

# Essays on Innovation, Productivity, and Talent Allocation

by

Pian Shu

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in partial fulfillment of the requirements for the degree of

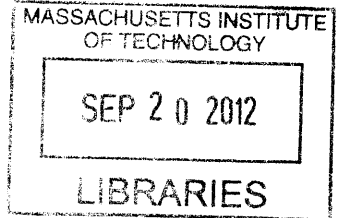
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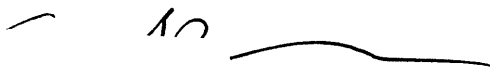
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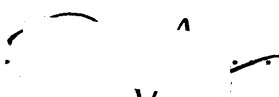


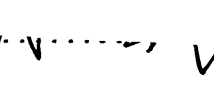
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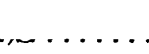
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## Abstract

This thesis contains three essays on innovation, productivity, and talent allocation.

The first essay explores a novel channel through which short-term economic fluctuations affect the long-term innovative output of the economy: innovators' accumulation of human capital. Using a newly constructed data set on the patenting history of all individuals obtaining a bachelor's degree from the Massachusetts Institute of Technology (MIT) between 1980 and 2005, I find that cohorts graduating during booms produce significantly fewer patents over the subsequent two decades. Initial economic conditions do not affect inventors' long-term occupational affiliation, suggesting that the main differences lie in their long-term level of inventive human capital. The decrease in patent output of cohorts graduating during booms is mainly from inventors with relatively low GPAs, and marginal patents receive fewer citations than the rest.

The second essay uses the 2008 financial crisis as a natural experiment to study the characteristics of recent graduates from MIT bachelor programs who pursued a career in finance immediately after graduation. I find that finance competes against science and engineering graduate programs for the best talent from MIT but values academic skills less. As a result of endogenous skill development during college, financiers have significantly lower academic skills than students entering graduate school at graduation, despite having similar levels of raw academic talent measured at college entrance. Marginal financiers have lower starting salaries than average financiers, suggesting that there is positive selection into finance.

The third essay examines the asset accumulation and labor force participation of Social Security Disability Insurance applicants. Using the RAND Health and Retirement Study panel data, I provide empirical support for the theory that an imperfectly screened disability insurance program encourages individuals who dislike work to save more in the present and plan to apply for disability insurance in the future, regardless of their future health. Despite exhibiting lower labor force

attachment and earning less than accepted applicants, rejected applicants have significantly more assets immediately prior to their application, but not in the several years before. Although imperfect, the current screening differentiates the applicants in meaningful ways without using assets as an additional criterion.

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*To my father Qin Shu  
and  
in loving memory of my mother Yihong Wang*



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# Chapter 1

## The Long-Term Impact of Business Cycles on Innovation: Evidence from the Massachusetts Institute of Technology<sup>1</sup>

### 1.1 Introduction

Allocating talent to innovative activities is key to promoting a country's long-term economic growth (Baumol, 1990; Murphy et al., 1991). However, empirically

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we know little about what factors affect talented individuals' innovative output. Do short-term shocks to individuals' career choices have a long-term impact on innovation? Who are the people most affected? In this paper, I provide empirical evidence to answer these questions by exploring one particular source of exogenous variation: economic conditions at the time of college graduation. Using individual patent output as a measure of innovative activities, I estimate the causal impact of initial labor market conditions on the long-term patent production of a sample of highly skilled individuals: the alumni of the Massachusetts Institute of Technology (MIT).

To show how initial labor market conditions could affect an individual's long-term patent production, I develop a two-sector two-period model. My model combines features from standard static Roy models (Roy, 1951; Willis and Rosen, 1979; Gould, 2002; Heckman and Honore, 1990; Mulligan and Rubinstein, 2008) as well as models with occupation-specific and task-specific human capital (Neal, 1995; Gibbons and Waldman, 2004). The theory indicates that, by changing initial career choices, initial economic conditions could affect future patent production in two ways. First, if individuals acquire occupation-specific human capital on the job, initial market conditions could affect individuals' long-term occupational affiliations.<sup>2</sup> Second, by altering graduates' career paths, initial economic conditions could affect their future level of human capital, even when there is no effect on long-term occupational affiliations.

I examine the empirical implications of my model using a newly constructed longitudinal data set on the patenting history of everyone who received a Bachelor's degree from MIT between 1980 and 2005. I match the alumni to the U.S.

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<sup>2</sup>Oyer (2006, 2008) provides empirical evidence on this observation. There are also other causes for sticky jobs, such as search frictions and employer's uncertainty about the workers' skill (Gibbons et al., 2005; Oreopoulos et al., 2012). I discuss their implications in Section 1.2.

inventor database from Lai et al. (2011b) based on names and locations.<sup>3</sup> My data include 27,145 graduates with over 475,000 person-year observations. Around 16% of the graduates have produced at least one patent in the years I study. Overall, the inventors have produced nearly 25,000 patents and received over 323,000 patent citations by the end of 2010. I link the patent data to individual-level administrative records on demographics and academic performance at MIT to control for a rich set of characteristics in my empirical analysis.

Since MIT is one of the major technology-based universities, MIT alumni are particularly suited for the purpose of this study. My sample has nearly 24,000 engineering and science graduates, who constitute 0.24% of the total number of engineering and science bachelor's degree recipients between 1980 and 2005 (NCES, 2011).<sup>4</sup> Previous studies have shown that firms founded by MIT alumni generate hundreds of billions of dollars in revenue and hundreds of thousands of jobs in the U.S. (Roberts and Eesley, 2009). It is thus not surprising that many alumni are productive inventors. The MIT alumni in my sample have produced around 1.2% of the utility patents with U.S. origin granted between 1981 and 2010 (USPTO, 2011). An average patent produced by the MIT graduates in my sample receives approximately 1 citation per year since the year of patent application, which is twice as much as an average U.S. utility patent produced during the same period.

I find that adverse labor market conditions at the time of college graduation lead to an *increase* in the future patent production of MIT alumni. A one-percentage-point increase in the national unemployment rate in the year of sched-

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<sup>3</sup>The raw patent data from the United States Patent and Trademark Office (USPTO) do not provide unique identifiers for inventors, making it difficult to track the output of an inventor over time. Lai et al. (2011b) provide a solution by employing a Bayesian supervised learning approach to match inventors to U.S. patents.

<sup>4</sup>Over 17,000 graduates in my sample are engineering majors, equivalent to 0.6% of the total engineering graduates between 1980 and 2005. There are over 4000 degree-granting institutions in the National Center of Education Statistics (NCES) population.

uled graduation increases the average graduate's annual patent output by around 5%, or approximately 2.5 patents per year for an average size cohort of 1000 graduates. A 1.25 standard deviation decrease in the equity market return during the students' sophomore and junior years has a similar effect. The effect of initial economic conditions on patent production increases over time and is largest between 10 and 20 years after graduation, which are also graduates' peak inventive years. Meanwhile, economic fluctuations have no measurable effect on the contemporaneous innovative output of graduates.

There are two possible explanations for these findings, which are not mutually exclusive. First, more graduates may become inventors as a result of graduating in a worse economy (changes at the extensive margin). Second, inventors who graduate in a worse economy may be more productive (changes at the intensive margin). Comparing the patent production of the 1980-1995 cohorts during their first 15 years after graduation, I find no evidence for changes at the extensive margin. Inventors from recession cohorts are not *ex ante* more likely to patent, where I use their cumulative grade point average (GPA) at MIT as a measure of their inventive ability at the time of graduation.<sup>5</sup> Thus, graduates who become inventors would most likely patent regardless of initial labor market conditions, but graduating in a worse economy increases the number of patents they produce.

The increase in patent production due to graduating in adverse labor market conditions comes primarily from science majors working in non-software engineering sectors, such as chemical, drugs and medical industries. Initial economic conditions have no significant effect on the distribution of the inventors' long-term sector. Furthermore, graduating in a worse economy has a significantly negative effect on the time that an inventor takes to produce their first patent. Taken to-

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<sup>5</sup>I normalize the GPA by major and cohort. The normalized GPA significantly predicts future patent production.

gether, these results suggest that the accumulation of human capital is likely to be the main channel through which initial labor market conditions affect long-term patent production. The most plausible explanation is that inventors from recession cohorts either start working in patent producing sectors sooner or are more likely to go to graduate school, though my data do not allow me to determine the relative importance of the these two channels.

I show that initial conditions affect the patent production of inventors with relatively low GPAs. Graduates with the highest inventive ability upon graduation do not seem to be affected. Consistent with the finding that the relatively less inventive individuals produce the marginal patents, those patents also receive slightly fewer citations than the average and median patents in my sample.<sup>6</sup> These results suggest that there exists positive sorting into patent production, where the most talented inventors produce the same patents regardless of their graduating economic conditions.

My results have several important implications. First, I provide some of the first empirical evidence on how talented individuals invent. Despite the large number of studies on the patent production of firms,<sup>7</sup> very few papers examine the determinants of patent production at the individual level. Compared with

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<sup>6</sup>It is important to note that the marginal patents still receive more citations than the average and median of all U.S. utility patents.

