0.05) [127]	0.588 (0.08) [68]	0.588 (0.15) [34]
English/Languages/Literature	0.116 (0.03) [2227]	0.228 (0.05) [552]	0.276 (0.04) [1293]	0.599 (0.12) [123]	0.645 (0.06) [231]	0.981 (0.14) [65]
Fine/Performing Arts	-0.026 (0.03) [2139]	0.205 (0.05) [174]	0.108 (0.03) [777]	0.35 (0.1) [38]	0.699 (0.09) [34]	0.789 (0.15) [29]
Other Humanities	0.042 (0.03) [2581]	0.19 (0.05) [449]	0.024 (0.04) [1185]	0.55 (0.08) [154]	0.711 (0.06) [432]	0.678 (0.12) [114]
Communications/Journalism	0.201 (0.03) [2079]	0.009 (0.11) [89]	0.341 (0.06) [330]	0.694 (0.19) [66]	0.577 (0.06) [54]	
Accounting	0.397 (0.02) [3432]	0.38 (0.15) [17]	0.577 (0.07) [472]	0.6 (0.06) [273]	0.764 (0.06) [93]	
Business	0.24 (0.02) [9370]	0.274 (0.08) [195]	0.477 (0.05) [1037]	0.451 (0.04) [1073]	0.718 (0.06) [252]	0.836 (0.21) [21]
Marketing	0.291 (0.03) [2020]	0.442 (0.12) [27]	0.476 (0.06) [219]	0.596 (0.07) [142]	0.799 (0.08) [21]	
Other Non-S and E Fields	0.196 (0.02) [5654]	0.203 (0.03) [180]	0.35 (0.02) [1231]	0.435 (0.07) [189]	0.453 (0.05) [65]	0.874 (0.03) [885]
Economics	0.375 (0.03) [1711]	0.089 (0.06) [38]	0.631 (0.04) [682]	0.647 (0.04) [311]	0.818 (0.04) [272]	0.629 (0.15) [28]
Political science	0.244 (0.02) [2211]	0.068 (0.07) [164]	0.446 (0.03) [801]	0.516 (0.05) [204]	0.697 (0.03) [1213]	1.112 (0.13) [20]
Psychology or Social Work	0.116 (0.02) [4007]	0.218 (0.02) [719]	0.251 (0.02) [2437]	0.537 (0.05) [205]	0.672 (0.06) [242]	0.95 (0.07) [185]
Other Social and related sciences	0.129 (0.02) [4735]	0.172 (0.03) [584]	0.27 (0.02) [2089]	0.382 (0.11) [249]	0.702 (0.04) [392]	0.844 (0.09) [75]
Nursing	0.374 (0.02) [1768]	0.2 (0.08) [50]	0.554 (0.02) [710]	0.571 (0.07) [49]	0.675 (0.08) [19]	0.974 (0.17) [15]
Biological/agricultural/environmental science	0.158 (0.01) [6224]	0.2 (0.03) [371]	0.303 (0.02) [2954]	0.472 (0.06) [270]	0.735 (0.1) [116]	0.914 (0.03) [2303]
Computer and mathematical sciences	0.411 (0.01) [6733]	0.246 (0.03) [282]	0.53 (0.02) [2184]	0.544 (0.05) [456]	0.788 (0.1) [67]	1.006 (0.09) [70]
Engineering	0.46 (0.01) [16663]	0.234 (0.12) [67]	0.616 (0.01) [7090]	0.67 (0.02) [1592]	0.853 (0.06) [155]	0.876 (0.07) [132]
Physical and related sciences	0.291 (0.02) [3854]	0.208 (0.06) [146]	0.423 (0.02) [2378]	0.503 (0.05) [240]	0.753 (0.09) [78]	0.967 (0.03) [557]
Other S and E-Related Fields	0.348 (0.03) [1791]	0.18 (0.06) [75]	0.413 (0.03) [723]	0.621 (0.07) [129]	0.507 (0.12) [24]	1.038 (0.1) [177]

This table reports estimates of the return (in logs) to various combinations of undergraduate degrees and graduate degrees relative to an undergraduate degree in education with no graduate degree. The table was constructed from a regression that includes the main effects of the undergraduate degree categories with education omitted. It also includes interactions between the undergraduate categories and the aggregated graduate degree categories. The row label specifies the undergraduate field and the column label indicates highest degree. The table also reports the number of observations underlying the main effects of the majors and the interaction terms. We suppress results based on fewer than 20 cases The other control variables include a cubic in age interacted with gender, father's education (6 categories) mother's education (6 categories), gender interacted with race (6 categories), and Hispanic. The data are from The National Survey of College Graduates, 1993 and 2010. The sample consists of persons with at least a BA/BS degree and is restricted to full-time workers between the ages of 24 and 59. The regression is weighted using survey weights. N=144635. R2 = 0.284. Source: AdvDegreeRegs_v3.log

