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Working Paper 16-067

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Evidence on Elite STEM Talent

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November, 2016

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This paper was previously circulated under the title: "Are the 'Best and Brightest' Going into Finance? Skill Development and Career Choice of MIT Graduates." I have benefited from the helpful comments and suggestions of Daron Acemoglu, David Autor, David Dorn, JB Doyle, Shane Greenstein, Robin Greenwood, Gordon Hanson, Victoria Ivashina, Ben Jones, Steven Kaplan, Lawrence Katz, Josh Lerner, John S. Reed, Antoinette Schoar, Erin Scott, Paula Stephan, Scott Stern, Jialan Wang, Heidi Williams, and seminar participants at numerous universities and conferences. I am grateful to Suzanne Berger, Maggy Bruzelius, Claude Canizares, Daniel Hastings, Ke-wei Huang, Elizabeth Hicks, Deborah Liverman, Brendon Puffer, Joseph Recchio, Ri Romano, Stuart Schmill, Lydia Snover, Ingrid Vargas, and especially Gregory Harris for help with data collection. Kristiana Laugen, Eamon O'Brien, Rohan Thavarajah, and Yue Wang provided excellent research assistance. This project was supported by the Kauffman Foundation and the Division of Research at Harvard Business School. All errors are my own.

Abstract

Using data on MIT bachelor's graduates from 1994 to 2012, this paper empirically examines the extent to which the inflow of elite talent into the financial industry affects the supply of innovators in science and engineering (S&E). I first show that finance does not systematically attract those who are best prepared at college graduation to innovate in S&E sectors. Among graduates who majored in S&E, cumulative GPA strongly and positively predicts long-term patenting; this result is robust to controlling for choices of major and career. In contrast, GPA negatively predicts the probability of taking a first job in finance after college. There is suggestive evidence that S&E and finance value different sets of skills: innovating in S&E calls for in-depth knowledge and/or interest in a specific subject area, whereas finance tends to value a combination of general analytic skills and social skills over academic specialization. I then provide evidence that anticipated career incentives influence students' acquisition of S&E human capital during college. The 2008–09 financial crisis, which substantially reduced the availability of jobs in finance and led to a worsening labor market in general, prompted some students to major in S&E instead of management or economics and/or to improve their academic performance. This response to the shock is driven by students with below-average academic credentials who were freshmen at the peak of the crisis.

1 Introduction

Finance is among the most popular career destinations for top U.S. college graduates. At elite universities like Massachusetts Institute of Technology (MIT), Harvard, Yale, and Princeton, finance consistently attracted between 20 and 30 percent of graduating seniors who entered the labor market prior to the recent financial crisis (Hastings et al., 2010; Rampell, 2011).[1] The inflow of top talent into finance may not be optimal for long-term economic growth if talented individuals are forgoing alternative career paths that offer lower private returns but produce higher social returns (Baumol, 1990; Murphy et al., 1991). The high relative wage in finance among top talent is well documented in the literature,[2] but the social returns of jobs in finance remain debatable and may not justify the private returns.[3]

In contrast, there is a longstanding consensus that scientific and technological innovations generate large and positive externalities (Nelson, 1959; Arrow, 1962; Jones, 2005; Bloom et al., 2013), and that a nation's supply of scientists and engineers is critical to its innovation and growth (Atkinson, 1990; Murphy et al., 1991; Stephan, 1996; Goolsbee, 1998; Romer, 2000). The degree to which finance may divert talent from innovating in science and engineering (S&E) thus has key implications for productivity. The possibility of such a substitution has been a worry widely shared in the popular press by prominent economists

[1]This calculation excludes graduating seniors who entered graduate school immediately after college.

[2]Oyer (2008) and Goldin and Katz (2008) find that, among Stanford MBA graduates and Harvard bachelor's graduates, those who work in finance earn substantially more than the rest. Kaplan and Rauh (2010) show that in 2004 the top 25 hedge-fund managers jointly earned more than all the CEOs of Standard & Poor's 500 companies combined. Philippon and Reshef (2012) find that the wage gap between financiers and engineers, conditional on earning a post-graduate degree, grew from less than 5 percent to over 30 percent between 1980 and the early 2000s. Bell and Van Reenen (2014) show that finance accounted for the majority of the increase in the top 1-percent earners' share of the UK wage bill since 1999.

[3]The theoretical literature treats moral hazard as an inherent feature of the financial sector, since the job content is complex and effort is difficult to monitor. Myerson (2012), Axelson and Bond (2015), and Biais and Landier (2015) use overlapping generation models to investigate how moral hazard in finance affects compensation structure, credit cycle, job assignment, and skill acquisition. Biais et al. (2015) and Bolton et al. (2016) argue that the equilibrium size of the financial sector could be larger than optimal due to excess entry of managers or dealers who extract informational rents.

and policymakers (e.g., Romer 2009; Shiller 2013; Mullainathan 2015; Obama 2016) and has motivated research on optimal taxation policy (Philippon, 2010; Lockwood et al., 2016). In 2009 the then-chair of the Council of Economic Advisers, Christina Romer, cautioned in a policy speech that "some of our brightest minds make small fortunes arranging the deals, rather than pursuing potentially more socially valuable careers in such fields as science, medicine, and education." President Barack Obama echoes this sentiment in an October 2016 essay published in The Economist, pointing out that "[t]oo many potential physicists and engineers spend their careers shifting money around in the financial sector, instead of applying their talents to innovating in the real economy."

This paper empirically examines the extent to which the inflow of top talent into finance influences the supply of innovators in S&E. I focus on elite college graduates instead of the general population because they are disproportionately innovative.[4] Conceptually, such influence could occur via two possible channels. First, finance may directly reward skills that are critical for innovating in S&E.[5] A basic Roy model would predict that, if the returns to innovation skills are higher in finance than in S&E sectors, the most innovative individuals would self-select into finance. This scenario would be particularly detrimental to the production of innovations in S&E, since star scientists and engineers generate a disproportionately large fraction of knowledge production and spillovers (Cole and Cole, 1972; Azoulay et al., 2010; Waldinger, 2010; Oettl, 2012). Alternatively, to the extent that finance values those skills less and that skill development is endogenous, the lure of finance could reduce talented students' incentives to develop the skills that are valuable for innovating in S&E.

I use detailed data on MIT bachelor's graduates to investigate the intensity of each

[4]Bell et al. (2016) find that graduates of the ten most inventive U.S. colleges (defined as those whose 1999–2012 graduates were awarded the most U.S. patents between 1996 and 2014) account for only 3.7% of U.S. college enrollments but 15% of citation-weighted patents. They are more than twice as likely to become inventors by age 30 as graduates of the ten next-most inventive colleges and 28 times as likely to do so as the average U.S. resident.

[5]Philippon and Reshef (2012) and Kirilenko and Lo (2013) document the growing complexity of tasks in finance and the recent rise of algorithm trading, indicating the increasing value of analytical and quantitative skills in finance.

channel. Although my sample is highly selective, it is particularly suitable for my research question since MIT graduates represent some of the best S&E talent and have made substantial contributions to national and local economies via innovation and entrepreneurship (Roberts and Eesley, 2009; Roberts et al., 2015).[6] I begin by showing that, at MIT, finance does *not* systematically attract those who are best prepared at college graduation to innovate in S&E sectors. I find that the college grade-point average (GPA) of S&E majors positively and significantly predicts post-college inventive output but negatively predicts the probability of entering finance. Among S&E majors in the classes of 1994–2008, and controlling for cohort, major, and demographics, a one-standard-deviation increase in GPA is on average associated with 28-percent, 40-percent, and 33-percent increases in, respectively, the probability of becoming an inventor after college, the number of patents produced after college, and the number of citations received for those patents. These relationships are robust to controlling for selection into careers and graduate programs. In contrast, among S&E majors in the classes of 2006–2008, a one-standard-deviation increase in college GPA is associated with a 44-percent (or 3.9-percentage-point) *decrease* in the probability of entering finance after graduation.[7] There is negative selection into both quantitative jobs (such as trading and quantitative analysis) and non-quantitative jobs (such as investment banking). College GPA positively and significantly predicts the probability of entering S&E sectors, which is driven by selection into S&E graduate programs.

The positive link between college academic performance and post-college inventive output is consistent with the observation that the production of innovations is highly cumulative and typically requires specialized knowledge and expertise (Jones, 2009, 2010).[8] I further

[6]Roberts et al. (2015) estimate that companies founded by MIT alumni generate annual global revenues of $1.9 trillion and employ 4.6 million individuals worldwide.

[7]Around 8.8 percent of S&E majors from the classes of 2006–2008 entered finance immediately after graduation.

[8]That knowledge generates more new knowledge is a central observation of macroeconomic theory on endogenous growth (Romer, 1990; Grossman and Helpman, 1991; Aghion and Howitt, 1992; Jones, 1995). Furman and Stern (2011), Williams (2013), and Galasso and Schankerman (2015) provide empirical evidence that institutional forces that help transfer or protect knowledge, such as biological resource centers and intellectual-property protection, can have significant positive

find that, across grades in each year of college, grades in senior year—when students take the most advanced courses in their field—have the strongest and most significant correlation with future patenting.

By contrast to those who specialize academically, finance attracts individuals who pursue diverse activities in college, and differences in skill development between the two groups are already evident at college entry. Compared to those who pursue S&E graduate degrees or take a first job in S&E industries at college graduation, those who enter finance earn significantly lower grades in each year of college— the difference is largest in senior year—and take fewer courses during their first two years. They are also more likely to join a Greek society or a varsity sports team, both time-consuming activities that students typically decide to pursue on arrival at MIT.[9] Graduates' self-reported assessments of skill improvement between college entry and college graduation reveal that those who enter finance report significantly less improvement in an array of critical-thinking and scientific-reasoning skills, especially in their ability to acquire in-depth knowledge of a field.

The results thus far indicate that, for elite talent, the returns to academic specialization in S&E subject areas are lower in finance than in S&E sectors, which could be driven by both skill demand in finance and top students' tastes for working in S&E.[10] To the extent that finance may reward specialized S&E human capital less, it is possible that the prospect of a career in finance could discourage talented students from majoring in S&E and/or investing in coursework during college. The 2008–09 financial crisis, which drastically reduced job prospects in finance and led to the Great Recession, provides an opportunity to examine whether MIT students' skill-development paths are sensitive to sudden changes in anticipated career incentives. I find that members of the class of 2012, who were freshmen at the peak

effects (in the case of transferring) or negative effects (in the case of protection) on follow-on innovations.

[9] Rush at MIT takes place in the fall of freshman year.

[10] Stern (2004) finds that postdoctoral biologists are willing to forgo better compensation for opportunities to perform independent research. See also Roach and Sauermann (2010) and Agarwal and Ohyama (2012) for evidence on the sorting of S&E doctoral candidates into academia versus industry.

of the crisis, are more likely to major in S&E and less likely to major in management or economics than the preceding cohorts. However, those whose choices of major are sensitive to the shock—between 3 and 4 percent of the cohort—have below-average academic credentials at college entry. Conditional on majoring in S&E, the class of 2012 also earned better grades on average, a phenomenon that is primarily driven by a large improvement in grades at the bottom of the grade distribution. There is no evidence that the crisis affected the choices of major or academic performance of the 2010 and 2011 cohorts, who were juniors and sophomores at the peak of the crisis.[11]

In the last part of the empirical analysis, I show that my findings about self-selection extend to other samples of top S&E talent. In particular, I hand-collect data on the career paths of 462 graduates from 82 universities using publicly available lists of top performers on the William Lowell Putnam Mathematical Competition. Within this sample of talented math students, I find that outcomes for MIT students do not differ significantly from outcomes for other students. I also find that the competition winners are significantly less likely to work in finance and more likely to work in academia or research-focused positions.

My findings suggest that, without taking into account both the investment in human capital required to innovate and the skill-development choices of elite talent, discussions of talent allocation may overstate the extent to which finance diverts the most skilled S&E graduates away from innovating in S&E. To the extent that such diversions exist, they are more likely to occur at college entry than at college graduation.

This study contributes to the literature on the labor supply of engineers and scientists. In contrast to the large body of evidence on individuals' decisions to pursue a bachelor's degree in S&E (e.g., Freeman, 1975a,b; Ryoo and Rosen, 2004; Stinebrickner and Stinebrickner, 2014; Arcidiacono et al., 2016), relatively little is known about the career choices of S&E degree-earners. This paper provides new evidence on this topic. Recent work uses population

[11]These results are consistent with Wiswall and Zafar (2014), who find that choices of major made by students at an earlier stage of college are more responsive to changes in future earnings, and that those with higher abilities have stronger preferences.

data to study selection into finance (Philippon and Reshef, 2012; Celerier and Vallee, 2015; Bohm et al., 2015) and characteristics of inventors (Aghion et al., 2016; Bell et al., 2016). This study relates to both literatures but with a distinct focus on top talent.

Section 2 of this paper describes the data. Section 3 presents the main results on the relationships among academic achievement, future patenting, and selection into initial careers. Section 4 provides additional evidence using more detailed data on skill development during college. Section 5 analyzes changes in students' skill development after the financial crisis. Section 6 examines the career paths of the top performers on the Putnam Competition. Section 7 concludes.

2 Data and Descriptive Statistics

I collect administrative and survey data from MIT about bachelor's graduates between 1994 and 2012 and observe such demographics as gender, birth year, ethnicity/nationality, high-school location, and financial aid received during senior year. I also observe major(s) at graduation and cumulative GPA in college. I exclude transfer students[12] from my analysis and use a graduate's class year, as self-reported to the Alumni Association, to determine his or her cohort.[13]

2.1 Long-term inventive output

I match MIT graduates to patent-inventor records in the U.S. Patent and Inventor Database, which includes all USPTO patents granted between 1976 and March 2013.[14] Appendix A.1 discusses the specifics and robustness of my matching procedure, which uses the graduates' names, locations, and employers (when available) and a Bayesian matching

[12]Transfer students make up around 2.7% of the classes of 1994–2012.

[13]The self-reported cohort is typically based on the year of college entry and occasionally differs from the graduation-year cohort.

[14]The data can be downloaded at https://github.com/funginstitute/downloads. See Li et al. (2014) for a data description.

algorithm similar to the methodology developed by Torvik et al. (2005) and Smalheiser and Torvik (2009). For each graduate, I construct three variables: whether the graduate becomes an inventor (defined as having been granted at least one utility patent since college graduation), how many utility patents he or she has been granted since graduation, and how many citations he or she has received for those patents.[15]

Table 1 reports the average inventive output of the classes of 1994–2008. Given patent applications' long processing time—close to three years, on average (Lerner and Seru, 2015)—I exclude the younger cohorts since they have had little time to be granted patents.[16] Among graduates in the classes of 1994–2008, those who majored in S&E (87.5% of all majors) are much more inventive than those who did not major in S&E.: around 13.4% of the S&E majors but only 3% of the non-S&E majors become inventors. An average S&E major from the classes of 1994–2008 has been granted 0.57 patents and received 2.23 citations between college graduation and March 2013. The average inventor who majored in S&E has been granted 4.24 patents and received 16.7 citations.

Bell et al. (2016) find that 5.6% of graduates of the ten most inventive U.S. colleges (defined as those whose 1999–2012 graduates were awarded the most U.S. patents between 1996 and 2014) have been awarded a patent by age 30. I find comparable but slightly higher rates among MIT graduates: 7.2% of S&E majors in the classes of 1994–2008 (and 6.5% of all majors) have a patent by age 30.

2.2 Selection into sectors

For the classes of 2006 to 2008, I identify the sector that a graduate enters immediately after college using the Graduating Student Surveys, which are administered to students in the spring of senior year by Career Services.[17] By using the cohorts that graduated in 2008

[15] I exclude patents applied for before college graduation, which are extremely rare.

[16] Only nine individuals in the classes of 2009–2012 had been granted a patent by March 2013.

[17] MIT grants degrees in February, June, and September; only June graduates, who represent the vast majority, are sent Graduating Student Surveys. Individual-level data with identifiers that can be linked to other administrative data are not available for the earlier cohorts.

and earlier, I study selection into finance before the financial crisis, when the sector was at its largest. Using the self-reported initial career outcome (intended graduate degree or future employer), I construct four indicators of initial sectors: (1) S&E graduate programs; (2) S&E industries (e.g., software, manufacturing, life sciences, and energy); (3) finance; and (4) other.[18] I consider a graduate to enter an S&E sector if he or she pursues graduate study in science or engineering or employment in an S&E industry. Given that non-S&E majors are unlikely to be inventive in S&E sectors, I focus on examining the initial career choices of S&E majors. Nearly 70 percent of 2006–2008 graduates who took a first job in finance had majored in S&E.[19]

A complicating factor when studying initial career outcomes is that some graduates may pursue their initial choice only briefly before changing sectors, such as earning a master's degree in S&E and then entering finance. To identify graduates' long-term sectors, I find their LinkedIn profiles using their names and MIT degrees, and then identify the sector listed as current on their LinkedIn profiles as of August 2014 (at least six years after graduation for the classes of 2006–2008).[20] For 676 S&E graduates in the classes of 2006–2008, I observe both the initial sector listed on the Graduating Student Surveys and the long-term sector listed on LinkedIn. Figure A.1 plots the distribution of long-term sector by initial sector and shows that transitions between finance and S&E sectors are uncommon. Nearly 90 percent of graduates who started out in S&E—either by pursuing a graduate degree in S&E or by working for an employer in an S&E industry—remained in S&E as of August 2014; under 5 percent switched to finance over the long term. The majority of graduates (61 percent) who started out in finance stayed in finance long-term.