<sup>7</sup>This literature provides ample evidence on the economic value of patented inventions. At the firm-level, the number of patents produced by a firm strongly and positively correlates with its research and development (R&D) expenditure, and this relationship holds across different industries (Griliches, 1990). Other inputs such as venture capital funding also significantly increase patents (Kortum and Lerner, 2000). Different measures of patent production, such as citation-weighted patent count, number of patents per R&D dollar, citations per patent, and a weighted index of multiple indicators of patent quality, are all found to boost firms' market value and productivity (Comanor and Scherer, 1969; Trajtenberg, 1990; Bloom and Van Reenen, 2002; Hagedoorn and Cloudt, 2003; Lanjouw and Schankerman, 2004; Hall et al., 2005). Studies also directly calibrate the economic value of patents using patent renewal data and surveys, and show that the value increases in the number of citations received (Schankerman and Pakes, 1986; Lanjouw et al., 1998; Harhoff et al., 1999). Although not all inventions are patentable, firms patent most of the inventions that can be patented, even in industries where patent protection is relatively unimportant (Mansfield, 1986; Cohen et al., 2000).

previous studies, my data have distinct advantages, as I observe a large group of potential innovators with homogenous training, characteristics, and abilities. Previous work such as Amesse et al. (1991), Kerr (2008), and Jones (2009) primarily uses samples of only inventors to study their behavior and characteristics.<sup>8</sup> Without a comparison group of non-inventors, these studies do not shed light on vital issues such as what leads talented individuals to invent. My data also include a rich set of individual characteristics, which helps to determine the factors that affect patent production.<sup>9</sup> Furthermore, my results are relevant for understanding how top engineering and science students in the U.S. innovate, which has key policy implications.<sup>10</sup> For instance, Romer (2001) argues that a top priority of the innovation policy in the U.S. should be to increase the supply of engineers and scientists. My results provide a first step towards quantifying the actual return, in terms of producing patented inventions, of a potential policy that provides incentives for engineering and science students to pursue careers in innovative sectors.

This study also presents some of the first evidence on the links between business cycles, talent allocation, and long-term innovation at the micro-level. A literature has analyzed the *contemporaneous* relationships between business cycles and relevant outcomes, including labor productivity (Bernanke and Parkinson, 1991; Goldin, 2000), technological progress (Field, 2003; Nicholas, 2003, 2008), and venture capital investment (Nanda and Rhodes-Kropf, 2011). My study complements

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<sup>8</sup>One exception is the study by Ding et al. (2006), which finds that female life scientists are less likely to patent than male life scientists.

<sup>9</sup>It also helps verify the accuracy of my matching procedure. For example, although I do not use majors at MIT in my matching, the engineering and science majors in my sample are significantly more likely to patent than the other majors.

<sup>10</sup>Compared with other top engineering and ivy league universities, MIT admits similar students based on standardized test scores (Grove, 2011). The 25th and 75th percentiles of the SAT math score of admitted students at MIT are 740 and 800, respectively. Other top engineering programs such as California Institute of Technology and the engineering school of Cornell University have similar score range for their admitted students. The 25th percentile of the SAT math score at ivy league universities and other top universities such as Stanford University and University of Chicago is around 680, and the 75th percentile is around 770.

this literature by showing that through changing talent allocation, business cycles could also have a *dynamic* effect on future inventive output. Since adverse labor market conditions change the relative demand for labor of different sectors, my results suggest that sectors producing more patented inventions are less cyclical, and that increasing labor demand from highly pro-cyclical sectors could potentially have a negative impact on long-term innovation. For example, graduating during a recession leads to higher graduate degree attainment and higher enrollment in PhD programs in science and engineering (Bedard and Herman, 2008; Kahn, 2010). In contrast, finance is a prominent example of a highly pro-cyclical sector (Oyer, 2008). However, the *causal* effect of going to finance (or graduate school) right after college on an individual's long-term innovative output remains unexamined. Although I do not directly estimate such effects in this paper, my results suggest that shocks to initial career choices could have long-term effect on producing innovations, pointing to the importance of potential follow-on research that addresses these open questions.

An influential line of work shows that, because innovation generates positive spillovers, innovators receive inadequate compensation relative to their contribution to society. As a result, the equilibrium level of innovation is less than optimal (Nelson, 1959; Arrow, 1962). While the patent system is designed to help inventors capture at least some of the benefits from their innovations, previous empirical studies suggest that there are large, positive social externalities to the creation of new ideas that are not fully internalized by the patent system (Mansfield et al., 1977; Jaffe, 1986; Trajtenberg, 1989; Jaffe et al., 1993; Caballero and Jaffe, 1993; Nadiri, 1993; Cockburn and Henderson, 1994; Hall, 1996; Jones and Williams, 1998; Hall et al., 2001; Bloom et al., 2012).<sup>11</sup> Since wages do not perfectly mea-

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<sup>11</sup>It is possible that patented inventions also generate negative externalities through patent races or patent blocking, but this large body of empirical evidence suggests that the positive spillovers

sure inventors' marginal product of labor, the growing literature that examines the effect of graduating economic conditions on private returns does not have clear implications for social welfare. For example, graduating in adverse labor market conditions has a negative long-term impact on the earnings of college graduates (Kahn, 2010; Oreopoulos et al., 2012), the career development of aspiring investment bankers (Oyer, 2008), and the productivity of economists (Oyer, 2006). In contrast, this paper is one of the first to focus on an outcome that generates potentially large social externalities.<sup>12</sup> My results suggest that a thorough welfare analysis of the impact of adverse labor market conditions should account for the potential social gains of the increased innovative output.<sup>13</sup>

My study also contributes to this literature by analyzing the relevance of sorting, which is important for both interpreting empirical results as well as conducting potential welfare analysis. For instance, Oyer (2008) finds that the MBA graduates who enter investment banking as a result of graduating in a booming stock market are more likely to stay in the industry. He argues that this is evidence for the existence of occupation-specific human capital in investment banking. However, without studying selection, he cannot exclude the possibility that graduates with higher innate ability could self-select into banking during booms.<sup>14</sup> The main

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outweigh the negative. Even with patent protection, research and development still creates sizable social returns that are at least twice as large as the private returns. Furthermore, patent citations are often used as a direct measure of knowledge spillovers (Caballero and Jaffe, 1993; Jaffe et al., 1993; Hall et al., 2005).

<sup>12</sup>Another study that looks at a socially important outcome is Schoar and Zuo (2011), who show that CEOs who start their careers during recessions have more conservative management styles.

<sup>13</sup>To perform such a welfare analysis, one would also need to observe several additional outcomes such as wages inclusive of non-pecuniary benefits and other measures of innovation like academic publications and new firm founding activities.

<sup>14</sup>Boehm and Watzinger (2011) is one of the first studies that examine sorting. They find that economics PhD candidates who graduate in a recession positively select into academia, in the sense that the average graduate staying in academia in a recession is better. But they use ex post publication records to measure ex ante ability. In contrast, Oyer (2006) finds that economics PhD graduates who enter the labor market in a recession tend to get jobs at lower-ranked schools, and consequently produce less research. This suggests that initial labor market conditions could have opposite effect on long-term outcomes through sorting. Genda et al. (2010) and Oreopoulos et al.

difficulty in empirically identifying selection is the lack of a good measure of ex ante ability. In my data, I am able to use cumulative grade point average (GPA) at MIT as a uniform measure of innate ability to invent, which is fully determined by the time of graduation.<sup>15</sup> I show that my results are not driven by selection, and that it is not the case that more skilled graduates become inventors as a result of graduating in bad economic conditions. Furthermore, I find that initial economic conditions only affect the patent production of inventors with relatively low GPAs, suggesting that this group may be particularly sensitive to changes in the relative incentives of going into different sectors upon graduation.

This chapter proceeds as follows. Section 1.2 derives the theoretical predictions using a simple two-period Roy-style model. Section 1.3 discusses the data and the patent matching procedure. I present the estimates of the main effect of initial labor market conditions on future patent production in Section 1.4, and decompose the effect in Section 1.5. Section 1.6 concludes.

## 1.2 Conceptual Framework

By affecting initial career choices, initial labor market conditions could affect long-term patent production in two ways: changing the level of human capital accumulated over time, and changing the future occupational affiliation. In this section, I formalize this idea using a two-sector two-period Roy-style model. Compared to a standard static Roy model, my model has two distinct features. The first is that I allow individuals to switch to a different sector after they enter the labor market. I define the path of human capital accumulation, and discuss the scenar-

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(2012) find low ability workers to be more sensitive to initial career shocks than high ability workers. This is not evidence for positive sorting into high paying sectors since the distributions of low and high ability workers are unknown.

<sup>15</sup>I normalize GPA by major and cohort. The normalized GPA strongly predicts future patent production.

ios in which individuals may have the incentive to switch sectors even at the cost of losing their accumulated occupation-specific human capital. The second feature is that I specify the externality of patent production. As a result, the career paths individuals choose to maximize their own utility could differ from the social optimum. I use the model to show how a temporary shock to initial career choices could affect patent production in the future. I also discuss the relevance of self-selection.

### 1.2.1 Assumptions

I consider the career choice problem of a single graduating cohort with  $P$  individuals. The economy contains two sectors of production, inventive (“I”) and non-inventive (“N”). Empirical examples of patent-producing sectors include graduate school in science or engineering and industries such as bio-technology and electrical engineering. Examples of non-patent-producing sectors include finance and management consulting. I assume that individuals live for two periods. During each period, a person is able to choose her sector of employment after observing the state of the economy. Let  $Q_i^t = I$  or  $N$  denote the sector chosen by individual  $i$  in period  $t = 1, 2$ . There are four possible career paths:  $(Q_i^1, Q_i^2) \in \{(I, I), (I, N), (N, I), (N, N)\}$ . An example of (N,I) is working in finance or consulting for two years before going back to graduate school in science or engineering.