Table 8: Empirical Studies of the Earnings Effects of College Major

Study	Data & Method	Types of controls used	Outcome variable	Majors	Results	
			Regression or Matching Based Studies			
Berger (1988)	NLS; conditional logit and selection correction in the wage equation	Log of years of experience, graduation-1986, and their interaction; IQ score and Knowledge of the World of Work score; US male unemployment rate, race, health status, married, residence in a standard metropolitan statistical area, South, enrolled in school, log of annual weeks worked; selction correction	Log hourly wages for the 1974 male college graduates in 1986 USD, corrected for selection bias		1 year exper	12 years experience
				Business	0.35	0.13
				Engineering	0.41	0.36
				Science	0.12	0.22
				Arts	0.10	-0.07
				Ref Cat: Education		
James et al. (1989)	NLS 72 (men only); WLS	Family background, SAT, high school rank, academic track, math credits, Catholic high school various college-level variables, labor market variables	1985 log annual earnings		Without occupation or industry dummies	With occupation and industry dummies
				Business	0.26	0.15
				Engineering	0.47	0.45
				Math and science	0.20	0.12
				Social science	0.24	0.18
				Humanities	0.06	-0.03
Altonji (1993)	NLS72; OLS	SAT, high school grades, self-assessment of college ability; various education interactions; experience and experience-squared, gender, race, family background; high school curriculum; postgraduate degree	Log of real hourly wage; coefficients on terminal majors presented (not all presented)		Men	Women
				Business	0.18	0.24
				Engineering	0.41	0.28
				Physical Science	0.24	0.07
				Math and Computer Science	0.39	0.23
				Life Science	0.12	0.21
				Social Science	0.10	0.01
				Humanities	0.06	0.00
				Ref Cat: Education		
Rumberger & Thomas (1993)	Survey of recent college graduates (1987); heirarchical linear modeling, OLS	Family background, race, GPA, private college, college selectivity, labor market variables	1987 log annual earnings		Men	Women
				Business	0.18	0.25
				Engineering	0.39	0.51
				Science and Math	0.26	0.30
				Health	0.30	0.44
				Social science	0.08	0.13
				Ref Cat: Education		
Loury & Garman (1995)	NLS72; OLS	College selectivity, years of education, parental income, GPA, SAT, weeks worked, rural dummy	Log weekly earnings, 1979 or 1986		Whites	Blacks
				Business	0.21	0.26
				Engineering and science	0.37	0.55
				Social science	0.09	-0.10
				Humanities	-0.16	0.03
				Ref Cat: Education		
Grogger & Eide (1995)	NLS72, HSB; GLS	Standard tests, high school grade; family income; experience; race; educational attainment (not shown: with occupation controls), full-time workers only	Log hourly wage 1977-1979, 1986		Men	Women
				Business	0.16	0.11
				Engineering	0.28	0.07
				Science	0.06	0.22
				Social science	0.02	0.02
				Ref Cat: Education		
Hamermesh & Donald (2008)	Graduates of University of Texas, Austin, 1980-2000 (selected years); double selection correction (into employment and survey nonresponse)	High-school background, college achievement, demographic, postgrad degree, hours worked, waudratic in propensity scores for working and survey response	Log earnings (selected majors presented only)	Business (hard)	0.49	
				Business (soft)	0.38	
				Engineering	0.32	
				Natural science	0.27	
				Social science	0.28	
				Humanities	0.09	
				Ref Cat: Education		

					Full sample	Men	Women	
Chevalier (2011)	LDLHE (UK) - random sample of one cohort; OLS, quantile regression	Ethnicity, age, disability status, parental social class, fee status, type of school attended and A-level score	Log earnings three years after graduation	Physical Science	-0.10	-0.09	0.16	
				Medicine	0.40	0.58	0.35	
				Biology, veterinary	-0.16	0.05	-0.23	
				Mathematics	-0.04	0.16	-0.11	
				Engineering and tech	0.02	0.20	-0.09	
				Business	-0.08	0.11	-0.14	
				Finance & Accounting	-0.17	0.18	-0.05	
				Economics	-0.04	0.20	-0.21	
				Architecture & Planning	0.04	0.21	-0.04	
				Social Studies	-0.10	0.07	-0.14	
				Law	-0.06	0.20	-0.16	
				Psychology	-0.17	0.03	-0.23	
				Communication	-0.17	-0.05	-0.19	
				Language and Literature	-0.16	0.08	-0.21	
				History and Philosoph	-0.19	-0.06	-0.19	
				Creative Arts	-0.18	-0.01	-0.24	
				Ref Cat: Education				
					Regression		Correction for	
Webber (2014)	NLSY79, NLY97, and American Community Survey, National Survey of College Graduates 1993, 2003. (United States); OLS with controls. OLS with bias corrections for selection on unobservables based on Altonji et al (2005)	See section 4.1: age, black, hispanic, AFQT, mother's education, Rotter scale score, Rosenberg Self-Esteem test		STEM	0.30		0.17	
				Business	0.28		0.17	
				Social Science	0.23		0.15	
				Arts/Humanities	0.16		0.13	
				Ref Cat: High School				
					Full sample	Highest Degree Bachelor's	Highest Degree Bachelor's	
							Men	Women
Del Rossi & Hersch (2008)	NSCG 2003; OLS	Sex, race, whether Hispanic or Latino, whether married or living in a marriage-like relationship, male * married indicator, age, age squared		Business	0.16	0.16	0.15	0.15
				Education	-0.09	-0.12	-0.13	-0.13
				Engineering	0.29	0.28	0.46	0.25
				Science/Math	0.14	0.15	0.16	0.13
				Ref Cat: Arts/Social Science [Single Major]				

Dynamic Discrete Choice Model

					Struct. Model, Unobs. Het	
					Males	Females
Arcidiacono (2004)	NLS72; dynamic discrete choice model	Demographics like gender and SAT scores		Science	0.20	0.20
				Business	0.13	0.24
				Social Sci/Humanities	0.05	0.06
				Education	0.01	0.07
				Ref Cat: High School		
					Struct. Model, Unobs. Het	
Beffy, Fougere and Maurel (2012)	French data; structural model of college major choice	Demographics, including gender, place of birth, parents' citizenship; year of labor market entry (1992 or 1998)		Returns to 4 years of college in:	1992	1998
				Science	0.15	0.27
				Law, Economics and Manageme	0.1	0.23
				Ref Cat: Humanities and Social Sciences		
					OLS	Struct. Model (ATE)
Kinsler and Pavan (2014)	Baccalaureate and Beyond; OLS, structural model of human capital	SAT, GPA, demographics		Business	0.18	0.15
				Science	0.21	0.18
				Ref Cat: Other majors		