[18]Assignment of an employer to an industry is performed manually via online search. In cases of missing information on an employer, I use the industry self-reported in the survey. Examples of "other" outcomes include entering a non-S&E graduate program, entering a non-S&E industry other than finance such as consulting, law, or architecture, and pursuing an activity other than employment or graduate school (e.g., a fellowship, travel, the military, and volunteer work).

[19]Excluded from the analysis are economics and management majors who do not pursue a second major in engineering or science. Although they have a high probability of entering finance, they are few in number and are thus a minority among graduates who took a first job in finance.

[20]For other studies that use LinkedIn data to study career trajectories, see Ge et al. (2016).

Table 2 reports mean characteristics of S&E majors by initial sector. I observe the initial sectors of 55% of S&E majors in the classes of 2006–2008.[21] Compared to all S&E majors, the sample of S&E majors whose initial sector I observe consists of more female graduates, more Caucasian and Asian American graduates, fewer Hispanic and African American graduates, and fewer non-American graduates. Oversampling of particular genders or ethnicities could bias my results on selection into finance if selection differs substantially by these characteristics. I investigate this possibility in supplementary analysis in the Appendix.

Of S&E majors whose initial post-graduation sectors are observed, 46.4 percent pursued graduate degrees in S&E and 19 percent pursued jobs in S&E. Around 9 percent took a first job in finance, making finance the most popular industry among S&E graduates entering the labor market.[22] Compared to those pursuing graduate degrees or jobs in S&E, those entering finance are on average much less likely to be female or Caucasian American and more likely to be Asian American or non-American; they also received less financial aid at MIT, on average, and are more likely to be engineering majors than science majors.

Figure 1 shows the distribution of S&E majors and the proportion of graduates in each major who entered finance right after college graduation. The propensity to enter finance ranges widely, from 24.5 percent for mathematics majors to 0 percent for earth sciences majors. Overall, the propensity to enter finance is higher among engineering and mathematics majors than other science majors; nearly 11.1 percent of engineering and mathematics majors took a first job in finance. In contrast, only 1.2 percent of other S&E majors (i.e., physics, life sciences, chemistry, and earth sciences) did so. Jointly, engineering and mathematics majors account for nearly 97 percent of S&E graduates who took a first job in finance.[23]

[21]This response rate is higher than those of Oyer (2008) and Goldin and Katz (2008), which report response rates of around 40% to surveys on the career outcomes of Stanford MBA graduates and Harvard bachelor's graduates respectively.

[22]Finance is 50 percent more popular than the most popular S&E industry, Computer/IT, which attracted 5.8 percent of S&E graduates.

[23]Using LinkedIn profiles, I find that the proportion of graduates in each major who work in finance several years after graduation exhibits largely consistent patterns: the propensity to remain in finance over the long term is relatively high for engineering and mathematics majors and low for science majors in fields other than mathematics and physics. Physics majors have a low propensity

2.3 Skill development in college

I collect several measures of academic and non-academic skills in addition to cumulative GPA. I use these variables to study how academic skill development in college relates to subsequent patenting and how students with different initial career outcomes differ in their skill development during college. For all classes in my sample, I observe the number of course units passed in each term and GPA in most terms.[24] To capture academic qualifications at college entry, I use an index score constructed by MIT's Admissions Office and available for the classes of 2006 and later. The admission index score consists of a weighted average of objective measures of academic achievement in high school, including standardized test scores, high-school grades, and the difficulty of high-school courses. Figure A.2 in the Appendix shows that admission index score and cumulative GPA are strongly and positively correlated. (The correlation between the two variables for the classes of 2006–2012 is 0.43.) For the classes of 2006 and 2008, I also collect student responses to Senior Surveys inquiring about participation in extracurricular activities during college and self-reported improvement in an array of critical-thinking and scientific-reasoning skills.[25]

I use the classes of 2006 to 2012 to examine the impact of the 2008–09 financial crisis on students' academic skill development. For these cohorts, I also obtain a student's first declared major to capture his or her early academic interest. Around 90 percent of students in the classes of 2006–2012 first declared a major in the fall semester of sophomore year. Conditional on declaring a first major in S&E, around 14 percent of students did not graduate in the major they had first declared, but only 3 percent switched to non-S&E majors.[26]

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to take a first job in finance (1.4 percent overall) but a fairly high propensity to work in finance over the long term (9.5 percent overall).

[24]For the classes of 2005 and earlier, I do not observe GPA in the first year; in that era, students only received a pass or no record during the first year. For the classes of 2006 and later, I do not observe GPA in the first term.

[25]Senior Surveys are administered every other year, and thus were not distributed to the class of 2007. The response rate in my sample is around 61%.

[26]The propensity to switch majors in my sample is similar to what Zafar (2011) finds using survey data on Northwestern University undergraduates; around 12% of the students in his sample changed majors between the fall of sophomore year and the fall of junior year.

3 College GPA, Post-College Patenting, and Selection into Careers

This section examines whether the most highly skilled S&E majors at college graduation are self-selecting into finance. Figure 2 illustrates how college GPA, post-college patenting, and probability of entering finance relate to each other. Among S&E majors in the classes of 1994–2008, the average number of patents produced after college increases sharply with GPA quartile. In contrast, the probability of entering finance declines sharply with GPA quartile among S&E majors in the classes of 2006–2008. Moreover, graduates in the top GPA quartile of S&E majors are especially inventive, producing 2.7 times as many patents as those in the bottom GPA quartile, and they are also disproportionately less likely to enter finance. Figure A.3 in the Appendix shows that these patterns also hold within the sample of mathematics and engineering majors, who among S&E majors have the highest tendencies to enter finance.

3.1 GPA and future patenting

To formally study the correlation between academic performance in college and post-college patenting, I estimate the following regression specification:

$$InventiveOutput_i = G\left(\alpha + \beta GPA_i + \gamma D_i^{Cohort} + \theta D_i^{Major} + \delta \chi_i + \epsilon_i\right) \tag{3.1}$$

where the dependent variable is whether individual i becomes an inventor after college, the number of patents that individual i produced since college graduation, or the number of citations that individual i received for those patents; GPA_i is cumulative GPA in college standardized among the S&E majors in each cohort; D_i^{Cohort} is the full set of cohort dummies; D_i^{Major} is the full set of major dummies, including an indicator for graduating with more than one major; and χ_i is the set of demographic controls for gender, age, ethnicity, high-school region, and financial aid. For probability of becoming an inventor, I estimate the regressions using Logit models. For the other two outcomes, I estimate the regressions using quasi-maximum-likelihood Poisson models. I report robust standard errors clustered by cohort and major.[27]

Table 3 presents the marginal effects from estimating Equation (3.1) with and without controls. For all three measures of inventive output, the coefficient estimates for GPA are positive and statistically significant; the estimates are not sensitive to the inclusion of controls. Controlling for cohort, major, and demographics, a one-standard-deviation increase in GPA is on average associated with 28-percent, 40-percent, and 33-percent increases in, respectively, the probability of becoming an inventor after college, the number of patents produced after college, and the number of citations received for those patents.

Table 4 shows that the relationship between college GPA and subsequent patenting is robust to controlling for selection into initial sectors using S&E majors from the classes of 2006–2008. Column (1) uses the same specification as in Table 3, column (4). Although the classes of 2006–2008 on average produce far fewer patents than the earlier cohorts, because they graduated from college more recently, the relationship between GPA and patenting remains strongly positive and significant. Column (2) restricts the sample to those whose initial sectors are observed, but uses the same specification as column (1); column (3) adds detailed sector dummies for whether the graduate enters an S&E graduate program, Computer/IT, another S&E industry, finance, or consulting; column (4) restricts the sample to those who initially pursued a graduate degree or a job in S&E and includes dummies for whether the graduate enters an S&E graduate program or Computer/IT. The results hold in all three columns. Among S&E majors in the classes of 2006–2008 who initially pursued a graduate degree or a job in S&E, a one-standard-deviation increase in cumulative GPA is associated with a 51.8 percent increase in patenting. Table A.1 in the Appendix shows that these results are robust to controlling for selection into long-term sectors.

[27]For students with more than one major, each combination of majors in a cohort is a separate cluster.

3.2 GPA and selection into careers

To examine the correlation between academic performance and propensity to enter finance, I estimate regressions of the following form:

$$Pr\left(Finance\right) = G\left(\alpha + \beta GPA_i + \gamma D_i^{Cohort} + \theta D_i^{Major} + \delta \chi_i + \epsilon_i\right), \qquad (3.2)$$

where the dependent variable is whether a graduate enters finance immediately after college graduation; GPA_i is cumulative GPA in college; and D_i^{Cohort}, D_i^{Major}, and χ_i are defined as in Equation (3.1). I estimate the regression in Logit models and use robust standard errors clustered by cohort and major.

Table 5 reports the estimated marginal effects. Columns (1) to (3) show that GPA negatively and significantly predicts the probability of entering finance; the results are robust to inclusion of various levels of controls. Among S&E majors in the classes of 2006–2008, conditional on cohort, major, and demographics, a one-standard-deviation increase in GPA is associated with a 3.9 percentage-point decrease in the proportion of graduates entering finance, equivalent to a 44.3 percent decrease from the baseline probability of 8.8 percent. Columns (4) and (5) show that there is negative selection into both quantitative and non-quantitative jobs in finance with similar magnitudes.[28]

Table A.2 in the Appendix shows that selection into finance differs significantly by gender but not by ethnicity: compared to male students, female students exhibit less negative correlations between college GPA and propensity to enter finance. Since the proportion of female students is larger in my sample of graduates with non-missing initial career choices than in the MIT student body as a whole (Table 2), it is possible that my results underestimate overall negative selection into finance at MIT based on college academic performance.

Table 6 compares selection into finance to selection into S&E sectors. In contrast to

[28]To identify quantitative jobs in finance, I construct an indicator variable that equals 1 if the employer is a hedge fund or if the job entails trading or quantitative analysis. The most common non-quantitative job in finance is investment-banking analyst.

negative selection into finance based on college GPA (column (1)), S&E majors are positively selected into S&E sectors (column (2)). More specifically, college GPA has a strong and positive correlation with entry into S&E graduate programs (column (3)); a one-standard-deviation increase in GPA is associated with a 42.5-percent increase in the probability of entering a S&E graduate program. There is negative selection into employment in S&E industries, and in unreported regressions I find that selection into finance is not significantly different from selection into S&E industries. Therefore, the most academically accomplished S&E graduates at college graduation are not systematically entering finance. Instead, they tend to pursue advanced degrees in S&E immediately after graduation.

4 Additional Evidence on Skill Development in College

This section uses additional skill measures to provide further evidence that finance does not systematically attract the S&E majors who are best prepared to innovate at college graduation. I first investigate how academic skill development in college relates to subsequent patenting. I then examine how students who pursue different career outcomes differ in their skill-development paths during college. I report results only for mathematics and engineering majors—the vast majority of S&E majors who enter finance—but my key findings extend to all S&E majors.

To earn a bachelor's degree from MIT, a student must satisfy the requirements of the core curriculum—which consists of courses on subjects ranging from science and engineering to humanities—and those of his or her department of choice. Freshmen and sophomores typically take core-curriculum courses and introductory courses in their fields of interest. In their junior and senior years, having declared majors, students take specialized courses. Figure 3 plots the relationships between future patenting and academic performance in high school and in each of the four years of college. I estimate each coefficient separately using the same specification as in Table 4, column (4), which restricts the analysis to those who entered S&E and controls for their initial outcomes. To make sure the sample is consistent across the regressions, I include only graduates who earned a bachelor's degree in exactly eight semesters.[29] I standardize each measure of academic performance by cohort within the sample. Figure 3 shows that academic performance during the senior year of college correlates most strongly and significantly with future patenting. The magnitude of the effect is quite large: a one-standard-deviation increase in senior-year GPA is associated with a nearly 100% increase in the number of post-college patents (or a 0.083 percentage-point increase from the baseline average of 0.083). Academic performance in the second year of college exhibits the second-strongest correlation: the magnitude of the coefficient estimate is around 58% of that of the estimate for senior-year GPA (or 0.048 percentage points). GPAs in the first and third years of college also predict future patenting positively but the coefficient estimates are smaller and marginally insignificant, possibly because GPAs in these years are relatively noisy measures of academic skills.[30] Academic performance in high school exhibits the weakest and most insignificant correlations with patenting. Overall, the correlations between grades and post-college patenting increase over the course of college. This pattern suggests that both general academic skill and field-specific knowledge/interest are valuable for inventing, but that the latter is particularly important.

Having established the link between academic specialization and post-college patenting, I next investigate the extent to which math and engineering students with different career outcomes pursue different skill-development paths in college. I provide evidence on both academic and non-academic skill development. For each skill measure, such as admission index score or GPA in each of the four years in college, I estimate in OLS the conditional means that capture the differences between those who enter finance and those who enter S&E sectors, controlling for cohort, major, and demographics and using robust standard

[29]This sample restriction eliminates around 16 percent of the math and engineering graduates. Reasons for not graduating in eight semesters include early graduation, taking a gap year, and returning to finish a degree after a hiatus.

[30]Due to MIT policies, the first-year GPA consissts only of grades during the second term . During junior year many students study abroad, and grading standards in exchange programs can vary widely.

errors clustered by cohort and majors.

Figure 4 plots the conditional means for academic skill measures. The sample includes all math and engineering majors from the classes of 2006–2008 who earned a bachelor's degree in exactly eight semesters and whose initial post-graduation sectors I observe. All skill measures are standardized by cohort within the sample. Panel I illustrates differences in academic performance over time between the math and engineering majors who enter S&E graduate programs or take first jobs in S&E and those who enter finance. The former group has significantly better admission index scores and significantly better GPAs in every year of college. The average difference in admission index score is relatively small (around 0.17 standard deviations); the differences in GPAs are much larger, and the largest is in the senior year. (The coefficient estimates are, in the order of college year, 0.45, 0.45, 0.42, and 0.63 standard deviations.) Panel II further shows that the former group also takes more courses every year; the differences are significant in the first two years. However, the magnitudes of the differences in course load are small: the average differences are only around 2.6 units in the first year and 5.1 units in the second year; a typical MIT course carries 12 units of credit. Figure A.4 in the Appendix shows that the differences in grades and course load decrease somewhat after controlling for decile dummies for admission index score but still remain large and significant; controlling for high-school academic achievement, the estimated difference in first-year GPA is 0.37 standard deviations and the estimated difference in senior-year GPA is 0.58 standard deviations.

Two other patterns in Figure 4 are interesting. First, differences in grades and course load do not grow in the second and third years. Thus, it is unlikely the case that unexpected poor academic performance in the freshman year systematically prompts students who will enter finance to expend even less academic effort in their second and third years. Second, differences in GPA become more negative during senior year, which suggests that differences in investment in coursework intensify once students have more or less chosen their future careers.

Table 7 reports the means and conditional means of graduates' rates of participation in various activities during college by initial sector. I subdivide these activities into four sets: fraternities and sororities, intercollegiate sports, performing arts (music, theater, and dance), and clubs (community service, student government, and student publications). Compared to math and engineering graduates who pursue a graduate degree or take a first job in S&E, those entering finance are 20.3 percentage points or 54 percent more likely to belong to a fraternity or sorority; they are also 15 percentage points or 50 percent more likely to participate in varsity sports. The two groups have similar rates of participation in performing arts. Those entering S&E are more likely to participate in student groups, but the differences are not significant. In unreported regressions I find that the differences in participation in extracurricular activities persist when controlling for admission index scores.

Table 8 compares graduates' self-reported improvement between college entry and graduation in an array of critical-thinking and scientific-reasoning skills. For each skill, Senior Surveys ask graduates to rate change in their skill level from 0 ("weaker") to 4 ("much stronger"); I standardize the responses and construct a z-score for the respondents to Senior Surveys. I include decile dummies of admission index score as additional controls, so that the reported conditional means hold constant college-entry qualifications. Table 8, Column (1), shows that, on average, math and engineering majors who enter S&E sectors report slightly better skill improvement than the average survey respondent; column (2) shows that math and engineering majors who enter finance report worse skill improvement than the average survey respondent. Column (3) shows that the differences between the two groups are significant at the 95-percent level for improvement in four skills: (1) gaining in-depth knowledge of a field; (2) understanding the process of science and experimentation; (3) planning and executing complex projects; and (4) formulating and creating original ideas and solutions. The largest and most significant difference is in the self-reported improvement in the ability to gain in-depth knowledge of a field. This finding is consistent with the previous finding that differences in academic performance between the two groups increase over time and are largest in senior year.