An individual chooses a career path that maximizes her total utility:

$$U_i(Q_i^1, Q_i^2) = W_i^1(Q_i^1) + \beta W_i^2(Q_i^2|Q_i^1) + \delta \sum_j Pat_{j \neq i}$$

where  $W_i^1(Q_i^1)$  is her wage in sector  $Q_i^1$  in period 1,  $W_i^2(Q_i^2|Q_i^1)$  is her wage in sector  $Q_i^2$  in period 2 conditional on working in sector  $Q_i^1$ , and  $\beta \leq 1$  is her discount rate.

I introduce the externality of patented inventions by assuming that each person's utility function depends on other individuals' patent production. The weight  $\delta$  thus captures, in reduced form, the magnitude of the externality from creating new patented technology. If  $\delta > 0$ , externality is positive, and if  $\delta < 0$ , it is negative.

### Earnings and human capital

Each graduate  $i$  is endowed with sector specific human capital, denoted  $h_{i,I}$  and  $h_{i,N}$ , which determine her initial wages. For simplicity, wages are linear in human capital and depend on the state of the economy. In period 1,

$$\begin{aligned} W_i^1(I) &= h_{i,I}; \\ W_i^1(N) &= h_{i,N} + s \end{aligned}$$

where  $s$  is the change in the wage in the non-inventive sector that depends on the state of the economy in period 1. I assume that  $s$  is constant across individuals and only affects wages in the non-inventive sector. The latter is without loss of generality, as only the change in the relative wage between the two sectors matters for equilibrium patent output. I discuss the equilibria in two cases:  $s = 0$  and  $s > 0$ .

In addition to their initial endowments, workers develop occupation-specific human capital on the job, denoted  $k_I$  and  $k_N$ . Thus wages in period 2 are

$$\begin{aligned} W_i^2(I|I) &= h_{i,I} + k_I; \\ W_i^2(N|I) &= h_{i,N}; \\ W_i^2(I|N) &= h_{i,I}; \\ W_i^2(N|N) &= h_{i,N} + k_N. \end{aligned} \tag{1.1}$$

Notice that I assume the shock  $s$  is temporary, only affecting wages in period 1. To focus on the effect of initial economic conditions, I assume that the economic conditions in period 2 do not affect wages in period 2.

### Patent production

Since graduates rarely produce patents right after graduation, I assume that patent production only occurs in period 2. Let  $Pat_i$  be the patent production of individual  $i$  in period 2. Define

$$Pat_i(Q_i^2|Q_i^1) = \begin{cases} W_i^2(I|Q_i^1) & \text{if } Q_i^2 = I; \\ 0 & \text{if } Q_i^2 = N. \end{cases}$$

That is, all patents are produced by the inventive sector. Notice that an individual is more inventive if she works in the inventive sector throughout her career (i.e. choosing  $(I, I)$ ) than if she only works in the inventive sector in period 2 (i.e. choosing  $(N, I)$ ). In order to obtain a closed-form solution, I assume that a graduate's patent production equals her inventive human capital in period 2. The results would be qualitatively the same if patent production were some other weakly increasing function of inventive human capital.

## 1.2.2 Career path and patent production

### Benchmark case: no shock

I start with the benchmark case where  $s = 0$ . An individual  $i$  chooses the career path  $(Q_i^1, Q_i^2)$  that maximizes  $U_i(Q_i^1, Q_i^2)$ . Since she cannot affect others' patent production, maximizing  $U_i(Q_i^1, Q_i^2)$  is equivalent to maximizing  $\tilde{U}_i(Q_i^1, Q_i^2) =$

$W_i^1(Q_i^1) + \beta W_i^2(Q_i^2|Q_i^1)$ . We have

$$\tilde{U}_i(I, I) = h_{i,I} + \beta (h_{i,I} + k_I); \quad (1.2)$$

$$\tilde{U}_i(I, N) = h_{i,I} + \beta h_{i,N}; \quad (1.3)$$

$$\tilde{U}_i(N, I) = h_{i,N} + \beta h_{i,I}; \quad (1.4)$$

$$\tilde{U}_i(N, N) = h_{i,N} + \beta (h_{i,N} + k_N). \quad (1.5)$$

**Proposition 1.2.1.** (*Competitive Equilibrium*) An individual chooses (I, I) if  $z_i \geq \frac{-\beta k}{1+\beta}$  and (N,N) otherwise, where  $z_i = h_{i,I} - h_{i,N}$  and  $k = k_I - k_N$ .

*Proof.* By comparing Equation (1.2) to Equation (1.5), it follows that

(1) An individual chooses (I,I) if and only if  $z_i \geq \max \left\{ -k_I, -\beta k_I, \frac{-\beta k}{1+\beta} \right\}$ .

(2) An individual chooses (I,N) if and only if  $z_i < -k_I$  and  $z_i \geq \max \{0, \beta k_N\}$ .

(3) An individual chooses (N,I) if and only if  $z_i \geq k_N$  and  $z_i < \min \{0, -\beta k_I\}$ .

(4) An individual chooses (N,N) if and only if  $z_i < \min \left\{ k_N, \frac{-\beta k}{1+\beta}, \beta k_N \right\}$ .

Since  $k_I$  and  $k_N$  are non-negative, both (I,N) and (N,I) are implausible. Moreover,

$\frac{-\beta k}{1+\beta} \leq \beta k_N \leq k_N$  and  $\frac{-\beta k}{1+\beta} \geq -\beta k_I \geq -k_I$ . Thus, an individual chooses (I, I) if  $z_i \geq \frac{-\beta k}{1+\beta}$  and (N,N) otherwise.  $\square$

Proposition 1 shows that individuals work in the inventive sector in period 1 if and only if the premium of working in  $I$  over  $N$  is sufficiently high. When  $s = 0$ , they have no incentive to switch to a different sector in period 2. It follows that patent production is

$$Pat_i = \begin{cases} (h_{i,I} + k_I) & \text{if } z_i \geq \frac{-\beta k}{1+\beta}; \\ 0 & \text{if } z_i < \frac{-\beta k}{1+\beta}. \end{cases}$$

## Social optimum in the benchmark case

Consider the problem of a social planner who chooses the career paths of all individuals to maximize social welfare,  $\sum_i U_i(Q_i^1, Q_i^2)$ . Because patent production directly enters agents' utility, this is equivalent to choosing  $(Q_i^1, Q_i^2)$  to maximize

$$SP_i(Q_i^1, Q_i^2) = W_I^1(Q_i^1) + \beta W_i^2(Q_i^2|Q_i^1) + \delta(P-1)Pat_i(Q_i^2|Q_i^1).$$

The following proposition shows that when patented inventions generate a positive externality, the equilibrium size of the inventive sector in period 2 is less than socially optimal.

**Proposition 1.2.2.** *When  $\delta > 0$  (i.e. positive externality), the social optimum has higher total patent production than the competitive equilibrium.*

*Proof.* Those who choose (I,I) do not change their path in the social optimum. Since  $\delta(P-1)Pat_i(I|I) = \delta(P-1)W_i^2(I|I) > 0$ , it is easy to see that individuals with  $-\delta(P-1)W_i^2(I|I) \leq \tilde{U}_i(I, I) - \tilde{U}_i(N, N) < 0$  choose (N, N) while the social planner would choose (I, I) or (N,I) for them. Thus, more individuals would work in the inventive sector in the second period and the total patent production is higher.<sup>16</sup>

□

## Temporary shock to the wage in the non-inventive sector

Now, consider a temporary shock to the economy in period 1 that changes the wage in the non-inventive sector,  $W_i^1(N)$ , from  $h_{i,N}$  to  $h_{i,N} + s$ . Suppose  $s > 0$ , so the non-inventive sector becomes temporarily more attractive in period 1.

<sup>16</sup>I do not explicitly solve for the social optimum here since it depends on both  $z_i$  and  $h_{i,I}$ . It also requires more assumptions on  $\delta(P-1)$ ,  $k_I$ , and  $k_N$ . For instance, given certain  $\delta(P-1)$ ,  $k_I$ , and  $k_N$ , it is possible for social planner to choose (N,I). I skip deriving the specific conditions here since they are irrelevant to the empirical predictions.

**Proposition 1.2.3.** (Competitive Equilibrium) There are two cases when  $s > 0$ .

Case I:  $s < k_N + \beta k_I$ . An individual chooses (I,I) if  $z_i \geq \frac{s-\beta k}{1+\beta}$  and (N,N) otherwise, where  $z_i = h_{i,I} - h_{i,N}$  and  $k = k_I - k_N$ .

Case II:  $s \geq k_N + \beta k_I$ . An individual chooses (I,I) if  $z_i \geq \frac{s-\beta k}{1+\beta}$ , (N,I) if  $k_N \leq z_i < \frac{s-\beta k}{1+\beta}$ , and (N,N) otherwise.

*Proof.* Compared to the benchmark case,  $\tilde{U}_i(N, I) = h_{i,N} + s + \beta h_{i,I}$  and  $\tilde{U}_i(N, N) = h_{i,N} + s + \beta (h_{i,N} + k_N)$ . The derivation then follows the same steps as the proof to Proposition 1.  $\square$

Graduates who choose (N,N) before have no incentive to change their career path. As the return to working in the non-inventive sector in period 1 increases, some who choose (I,I) in the benchmark case may switch to (N,I) or (N,N). Notice that initial jobs are sticky because of positive human capital accumulation. If  $k_I = k_N = 0$ , then the temporary shock in period 1 has no effect on individuals' occupation in period 2. Because starting in the non-inventive sector helps a graduate to gain specific human capital in N, some of the individuals that switch to N in period 1 stay in N in period 2. However, if the incentive to working in N is sufficiently high, it would attract workers with high premium of working in I over N to temporarily work in N in period 1, but switch back to the inventive sector in period 2.