Fuzzy Regression Discontinuity Design Using Field Specific Admissions Thresholds

					Less Selective	More Selective	
Hastings, Neilson, and Zimmerman (2014)	Chilean data; 2SLS-fuzzy RD design using instruments based on whether index of grades and test scores exceeds program specific admission thresholds	Gender, socioeconomic status, relative proficiency in math and reading	Business	0.06	-0.03	0.17	
			Art/Architecture	-0.03	0.01	0.00	
			Education	0.00	0.00	0.00	
			Law	0.11	-0.04	0.19	
			Health	0.21	0.10	0.27	
			Sci/Tech	0.08	0.01	0.18	
			Humanities	-0.05	-0.01	0.04	
			Social Sciences	0.12	0.02	0.21	
				Return to Completed Field			
				Levels	Levels	log spec.	log spec
Kirkeboen, Leuven, Mogstad (2015)	Norwegian data; 2SLS-fuzzy RD design using instruments based on whether index of grades and test scores exceeds program specific admission thresholds.	Application score (running variable), gender, cohort and age at application	Humanities	-0.05	-0.35	-0.19	-0.56
			Social Science	0.08	-0.20	-0.08	-0.3
			Health	0.07	-0.11	0.07	-0.19
			Education		-0.11		-0.12
			Science	0.26	-0.03	0.49	0.03
			Engineering	0.42	-0.08	1.28	0.11
			Technology	0.17	0.04	0.27	0.23
			Business	0.22		0.43	
			Law	0.25	-0.01	0.40	0.11
			Medicine	0.37	0.12	0.83	0.4
			Ref Cat. Education, Educ is next best field				

Notes: A few entries in the Table are taken from Altonji et al (2012) Table 2.
Webber (2014). Calculated from rows 1 and 5 of his table 6. Percentage gains converted to log point.
Arcidiacono (2004). Calculated from his Table 7.
Beffy, Fougere and Maurel (2012). Calculated from Table 3.
Chevalier (2011). Estimates are based on his Table 2, column 6 and Table 3. Values renormed so that education is the reference category.
We have excluded some majors that he reports results for.
Kinsler and Pavan (2014). From Table 3, column 3.
Del Rossi and Hersch (2008). From Table 3. Full Sample, controlling for graduate/professional degrees.
HNZ (2014). From Table 5, column 3 and Table 6, columns 2 and 4. Values renormed so that education is the reference category.

KLM (2015). The first two columns are calculated from Table 4 using the average value across preferred fields of 46.15 (75.61)when teaching (business) is the next best alternative. The second two columns (log spec.) are from Table A7, which reports log returns for preferred field/next best alternative pairs based on a log specification.

Table 9: Returns to Undergraduate Degrees using Different Sets of Controls (NLSY79)

Coefficient (Standard Error)

	(1) Demographics	(2) Demographics and Parental Education	(3) Demographics, Parental Education and ASVAB	(4) Demographics, Parental Education, ASVAB and Personality Traits (Rotter and Rosenberg scales)
Engineering	0.284 (0.04)	0.282 (0.04)	0.285 (0.04)	0.316 (0.03)
Computer and Information Sciences	0.274 (0.04)	0.269 (0.04)	0.264 (0.04)	0.264 (0.04)
Military Sciences	0.256 (0.09)	0.253 (0.10)	0.232 (0.10)	0.185 (0.07)
Health Professions	0.232 (0.03)	0.230 (0.03)	0.225 (0.03)	0.221 (0.03)
Business and Management	0.200 (0.02)	0.197 (0.02)	0.193 (0.02)	0.183 (0.02)
Foreign Languages	0.191 (0.08)	0.176 (0.08)	0.173 (0.08)	0.182 (0.07)
Mathematics	0.180 (0.07)	0.178 (0.07)	0.166 (0.07)	0.163 (0.07)
Public Affairs and Services	0.162 (0.04)	0.158 (0.04)	0.157 (0.04)	0.149 (0.04)
Physical Sciences	0.149 (0.07)	0.134 (0.07)	0.134 (0.07)	0.133 (0.06)
Other Fields	0.141 (0.05)	0.147 (0.05)	0.149 (0.05)	0.145 (0.05)
Architecture and Environmental Design	0.128 (0.06)	0.112 (0.06)	0.119 (0.06)	0.114 (0.05)
Social Sciences	0.096 (0.03)	0.083 (0.04)	0.086 (0.03)	0.079 (0.03)
Library Science	0.090 (0.10)	0.075 (0.10)	0.060 (0.11)	0.063 (0.09)
General Studies	0.083 (0.10)	0.067 (0.11)	0.056 (0.11)	0.039 (0.11)
Communications	0.073 (0.04)	0.066 (0.04)	0.072 (0.04)	0.093 (0.04)
Biological Sciences	0.049 (0.05)	0.045 (0.05)	0.036 (0.05)	0.032 (0.05)
Psychology	0.027 (0.05)	0.020 (0.05)	0.018 (0.05)	0.003 (0.05)
Education	Ref	Ref	Ref	Ref
Letters	-0.017 (0.05)	-0.025 (0.05)	-0.029 (0.05)	-0.014 (0.05)
Fine and Applied Arts	-0.017 (0.04)	-0.030 (0.04)	-0.019 (0.04)	-0.002 (0.04)
Agriculture and Natural Resources	-0.063 (0.06)	-0.063 (0.06)	-0.063 (0.06)	-0.083 (0.07)
Home Economics	-0.132 (0.07)	-0.145 (0.07)	-0.137 (0.07)	-0.095 (0.07)
Area Studies	-0.145 (0.14)	-0.182 (0.14)	-0.191 (0.14)	-0.177 (0.14)
Theology	-0.231 (0.08)	-0.244 (0.08)	-0.226 (0.08)	-0.199 (0.08)