Taken together, the results in this section suggest that innovating in S&E calls for field-specific knowledge/interest, which students accumulate by investing in coursework during college. However, those who enter finance tend to pursue diverse activities in college instead of specializing in academics, which could be driven by both their abilities and preferences. To the extent that a student's admission index score is only a coarse measure of his or her underlying academic capability, it is possible that those who enter finance may simply be less academically skilled than those who enter S&E. Alternatively, students with similar academic aptitudes may choose to spend their time and energy in college differently due to preferences for activities and/or intended careers. Moreover, participating in a Greek society or a varsity sports team could have a causal impact on a student's academic achievement and propensity to enter finance.[31] All of these scenarios imply that the returns to academic specialization in S&E subject areas are lower in finance than in S&E sectors.

5 The Impact on Skill Development of the Financial Crisis and Great Recession

Given the differential returns to skills, it is possible that the lure of finance could reduce students' incentives to develop specialized S&E human capital. The 2008–09 financial crisis provides an opportunity to identify whether students' skill-development choices are sensitive to sudden changes in anticipated career incentives. In the fall of 2008, Lehman Brothers filed for Chapter 11 bankruptcy protection, Merrill Lynch was acquired under duress by Bank of America, and the U.S. Treasury and Federal Reserve Bank issued a $700 billion emergency bailout. In addition to directly shrinking the pool of available jobs in finance, the crisis and events like the Occupy Wall Street protests may also have increased the perceived riskiness of a career in finance and diminished its perceived social value. The MIT cohorts that

[31] Prior studies have found peer effects on time use in college (Stinebrickner and Stinebrickner, 2006) and on career choice (Marmaros and Sacerdote, 2002).

graduated after the crisis are substantially less likely to enter finance. For instance, only 5.3 percent of S&E majors in the 2009 cohort took a first job in finance, 40 percent fewer than S&E majors in the 2006–2008 cohorts. After the financial crisis the U.S. economy entered the Great Recession, during which the unemployment rate increased from 5.8 percent in 2008 to 9.3 percent in 2009. The worsening overall job market may also have had an effect on undergraduates' skill development regardless of their interest in finance.[32] This section first studies the impact of the crisis and recession on students' choices of major, and then examines its impact on investment in coursework conditional on choices of major.

5.1 Impact on choice of major

To examine the impact of economic crisis on students' choices of major, I estimate the following regressions:

$$Pr(Major_i = S) = \alpha_S + \beta_S D_i^{Cohort} + \delta_S \chi_i + \theta_S f\left(AI_i\right) + \epsilon_{S,i} \tag{5.1}$$

where the dependent variable is an indicator variable that captures either first declared major or major at graduation; and D_i^{Cohort} and χ_i are cohort dummies and demographic controls, both defined earlier. I also include decile dummies for admission index scores ($f\left(AI_i\right)$) to control for high-school academic achievement. The class of 2008, who graduated from college immediately before the peak of the financial crisis, is the omitted group. The identifying assumption is that students who graduated after 2008 would have exhibited patterns of majors similar to those of the classes of 2008 and earlier if not for the influence of the crisis and Great Recession.

Figure 5 plots the coefficient estimates of β_S and 95-percent confidence intervals by cohort.

[32]Blom et al. (2015) find that students pursue more technical and difficult majors, such as STEM fields, during bad economic conditions. Altonji et al. (2015) show that the Great Recession had a particularly severe and negative impact on recent college graduates' earnings, and that the magnitude of the impact is larger than that of other recessions. Bedard and Herman (2008) find that students are more likely to enter graduate school when they graduate during periods of economic crisis.

No statistically significant differences are evident between the 2008 cohort and those who graduated by 2010—who had declared first majors before the financial crisis; nor does the class of 2011, who were sophomores in late 2008, exhibit statistically significant differences in choice of major. Compared to the previous cohorts, the class of 2012, who were freshmen in late 2008, was significantly less likely to major in management/economics and significantly more likely to major in S&E. The magnitude of the decrease in propensity to major in management/economics, relative to the class of 2008, is around 3.6 percentage points, which is comparable to the corresponding magnitude of the increase in propensity to major in S&E (3.0 percentage points). This shift is apparent as early as fall 2009, when most of the 2012 cohort first declared majors (panel II).

The 3-percentage-point increase in propensity to major in S&E may seem small compared to the baseline probability of doing so (around 88 percent in 2008); it could have large implications for innovation, however, if it consists of the students with the best academic credentials at college entry. To examine the qualifications of students at the margin between management/economics and S&E majors, I use an empirical test similar to that of Gruber et al. (1999) and Chandra and Staiger (2007):

$$Y_i = \alpha + \delta S_j + \epsilon_i \tag{5.2}$$

where the dependent variable is the standardized admission index and S_j is the share of management/economics majors in cohort j. The regression is estimated only within the sample of management/economics majors. Intuitively, δ measures how much the average admission index of management/economics majors changes when they are more numerous. A negative δ implies that students who remain management/economics majors are more highly qualified than students who switch to another major. Similarly, estimating the equation within the sample of S&E majors—where S_j is the share of S&E majors in cohort j—shows how each additional S&E major compares to the average S&E major.

Table 9, column (1), shows that marginal management/economics majors have much lower admission-index scores than the average management/economics major; the estimated difference is almost half of the standard deviation. Column (2) shows that, although there are fewer management/economics majors in the 2012 cohort, their average admission index is higher than those of management/economics majors in previous cohorts. The coefficient estimates in both columns are statistically significant. Columns (3) and (4) show that marginal S&E majors are also less qualified than the average S&E major; the differences are not statistically significant because the fluctuations in the proportion of S&E majors are relatively small.

Comparing the raw numbers yields conclusions similar to those of Table 9. Around 12 percent of the class of 2008 majored in management/economics; their mean admission index is 0.06. Around 8 percent of the class of 2012 majored in management/economics; their mean admission index is 0.26. A back-of-the-envelope calculation shows that those who would have majored in management/economics if they had belonged to the 2008 cohort instead of the 2012 cohort have a mean admission index that is 0.34 standard deviations below the cohort mean.

5.2 Impact on academic performance

To study changes in students' academic performance, I estimate the following specification:

$$GPA_i = \alpha + \beta D_i^{Cohort} + \mu D_i^{Major} + \delta \chi_i + \theta f\left(AI_i\right) + \epsilon_i \tag{5.3}$$

where the dependent variable is cumulative GPA. This specification is similar to Equation (5.1) but with controls for selection into major (i.e., dummies for major and a dummy for graduating with more than one major). I report only the results for S&E majors, but the results for all majors are very similar.

Figure 5 plots the OLS coefficient estimates for β with robust standard errors. There are no statistically significant differences between the 2008 cohort and the cohorts who graduated before 2012. But the S&E majors in the class of 2012 earned significantly better grades than the previous cohorts. The estimated average increase in cumulative GPA for the 2012 cohort is 0.096, which is 23 percent of the standard deviation within the sample (0.419). This magnitude is non-trivial, since a 0.23-standard-deviation increase in overall GPA among S&E majors is associated with a 9.3 percent increase in post-college patenting not controlling for post-college career outcomes (Table 3).

In addition to OLS, I also estimate Equation (5.3) using quantile regressions. Figure 7 shows that, among the cohorts that graduated before 2012, there are small and insignificant differences across GPA distributions. Together with Figure 5, this result indicates that the increase in grades for the class of 2012 is unlikely to be driven by institutional forces such as grade inflation. Figure 7 also shows that the increase in GPA for S&E majors in the class of 2012 is primarily driven by those in the lower half of the grade distribution; the magnitudes of the coefficient estimates decline substantially with GPA percentile. The estimated changes at the 10th, 50th, and 80th percentile are respectively 0.19, 0.084, and 0.034.

The results in this section show that the financial crisis and subsequent recession had a significant impact on the academic skill development of below-average MIT students who were freshmen at the peak of the crisis. One potential concern is that there may be unobserved differences between the class of 2012 and the previous cohorts. There is no indication that MIT drastically changed its admission policies for the class of 2012. To provide additional robustness checks, I collect information on participation in and leadership of extracurricular activities in high school, which is available for the classes of 2010–2012.[33] Table A.3 in the Appendix shows that adding these variables as controls does not change the key findings.

[33]The data came from surveys conducted by the Admissions Office; comparable data are not available for the earlier cohorts.

6 Career Outcomes of Top Performers on the Putnam Competition

Focusing on a single institution, MIT, allows me to observe students' characteristics, skill measures, and outcomes in detail. However, it is possible that the self-selection of MIT S&E graduates differs from that of S&E graduates of other top programs. The most academically skilled MIT S&E graduates, for instance, may have strong preferences for innovating that equally qualified S&E students at other institutions do not share. This section uses data on top scorers on the William Lowell Putnam Mathematical Competition to examine the external validity of my key findings. The Putnam Competition, established in 1938, is an annual math competition for undergraduates enrolled in North American universities. The competition takes place on a single day; contestants are asked to solve 12 questions in two three-hour sittings. The questions range in difficulty and are designed to test both technical competence and originality. In 2011, 4440 students from 572 institutions took part in the competition (Gallian, 2015). The names and schools of the top 100 individual scorers are published in American Mathematical Monthly each year, and historical lists dating back to 1994 are available online.[34] These lists of top performers allow me to construct a sample of comparably skilled math students across multiple universities. The focus on math is informative, since math is the S&E major with the highest percentage of MIT graduates who pursue careers in finance (Figure 1).

Around 860 individuals have been among the top 100 individual scorers between 1994 and 2014.[35] I hand collected the career outcomes of 462 individuals based on LinkedIn profiles, personal websites, and other online sources. Using this data, I regress career outcomes on five dummies for the institutions with the most top performers (MIT, Harvard, Princeton, Stanford, and California Institute of Technology), and dummies for the most recent year

[34] The lists can be accessed at http://kskedlaya.org/putnam-archive/.

[35] A given student can participate in the Putnam Competition up to four times and thus can appear as a top performer multiple times.

in which the individual was a top scorer (as a proxy for his or her college cohort). I also include a dummy for whether the individual is a Putnam Fellow, which is awarded to the five individuals with the highest scores each year along with a cash prize of $2500. Putnam Fellows represent the very best math talent in the world; past Putnam Fellows include three Field Medalists (David Mumford, Daniel Quillen, and Paul Cohen), two Nobel laureates in physics (Richard Feynman and Kenneth Wilson), four American Mathematical Society presidents, and 16 National Academy of Sciences members (Gallian, 2015).

Table 10 shows no significant university-level differences in the career outcomes of top performers with the exception of Harvard graduates, who are much more likely to work in finance. It also shows that compared to all the top performers on the Putnam Competition, Putnam Fellows are significantly less likely to have had any experience in finance, including an internship during college, a first job in finance after graduation, or long-term employment in finance. They are instead much more likely to enter a graduate program in S&E (typically a doctoral program in math) immediately after college graduation and to work in academia or a research sector over the long term. The results thus indicate that there is also negative selection into finance among the best math students across a range of colleges.[36]

7 Conclusion

How does the inflow of top college graduates into the financial industry affect the supply of innovators in S&E? Using data on MIT bachelor's graduates, I find that the S&E majors who are most academically accomplished at the time of college graduation—those with the highest potential to produce inventions in the future—are *not* systematically entering finance. In contrast, finance tends to attract S&E majors who are less academically oriented but more socially oriented. These findings are consistent with two explanations that are not mutually

[36]A related piece of evidence is that the top performers on the Putnam Competition are on average much less likely to take a first job in finance than the average math major at MIT. Around 10.2 percent of top Putnam performers in the 2006–2008 cohorts took a first job in finance, less than half of the same figure for math majors from the MIT classes of 2006–2008 (Figure 1).

exclusive. First, finance may prize specialized S&E human capital less than S&E sectors do, and may call for other skills, such as social skills, more than those sectors do. In this scenario, finance does not attract the most inventive future scientists and engineers from MIT; it hires those who will be best suited to working in finance. Second, employers in finance may seek the most academically talented S&E students, but find that these students have strong preferences for careers in S&E. In both cases, the returns to academic specialization in S&E subject areas are lower in finance than in S&E sectors. This pattern is not unique to MIT graduates, as I also find negative selection into finance and positive selection into S&E sectors among top math students across a range of North American universities.

The 2008–09 financial crisis and the subsequent Great Recession encouraged some MIT students in the class of 2012 to major in S&E and/or to improve their academic performance, which indicates that anticipated career incentives do influence the acquisition of specialized S&E human capital during college. However, there is no evidence that those who were sophomores and juniors at the peak of the crisis changed their skill-development paths in response, suggesting that skill-development choices become much less elastic after the first year of college. Moreover, the students with the best academic qualifications are the least responsive to the shock. These findings have implications for policies intended to influence top college students' career choices—to the extent that they are warranted.

Beyond directly affecting the supply of innovators in S&E, the inflow of top talent into finance could influence the production of innovations in other ways that I did not examine in this paper. Without becoming prolific inventors, S&E graduates could still support the production of innovations in S&E sectors via other job functions, such as managing R&D projects. The talent inflow into finance could also promote the production of innovations by improving the financing of innovations and R&D (Kortum and Lerner, 2000; Hall and Lerner, 2010). Further investigations of the social returns of different career paths are needed in order to determine the optimal talent allocation, which I leave to future work.

References

Agarwal, Rajshree and Atsushi Ohyama, "Industry or Academia, Basic or Applied? Career Choices and Earnings Trajectories of Scientists," *Management Science*, October 2012, *59* (4), 950–970.

Aghion, Philippe and Peter Howitt, "A Model of Growth Through Creative Destruction," *Econometrica*, March 1992, *60* (2), 323–351.

_ , Ufuk Akcigit, Ari Hyytinen, and Otto Toivanen, "Living the American Dream in Finland: The Social Mobility of Inventors," *Working Paper*, July 2016.

Altonji, Joseph G., Lisa B. Kahn, and Jamin D. Speer, "Cashier or Consultant? Entry Labor Market Conditions, Field of Study, and Career Success," *Journal of Labor Economics*, December 2015, *34* (S1), S361–S401.

Arcidiacono, Peter, Esteban M. Aucejo, and V. Joseph Hotz, "University Differences in the Graduation of Minorities in STEM Fields: Evidence from California," *American Economic Review*, March 2016, *106* (3), 525–562.

Arrow, Kenneth, "Economic Welfare and The Allocation of Resources for Invention," in "The Rate and Direction of Inventive Activity," Princeton University Press and NBER, 1962, pp. 609–25.

Atkinson, Richard C., "Supply and Demand for Scientists and Engineers: A National Crisis in the Making," *Science*, 1990, *248* (4954), 425–32.

Axelson, Ulf and Philip Bond, "Wall Street Occupations," *The Journal of Finance*, October 2015, *70* (5), 1949–1996.

Azoulay, Pierre, Joshua S. Graff Zivin, and Jialan Wang, "Superstar Extinction," *The Quarterly Journal of Economics*, May 2010, *125* (2), 549–589.

Baumol, William J., "Entrepreneurship: Productive, Unproductive, and Destructive," *Journal of Political Economy*, October 1990, *98* (5-1), 893–921.

Bedard, Kelly and Douglas A. Herman, "Who Goes to Graduate/Professional School? The Importance of Economic Fluctuations, Undergraduate Field, and Ability," *Economics of Education Review*, 2008, *27* (2), 197–210.

Bell, Alexander, Raj Chetty, Xavier Jaravel, Neviana Petkova, and John Van Reenen, "The Lifecycle of Inventors," *Working Paper*, June 2016.

Bell, Brian and John Van Reenen, "Bankers and Their Bonuses," *The Economic Journal*, February 2014, *124* (574), F1–F21.

Biais, Bruno and Augustin Landier, "Endogenous Agency Problems and the Dynamics of Rents," *Working Paper*, May 2015.

_ , **Jean-Charles Rochet, and Paul Woolley**, "Dynamics of Innovation and Risk," *Review of Financial Studies*, May 2015, *28* (5), 1353–1380.

Blom, Erica, Brian C. Cadena, and Benjamin J. Keys, "Investment Over the Business Cycle: Insights from College Major Choice," *Working Paper*, September 2015.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen, "Identifying Technology Spillovers and Product Market Rivalry," *Econometrica*, July 2013, *81* (4), 1347–1393.

Bohm, Michael, Daniel Metzger, and Per Stromberg, "Since you're so rich, you must be really smart: Talent and the Finance Wage Premium," *Working Paper*, 2015.

Bolton, Patrick, Tano Santos, and Jose A. Scheinkman, "Cream-Skimming in Financial Markets," *The Journal of Finance*, April 2016, *71* (2), 709–736.

Celerier, Claire and Boris Vallee, "Returns to Talent and the Finance Wage Premium," *Working Paper*, 2015.

Chandra, Amitabh and Douglas Staiger, "Productivity Spillovers in Health Care: Evidence from the Treatment of Heart Attacks," *Journal of Political Economy*, 2007, *115*, 103–140.