Consider the case where  $s \geq k_N + \beta k_I$ , the change in an individual's patent production relative to the benchmark case is

$$\Delta Pat_i = \begin{cases} -(h_{i,I} + k_I) & \text{if } \frac{-\beta k}{1+\beta} \leq z_i < k_N; \\ -k_I & \text{if } k_N \leq z_i < \frac{s-\beta k}{1+\beta}; \\ 0 & \text{otherwise.} \end{cases}$$

Therefore, a shock that temporarily makes working in the non-inventive sector more profitable in period 1 affects patent production in period 2. In the presence of such a shock, patent production is lower as fewer graduates work in the inventive sector and some of those who still do have less inventive human capital. There are two channels for the effect. When  $\frac{-\beta k}{1+\beta} \leq z_i < k_N$ , an individual switches from (I,I) to (N,N), and her patent production decreases from  $(h_{i,I} + k_I)$  to 0. I refer to this as the “occupational choice channel,” where an individual’s patent production changes as a result of working in a different sector. When  $k_N \leq z < \frac{s-\beta k}{1+\beta}$ , an individual switches from (I,I) to (N,I), and her patent production decreases from  $(h_{i,I} + k_I)$  to  $h_{i,I}$ . I call this the “human capital channel” since her occupational affiliation in period 2 does not change.<sup>17</sup> The key difference between the occupational choice and the human capital channels is that in the former, the effect results from graduates switching sectors in the long-run, whereas in the latter it does not.<sup>18</sup> Similarly, if  $s < 0$ , individuals who work in (N,N) may switch to (I,I) or (I,N). Total patent production would be higher than in the benchmark case. Without knowing the sign of  $s$ , the effect of adverse labor market conditions at the time of graduation on future patent production could be either positive or negative and remains an empirical question.

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<sup>17</sup>The human capital channel only occurs when  $s$  is sufficiently large and  $k_I > 0$ . If  $k_I = 0$ , then there is obviously no change in patent production.

<sup>18</sup>There are several ways to extend the predictions of the model. First, one can easily add labor market frictions, such as search costs, but they would only complement the effect of the human capital accumulation on occupational choice. Substituting labor market frictions for human capital accumulation is equivalent to assuming that  $k_I$  and  $k_N$  only matter for earnings but not patent production. In this case, patent production only changes through the occupational choice channel. Second, one can include non-pecuniary returns of working in different occupations. See Bayer et al. (2011); Maurel and D’Haultfoeuille (2011) for examples of estimating the non-pecuniary returns in an extended Roy model. It is possible that individuals fully internalize the externality of their patent production by deriving enough non-pecuniary benefits from innovating. In this case, the equilibrium patent production is the same as in the social optimum. Finally, switching jobs could be more likely than what the stylized model predicts. For instance, if individuals get positive non-pecuniary returns from trying different jobs or if they have uncertainty about the returns from working in a particular sector.

## Sorting

As the model shows, initial labor market conditions are unlikely to affect every graduate's patent production. I thus classify the workers into three groups: "non-inventors," "marginal inventors," and "infra-marginal inventors." Regardless of graduating economic conditions, the non-inventors never patent and the infra-marginal inventors always patent. However, the marginal inventors produce patents only if they graduate in certain economic conditions. Importantly, the infra-marginal inventors' patent production could change at the intensive margin. Hence, the total change in patent production, due to a change in initial economic conditions, has two components: patents from the marginal inventors (changes at the extensive margin) and patents from the infra-marginal inventors (changes at the intensive margin).<sup>19</sup>

For any potential policy analysis, it is important to understand where the marginal patents come from. Are marginal inventors more or less skilled than infra-marginal inventors? Do marginal patents have higher or lower quality than average patents? Suppose a policy aims to increase patent production by temporarily rewarding individuals for entering the inventive sector upon college graduation. This is equivalent to introducing a negative  $s$  in the simple model. If the most skilled workers are already working in the inventive sector, the return to such a policy, in terms of the increase in the production of innovation, is decreasing in the size of the inventive sector.

To see this mathematically, I consider the special case where  $\beta = 1$  and  $k_I = k_N$ .

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<sup>19</sup>Since I assume that the non-inventive sector has no patent production, changes in patent production at the intensive margin could only happen through the human capital channel. In practice, there are different occupations with different levels of patent production, so both channels could potentially change patent production at the extensive and intensive margins.

I also assume that

$$\begin{pmatrix} h_{i,I} \\ h_{i,N} \end{pmatrix} \sim N \begin{pmatrix} \mu & \sigma_I^2 & \sigma_{IN}^2 \\ \mu & \sigma_{IN}^2 & \sigma_N^2 \end{pmatrix}, \text{ and } z_i = h_{i,I} - h_{i,N} \sim N(0, \sigma_z^2).$$

**Proposition 1.2.4.**  $E(h_{i,I}|z_i = s)$  is decreasing in  $s$  if and only if  $\rho_{Iz} = \text{Corr}(h_{i,I}, z_i) < 0$  (i.e.,  $\sigma_I^2 > \sigma_{IN}^2$ ).

*Proof.* Given the distributional assumptions,  $E(h_{i,I}|z_i = s) = \mu_I + \rho_{Iz}\sigma_I s$ . Thus  $\frac{\partial E(h_{i,I}|z_i=s)}{\partial s} = \rho_{Iz}\sigma_I < 0$  if and only if  $\rho_{Iz} < 0$ .  $\square$

Without any shock,  $E(h_{i,I}|Q_i^2 = I) = E(h_{i,I}|z_i > 0) = \mu_I + \rho_{Iz}\sigma_I\lambda(0)$ , where  $\lambda(0) = \phi(0)/\Phi(0)$  is the inverse mills ratio. Thus,  $\rho_{Iz} > 0$  implies that there is positive sorting into the inventive sector, defined as  $E(h_{i,I}|Q_i^2 = I) > E(h_{i,I})$ . In other words, the average inventive skill ( $h_I$ ) of the inventors is higher than the average for the entire cohort.<sup>20</sup> When  $s$  becomes marginally negative, individuals with  $z_i = s \approx 0$  switch from (N,N) to (I,I). The gain in total patent production is  $E(h_{i,I}|z_i = s) + k_I$ . Proposition 4 shows that, as  $s$  becomes more negative, the gain in patent production is decreasing if and only if there is positive sorting into the inventive sector.

In practice, it is possible that a shock changes the composition of workers in each sector through sorting even without affecting the size of either sector. For instance, in response to a shock, people with high inventive ability may select out of the inventive sector and get replaced by less skilled inventors.<sup>21</sup> In the empirical section, I identify the nature of sorting by examining how the distribution of inven-

<sup>20</sup>Negative sorting implies that the most inventive individuals are inclined to work in the *non-inventive* sector. This is counter-intuitive, but theoretically possible, for instance if the return to the inventive skill is higher in the non-inventive sector than the inventive sector.

<sup>21</sup>This could happen in a standard Roy model if the return to skill in the inventive sector decreases. See Gould (2002); Mulligan and Rubinstein (2008) for detailed discussions on similar models.

tors' ex ante ability changes with graduating economic conditions. These results are discussed in detail in Section 1.5.

## 1.3 Data

### 1.3.1 Sample Construction

#### Data from MIT

MIT Office of the Registrar and the Alumni Association have generously provided individual-level data on every student that received a bachelor's degree from MIT between 1980 and 2005.<sup>22</sup> I observe basic demographic information such as gender and ethnicity, as well as information about their degree such as year of graduation, major(s) and cumulative grade point average. I group the graduates into three fields based on their major: Engineering; Science; and Others ("Non-SE").<sup>23</sup> I also observe the current employer of the alumni as self-reported on Infinite Connection in June 2011.<sup>24</sup> For those with available information on their employer, I assign their currently employed sector as Technology & Industrial, Academia, or Non-Science and Non-Engineering ("Non-SE"). Appendix 1.8.1 explains how I assign the sectors based on the employers.

#### Patent Matching

To match graduates to their patents, I employ a separate database containing the full names of all alumni in the base sample as well as their addresses at the city level. For names, I observe both the Registrar's records and the ones currently used

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<sup>22</sup>Although I have information on individuals that received a graduate degree from MIT during the same time period, I exclude them from the analysis and focus only on the Bachelor's population. The graduate population is much more heterogeneous than the undergraduate population.

<sup>23</sup>For the few incidences of double majors, I use whichever major declared first.

<sup>24</sup>Infinite Connection is an online alumni directory hosted by the MIT Alumni Association.

by the Alumni Association to contact the alumni. For locations, I observe the last two work addresses and home addresses reported on Infinite Connection. Each graduate has at least one home address in the data. For those that have never updated their alumni profiles on Infinite Connection, the home address information is from their Registrar's records at MIT.

I match this data to the U.S. patent inventor database from Lai et al. (2011b). The U.S. Patent and Trademark Office (USPTO) does not provide unique identifiers for inventors, making it difficult to track all the patents produced by the same inventor. Lai et al. (2011b) apply a Bayesian supervised learning approach and match inventors across all the U.S. utility patents granted between 1975 and 2010. Compared to the raw patent data from USPTO, the database from Lai et al. (2011b) allows me to match the alumni to inventors rather than patents.<sup>25</sup> Since the amount of individual information provided by an inventor could differ across patents, matching the alumni to inventors increases the likelihood that all patents from the same alumni inventor are included.<sup>26</sup>

I explain the matching procedure in Appendix 1.8.2. Although matching errors are inevitable, they are unlikely to cause serious concerns for my empirical analysis. First, the summary statistics reported in Table 1.2 show that the science and engineering students have much higher inventive output than the non-SE students. Since the matching errors should be randomly distributed across different majors, one can use the patent output of the non-SE students as an upper bound for the amount of false positives. Under the extreme assumption that the non-

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<sup>25</sup>Lai et al. (2011b) present two sets of results using different blocking rules. One minimizes the probability of lumping multiple individuals as one inventor, while the other minimizes the probability of splitting one individual into multiple inventors. See Lai et al. (2011a) for a detailed explanation of their procedure. Since each alumnus can be matched to multiple inventors, errors from splitting are less of a concern than errors from lumping. Thus I use the former set of results in my matching. My findings change little if I use the other.