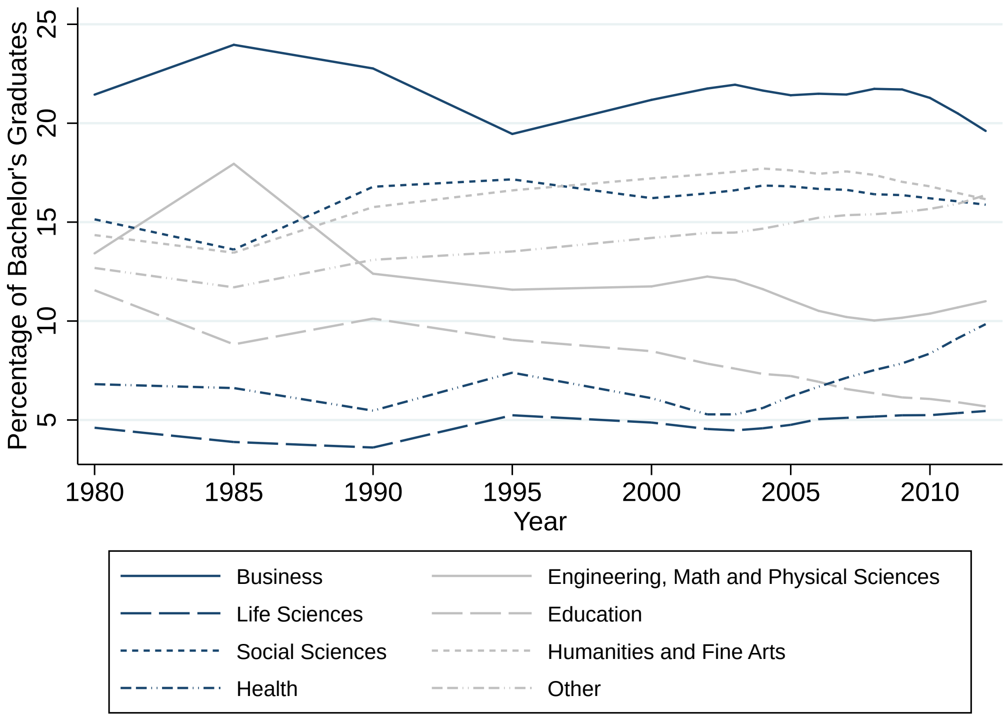
This table reports estimates of the return (in logs) to various undergraduate degrees relative to a Bachelor's in Education. The table was constructed from a regression that includes the undergraduate degree categories, and two dummy variables for high school only and some college education only. The other control variables include (1) a quadratic in age, gender, race, and Hispanic, (2) father's and mother's highest grade completed, (3) Six components of the ASVAB test (Arithmetic Reasoning, Numerical Operation, Coding Speed, Mathematics Knowledge, Paragraph Comprehension, and Word Knowledge), and (4) Rosenberg Self-Esteem and Rotter Locus of Control Scales . The data are from the National Longitudinal Survey of Youth 1979. The sample is constructed by pooling across survey waves (1981 to 2012) the observations of persons with at least a high school degree, who are 24 years old or older and work 30 hours or more per week. N=55724 observations (9117 individuals). Standard errors are clustered at the individual level.

Appendix Table 1: The Distribution of Male and Female College Graduates by Field of Degree			
	All	Male	Female
	(1)	(2)	(3)
Education	0.106	0.053	0.151
English/Languages/Literature	0.039	0.025	0.051
Fine/Performing Arts	0.044	0.039	0.048
Other Humanities	0.054	0.055	0.053
Communications/Journalism	0.045	0.035	0.053
Accounting	0.047	0.051	0.043
Business	0.138	0.165	0.114
Marketing	0.030	0.032	0.029
Other Non-S and E Fields	0.021	0.025	0.019
Economics	0.022	0.032	0.013
Political science	0.034	0.041	0.029
Psychology or Social Work	0.065	0.037	0.089
Other Social and related sciences	0.057	0.042	0.070
Nursing	0.029	0.005	0.049
Biological/agricultural/environmental science	0.068	0.073	0.064
Computer and mathematical sciences	0.048	0.071	0.029
Engineering	0.073	0.132	0.023
Physical and related sciences	0.023	0.034	0.014
Other S and E-Related Fields	0.056	0.054	0.058
Total	1	1	1
N	59273	31743	27530

Source: AdvDegreeStats_v3.do. Data: National Survey of College Graduates 2010. The sample includes individuals aged 24 to 59. Estimates are weighted using sample weights.