Cole, Jonathan R. and Stephen Cole, "The Ortega Hypothesis," *Science*, October 1972, *178* (4059), 368–375.

Freeman, Richard B., "Cobweb Model of the Supply and Starting Salary of New Engineers, A," *Industrial and Labor Relations Review*, 1975, *29*, 236.

_ , "Supply and Salary Adjustments to the Changing Science Manpower Market: Physics, 1948-1973," *American Economic Review*, March 1975, *65* (1), 27–39.

Furman, Jeffrey L. and Scott Stern, "Climbing atop the Shoulders of Giants: The Impact of Institutions on Cumulative Research," *The American Economic Review*, August 2011, *101* (5), 1933–1963.

Galasso, Alberto and Mark Schankerman, "Patents and Cumulative Innovation: Causal Evidence from the Courts," *The Quarterly Journal of Economics*, February 2015, *130* (1), 317–369.

Gallian, Joseph, "The Putnam Competition from 1938-2015," 2015.

Ge, Chunmian, Ke-Wei Huang, and Ivan P. L. Png, "Engineer/scientist careers: Patents, online profiles, and misclassification bias," *Strategic Management Journal*, January 2016, *37* (1), 232–253.

Goldin, Claudia and Lawrence F. Katz, "Transitions: Career and Family Life Cycles of the Educational Elite," *American Economic Review: Papers and Proceedings*, May 2008, *98* (2), 363–369.

Goolsbee, Austan, "Does Government R&D Policy Mainly Benefit Scientists and Engineers?," *American Economic Review: Papers and Proceedings*, May 1998.

Grossman, Gene M. and Elhanan Helpman, "Quality Ladders in the Theory of Growth," *Review of Economic Studies*, January 1991, *58* (1), 43–61.

Gruber, Jonathan, Phillip Levine, and Douglas Staiger, "Abortion Legalization and Child Living Circumstances: Who is The "Marginal Child"?," *Quarterly Journal of Economics*, 1999, *114* (1), 263–291.

Hall, Bronwyn and Josh Lerner, "The Financing of R&D and Innovation," in B.H. Hall and N. Rosenberg, eds., *Elsevier Handbook of Economics of Innovation*, Elsevier, April 2010, pp. 609–639.

Hastings, Daniel, Steven Lerman, and Melanie Parker, "The Demand for MIT Graduates," *MIT Faculty Newsletter*, February 2010, *XXII* (3).

Jones, Benjamin F., "The Burden of Knowledge and the "Death of the Renaissance Man": Is Innovation Getting Harder?," *Review of Economic Studies*, January 2009, *76* (1), 283–317.

Jones, Benjamin F, "Age and Great Invention," *Review of Economics and Statistics*, January 2010, *92* (1), 1–14.

Jones, Charles I., "R & D-Based Models of Economic Growth," *Journal of Political Economy*, August 1995, *103* (4), 759–784.

_ , "Chapter 16 - Growth and Ideas," in Philippe Aghion and Steven N. Durlauf, ed., *Handbook of Economic Growth*, Vol. 1, Part B, Elsevier, 2005, pp. 1063–1111.

Kaplan, Steven N. and Joshua Rauh, "Wall Street and Main Street: What Contributes to the Rise in the Highest Incomes?," *Review of Financial Studies*, March 2010, *23* (3), 1004–1050.

Kirilenko, Andrei A. and Andrew W. Lo, "Moore's Law versus Murphy's Law: Algorithmic Trading and Its Discontents," *Journal of Economic Perspectives*, April 2013, *27* (2), 51–72.

Kortum, Samuel and Josh Lerner, "Assessing the Contribution of Venture Capital to Innovation," *RAND Journal of Economics*, 2000, *31* (4), 674–692.

Lerner, Josh and Amit Seru, "The Use and Misuse of Patent Data: Issues for Corporate Finance and Beyond," *Mimeo, Harvard University*, 2015.

Li, Guan-Cheng, Ronald Lai, Alexander D'Amour, David M. Doolin, Ye Sun, Vetle I. Torvik, Amy Z. Yu, and Lee Fleming, "Disambiguation and co-authorship networks of the U.S. patent inventor database (1975-2010)," *Research Policy*, July 2014, *43* (6), 941–955.

Lockwood, Benjamin B., Charles Nathanson, and E. Glen Weyl, "Taxation and the Allocation of Talent," *Journal of Political Economy*, April 2016, *Forthcoming.*

Marmaros, David and Bruce Sacerdote, "Peer and social networks in job search," *European Economic Review*, May 2002, *46* (4-5), 870–879.

Mullainathan, Sendhil, "Why a Harvard Professor Has Mixed Feelings When Students Take Jobs in Finance," *The Upshot, NYTimes.com*, April 2015.

Murphy, Kevin M., Andrei Shleifer, and Robert W. Vishny, "The Allocation of Talent: Implications for Growth," *The Quarterly Journal of Economics*, May 1991, *106* (2), 503–530.

Myerson, Roger B., "A Model of Moral-Hazard Credit Cycles," *Journal of Political Economy*, October 2012, *120* (5), 847–878.

Nelson, Richard R., "The Simple Economics of Basic Scientific Research," *Journal of Political Economy*, 1959, *67* (3), 297–306.

Obama, Barack, "The way ahead," *The Economist*, October 2016.

Oettl, Alexander, "Reconceptualizing Stars: Scientist Helpfulness and Peer Performance," *Management Science*, January 2012, *58* (6), 1122–1140.

Oyer, Paul, "The Making of an Investment Banker: Stock Market Shocks, Career Choice, and Lifetime Income," *Journal of Finance*, December 2008, *63* (6), 2601–2628.

Philippon, Thomas, "Financiers versus Engineers: Should the Financial Sector be Taxed or Subsidized?," *American Economic Journal: Macroeconomics*, 2010, *2* (3), 158–182.

_ **and Ariell Reshef**, "Wages and human capital in the U.S. finance industry: 1909-2006," *The Quarterly Journal of Economics*, November 2012, *127* (4), 1551–1609.

Rampell, Catherine, "Out of Harvard, and Into Finance," *The Economix Blog, NYTimes.com*, 2011.

Roach, Michael and Henry Sauermann, "A taste for science? PhD scientists' academic orientation and self-selection into research careers in industry," *Research Policy*, April 2010, *39* (3), 422–434.

Roberts, Edward B. and Charles E. Eesley, "Entrepreneurial Impact: The Role of MIT," *Report to the Kauffman Foundation*, February 2009.

_ **, Fiona Murray, and J. Daniel Kim**, "Entrepreneurship and Innovation at MIT: Continuing Global Growth and Impact," *MIT Innovation Initiative Report*, December 2015.

Romer, Christina, "Growth without Bubbles," May 2009.

Romer, Paul M., "Endogenous Technological Change," *Journal of Political Economy*, October 1990, *98* (5), S71–S102.

_ , "Should the Government Subsidize Supply or Demand in the Market for Scientists and Engineers?," *Innovation Policy and the Economy*, January 2000, *1*, 221–252.

Roy, A. D., "Some Thoughts on the Distribution of Earnings," *Oxford Economic Papers*, 1951, *3* (2), 135–146.

Ryoo, Jaewoo and Sherwin Rosen, "The Engineering Labor Market," *Journal of Political Economy*, February 2004, *112* (S1), S110–S140.

Shiller, Robert J., "The Best, Brightest, and Least Productive?," *Project Syndicate*, September 2013.

Smalheiser, Neil R. and Vetle I. Torvik, "Author name disambiguation," *Annual Review of Information Science and Technology*, January 2009, *43* (1), 1–43.

Stephan, Paula E., "The Economics of Science," *Journal of Economic Literature*, September 1996, *34* (3), 1199–1235.

Stern, Scott, "Do Scientists Pay to Be Scientists?," *Management Science*, June 2004, *50* (6), 835–853.

Stinebrickner, Ralph and Todd R. Stinebrickner, "What can be learned about peer effects using college roommates? Evidence from new survey data and students from disadvantaged backgrounds," *Journal of Public Economics*, September 2006, *90* (8-9), 1435–1454.

_ **and** _ , "A Major in Science? Initial Beliefs and Final Outcomes for College Major and Dropout," *Review of Economic Studies*, January 2014, *81* (1), 426–472.

Torvik, Vetle I., Marc Weeber, Don R. Swanson, and Neil R. Smalheiser, "A probabilistic similarity metric for Medline records: A model for author name disambiguation," *Journal of the American Society for Information Science and Technology*, January 2005, *56* (2), 140–158.

Waldinger, Fabian, "Quality Matters: The Expulsion of Professors and the Consequences for PhD Student Outcomes in Nazi Germany," *Journal of Political Economy*, August 2010, *118* (4), 787–831.

Williams, Heidi L., "Intellectual Property Rights and Innovation: Evidence from the Human Genome," *Journal of Political Economy*, 2013, *121* (1), 1–27.

Wiswall, Matthew and Basit Zafar, "Determinants of College Major Choice: Identification using an Information Experiment*," *The Review of Economic Studies*, December 2014.

Zafar, Basit, "How Do College Students Form Expectations?," *Journal of Labor Economics*, April 2011, *29* (2), 301–348.

Table 1. Patent and Citation Statistics. Sample: Classes of 1994–2008

Major	S&E	Non-S&E
Inventor	13.4%	3.0%
Number of patents	0.57	0.10
Number of citations	2.23	0.43
Number of patents per inventor	4.24	3.21
Number of citations per inventor	16.7	14.4
N	13,167	1,888

Note: Person-level observations.

Table 2. Mean Characteristics of Graduates by Initial Sector. Sample: S&E Majors from Classes of 2006–2008

Sample	All	Initial Sector Observed	S&E Grad. Programs/ Industries	Finance
	(1)	(2)	(3)	(4)
N	2,562	1,411	923	124
Female	42.4%	46.0%	45.9%	25.0%
Age at graduation	22.2	22.2	22.2	22.2
Caucasian American	36.8%	39.3%	40.4%	33.9%
Asian American	27.7%	29.2%	27.6%	37.9%
Hispanic American	10.4%	9.4%	9.5%	6.5%
African American	4.8%	3.7%	4.0%	1.6%
Non-American	8.7%	7.0%	7.0%	10.5%
Financial aid received in senior year	\$13,193	\$13,115	\$13,436	\$12,081
Engineering	68.2%	69.4%	69.6%	75.8%
Science	38.9%	38.5%	39.4%	32.3%
Initial Career Outcome				
S&E graduate programs		46.4%		
S&E industries		19.0%		
Finance		8.8%		
Other		25.8%		

Notes: Person-level observations. In column (1), the sample consists of non-transfer graduates from the 2006–2008 cohorts with a major in engineering or science. In column (2), the sample consists of non-transfer graduates from the 2006–2008 cohorts with a major in engineering or science and whose initial sectors I observe. In column (3), the sample consists of graduates from the 2006–2008 cohorts with a major in engineering or science who pursued a graduate degree in S&E or took a first job in an S&E industry after college graduation. In column (4), the sample consists of graduates from the 2006–2008 cohorts with a major in engineering or science who took a first job in finance after college graduation. Financial aid received in senior year is in 2008 dollars.

Table 3. Estimated Correlation between College GPA and Patenting. Sample: S&E Majors from Classes of 1994–2008

Dependent variable	Becoming an inventor		Number of patents		Number of citations	
	(1)	(2)	(3)	(4)	(5)	(6)
Standardized GPA	0.037**	0.038**	0.228**	0.229**	0.722˜	0.744*
	(0.005)	(0.003)	(0.045)	(0.039)	(0.387)	(0.345)
Model	Logit	Logit	Poisson	Poisson	Poisson	Poisson
Controls	N	Y	N	Y	N	Y
N	13,167	13,167	13,167	13,167	13,167	13,167
Mean DV	0.134	0.134	0.567	0.567	2.233	2.233

Notes: Person-level observations. Coefficients reported are marginal effects from Logit models (columns (1) and (2)) or quasi–maximum-likelihood Poisson models (columns (3)–(6)). Robust standard errors clustered by cohort and majors are shown in parentheses. ˜ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. The sample consists of non-transfer graduates from the 1994–2008 cohorts with a major in engineering or science. In columns (1) and (2), the dependent variable is whether the graduate is awarded any patents after college. In columns (3) and (4), the dependent variable is number of patents awarded after college. In columns (5) and (6), the dependent variable is number of citations received by patents awarded after college. *Standardized GPA* is cumulative GPA standardized within the engineering and science majors in each cohort. Controls include a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (Caucasian American, Asian American, Hispanic American, African American, and non-American), dummies for high-school region (northeast, midwest, south, and west), dummies for cohort, dummies for majors at graduation, a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars.

Table 4. Estimated Correlation between College GPA and Patenting: Robustness to Selection into Initial Sectors. Sample: S&E Majors from Classes of 2006–2008. Dependent Variable: Number of Patents since Graduation

Sample	All graduates	Initial sector observed	Initial sector observed	Initial sector: S&E
	(1)	(2)	(3)	(4)
Standardized GPA	0.033**	0.033*	0.034*	0.043˜
	(0.008)	(0.015)	(0.017)	(0.024)
N	2,562	1,411	1,411	923
Detailed sector dummies	N	N	Y	Y
Mean DV	0.056	0.064	0.064	0.083

Notes: Person-level observations. Coefficients reported are marginal effects from quasi–maximum-likelihood Poisson models. Robust standard errors clustered by cohort and majors are shown in parentheses. ˜ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. The dependent variable is number of patents awarded after college. In column (1), the sample consists of non-transfer graduates from the 2006–2008 cohorts with a major in engineering or science. In columns (2) and (3), the sample consists of non-transfer graduates from the 2006–2008 cohorts with a major in engineering or science and whose initial sectors I observe. In column (4), the sample consists of graduates from the 2006–2008 cohorts with a major in engineering or science who pursued a graduate degree in S&E or took a first job in an S&E industry after college graduation. *Standardized GPA* is cumulative GPA standardized within the engineering and science majors in each cohort. In columns (3), *Detailed sector dummies* include indicators for entering S&E graduate programs, computer/IT, other S&E industries, finance, or consulting. In columns (4), *Detailed sector dummies* include indicators for entering S&E graduate programs or computer/IT. All regressions include a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (Caucasian American, Asian American, Hispanic American, African American, and non-American), dummies for high-school region (northeast, midwest, south, and west), dummies for cohort, dummies for majors at graduation, a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars.

Table 5. Selection into Finance by College GPA. Sample: S&E Majors from Classes of 2006–2008 with Initial Sector Observed

Dependent variable	Taking a first job in finance			First job in quantitative finance	First job in non-quantitative finance
	(1)	(2)	(3)	(4)	(5)
Standardized GPA	-0.022**	-0.022**	-0.039**	-0.016**	-0.025**
	(0.008)	(0.008)	(0.007)	(0.004)	(0.007)
Cohort dummies	N	Y	Y	Y	Y
Major dummies	N	N	Y	Y	Y
Demographics	N	N	Y	Y	Y
N	1,411	1,411	1,411	1,265	1,411
Mean DV	0.088	0.088	0.088	0.028	0.062

Notes: Person-level observations. Coefficients reported are marginal effects from Logit models. Robust standard errors clustered by cohort and majors are shown in parentheses. ˜ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. In columns (1)–(3), the dependent variable is whether the graduate takes a first job in finance after graduation. In column (4), the dependent variable is whether the graduate takes a quantitative job in finance after graduation (e.g., trading or quantitative analysis). In column (5), the dependent variable is whether the graduate takes a non-quantitative job in finance after graduation (e.g., investment banking). The sample consists of non-transfer graduates from the 2006—2008 cohorts with a major in engineering or science and whose initial sectors I observe. *Standardized GPA* is cumulative GPA standardized within the engineering and science majors in each cohort. All regressions include a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (Caucasian American, Asian American, Hispanic American, African American, and non-American), dummies for high-school region (northeast, midwest, south, and west), dummies for cohort, dummies for majors at graduation, a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars.

TABLE 6. Selection into Initial Sectors by College GPA. Sample: S&E Majors from Classes of 2006–2008 with Initial Sector Observed.

Dependent variable	Taking a first job in finance	First job or graduate program in S&E	Graduate program in S&E	First job in S&E
	(1)	(2)	(3)	(4)
Standardized GPA	-0.039**	0.100**	0.197**	-0.076**
	(0.007)	(0.011)	(0.015)	(0.010)
N	1,411	1,411	1,411	1,411
Mean DV	0.088	0.654	0.464	0.190

Notes: Person-level observations. Coefficients reported are marginal effects from Logit models. Robust standard errors clustered by cohort and majors are shown in parentheses. ~ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. In column (1), the dependent variable is whether the graduate takes a first job in finance after graduation. In column (2), the dependent variable is whether the graduate pursues a graduate degree in S&E or takes a first job in an S&E industry after graduation. In column (3), the dependent variable is whether the graduate pursues a graduate degree in S&E after graduation. In column (4), the dependent variable is whether the graduate takes a first job in an S&E industry after graduation. The sample consists of non-transfer graduates from the 2006--2008 cohorts with a major in engineering or science and whose initial sectors I observe. *Standardized GPA* is cumulative GPA standardized within the engineering and science majors in each cohort. All regressions include a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (Caucasian American, Asian American, Hispanic American, African American, and non-American), dummies for high-school region (northeast, midwest, south, and west), dummies for cohort, dummies for majors at graduation, a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars.