<sup>26</sup>For instance, an inventor with a middle name may list the full middle name on some patents but only the initial on the others.

SE students should not produce any patents, there is still a significant amount of patent production from the science and engineering students. Second, the errors are not correlated with economic conditions at time of graduation and thus do not cause omitted variable bias (Figure A1.1). Finally, as patent output is the dependent variable, measuring it with classical measurement errors could only increase the variance of the residual without generating any bias in the estimator.

I use the matching results to construct the patenting history of the alumni in my sample. For each graduate in each year after graduation, I calculate the number of granted patents which were applied for in that year and the subsequent number of citations received for those patents. The MIT Office of Provost Institutional Research then links the patent data to the base sample with individual characteristics.

## 1.3.2 Descriptive Statistics

### Characteristics

Table 1.1 shows the mean characteristics for four groups: everyone, engineering majors, science majors, and inventors.<sup>27</sup> 68% of all the alumni in my sample are male; 58% are white; and 41% went to high school in the northeast of the United States. 63% of the graduates majored in engineering and nearly 25% majored in science; only 13% of the graduates majored in non-science and non-engineering (“non-SE”) fields.<sup>28</sup> The engineering majors have less females, while the science majors have more females. The science majors also have more white and Asian American students.

Around 16% of all the graduates in my sample are inventors, that is, they have positive patent production since graduation. The inventors are more likely to be

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<sup>27</sup> An “inventor” is someone with positive patent production since graduation.

<sup>28</sup> Around half of the graduates with non-SE majors majored in economics or management.

male, engineering majors and Caucasian. Less than 4% of the inventors majored in non-SE fields. The inventors have above average GPA, where the GPA is normalized by major and year of graduation. Specifically, the average normalized GPA of the inventors is around 0.22 standard deviations higher than the sample average.

About 78% of the sample report their employers on Infinite Connection, based on which I assign a sector.<sup>29</sup> Approximately 45% of the alumni with non-missing employer information currently work in industries that are generally related to engineering and science, such as technology and industrial. 16% work in academia, and 26% work in non-SE industries such as finance and consulting. Around 13% of the alumni work for firms where I cannot immediately assign a sector based on the firm name.<sup>30</sup> The inventors have a higher proportion that currently works in technology and industrial industries and a lower proportion that works in non-SE industries.

## **Patent Production**

Figure 1-1 plots the average number of patents produced and the number of citations received in each year since graduation against two x-axes: year since graduation and year of patent application. All of the four series have an inverse “U” shape. Patent production increases over time in the first 15 years after graduation, which is consistent with the assumption in the conceptual framework that individuals accumulate inventive human capital from experience. There is also an upward trend in patent production before 2000, which is consistent with the aggregate trend in national patent statistics (Hall et al., 2001; USPTO, 2011). Since some

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<sup>29</sup>The employers are as of the last time they updated their alumni profile on Infinite Connection before June 2011. Although it is possible that the alumni have switched jobs and not updated on Infinite Connection, I assume that they stay in the same sector, and use the reported employers to determine the current sector.

<sup>30</sup>These would include, for example, small firms that do not indicate what they do in the company name.

of the patent applications in more recent years are still under review and I only observe the granted patents, the data are truncated from the right. Thus, there are downward trends in patent production after 2000. While this is a relevant concern for the interpretation of descriptive statistics, I will control for the truncation in my regression analysis.

Table 1.2 shows summary statistics for annual patent production. The unit of observation is person by year. In an average year, an average cohort with a size of 1000 graduates produces around 52 patents. These patents together receive on average 681 citations by the end of 2010. Engineering graduates on average produce more patents than science and non-SE graduates, and non-SE graduates are the least likely to participate in inventive activities. An average patent from an MIT alumni inventor receives around 1 citation per year, which is twice as much as an average patent produced between 1981 and 2010. Since inventors only produce patents in some years, their annual patent production can be zero.

Table 1.3 shows the distribution of the patents' technology fields by inventors major. Following Hall et al. (2001), I classify patents into four technology fields based on their primary class: 1) Computer and Communications; 2) Electrical & Electronic and Mechanical; 3) Chemical and Drugs & Medical; and 4) Others.<sup>31</sup> Nearly half of all patents are from graduates majoring in electrical engineering and computer science (EECS), who patent mostly in computer and communications. Not surprisingly, alumni inventors tend to patent in their field of study. For example, graduates who majored in mechanical engineering and material science patent more in hardware engineering, while those that studied chemical engineering, chemistry or biology in college patent more in bio-tech related field. Few patents are in the "Others" field.

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<sup>31</sup>Hall et al. (2001) has six technology categories. I combine Electrical & Electronic and Mechanical into one field. I also combine Chemical and Drugs & Medical into one field.

## **1.4 Initial Labor Market Conditions and Patent Output**

### **1.4.1 An Illustrative Example: MIT Class of 1983 versus Class of 1984**

Before presenting the regression estimates, I first discuss an illustrative example, which compares the patent output of the 1983 versus the 1984 graduate cohorts. The two classes have similar characteristics, though the class of 1983 has slightly fewer engineering and science majors (Table A1.2). They overlapped for 3 years at MIT and experienced largely the same economic environment during college. By far, the most substantial difference between the two classes was the state of the economy at the time of their graduation. The class of 1983 graduated at the end of a recession. The annual unemployment rate was 9.6%, and the 2-year equity market return from the Center for Research in Security Prices (CRSP) before their senior year was 7.8%. By contrast, class of 1984 graduated during a recovery period when the annual unemployment rate was 7.5%, and the 2-year CRSP market return was 50%. Figure 1-2 plots each cohort's average patent output by year of graduation and year of application. In almost every year, the patent output of the class of 1983 surpasses the output of the 1984 cohort. The differences are especially large between 10 and 20 years after graduation. In total, the graduates in the class of 1983 have produced 2022 patents while the class of 1984 have produced only 1602 patents in their first 25 years after graduation. Table A1.2 shows that both classes have similar proportion of inventors. The class of 1983 alumni are slightly more likely to work in the technology and industrial sector and less likely to work in the non-SE sector, although the differences are not statistically significant in the

t-test.

## 1.4.2 Baseline Regression

### Specification

For graduate  $i$  in year  $t$ , I observe the number of patents she produced that year, denoted by  $Pat_{it}$ , where this is computed as the number of patents she applied for in year  $t$  that were ultimately granted at some time prior to the end of my sample. I estimate the following equation:

$$(Pat)_{it} = G(\theta R_j + \delta(Controls)_{ijt} + \epsilon_{it}) \quad (1.6)$$

where  $j$  denotes the year of graduation, and  $R_j$  is either the national unemployment rate in year  $j$  or the CRSP stock market return from September  $j - 3$  to September  $j - 1$  or both. Since my outcome, the number of patents produced by each individual in each year, is non-negative and discrete, I estimate Equation (1.6) using quasi-maximum likelihood Poisson model and  $G(\cdot)$  denotes the likelihood function.<sup>32</sup>

Following the literature, I use the national unemployment rate in the year of college graduation as my main measure of initial labor market conditions.<sup>33</sup> Although MIT alumni are generally unlikely to be unemployed upon graduation, the aggregate economy still affects the availability and payoff of certain jobs. As a result, those graduating in a recession may pursue different career paths than those graduating in a booming economy. For instance, the MIT Class of 2009, who

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<sup>32</sup>Compared to alternative count models such as negative binomial, the Poisson model has the advantage of being robust to model mis-specification (Cameron and Trivedi, 2001; Wooldridge, 2002). The quasi-ML Poisson model also accounts for any over dispersion in the data.

<sup>33</sup>Examples of other studies using the same measure include Kahn (2010); Genda et al. (2010); Oreopoulos et al. (2012).

graduated during the financial crisis, still had high job placement rate comparable to the previous classes. But they have a higher proportion going to graduate school and a lower proportion entering the financial sector (Hastings et al., 2010). Unfortunately, I do not observe the initial career choices of the 1980-2005 cohorts, and thus cannot estimate the effect of initial economic conditions on selecting into different initial placements.

I also control for a rich set of characteristics including gender, age, ethnicity/citizenship, high school region, dummies for fields of study (Engineering, Science, and Non-SE), and GPA standardized by major and cohort. The log of the federal research and development expenditure as a ratio of U.S. GDP in the year of college graduation controls for the demand for engineers and scientists (Goolsbee, 1998; Ryoo and Rosen, 2004; Majumdar and Shimotsu, 2006; National Science Foundation, 2010). To control for the potential nonlinear effects of patent application year, I include dummies for the application years. I also control for experience dummies, which are indicator variables that equal 1 for each year since graduation.