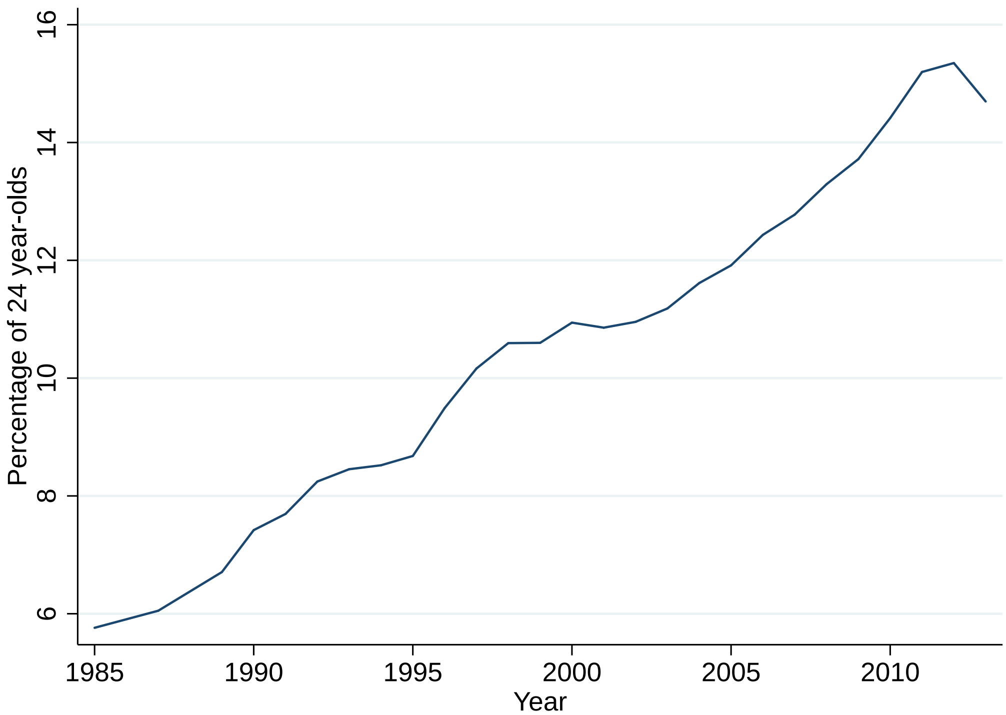
8 Figures

Figure 1: Percentage of Bachelor's degrees in each field



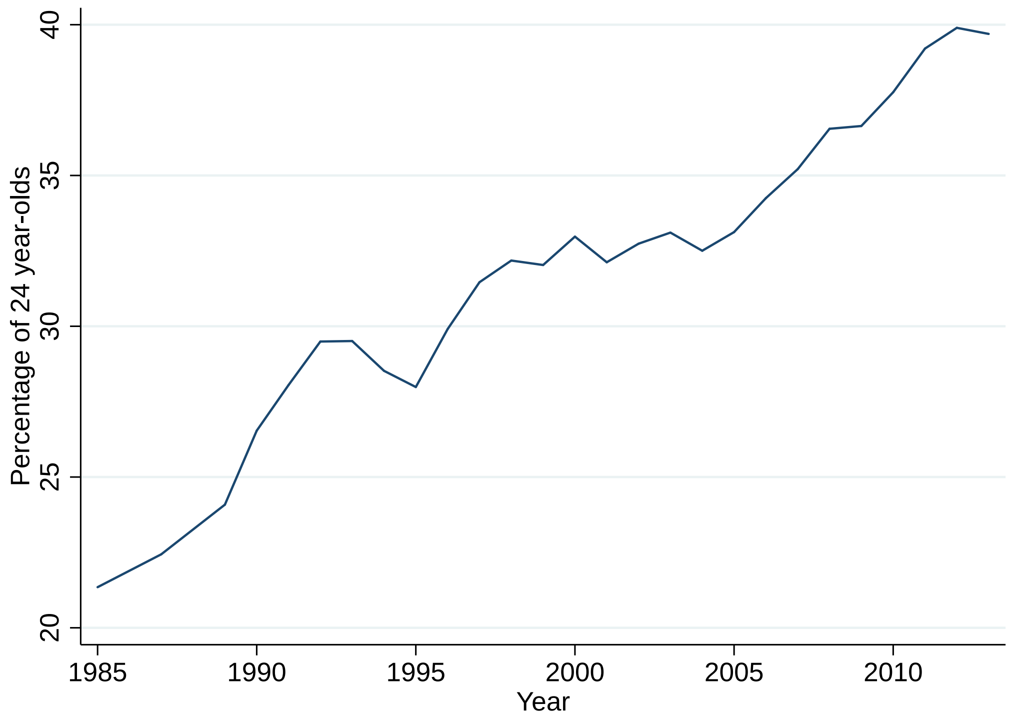
Source: U.S. Dept. of Education (NCES), Higher Education General Information Survey (HEGIS), 1980-81 through 1985-86; Integrated Postsecondary Education Data System (IPEDS), 1990-91 to 2012-13.

Figure 2: Share of Master's graduates



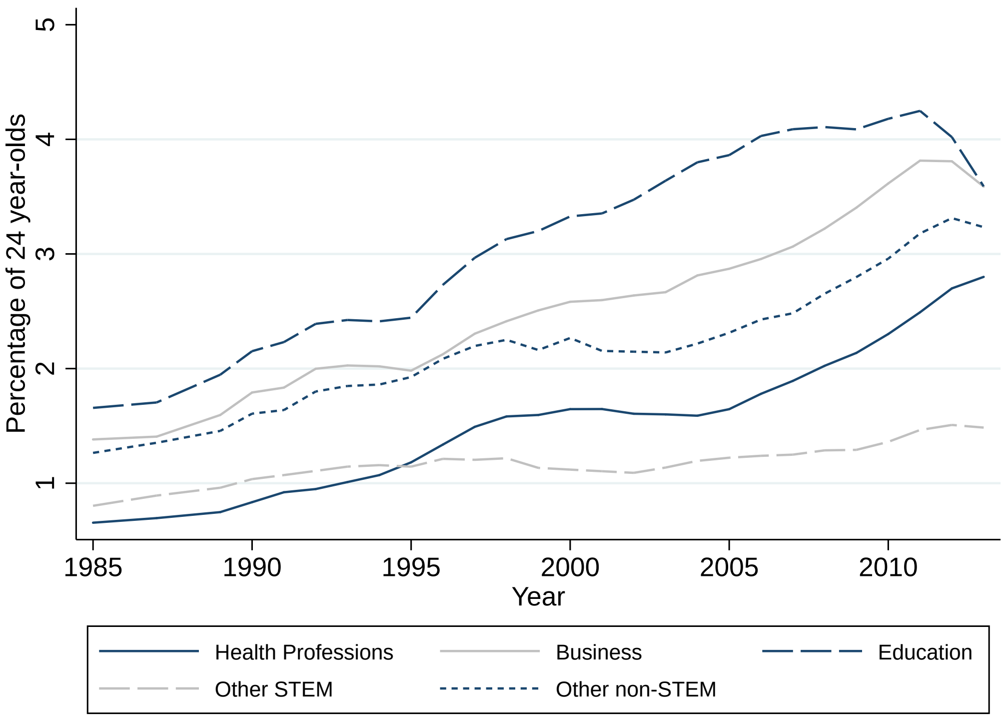
Source, Master's graduates: U.S. Dept. of Education (NCES), Higher Education General Information Survey (HEGIS), 1985-86; Integrated Postsecondary Education Data System (IPEDS), 1990-91 to 2012-13.
Source, population: U.S. Census Bureau, Population Division; Quarterly U.S. Population Estimates by Age, Sex, Race, and Hispanic Origin (1980-1989); Monthly Intercensal Estimates of the U.S. Population by Age and Sex (1990-2000); Intercensal Estimates of the Resident Population by Single Year of Age, Sex, Race, and Hispanic Origin for the U.S. (2000-2010); Annual Estimates of the Resident Population by Single Year of Age and Sex for the U.S. (2011-2013).