TABLE 7. Differences in Non-Academic Skill Development. Sample: Mathematics and Engineering Majors from Classes of 2006 and 2008 with Initial Sector and Extracurricular Activities Observed

	(1)	(2)	(3)
Statistics	Mean (S&E Sectors)	Mean (Finance)	Conditional Means
Fraternity or sorority	37.4%	59.6%	-0.203**
			(0.061)
Intercollegiate sports	30.1%	40.4%	-0.150*
			(0.073)
Performing arts	20.5%	17.5%	0.024
			(0.062)
Student clubs	51.8%	38.6%	0.128
			(0.088)

Notes: Person-level observations. The sample consists of non-transfer graduates from the 2006 and 2008 cohorts with a major in mathematics or engineering and whose initial sectors and participation in college extracurricular activities I observe (533 graduates). Each dependent variable is an indicator for whether the graduate participated in the activity during college, as reported on the Senior Survey. Column (1) reports the mean of each variable for graduates taking a first job or pursuing a graduate degree in S&E after graduation. Column (2) reports the mean of each variable for graduates taking a first job in finance after graduation. Column (3) reports the differences in the means, controlling for a dummy for entering initial sectors other than finance or S&E, a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (Caucasian American, Asian American, Hispanic American, African American, and non-American), dummies for high-school region (northeast, midwest, south, and west), dummies for cohort, dummies for majors at graduation, a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars. The conditional means are estimated in OLS with robust standard errors clustered by cohort and majors. ˜ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$.

TABLE 8. Differences in Self-Reported Skill Improvement in College Conditional on High-School Academic Achievement. Sample: Mathematics and Engineering Majors from Classes of 2006 and 2008 with Initial Sector, Admission Index Score, and Self-Reported Skill Improvement Observed

	(1)	(2)	(3)
Statistics	Mean (S&E Sectors)	Mean (Finance)	Cond. Means
Self-reported improvement in ability to (z-score):			
Gain in-depth knowledge of a field	0.140	-0.335	0.538**
			(0.130)
Think analytically and logically	0.090	-0.043	0.239
			(0.208)
Acquire new skills and knowledge on one's own	0.043	-0.095	0.211
			(0.155)
Formulate and create original ideas and solutions	0.055	-0.247	0.377*
			(0.155)
Synthesize and integrate ideas and information	0.044	-0.165	0.248˜
			(0.145)
Plan and execute complex projects	0.127	-0.265	0.396*
			(0.193)
Understand process of science and experimentation	0.063	-0.504	0.503**
			(0.170)

Notes: Person-level observations. The sample consists of non-transfer graduates from the 2006–2008 cohorts with a major in mathematics or engineering for whom I observe initial sectors, admission index scores, and self-reported skill improvement (438 graduates). Each dependent variable is a z-scored measure of self-reported improvement in the skill between college entry and college graduation, where the original responses range from 0 ("weaker") to 4 ("much stronger"). The measures are standardized among respondents to the Senior Survey. Column (1) reports the mean of each variable for graduates taking a first job or pursuing a graduate degree in S&E after graduation. Column (2) reports the mean of each variable for graduates taking a first job in finance after graduation. Column (3) reports the differences in the means, controlling for nine decile dummies for admission index score, a dummy for entering initial sectors other than finance or S&E, a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (Caucasian American, Asian American, Hispanic American, African American, and non-American), dummies for high-school region (northeast, midwest, south, and west), dummies for cohort, dummies for majors at graduation, a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars. The conditional means are estimated in OLS with robust standard errors clustered by cohort and majors. ˜ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$.

Table 9. Marginal and Average College Qualifications, Majors in Management/Economics and S&E. Sample: Classes of 2006–2012

Sample	Management/Economics		S&E	
Dep. Var. = Admission Index	(1)	(2)	(3)	(4)
Δ(Marginal - Average)	-0.446˜		-0.671	
	(0.234)		(0.878)	
D^{2012}		0.228*		-0.023
		(0.109)		(0.038)
N	735	735	5,769	5,769

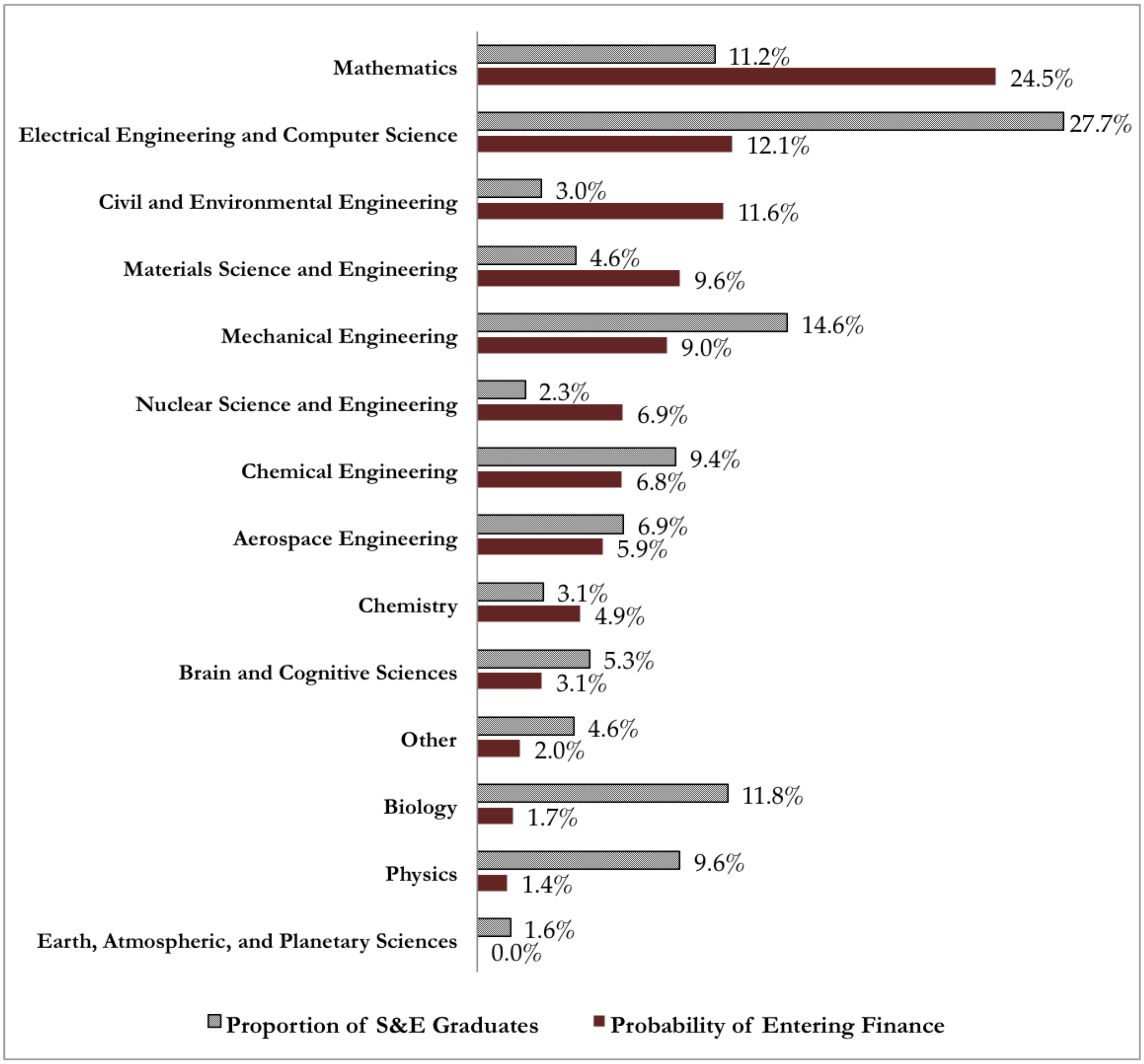
Notes: Person-level observation. All estimates are from ordinary-least-squares (OLS) with robust standard errors. ˜ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. The dependent variable is admission index normalized within the cohort. The sample for columns (1) –(2) consists of graduates from the 2006–2012 cohorts with a major in management or economics. The sample for columns (3)–(4) consists of graduates from the 2006–2012 cohorts with a major in S&E. D^{2012}: indicator variable for the 2012 cohort.

Table 10. Selection into Careers among Top Performers on the William Lowell Putnam Competition, 1994–2014

Dependent variable	Any experience in finance (1)	First job in finance (2)	Graduate program in S&E (3)	First job in S&E (4)	Long-term research (5)
Putnam Fellow	-0.154*	-0.095**	0.128*	-0.022	0.201**
	(0.068)	(0.024)	(0.061)	(0.044)	(0.060)
Dummies for five schools with the most top performers					
MIT	-0.026	0.017	-0.016	0.052	-0.020
	(0.051)	(0.037)	(0.035)	(0.046)	(0.032)
Harvard	0.181*	0.139*	-0.094	-0.037	0.004
	(0.081)	(0.049)	(0.061)	(0.031)	(0.067)
Stanford	-0.008	-0.003	-0.116	0.106	0.011
	(0.067)	(0.044)	(0.081)	(0.062)	(0.119)
Princeton	0.047	0.045	-0.095	-0.062	0.093
	(0.117)	(0.063)	(0.090)	(0.046)	(0.082)
CalTech	0.059	0.014	0.009	-0.045	-0.120
	(0.109)	(0.047)	(0.083)	(0.046)	(0.103)
N	462	462	462	462	462
Mean DV	0.255	0.082	0.751	0.102	0.366

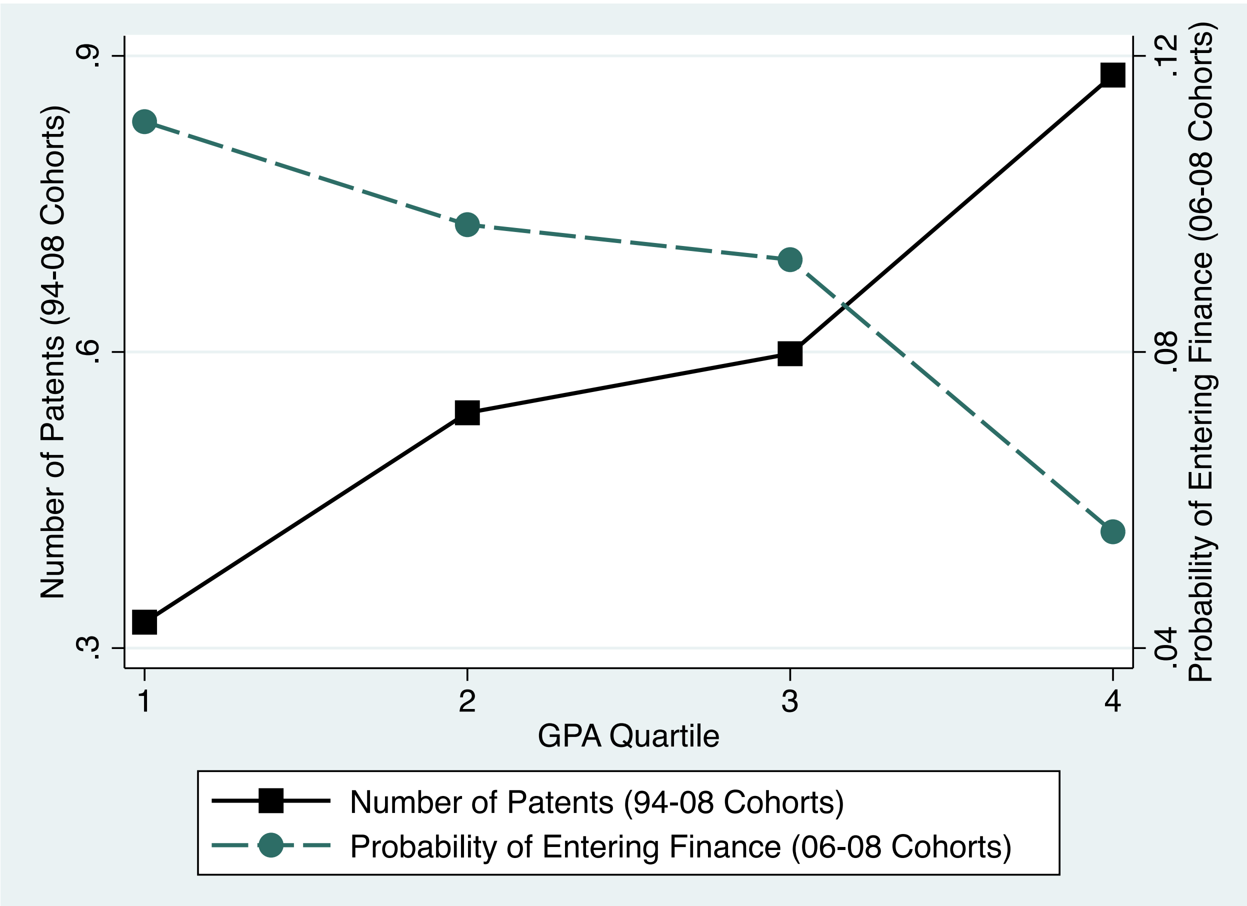
Notes: Person-level observations. Coefficients reported are from linear probability models. Robust standard errors clustered by the year when an individual last appeared as a top performer are shown in parentheses. ~ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. In column (1), the dependent variable is whether the individual has had any experience in finance (including internship). In column (2), the dependent variable is whether the individual takes a first job in finance after graduation. In column (3), the dependent variable is whether the individual pursues a graduate degree in S&E immediately after graduation. In column (4), the dependent variable is whether the individual takes a first job in an S&E industry after graduation. In column (5), the dependent variable is whether the individual works in academia or research as of May 2016. The sample consists of individuals who earned honorable mention or above for individual performance in the William Lowell Putnam Mathematical Competition between 1994 and 2014, and for whom I observe the initial and long-term sectors. *Putnam Fellow* is an indicator for whether the individual was among the five top-ranking individuals in any year. All regressions include dummies for the year an individual last appeared as a top performer.

Figure 1. Distribution and Probability of Entering Finance by Major. Sample: S&E Majors from Classes of 2006–2008



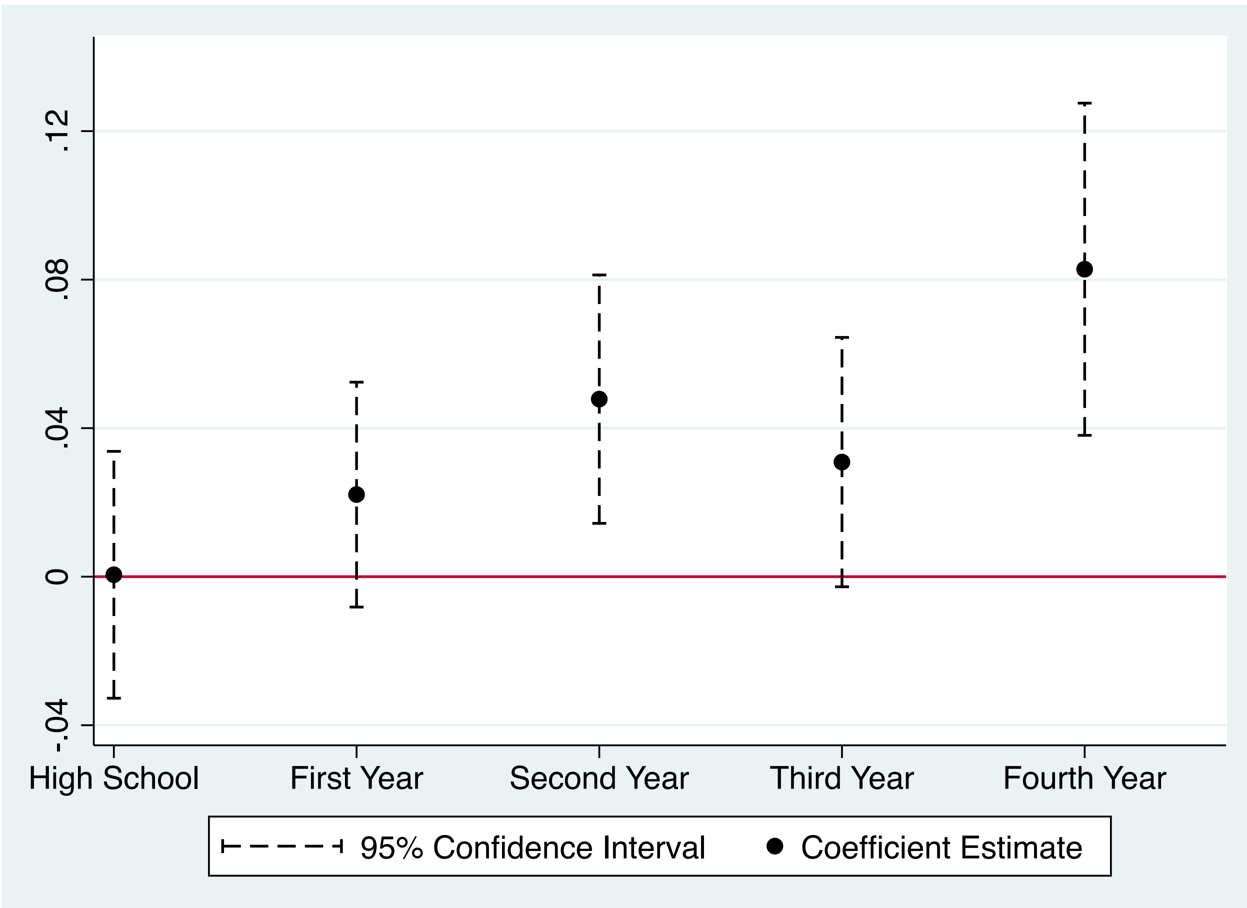
Notes: Person-level observations. This figure plots the share of S&E graduates in each major and the proportion of graduates in each major who took a first job in finance after graduation. The sample consists of non-transfer graduates from the 2006–2008 cohorts with a major in engineering or science.