## Results

Table 1.4 shows the coefficient estimates for the two measures of initial labor market conditions, using quasi-maximum likelihood Poisson models with different levels of controls. All standard errors are corrected for heteroskedascity and clustered by cohort and application year.<sup>34</sup> The effect of the unemployment rate is robust to alternative controls and the inclusion of the stock market return. Column (3) shows that a one percentage point increase in the national unemployment rate at the time of graduation increases the expected annual patent output of that cohort by almost 5.4%. Since an average cohort with a size of 1000 graduates produces 52

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<sup>34</sup>The effect of the unemployment rate is robust to clustering the standard errors by cohort.

patents, a 5.4% change is equivalent to 2.8 patents per year. The effect of the stock market return is only significant when all controls are included. Column (6) shows that a one standard deviation decrease in the stock market return, equivalent to around 18%, increases the expected future annual patent output of the graduating cohort by 4.2%. However, it does not have any additional effect on patenting once the unemployment rate is included (since these are alternative measures of economic conditions). Table A1.3 reports the coefficient estimates for individual characteristics from Column (7). As the descriptive statistics suggest, engineering and science majors are significantly more likely to produce patents than the non-SE majors. Engineering and science majors with higher GPA produce significantly more patents. Female graduates are less likely to produce patents.<sup>35</sup>

Figure 1-3 plots the persistence of the impact of graduating conditions on future patent production. I interact  $R_j$  with the experience dummies and plot the coefficients of the interaction terms against year since graduation for 25 years after graduation.<sup>36</sup> The effect of unemployment rate is insignificant in early years but becomes significant and persistent between 10 and 20 years after graduation. The effect of stock market return peaks around 13 years after graduation but is largely insignificant.

### **Robustness Checks**

Table A1.4 in the Appendix shows a set of robustness checks. Panel A shows the results in OLS and 2SLS using birth year dummies as the instruments for graduating economic conditions. Panel B restricts the sample to balance panels from the 1980-1995 cohorts on patent production in the first 15 years after graduation

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<sup>35</sup>Ding et al. (2006) find that there exists gender difference in the tendency to patent among the life scientists. Female scientists are less likely to patent than male scientists.

<sup>36</sup>Only the early few cohorts are observed 25 years after graduation.

or between 2000 and 2010. Panel C excludes the top inventors in two ways: first by using an indicator variable that equals 1 if the annual number of patents produced is greater than zero as the dependent variable; and second by excluding the 100 graduates with the most patent production. The results that initial labor market conditions significantly affect future patent production are robust across all the alternative specifications. Table A1.5 in the Appendix shows that initial labor market conditions do not change the students' choice of major at the time of college graduation.

### 1.4.3 Initial Conditions versus Current Conditions

To see whether contemporaneous economic conditions affect patent output in addition to economic conditions at the time of graduation, I use the following specification:

$$(Pat)_{it} = G(\theta R_j + \beta R_t + \delta(Controls)_{it} + \epsilon_{it}) \quad (1.7)$$

where I include  $R_t$ , the labor market condition at time  $t$ , as well its 1 or 2-year lag in various specifications. Since the lagged current conditions are just the initial conditions for recent graduates, I exclude all the observations where  $t$  (the observation year) is less than  $j + 2$  when I include one lag and  $j + 3$  when I include two lags. Since I can no longer control for application year fixed effects, I include the application year and cohort year trends. Estimation of this model on the full sample is no longer possible since patents applied for more recently are less likely to show up in the data due to the lag between patent application and patent grant. To ensure that there is no spurious correlation caused by data truncation, I run the regression only on the sample with observation-years before 2000. Table 1.5 shows that the coefficients on initial conditions do not change from the previous table. Contemporaneous economic conditions have no significant effect on patent

output.

## 1.5 Understanding the Effect of Initial Labor Market Conditions

The unemployment rate at the time of college graduation has a positive and significant impact on a graduate's patent production over the next 20 years. Two important questions remain. Which individuals' patent production is most affected by initial labor market conditions? Do marginal patents have higher or lower quality than average patents? As discussed in Section 1.2, the answers to these questions have important implications for potential welfare and policy analysis. In order to frame the discussion, I define the following terminology.

a) "Marginal inventors" are graduates whose decision to become inventors (i.e., produce at least one patent) is affected by graduating economic conditions.

b) "Infra-marginal inventors" are graduates who become inventors regardless of initial labor market conditions.

c) "Marginal patents" are patents whose production is contingent upon labor market conditions at graduation. Marginal patents could be produced by either marginal inventors or infra-marginal inventors.

The characteristics of the marginal inventors and the marginal patents are of primary interest to me as they provide vital information about the impact of initial labor market conditions. In this section, I provide empirical analysis in two steps. First, I identify which of the marginal patents come from marginal inventors and which come from infra-marginal inventors. Second, I study the characteristics of the marginal patents and how they differ from the average patents. Since the analysis is cross-sectional (i.e., at the inventor-level or patent-level), it is im-

possible to control for application year fixed effects as in the panel data. In order to accommodate the fact that each cohort has experienced a different number of post-graduation years, I use a balanced panel that includes the 1980-1995 cohorts, observed for the first 15 years after graduation.<sup>37</sup> Hence, all the cohorts have the same amount of time to produce patents. Column (B1) in Table A1.4 also confirms that the results from the previous section hold for a balanced panel. A one percentage point increase in the unemployment rate at the time of graduation increases the average annual patent production in the first 15 years after graduation by around 4.2% for the 1980-1995 cohorts. The average number of patents produced per person per year is 0.054. Thus, a 4.2% change in the annual patent production for a cohort is equivalent to around 34 patents in 15 years.

## 1.5.1 Decomposition

### Entry into Invention

I first estimate the effect of the initial unemployment rate on the probability of becoming an inventor in the first 5, 10, or 15 years after graduation. To test whether there are more graduates producing patents from recession cohorts, I estimate the following Linear Probability Model:<sup>38</sup>

$$Pr(D_i = 1) = \theta R_j + \delta(Controls)_{ij} + \epsilon_i. \quad (1.8)$$

where  $R_j$  is the national unemployment rate at the time of graduation,  $D_i = 1$  for all graduates who patent in the first 5, 10, or 15 years after graduation, and observations are at the individual level. I control for a linear and quadratic cohort graduation year trend since different cohorts experience different aggregate patenting

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<sup>37</sup>This excludes the year of graduation.

<sup>38</sup>Probit and Logit models give almost identical estimates.

trends in their first 15 years. I also control for observed individual characteristics.

Table 1.6 reports the estimated effects. Although the coefficient estimates are small and positive for 5 and 10 years after graduation, they are not significant once I control for individual characteristics (Columns (2) and (4)). The coefficient estimates for 15 years are also very small and insignificant (Columns (5) and (6)). Thus, the initial unemployment rate has no significant effect on the probability of becoming an inventor.

### **Distribution of Inventors' Ability and Characteristics**

As shown in the conceptual framework, if initial economic conditions change the nature of sorting into inventive careers, it is possible that the average inventors from a recession cohort have higher innate ability even when the number of inventors stays the same.<sup>39</sup> To examine whether the distribution of inventors' ability changes with initial labor market conditions, I estimate the following equation *only on the sample of inventors*:

$$(ability)_i = \theta R_j + \delta(Controls)_{ij} + \epsilon_i. \quad (1.9)$$

where *ability* is measured by GPA, and I control for the linear and quadratic cohort graduation year trend. Since the regression is estimated only on the sample of inventors,  $\theta$  is the effect of the initial unemployment rate on the ability of the average inventors.<sup>40</sup> If the inventors from a recession cohort have higher ability

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<sup>39</sup>In a standard Roy model, this would happen if the return to skill in the more inventive sector increases.

<sup>40</sup>This set-up is similar to the reduced-form specification that tests the difference between the marginal and average outcomes in Gruber et al. (1999) and Chandra and Staiger (2007). In theory, I can use the log of risk-adjusted proportion of inventors, instrumented by  $R_j$ , on the right-hand side to test whether the average ability of inventors changes with any change in the size of the inventor population induced by initial labor market conditions. However, doing so requires a first stage where  $R_j$  significantly affects the proportion of inventors, which does not exist in the data.

than the inventors from a boom cohort,  $\theta$  from Equation (1.9) should be positive. As an alternative to *GPA*, I also consider separately a dummy for both engineering and science majors on the left-hand side. Panel A from Table 1.7 suggests that the average inventors' GPA does not vary with graduating economic conditions, and that the average inventors' tendency to major in engineering or science is unaffected as well. To uncover the effect on the distribution of inventors' GPA, I also estimate Equation (1.9) with a quantile regression. Figure 1-4 plots the coefficient estimates with 95% confidence intervals for different quantiles. The estimates are generally insignificant and close to zero. Taken together, Panel A from Table 1.7 and Figure 1-4 suggest that the initial unemployment rate does not affect which graduates become inventors, at least in terms of their GPA and majors.

Since I find no evidence of changes at the extensive margin or in the nature of sorting, at least the majority of the change in patent production is at the intensive margin. Thus, there are no marginal inventors. But there are two types of infra-marginal inventors: those that produce the marginal patents, and those unaffected by initial economic conditions. As discussed in Section 1.2, there are two possibilities:

1. Initial economic conditions do not affect a graduate's long-term occupational affiliation, but graduating in a worse economy increases an individual's accumulation of inventive human capital over time.<sup>41</sup> In this case, I expect initial economic conditions to have no effect on an inventor's sector.
2. Initial economic conditions change a graduate's long-term occupational affiliation. Graduating in a worse economy leads more graduates to work in patent-producing sectors.