Figure 3: Share of Bachelor's graduates



Source, Bachelor's graduates: U.S. Dept. of Education (NCES), Higher Education General Information Survey (HEGIS), 1985-86; Integrated Postsecondary Education Data System (IPEDS), 1990-91 to 2012-13. Source, population: U.S. Census Bureau, Population Division; Quarterly U.S. Population Estimates by Age, Sex, Race, and Hispanic Origin (1980-1989); Monthly Intercensal Estimates of the U.S. Population by Age and Sex (1990-2000); Intercensal Estimates of the Resident Population by Single Year of Age, Sex, Race, and Hispanic Origin for the U.S. (2000-2010); Annual Estimates of the Resident Population by Single Year of Age and Sex for the U.S. (2011-2013).

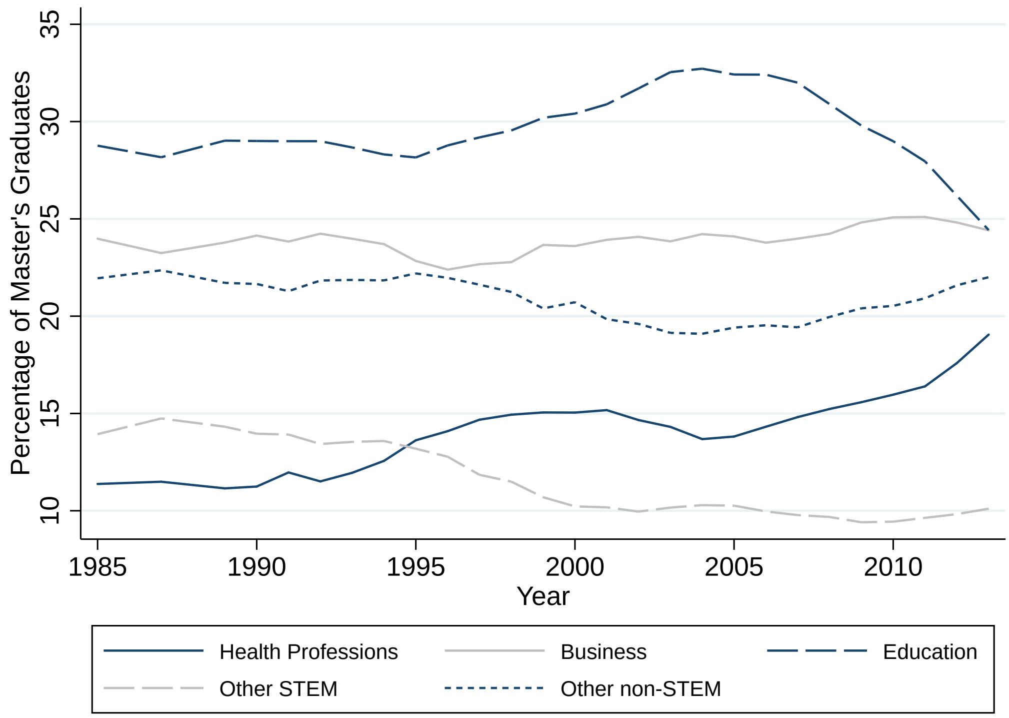
Figure 4: Share of Master's graduates broken down by field



Source, field of study: U.S. Dept. of Education (NCES), Higher Education General Information Survey (HEGIS), 1985-86; Integrated Postsecondary Education Data System (IPEDS), 1990-91 to 2012-13.

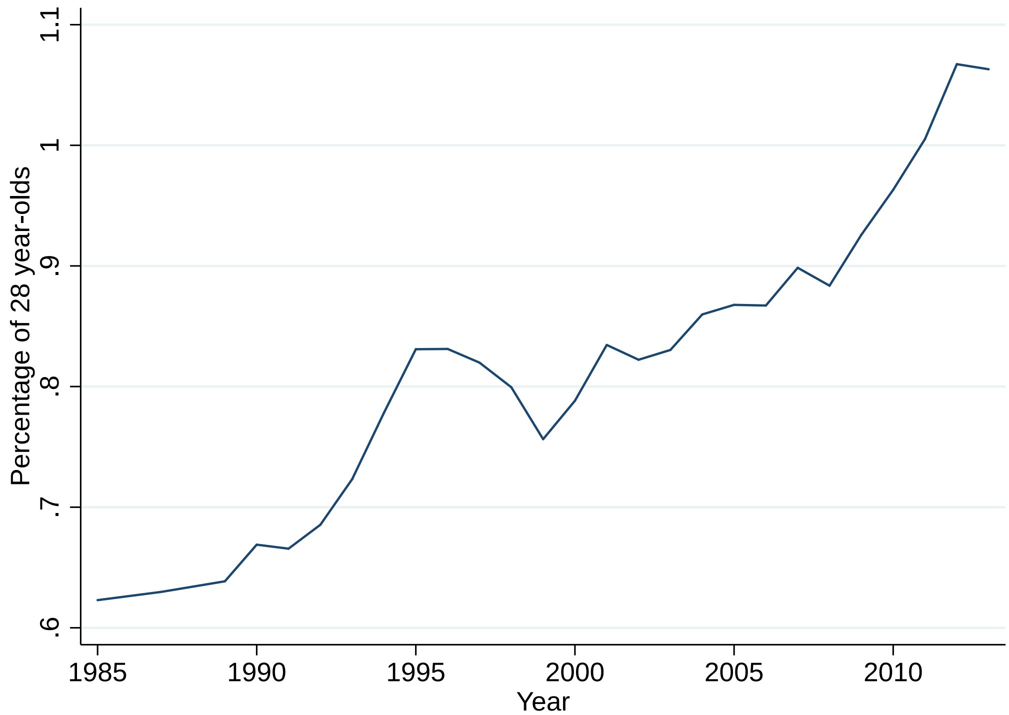
Source, population: U.S. Census Bureau, Population Division; Quarterly U.S. Population Estimates by Age, Sex, Race, and Hispanic Origin (1980-1989); Monthly Intercensal Estimates of the U.S. Population by Age and Sex (1990-2000); Intercensal Estimates of the Resident Population by Single Year of Age, Sex, Race, and Hispanic Origin for the U.S. (2000-2010); Annual Estimates of the Resident Population by Single Year of Age and Sex for the U.S. (2011-2013).