Figure 2. Patenting and Selection into Finance by GPA Quartile. Sample: S&E Majors from Classes of 1994–2008



Notes: Person-level observations. This figure plots the mean number of patents awarded after college and the mean probability of taking a first job in finance by GPA quartile. For number of patents awarded after college, the sample consists of non-transfer graduates from the 1994–2008 cohorts with a major in engineering or science. For probability of taking a first job in finance, the sample consists of non-transfer graduates from the 2006–2008 cohorts with a major in engineering or science and whose initial sectors I observe.

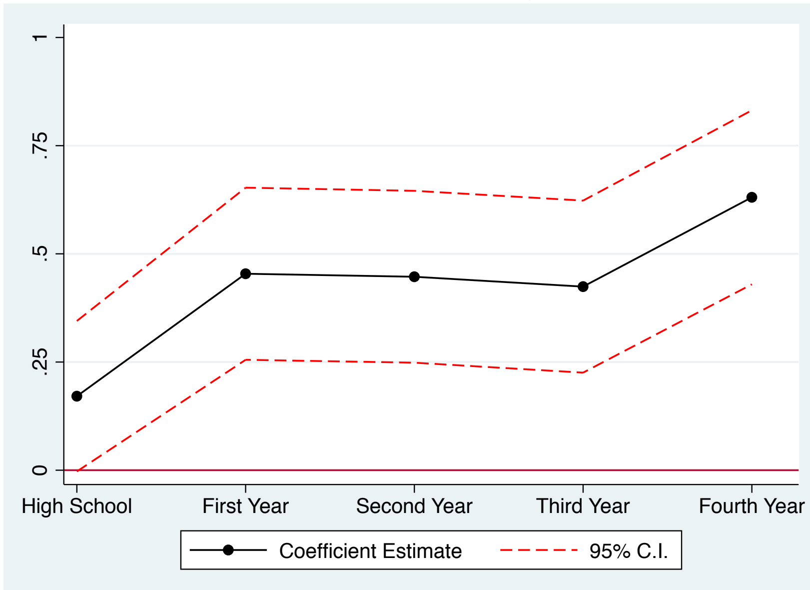
Figure 3. Estimated Correlations between Academic Performances over Time and Patenting. Sample: Mathematics and Engineering Majors from Classes of 2006–2008 Entering S&E Graduate Programs or Industries



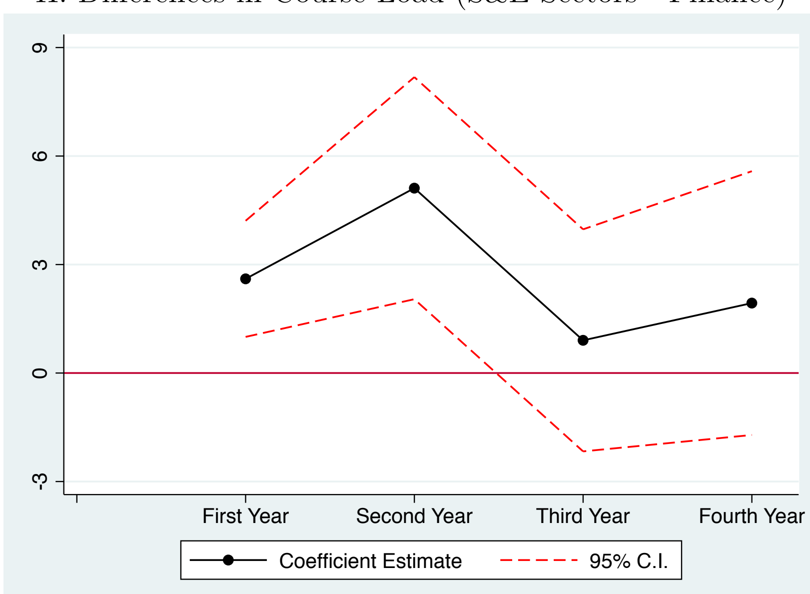
Notes: Person-level observations. This figure plots the marginal effects and 95-percent confidence intervals estimated from quasi–maximum-likelihood Poisson models with robust standard errors clustered by cohort and majors. The estimates plotted are from five separate regressions where the dependent variable is number of patents and the independent variables are respectively admission index score, GPA in first year of college, GPA in second year of college, GPA in third year of college, and GPA in fourth year of college. The sample consists of graduates from the 2006–2008 cohorts who majored in mathematics or engineering, earned a degree in exactly eight semesters, and pursued a graduate degree in S&E or took a first job in an S&E industry after college graduation. Academic performance measures are standardized by cohort within the sample. All regressions include a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (Caucasian American, Asian American, Hispanic American, African American, and non-American), dummies for high-school region (northeast, midwest, south, and west), dummies for cohort, dummies for majors at graduation, a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars.

Figure 4. Estimated Differences in Academic Skill Development. Sample: Mathematics and Engineering Majors from Classes of 2006–2008 with Initial Sector Observed

I. Differences in Academic Performance (S&E Sectors - Finance)



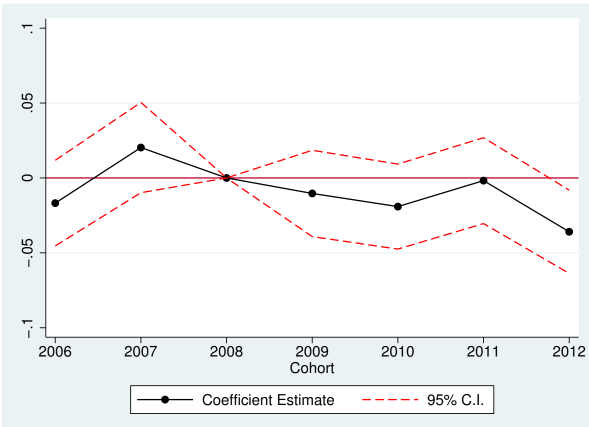
II. Differences in Course Load (S&E Sectors - Finance)



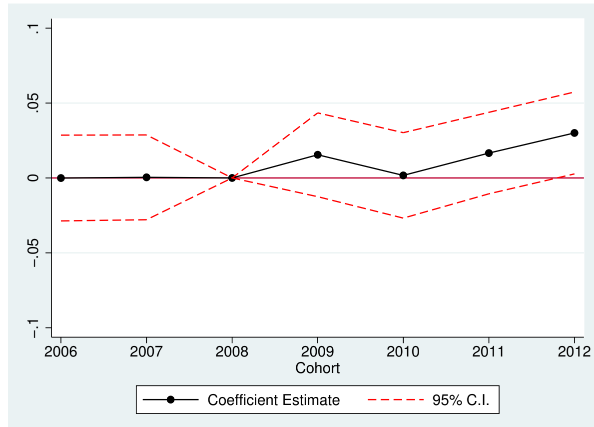
Notes: Person-level observations. This figure plots the conditional means for the differences between graduates taking a first job or pursuing a graduate degree in S&E and graduates taking a first job in finance. The sample consists of graduates from the 2006–2008 cohorts who majored in mathematics or engineering, earned a degree in exactly eight semesters, and whose initial sectors I observe. The dependent variables are admission index score, GPA in first year of college, GPA in second year of college, GPA in third year of college, and GPA in fourth year of college. Each dependent variable is standardized within the sample. The conditional means are estimated in OLS with robust standard errors clustered by cohort and majors; controls include a dummy for entering initial sectors other than finance or S&E, a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (Caucasian American, Asian American, Hispanic American, African American, and non-American), dummies for high-school region (northeast, midwest, south, and west), dummies for cohort, dummies for majors at graduation, a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars.

Figure 5. Estimated Cohort Variations in Likelihood of Major. Sample: Classes of 2006–2012

I. Major at Graduation

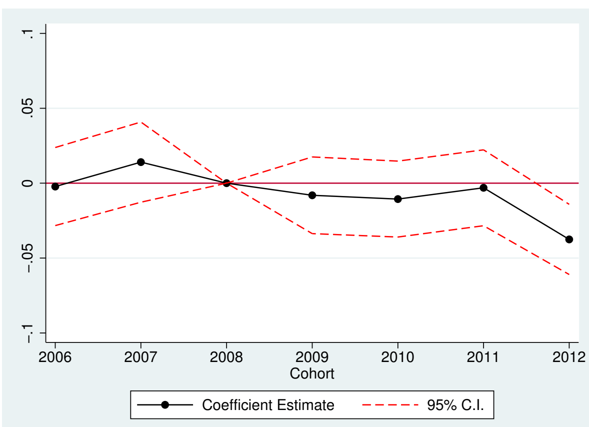


Management/Economics

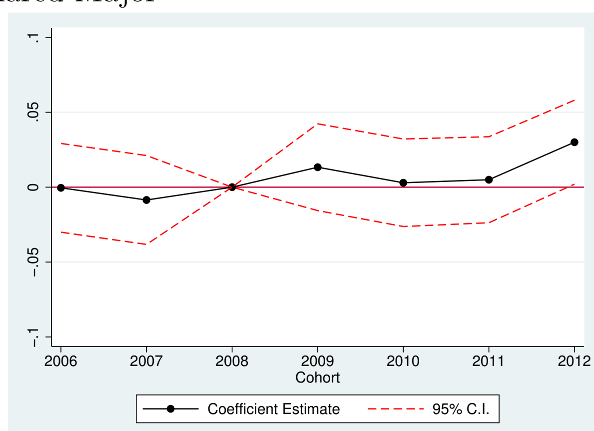


S&E

II. First Declared Major



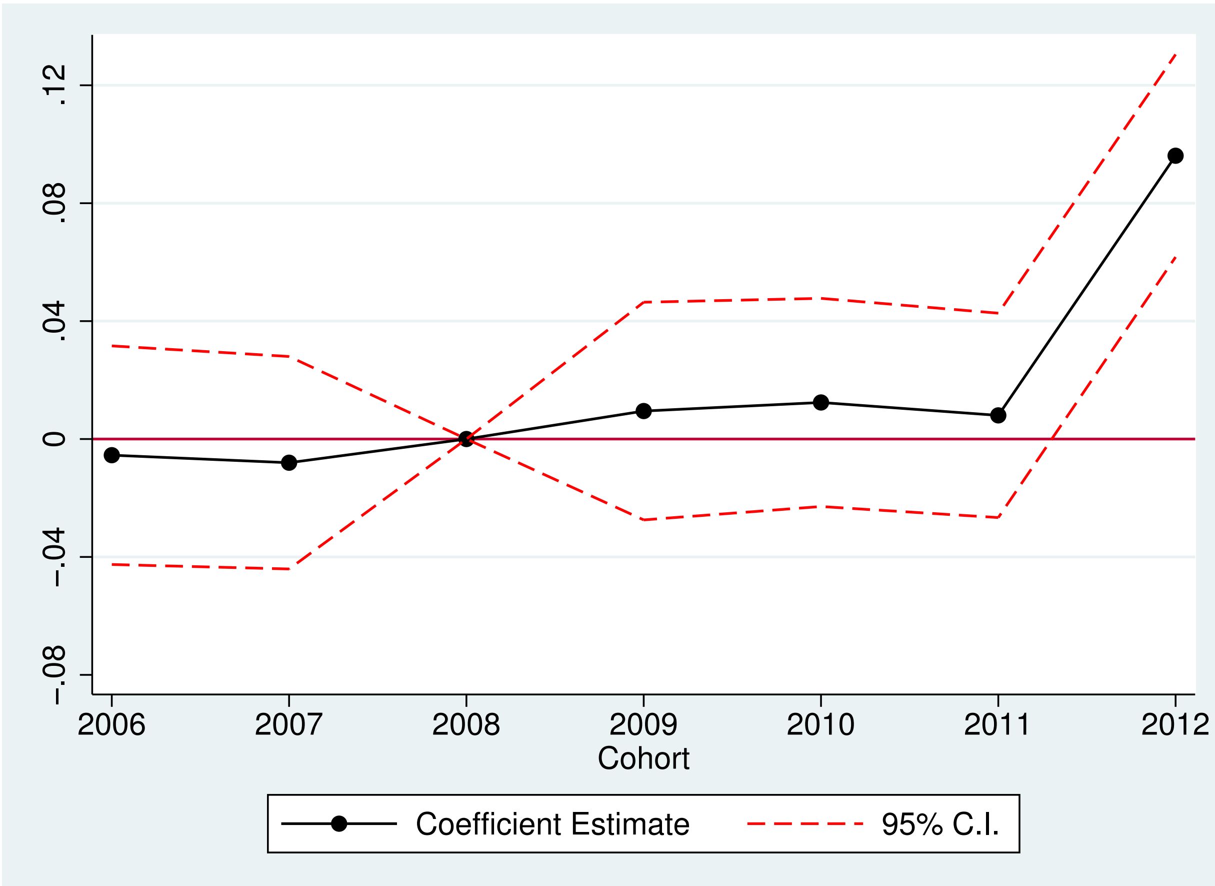
Management/Economics



S&E

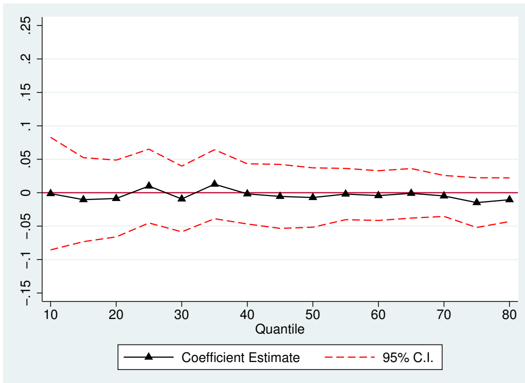
Notes: Person-level observation. This figure plots, by cohort, the OLS coefficient estimates and 95-percent confidence intervals for D^{Cohort} from Equation (5.1) with robust standard errors. The sample consists of all non-transfer students in the 2006–2012 cohorts. In Panel I, the dependent variable is whether the student graduated with a major in management/economics (on the left) or in S&E (on the right). In panel II, the dependent variable is whether the first declared major is management/economics (on the left) or S&E (on the right). All regressions include decile dummies for admission index score, a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (international, Caucasian American, Asian American, Hispanic American, and African American), dummies for high-school region (northeast, midwest, south, and west), and financial aid received in senior year in 2008 dollars.

FIGURE 6. Estimated Cohort Variations in Academic Performances. Sample: S&E Majors from Classes of 2006–2012

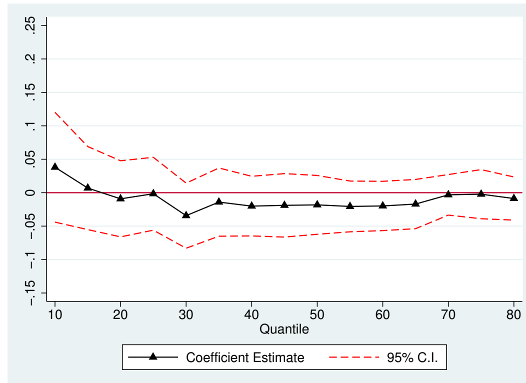


Notes: Person-level observation. This figure plots, by cohort, the OLS coefficient estimates and 95 percent confidence intervals for D^{Cohort} from Equation (5.3) with robust standard errors. The sample consists of all non-transfer students in the 2006–2012 cohorts who majored in S&E. The dependent variable is cumulative GPA. The regression also includes decile dummies for admission index score, a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (international, Caucasian American, Asian American, Hispanic American, and African American), dummies for high-school region (northeast, midwest, south, and west), dummies for majors at graduation, a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars.