To test whether the change happens through the occupational choice channel, I

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<sup>41</sup>For instance, by increasing graduate school enrollment.

estimate the following equation using a Linear Probability Model *at the inventor level*:

$$Pr(Field_i = k) = \theta R_j + \delta(Controls)_{ij} + \epsilon_i \quad (1.10)$$

where  $Field_i$  is the technology field in which inventor  $i$  patents the most, and  $(Controls)_{ij}$  include linear and quadratic cohort graduation year trends as well as individual characteristics.<sup>42</sup> As an alternative measure of inventors' long-term occupation, I use the sector of employment reported on Infinite Connection as of June 2011. Panels B and C from Table 1.7 report the OLS estimates.<sup>43</sup> None of the estimates are statistically significant, suggesting that initial labor market conditions do not affect inventors' long-term occupational affiliation.<sup>44</sup> These results suggest that the change in patent production is most likely caused by a change in inventors' post-graduation human capital accumulation rather than their long-term occupational choice.

As a robustness check, I also consider the effect of initial economic conditions on the time it takes an inventor to produce her first patent after graduation. If human capital accumulation is important, then one would expect inventors from recession cohorts to patent sooner. In order to evaluate whether or not this is true, I estimate the following equation by OLS:

$$T_i = \theta R_j + \delta(Controls)_{ij} + \epsilon_i. \quad (1.11)$$

where  $T_i$  is the number of years between the first patent and the time of graduation. In addition to the cohort trend and demographics, I also include dummies for the

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<sup>42</sup>73% of the inventors patent in only one field.

<sup>43</sup>Logit and Multinomial Logit regressions produce very similar results.

<sup>44</sup>Since the classification of sectors is fairly coarse, it is possible that initial labor market conditions change the inventors' sub-sector or firm. However, the differences in the mean level of patent production should be much larger across the general sectors than within a sector.

inventor's technology field to control for differences in the mean time to patent across fields. Panel D from Table 1.7 reports the OLS estimates.<sup>45</sup> Columns (D1) to (D3) show that a one percentage point increase in the unemployment rate at the time of graduation significantly decreases the time to the first patent by around 0.1 years. Given that the average of  $T_i$  is 7.95, the magnitude of the effect is very small.

Taken together, these results suggest that initial labor market conditions do not affect inventors' long-term occupation. Thus, the most likely hypothesis is that initial labor market conditions affect inventors' post-graduation human capital accumulation by affecting their *initial* career choices. For instance, a graduate may go directly into graduate school in science or engineering if she graduates in a recession, while in a boom she may initially work in a non-patent-producing sector such as finance or management consulting. Even though she could end up being an engineer in 10 years in both cases, in the former case she is likely to develop more skills that are relevant for inventing. It is important to note that human capital accumulation could occur if an inventor starts her career in a patent-producing sector such as high-technology, or goes directly to graduate school. Unfortunately, without observing graduates' initial career choices, I cannot estimate the return to going to graduate school (or starting in an inventive sector) in terms of increased patent production.

## 1.5.2 Sorting

### Inventors' Ability

The evidence suggests that initial economic conditions do not affect the probability of becoming an inventor in the first 15 years after graduation. Thus, to identify the nature of sorting, I compare the marginal *patents* to the average *patents*. I

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<sup>45</sup>Quasi-maximum likelihood Poisson regressions have almost identical estimates.

estimate the following equation by OLS at the patent level:

$$(ability)_p = \theta R_j + \delta(j, j^2) + \epsilon_p. \quad (1.12)$$

where *ability* is defined as in Equation (1.9). The key difference from before is that Equation (1.12) is *estimated at the patent level*. One can think of the dependent variable as the inventors' average ability weighted by how many patents they produce. Thus  $\theta$  estimates the effect of initial economic conditions on the patent-weighted average GPA. A negative  $\theta$  implies that the inventors who produce the marginal patents have lower GPAs than the average inventors; a positive  $\theta$  suggests the opposite. Panel A from Table 1.8 shows that the national unemployment rate at the time of graduation has no effect on the average patent-weighted GPA of the inventors. Columns (A2) and (A3) suggest that the inventors who produce the marginal inventions are more likely to be science majors and less likely to be engineering majors.

Although there is no change in the average patent-weighted GPA, it is possible that there is a change in its distribution. Figure 1-5 presents two plots on the distribution of patent-weighted GPA. The left panel of Figure 1-5 plots the coefficient estimates with 95% confidence intervals by quantile from a quantile regression of Equation (1.12). The positive coefficients at around the 20% quantile and the negative coefficients around the 60%-80% suggest that a disproportionate share of patents created by inventors graduating in a bad economy are from those with relatively low GPAs. This is also consistent with the right panel of Figure 1-5, which plots the kernel density of patent-weighted GPA separately for the cohorts above and below the median initial unemployment rate (7%). The patents produced by cohorts graduating in a bad economy are more likely to be from those inventors with GPAs around or below the median (0.48). Hence, initial labor market condi-

tions affect the patent production of the inventors with relatively low GPAs.<sup>46</sup> But inventors with the highest GPAs are unaffected. There are two explanations for these findings. The first is that initial labor market conditions only affect the initial career choices of the inventors with lower GPAs. For example, it could be that the students with the best GPAs go to graduate school regardless of the economic conditions. The second possibility is that initial labor market conditions affect everyone's initial career choices, but initial career choices do not affect human capital accumulation for the most able inventors.

### Technology Field

Before analyzing the quality of the marginal patents, it is important to know which technology fields they are from since the tendency to cite differs across fields.<sup>47</sup> I examine the change in the distribution of technology field at the patent level and estimate the following equation:

$$Pr(Field_p = k) = \theta_1 R_j + \theta_2 R_j * Science_i + \delta(Controls)_p + \epsilon_t \quad (1.13)$$

which is similar to Equation (1.10) but estimated at the patent level. Since the marginal patents are likely from science majors, I also interact  $R_j$  with an indicator variable for being a science major, allowing the effect of graduating conditions to differ for the science majors. I also control for a cohort graduation year trend, an application year trend, and individual characteristics. Panel B from Table 1.8 reports the OLS estimates. An increase in the national unemployment rate at the time of graduation does not have a significant effect on the technology field of the

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<sup>46</sup>Notice that inventors on average have higher GPAs than non-inventors, so a relatively low GPA for an inventor is still around the mean of the population (around 0).

<sup>47</sup>For instance, computer and communications patents on average receive significantly more citations than mechanical patents.

patents from the average inventors. But it does have a significantly different effect on the technology field of the patents from inventors with science majors. In particular, the patents from science majors graduating in worse economic conditions are more likely to be in the chemical, drugs and medical field.<sup>48</sup> This is consistent with the finding that the marginal patents are likely from science majors, who are also more likely to patent in the chemical, drugs and medical field than engineering majors (Table 1.3).

### Citations

I measure the quality of a patent using the number of patent citations it received by the end of 2010. I estimate the following equation at the patent level:

$$(Citations)_p = \alpha + \theta R_j + \delta(Controls)_p + \epsilon_p \quad (1.14)$$

where I control for inventor characteristics, linear and quadratic cohort graduation year trends, dummies for technology field, and dummies for year of patent application. Following the same logic as in Equation (1.12),  $\theta$  in Equation (1.14) measures the change in the average quality of the patents as a result of a change in the national unemployment rate in the year of graduation.<sup>49</sup> A negative  $\theta$  implies that the marginal patents have lower quality than the average patents.

The mean citations received in the overall sample is 17.72 and the median is 7. Since the distribution is skewed, I estimate Equation (1.14) using both OLS and median regressions. Panel A from Table 1.9 reports the OLS estimates, which are

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<sup>48</sup>There is a particular concern that software patents have negative externalities due to the patent war in the industry. The results here suggest that the marginal patents are not software patents.

<sup>49</sup>Note that it is possible though less likely for initial labor market conditions to influence the quality of the patents without changing the number of patents produced by an inventor. This does not affect the interpretation of the empirical results. One can just re-define the marginal patents to be the ones whose existence as well as quality are affected by inventors' graduating economic conditions.

negative but insignificant. Panel B reports the estimates from median regressions, in which the effect is negative and marginally significant. These results suggest that initial economic conditions have no significant effect on the mean or median quality of patents.

Similar to Figure 1-5, Figure 1-6 shows two plots on the distribution of citations. The left panel shows the coefficients from the quantile regression using the specification in Column (B3). The coefficients are significantly negative between the 55% and 85% quantile, suggesting that the quality of the marginal patents is likely below the median. This is consistent with the right panel of Figure 1-6, which plots the kernel density of the risk-adjusted citations. The risk-adjusted citations are the residuals from regressing citations on the list of controls in Equation (1.14). The residuals adjust for the effect of other covariates, such as application year, on the distribution of citations. Based on the figure, it is clear that the quality of the marginal patents is below the median and the mean. Together with Figure 1-5, the results suggest that the marginal patents are of below median quality and are produced by inventors with median ability.

## 1.6 Conclusion

In this paper, I explore a novel channel through which short-term economic fluctuations affect the long-run innovative output of the U.S. economy: college graduates' initial career choices. Using a newly constructed data set on the patenting history of MIT alumni, I find that cohorts graduating during economic downturns produce significantly more patents over the subsequent two decades. This effect stems from initial career choices; economic fluctuations have no measurable effect on the contemporaneous innovative output of graduates during their peak inventive years. Graduating in bad economic conditions leads inventors to select

career paths that help them accumulate more inventive human capital. Consequently, they take less time to start producing patents, and produce more patents over the 20 years after graduation. I show that the inventors who produce more patents as a result of graduating in adverse labor market conditions are likely to be science graduates who work in non-software-engineering sectors such as biotechnology. My results also suggest that there exists positive sorting into inventing: graduates who are ex ante more inventive are also more likely to self-select into producing patents regardless of initial labor market conditions.