Figure 5: Percentage of Master's degrees in each field



Source, field of study: U.S. Dept. of Education (NCES), Higher Education General Information Survey (HEGIS), 1985-86; Integrated Postsecondary Education Data System (IPEDS), 1990-91 to 2012-13.

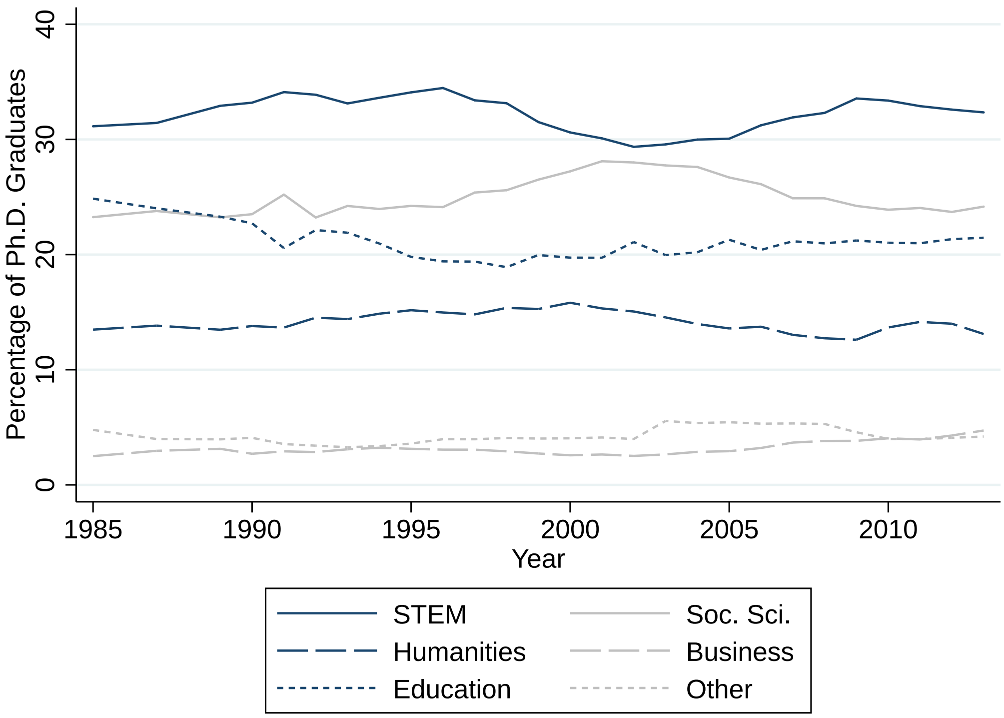
Figure 6: Share of Ph.D. graduates



Source, field of study: U.S. Dept. of Education (NCES), Higher Education General Information Survey (HEGIS), 1985-86; Integrated Postsecondary Education Data System (IPEDS), 1990-91 to 2012-13.

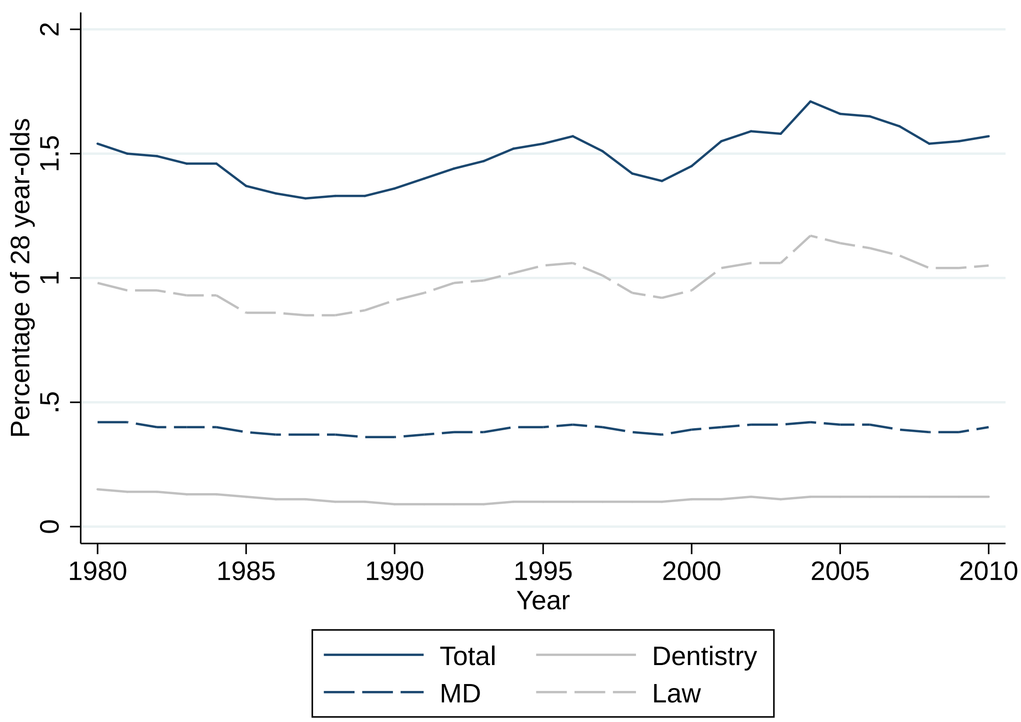
Source, population: U.S. Census Bureau, Population Division; Quarterly U.S. Population Estimates by Age, Sex, Race, and Hispanic Origin (1980-1989); Monthly Intercensal Estimates of the U.S. Population by Age and Sex (1990-2000); Intercensal Estimates of the Resident Population by Single Year of Age, Sex, Race, and Hispanic Origin for the U.S. (2000-2010); Annual Estimates of the Resident Population by Single Year of Age and Sex for the U.S. (2011-2013).