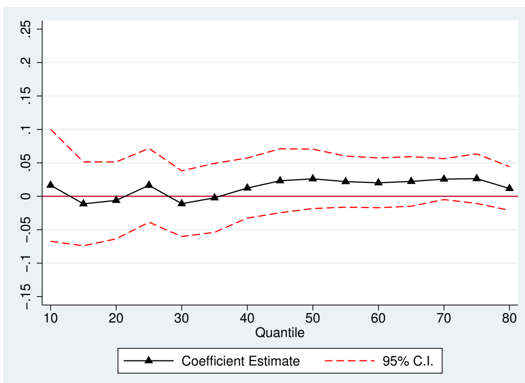
Figure 7. Quantile Regression Estimates for Cohort Variations in Cumulative GPA. Sample: S&E Majors from Classes of 2006–2012



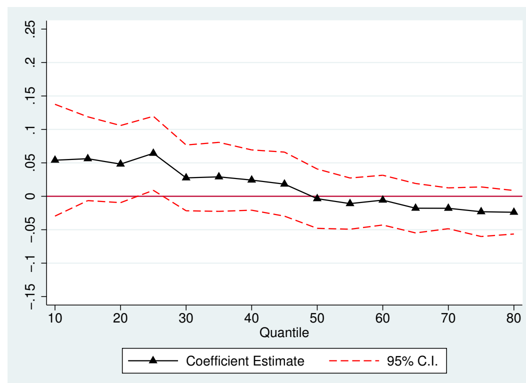
D^{Cohort}=2006



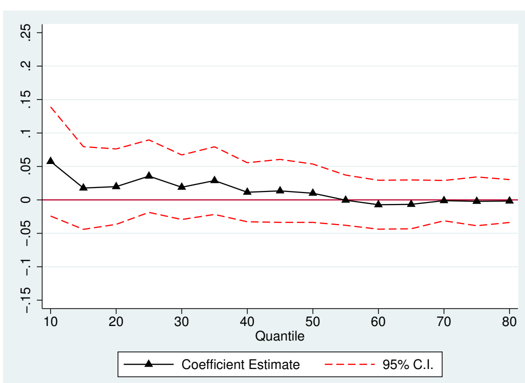
D^{Cohort}=2007



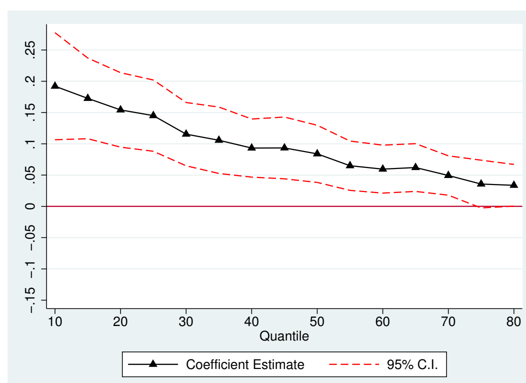
D^{Cohort}=2009



D^{Cohort}=2010



D^{Cohort}=2011



D^{Cohort}=2012

Notes: Person-level observation. This figure plots the quantile-regression coefficient estimates and 95 percent confidence intervals for D^{Cohort} from Equation (5.3) with robust standard errors. The sample consists of all non-transfer students in the 2006–2012 cohorts who majored in S&E. The dependent variable is cumulative GPA. All regressions include decile dummies for admission index score, a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (international, Caucasian American, Asian American, Hispanic American, and African American), dummies for high-school region (northeast, midwest, south, and west), dummies for majors at graduation, and a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars.

Appendix

A.1 Matching MIT alumni to USPTO patents

I match MIT graduates to the U.S. Patent and Inventor Database constructed by Li, Lai, D'Amour, Doolin, Sun, Torvik, Yu, and Fleming (2014). My matching procedure consists of three main steps. The first step generates the sample of potential matches using first and last names. The matching is done at the graduate/patent/inventor level. The second step uses additional information, such as middle names and locations, to calculate a likelihood score for each graduate/patent/inventor pair. Pairs that generate sufficiently high scores are considered correct matches. The final step ensures that each patent-inventor record is matched to only one graduate and collapses the data at the graduate/patent level. I discuss each step in detail below.

A.1.1 Initial matching using first and last names

The first step employs both exact and fuzzy name matching. I use records from the MIT Registrar's Office, the Alumni Association, and LinkedIn to capture possible name variations and name changes for MIT graduates. The patent-inventor records include inventors' full names and distinguish between first and last name fields; middle names can be included in either name field. I treat the first word in an inventor's first-name field and the last word in his or her last-name field as first and last names respectively. In cases of exact matching, an MIT graduate's first and last name perfectly match an inventor's imputed first and last name.[37] In cases of fuzzy matching, a graduate's first and last names both appear in an inventor's full name and the remainder of the name could match. I drop pairs in which both graduate and inventor have middle names but those middle names are completely different.

[37]In cases in which a graduate has a two-word first or last name (e.g., MARY JANE), I create permutations of the name (e.g., MARY and MARYJANE).

A.1.2 Determining the likelihood of a match

The second step calculates the likelihood that each graduate/patent/inventor pair is a correct match based on (a) how well the middle names match, (b) how well the locations match, and (c) how rare the first and last names are. Intuitively, if the middle names and locations match well and the graduate has an uncommon name, the pair is very likely to be a correct match. If the names are common and the additional information does not quite match, the pair is unlikely to be a correct match. I follow the Bayesian methodology developed by Torvik, Weeber, Swanson, and Smalheiser (2005) and Smalheiser and Torvik (2009) to calculate a likelihood score. The detailed steps are:

1. For each graduate/patent/inventor pair, construct a two-dimensional vector $x = (x_1, x_2)$, where x_1 measures how well the middle names match and x_2 measures how well the locations match. The values of x_1 are determined as follows:

   - 4: the two middle names match exactly, or neither has a middle name.
   - 3: one or both names are initials and the initials match; or the middle names are not initials but one includes the other.
   - 2: the graduate has a middle name but the inventor's middle name is missing (possibly because he or she did not list a middle name on patents); or the first and last names are fuzzily matched and the middle names are similar.
   - 1: the graduate does not have a middle name but the inventor does.

   The values of x_2 are determined as follows:

   - 4: both are from the same U.S. city, or the distance between listed cities and/or zip codes is less than 15 miles.
   - 3: both are from the same state, or the distance between their locations is less than 50 miles.

- 2: the inventor's location is in Massachusetts or California, or the distance is less than 150 miles,
- 1: all other cases (including international/mismatched/missing locations)

2. Calculate the probability of x conditional on being a correct match, $P(x|M)$, using a training dataset with highly likely matches. The highly likely matches satisfy *all* of the following criteria:

   - The assignee of the patent matches one of the organizations that the graduate has worked for or studied in post-college, according to his/her profile on LinkedIn and the Alumni Directory (excluding MIT). The matching between assignees and organizations follows the methodology developed by Autor, Dorn, Hanson, Pisano, and Shu (2016).
   - The application year on the patent is not earlier than the year of college graduation.

   Some graduates list their patents on their LinkedIn profiles; those patents are added to the training data. $P(x|M)$ is calculated as the number of highly likely matches for a given x divided by the total number of highly likely matches.

3. Calculate the probability of x conditional on being an incorrect match, $P(x|N)$, using a training dataset with highly unlikely matches. The highly unlikely matches satisfy *one* of the following criteria:

   - If an inventor record is matched to multiple graduates and one of them is a highly likely match, as determined above, the rest of the matches are considered highly unlikely.
   - The patent is applied for more than four years before college graduation.

   As above, $P(x|N)$ is calculated as the number of highly unlikely matches for a given x divided by the total number of highly unlikely matches.

4. Calculate the raw likelihood ratio $\widetilde{r(x)} = \frac{P(x|M)}{P(x|N)}$ and apply monotonic smoothing. The likelihood ratio, $r(x)$, is calculated as having the closest sum of distance squared to $\widetilde{r(x)}$ conditional on the monotonic constraint. The monotonic constraint is that for two x^a and x^b where $x_1^a \geq x_1^b$ and $x_2^a \geq x_2^b$, $r(x^a) \geq r(x^b)$. The correlation between the raw ratio and the monotonically smoothed ratio is 0.952.

5. Calculate the a priori match probability $P(M)$ based on the commonality of first and last names. For each first and last name, I calculate the number of unique graduate/inventor pairs who share the names; a higher number means a more common name. I regress the probability of being a highly likely match on the log of this number, within the training data of highly likely and unlikely matches. $P(M)$ is the predicted probability from the logistic regression.

6. Based on Bayes' Theorem, the likelihood score is then calculated as

$$P(M|x) = \frac{1}{1 + \frac{1-P(M)}{P(M)} \frac{1}{r(x)}}.$$

I consider a pair to be a match if the likelihood score is above a certain threshold (and not a highly unlikely match). Torvik, Weeber, Swanson, and Smalheiser (2005) use 0.5 as the cutoff, which means that false-positive matches are penalized to the same degree as false-negative matches. In my case, however, the false-positive matches are more damaging than the false-negative matches since patenting is a relatively rare event. After manually inspecting the matching pairs at the margin, I choose a threshold of 0.845, which is at the 95th percentile for highly unlikely matches and the 12th percentile for highly likely matches. Using a slightly higher or lower threshold does not change my key empirical findings.

A.1.3 Finalizing the data

In the rare cases where the same patent-inventor record is matched to multiple graduates, I apply the following tie-breakers:

1. Keep the graduate who appears in the training data of highly likely matches, if any.

2. Use the pair with the highest matching score.

3. Use the graduate with the most patents.

As the final step, I keep only utility patents applied for after college graduation, and collapse the data at the graduate/patent level.

A.1.4 Robustness of matching

I use two exercises to check the robustness of my matching algorithm. First, I identify the top MIT inventors from my matched data and verify the accuracy of matching using their online bios and/or LinkedIn profiles. Second, I compare graduates' majors to their patents' technology categories as classified by Hall, Jaffe, and Trajtenberg (2001). I find that MIT inventors tend to patent in technology categories related to their fields of study. MIT inventors with a major in electrical engineering and computer science, for instance, predominantly patent in the Computer & Communications category; those with a major in chemical engineering mainly patent in the Chemical category.

A.2 Using LinkedIn to construct long-term career outcomes

To collect public profiles on LinkedIn, I search for graduates by first and last names and then use major and year of graduation from MIT to identify the correct profiles. In the rare instances when this information is not sufficient, I use the individual's profile in the MIT Alumni Association's web directory to match location and employer. I exclude profiles with fewer than 50 LinkedIn connections since they are likely to be inactive.

I use the current industry designated in a profile's headline to assign an individual to a sector. I assign the following industries to the Science & Engineering sector: computer & network security; computer games; computer hardware; computer networking; computer software; consumer electronics; e-learning; information technology & services; internet; online media; technology & services; wireless; alternative medicine; biotechnology; cosmetics; health care; health, wellness & fitness; hospital & health care; medical devices; medical practice; mental health care; pharmaceuticals; veterinary; airlines & aviation; automotive; aviation & aerospace; chemicals; civil engineering; construction; consumer goods; defense & space; design; electrical/electronic manufacturing; energy; environment; environment & renewable energy; environmental services; food & beverages; food production; industrial automation; logistics & supply chain; maritime; mechanical or industrial engineering; metals; mining & metals; nanotechnology; oil & energy; packaging & containers; renewables & environment; semiconductors; space; sporting goods; telecommunications; textiles; transportation/trucking/railroad; utilities; warehousing; wine & spirits; higher education; military; and research.

I assign the following industries to Finance: banking; capital markets; financial services; insurance; investment banking; investment management; private equity; and venture capital & private equity.

The following industries are categorized as Other: accounting; animation; apparel & fashion; architecture & planning; arts & crafts; broadcast media; building materials; civic & social organization; commercial real estate; consumer services; diplomatic service; education management; entertainment; executive office; fashion; fine art; foreign affairs; fund raising; gambling & casinos; government administration; government relations; graphic design; gambling casinos; hospitality; human resources; individual & family services; international affairs; international trade & development; law enforcement; law practice; legal services; leisure travel & tourism; libraries; luxury goods & jewelry; management consulting; market research; marketing & advertising; media production; motion pictures & film; museums & institutions; music; non-profit organization management; performing arts; philanthropy; photography; political organization; printing; primary/secondary education; professional training & coaching; program development; public policy; public relations and communications; public safety; public service; publishing; real estate; restaurants; retail; sports; security & investigations; staffing & recruiting; sports; supermarkets; think tanks; tourism; and writing & editing.

A.3 Additional Tables and Figures

TABLE A.1. Correlation between College GPA and Patenting: Robustness to Selection into Long-term Sectors. Sample: S&E Majors from Classes of 1994–2008. Dependent Variable: Number of Patents since Graduation.

Sample	All graduates	Long-term sector observed	Long-term sector observed	Long-term sector: S&E
	(1)	(2)	(3)	(4)
Standardized GPA	0.229**	0.252**	0.253**	0.303**
	(0.039)	(0.061)	(0.063)	(0.074)
Detailed sector dummies	N	N	Y	Y
Mean DV	0.567	0.656	0.656	0.715
N	13,167	4,297	4,297	3,634

Notes: Person-level observations. Coefficients reported are marginal effects from quasi–maximum-likelihood Poisson models. Robust standard errors clustered by cohort and majors are shown in parentheses. ˜ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. The dependent variable is number of patents awarded after college. In column (1), the sample consists of non-transfer graduates from the 1994–2008 cohorts with a major in engineering or science. In columns (2) and (3), the sample consists of non-transfer graduates from the 1994–2008 cohorts with a major in engineering or science and whose long-term sectors I observe. In column (4), the sample consists of graduates from the 1994–2008 cohorts with a major in engineering or science and long-term employment in a science and engineering sector. *Standardized GPA* is cumulative GPA standardized within the engineering and science majors in each cohort. In columns (3), *Detailed sector dummies* include indicators for computer/IT, biotech/health care, manufacturing/hardware, finance, or consulting. In columns (4), *Detailed sector dummies* include indicators for computer/IT, biotech/health care, and manufacturing/hardware. All regressions include a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (Caucasian American, Asian American, Hispanic American, African American, and non-American), dummies for high-school region (northeast, midwest, south, and west), dummies for cohort, dummies for majors at graduation, a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars.

Table A.2. Selection into Finance based on College GPA by Gender and Ethnicity. Sample: S&E Majors from Classes of 2006–2008 with Initial Sector Observed. Dependent Variable: Probability of Entering Finance

	(1)	(2)	(3)	(4)
Standardized GPA	-0.056**	-0.041**	-0.033**	-0.043**
	(0.013)	(0.012)	(0.010)	(0.011)
Standardized GPA* Characteristic	0.039*	0.004	-0.027	0.025
	(0.016)	(0.014)	(0.020)	(0.021)
Characteristic	Female	Caucasian American	Asian American	Hispanic / African American

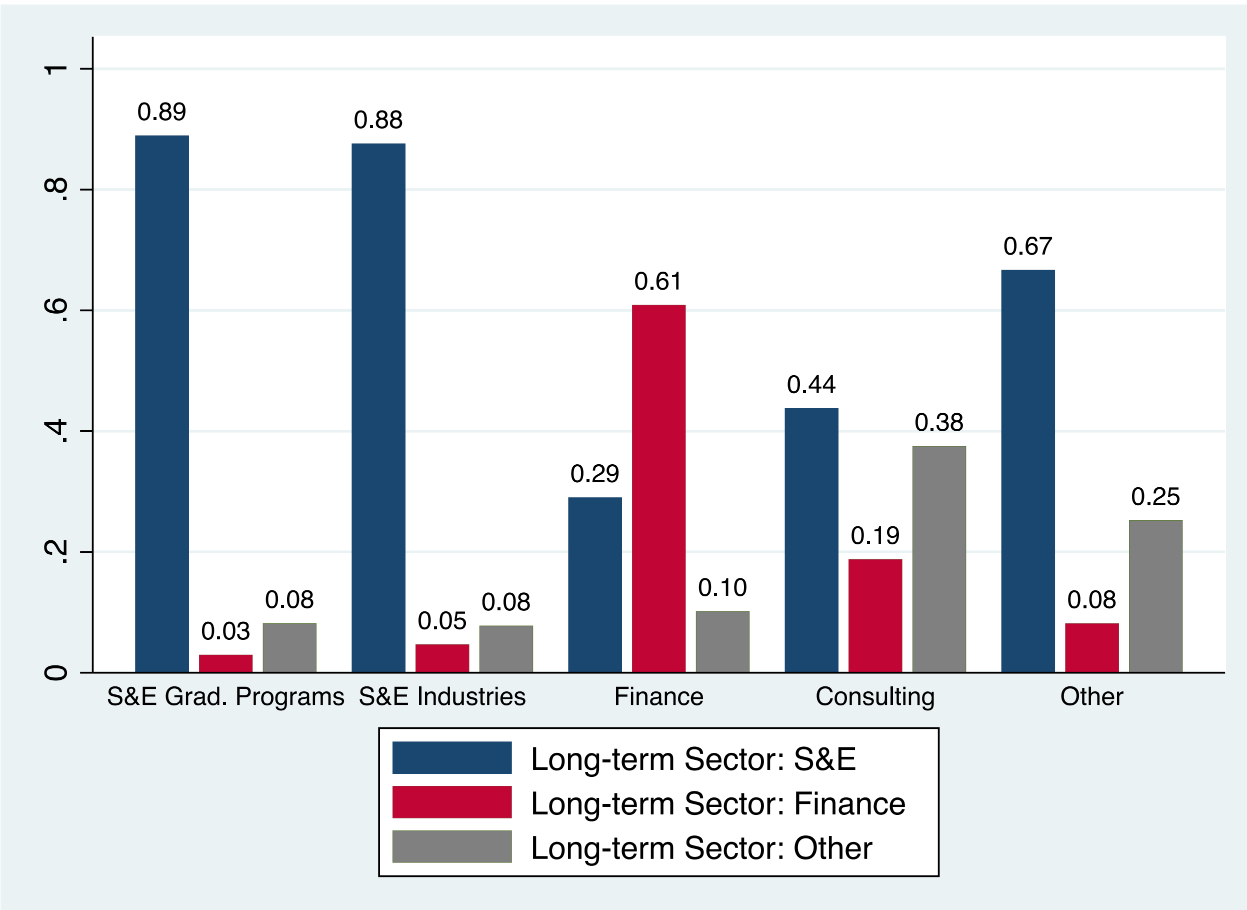
Notes: Person-level observations. Coefficients reported are from OLS regressions. Robust standard errors clustered by cohort and majors are shown in parentheses. ~ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. The dependent variable is whether the graduate takes a first job in finance after graduation. The sample consists of non-transfer graduates from the 2006—2008 cohorts with a major in engineering or science and whose initial sectors I observe. *Standardized GPA* is cumulative GPA standardized within the engineering and science majors in each cohort. In each column, I report the coefficient estimates on standardized GPA and its interaction with a demographic characteristic. All regressions include a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (Caucasian American, Asian American, Hispanic American, African American, and non-American), dummies for high-school region (northeast, midwest, south, and west), dummies for cohort, dummies for majors at graduation, a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars.

Table A.3. Estimated Cohort Variations in College Skill Development Conditional on High-School Activities. Sample: Classes of 2010–2012

Dep. Var.	First Major in Mgmt/Econ		First Major in S&E		Major in S&E		Cumulative GPA	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D^{2011}	0.007	0.004	0.002	0.004	0.016	0.017	-0.004	-0.005
	(0.013)	(0.013)	(0.015)	(0.015)	(0.014)	(0.014)	(0.017)	(0.017)
D^{2012}	-0.032**	-0.031**	0.034*	0.033*	0.035*	0.034*	0.083**	0.083**
	(0.012)	(0.012)	(0.015)	(0.015)	(0.014)	(0.014)	(0.017)	(0.017)
High-school activities		Y		Y		Y		Y
Major dummies							Y	Y
N	2,658	2,658	2,658	2,658	2,658	2,658	2,658	2,658

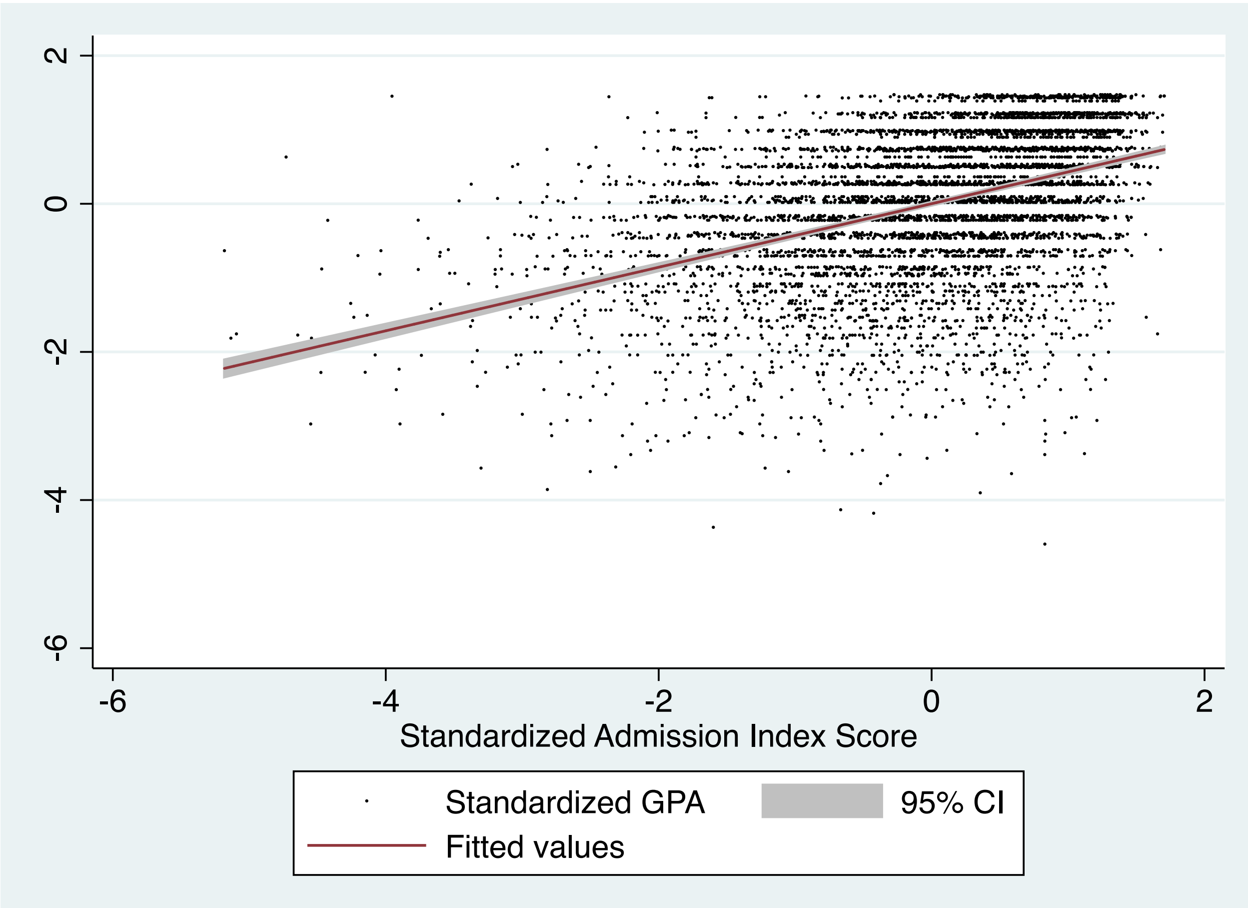
Notes: Person-level observation. All estimates are from OLS with robust standard errors. ~ $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. The sample consists of graduates from the 2010–2012 cohorts with valid responses on high-school activities (97.7 percent of the 2010–2012 cohorts). In columns (1)–(2), the dependent variable is an indicator variable for declaring a first major in management or economics. In columns (3)–(4), the dependent variable is an indicator variable for declaring a first major in S&E. In columns (5)–(6), the dependent variable is an indicator variable for graduating with a major in S&E. In columns (7)–(8), the dependent variable is cumulative GPA. D^{2011}*:* indicator variable for the 2011 cohort. D^{2012}*:* indicator variable for the 2012 cohort. *High-school activities* include indicator variables for participation in varsity sports, performing arts (music/theater/dance), and clubs (community service, student government, student publications) and for leadership in these activities. *Major dummies* include dummies for majors at graduation and a dummy for graduating with more than one majors. All regressions include decile dummies for admission index score, a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (Caucasian American, Asian American, Hispanic American, African American, and non-American), dummies for high-school region (northeast, midwest, south, and west), and financial aid received in senior year in 2008 dollars.

Figure A.1. Relationship between Initial and Long-Term Sector. Sample: S&E Majors from Classes of 2006–2008 with Both Outcomes Observed



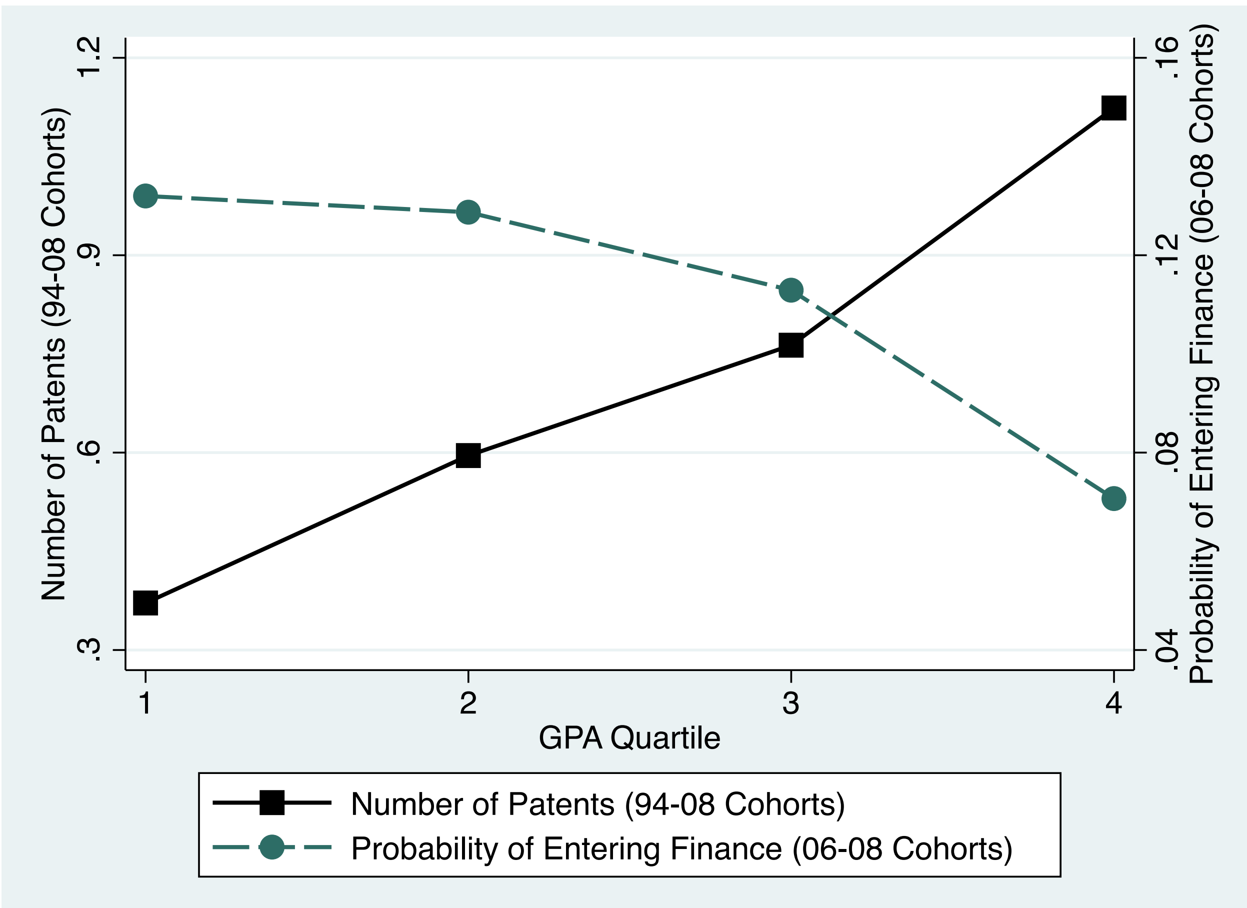
Notes: Person-level observations. This figure plots the share of graduates in each long-term sector by their initial sector. The sample consists of non-transfer graduates from the 2006—2008 cohorts with a major in engineering or science and whose initial and long-term sectors I observe.

FIGURE A.2. Correlation between Admission Index Score and GPA. Sample: Classes of 2006–2012



Notes: Person-level observations. This figure shows scatter plot and linear fit of the raw relationship between admission index score and cumulative GPA, both of which are standardized within each cohort. The sample consists of non-transfer graduates from the 2006–2012 cohorts.

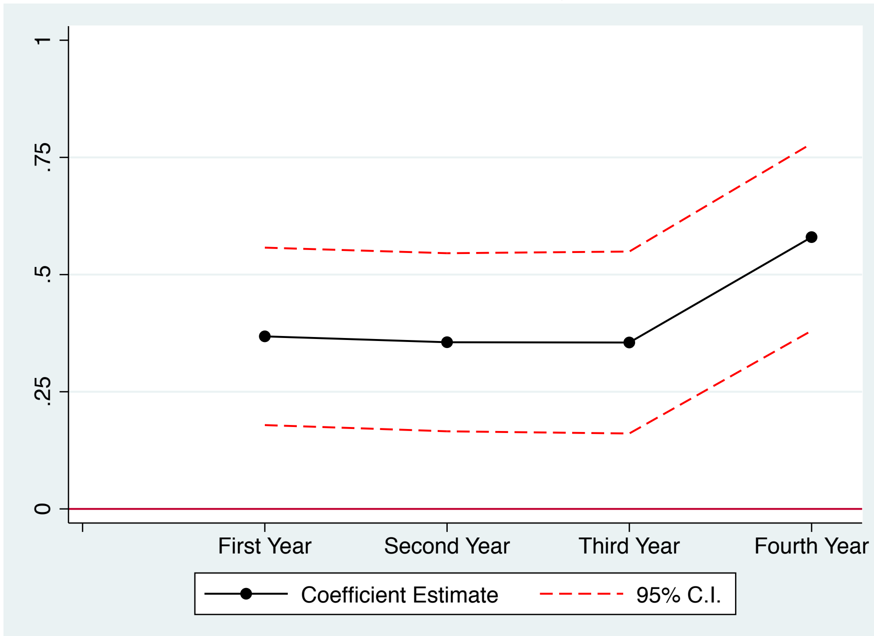
Figure A.3. Patenting and Selection into Finance by GPA Quartile. Sample: Mathematics and Engineering Majors from Classes of 1994–2008



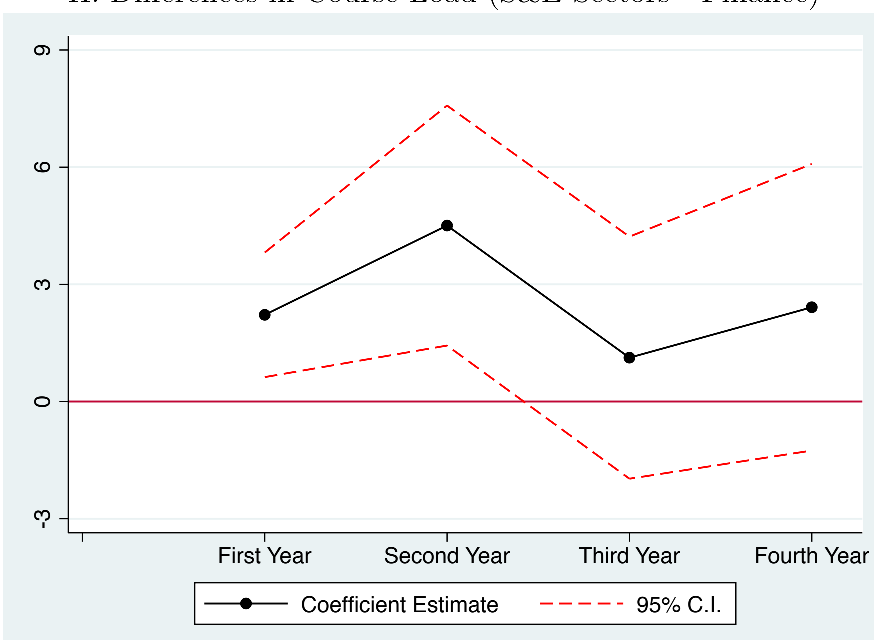
Notes: Person-level observations. This figure plots the mean number of patents invented after college and the mean probability of taking a first job in finance by GPA quartile. For the number of patents invented after college, the sample consists of non-transfer graduates from the 1994–2008 cohorts with a major in mathematics or engineering. For the probability of taking a first job in finance, the sample consists of non-transfer graduates from the 2006–2008 cohorts with a major in mathematics or engineering and whose initial sectors I observe.

Figure A.4. Differences in Academic Skill Development Conditional on High-School Academic Achievement. Sample: Mathematics and Engineering Majors from Classes of 2006–2008 with Initial Sector Observed.

I. Differences in Academic Performance (S&E Sectors - Finance)



II. Differences in Course Load (S&E Sectors - Finance)



Notes: Person-level observations. This figure plots the conditional means for the differences between graduates taking a first job or pursuing a graduate degree in S&E and graduates taking a first job in finance. The sample consists of graduates from the 2006–2008 cohorts who majored in mathematics or engineering, earned a degree in exactly eight semesters, and whose initial sectors I observe. The dependent variables are GPA in first year of college, GPA in second year of college, GPA in third year of college, and GPA in fourth year of college. Each dependent variable is standardized within the sample. The conditional means are estimated in OLS with robust standard errors clustered by cohort and majors; controls include decile dummies for admission index score, a dummy for entering initial sectors other than finance or S&E, a dummy for being female, dummies for age (equals 22, greater than 22), dummies for ethnicity (Caucasian American, Asian American, Hispanic American, African American, and non-American), dummies for high-school region (northeast, midwest, south, and west), dummies for cohort, dummies for majors at graduation, a dummy for graduating with more than one major, and financial aid received in senior year in 2008 dollars.