Figure 7: Percentage of Ph.D. degrees in each field



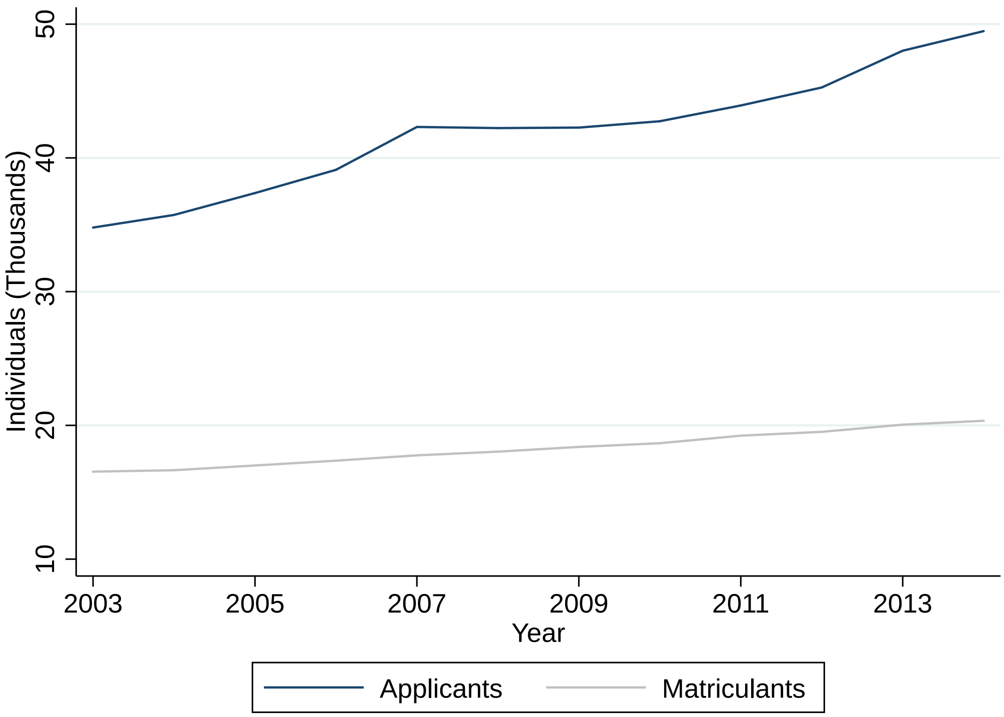
Source: U.S. Dept. of Education (NCES), Higher Education General Information Survey (HEGIS), 1985-86; Integrated Postsecondary Education Data System (IPEDS), 1990-91 to 2012-13.

Figure 8: Share of individuals graduating with a MD, JD or Dental degree



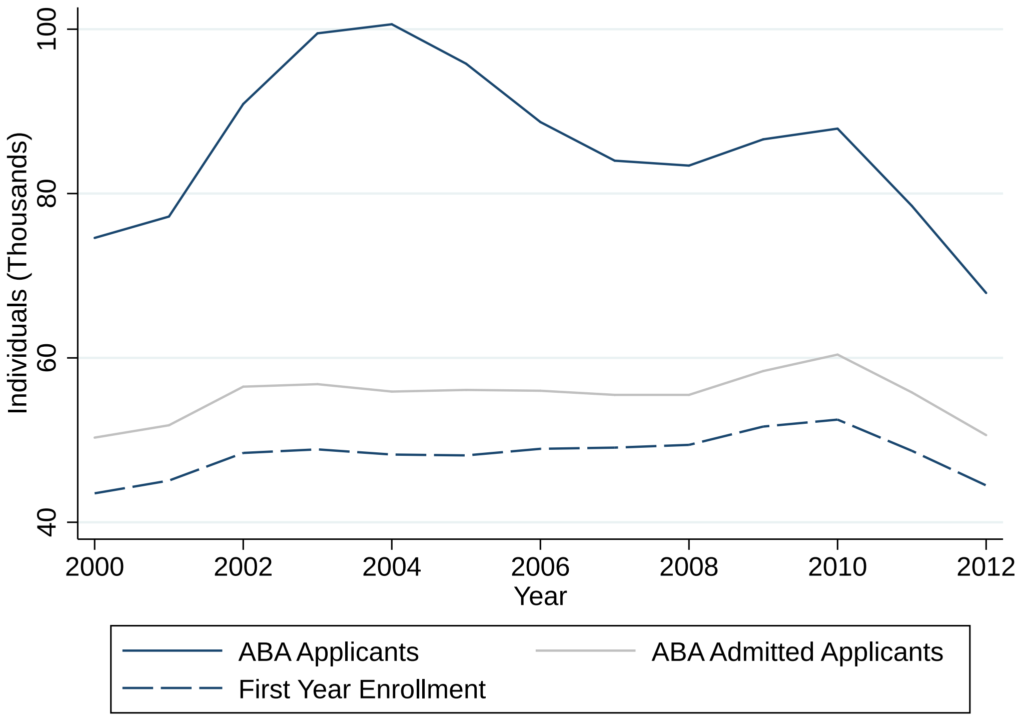
Source: U.S. Dept. of Education (NCES), Higher Education General Information Survey (HEGIS) Degrees and Other Formal Awards Conferred surveys (1980-1985), Integrated Postsecondary Education Data System (IPEDS) Completions Survey (1987-1999), IPEDS Completions component (2000-2010).

Figure 9: MD degrees: Number of applicants and matriculants



Source: Association of American Medical Colleges

Figure 10: JD degrees: Number of applicants, admitted applicants and first-year enrollments



Source, applicants: Law School Admission Council, National Decision Profiles (2015)

Source, enrollment: American Bar Association, Section of Legal Education and Admission to the Bar