There are several promising directions for future research. Compared to the average engineering and science student population, MIT graduates are expected to have higher ability.<sup>50</sup> On one hand, MIT graduates are potentially less sensitive to labor market shocks if they have more skills (Oreopoulos et al., 2012). On the other hand, they may also be more productive at innovating, so any small change in their initial career choices could lead to relatively large changes in innovative output. Thus, it is not clear whether my results would generalize to the average college population. Studying the effect of initial labor market conditions on the patent production of other populations of engineering and science students would be a valuable extension. Second, since I do not directly observe initial career choice or graduate school enrollment in my data, I cannot estimate the causal impact of working in a certain sector or going to graduate school on long-term patent production. Future work identifying the return (in terms of innovative output) to different initial career choices would have important policy implications. Finally, my results are not a welfare analysis of the impact of initial labor market conditions. A comprehensive welfare analysis that accounts for wages as well as the externalities of patented invention would be very informative.

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<sup>50</sup>For instance, Grove (2011) shows that students accepted by MIT have higher SAT scores than those accepted by public universities.

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## 1.7 Tables and Figures

Table 1.1: Mean Characteristics for Person-level Data

	All	Engineering	Science	Inventors
Proportion Female	0.319	0.267	0.398	0.152
Age at Graduation	22.58	22.621	22.376	22.56
GPA (Normalized)	-0.006	-0.005	-0.003	0.214
Engineering	0.626	1	0	0.784
Science	0.245	0	1	0.177
Non-SE Majors	0.128	0	0	0.039
<i>Ethnicity/Citizenship</i>				
White	0.584	0.577	0.627	0.676
Asian American	0.197	0.189	0.207	0.167
International	0.079	0.085	0.064	0.077
Other Minorities	0.140	0.149	0.102	0.080
<i>High School Region</i>				
Northeast	0.406	0.393	0.427	0.421
Midwest	0.133	0.135	0.136	0.151
South	0.183	0.187	0.175	0.165
West	0.143	0.146	0.140	0.137
International	0.136	0.139	0.123	0.126
N	27,145	17,002	6,662	4,356
<i>Currently Employed Sector</i>				
Tech. and Industrial	0.450	0.542	0.294	0.631
Academia	0.157	0.104	0.328	0.125
Non-SE	0.260	0.217	0.270	0.112
Unassigned	0.134	0.137	0.107	0.132
N	21,178	13,576	4,896	3,836

Notes: This table reports the mean of individual characteristics by person. An “inventor” is anyone that has produced at least one patent since graduation. *Currently Employed Sector* is assigned from alumni’s current employer as reported on Infinite Connection in June 2011 (see Appendix 1.8.1); missing values are excluded.

Table 1.2: Patent and Citation Statistics for Person\*Year-Level Data

	Mean	Std.Dev.	Min.	Max.
<i>Panel A: All Fields (N=475,636)</i>				
Num. of Patents	0.052	0.448	0	48
Num. of Citations	0.681	11.956	0	2557
<i>Panel B: Engineering (N=303,506)</i>				
Num. of Patents	0.064	0.501	0	48
Num. of Citations	0.859	12.848	0	2095
<i>Panel C: Science (N=114,593)</i>				
Num. of Patents	0.040	0.387	0	27
Num. of Citations	0.477	12.138	0	2557
<i>Panel D: Non-SE (N=57,537)</i>				
Num. of Patents	0.012	0.191	0	14
Num. of Citations	0.144	4.119	0	500
<i>Panel E: Inventors (N=89,435)</i>				
Num. of Patents	0.276	1.004	0	48
Num. of Citations	3.620	27.378	0	2557

Notes: This table reports the summary statistics of the patents and citations at the person\*year level. Note that inventors could produce zero patents in some years since they are defined as anyone with positive patent production since graduation.

Table 1.3: Patents' Technology Fields By Inventors' Major

	[1]	[2]	[3]	[4]	[5]
<i>Engineering</i>					
EECS	26.55%	12.61%	2.87%	1.26%	43.29%
Mechanical	3.95%	6.31%	4.84%	2.08%	17.17%
Chemical	0.93%	1.69%	3.27%	0.71%	6.60%
Material	0.67%	3.35%	1.18%	0.36%	5.57%
Aeronautics	1.76%	1.74%	1.03%	0.53%	5.07%
Other	0.41%	0.26%	0.21%	0.18%	1.05%
All Engineering	34.28%	25.95%	13.40%	5.12%	78.75%
<i>Science</i>					
Physics	2.10%	3.89%	1.35%	0.20%	7.54%
Chemistry	0.47%	0.76%	2.88%	0.17%	4.28%
Mathematics	2.12%	0.58%	0.23%	0.10%	3.03%
Biology	0.60%	0.38%	1.65%	0.11%	2.74%
Other	0.43%	0.33%	0.01%	0.03%	0.79%
All Science	5.72%	5.94%	6.12%	0.60%	18.39%

Notes: This table reports the fraction of patents in a specific technology field produced with inventors with a specific major. Technology fields are compiled from the six "Technology Categories" defined in Hall et al. (2001). The columns are: [1] Computer & Communications; [2] Electrical & Electronic, Mechanical; [3] Chemical, Drugs & Medical; [4] Others; [5] Total. "Other" engineering majors include Civil & Environmental; Ocean; and Nuclear. "Other" science majors include Brain and Cognitive Sciences; Earth, Atmospheric, and Planetary Sciences.

Table 1.4: Panel Estimates of the Impact of Graduating Conditions on Patent Production (Dep.Var. = Num. of Patents, Mean = 0.052)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unemployment Rate	0.100*** (0.023)	0.056*** (0.011)	0.053*** (0.011)				0.044*** (0.013)
<i>Marginal Effect</i>	0.105	0.058	0.054				0.045
2 Year Market Return				0.236 (0.201)	-0.244*** (0.074)	-0.263*** (0.070)	-0.105 (0.082)
<i>Marginal Effect</i>				0.266	-0.216	-0.231	-0.100
Log (Fed R&D/GDP)	No	No	Yes	No	No	Yes	Yes
Characteristics	No	Yes	Yes	No	Yes	Yes	Yes
Experience Dummies	No	Yes	Yes	No	Yes	Yes	Yes
Current Year Dummies	No	Yes	Yes	No	Yes	Yes	Yes
N	475,636	475,636	475,636	475,636	475,636	475,636	475,636

Notes: Person-year-level observation. All estimates are from quasi-maximum likelihood Poisson models. Sample includes all person-years from the year after graduation to 2010 for the 1980-2005 cohorts. Robust standard errors clustered at the cohort-year level are shown in parentheses. \* :  $p < 0.10$ ; \*\* :  $p < 0.05$ ; \*\*\* :  $p < 0.01$ . Dependent variable is the number of granted patents a graduate applies for in the current year. *Unemployment rate*: the annual unemployment rate in the year of graduation. *2 year market return*: the CSRP market return during the sophomore and junior years. *Log (Fed R&D/GDP)*: the log of federal R&D expenditure as a ratio of U.S. GDP in the year of graduation. *Characteristics*: include age, cumulative GPA standardized by major and cohort, indicator variables for gender, race, engineering or science student, high school region. *Experience dummies*: 0/1 indicator variables for the difference between the current year and year of graduation. *Current year dummies*: 0/1 indicator variables for the current year.

Table 1.5: Panel Estimates of the Impact of Current Economic Conditions on Patent Production (Dep.Var. = Num. of Patents)

	(1)	(2)	(3)	(4)	(5)	(6)
	<i>R</i> = Unemployment Rate			<i>R</i> = Stock Return		
<i>R<sub>j</sub></i> (Initial)	0.060*** (0.013)	0.057*** (0.013)	0.058*** (0.013)	-0.356*** (0.094)	-0.363*** (0.095)	-0.372*** (0.095)
<i>R<sub>t</sub></i> (Current)	-0.041 (0.028)	-0.074* (0.040)	-0.011 (0.061)	-0.082 (0.120)	-0.113 (0.132)	-0.112 (0.178)
<i>R<sub>t-1</sub></i>		0.039 (0.038)	-0.068 (0.078)		0.040 (0.164)	-0.009 (0.187)
<i>R<sub>t-2</sub></i>			0.074 (0.047)			0.060 (0.163)
Log (Fed R&D/GDP)	Yes	Yes	Yes	Yes	Yes	Yes
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Experience dummies	Yes	Yes	Yes	Yes	Yes	Yes
Current Year Trend	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Trend	Yes	Yes	Yes	Yes	Yes	Yes
N	198,804	178,990	160,228	198,804	178,990	160,228

Notes: Person-year-level observation. All estimates are from quasi-maximum likelihood Poisson models. Column (1) and (4) includes all person-years from two years after graduation to 2000 for the 1980-1998 cohorts. Column (2) and (4) includes all person-years from three years after graduation to 2000 for the 1980-1997 cohorts. Column (3) and (6) includes all person-years from four years after graduation to 2000 for the 1980-1996 cohorts. Robust standard errors clustered at the cohort-year level are shown in parentheses.\* :  $p < 0.10$ ; \*\* :  $p < 0.05$ ; \*\*\* :  $p < 0.01$ . Dependent variable is the number of granted patents a graduate applies for in the current year.  $R_j$  is the annual unemployment rate in the year of graduation or the CSRP market return during the sophomore and junior years.  $R_t$  is the annual unemployment rate in the current year or the CSRP market return in the two years before. *Log (Fed R&D/GDP)*: the log of federal R&D expenditure as a ratio of U.S. GDP in the year of graduation. *Characteristics*: include age, cumulative GPA standardized by major and cohort, indicator variables for gender, race, engineering or science student, high school region. *Experience dummies*: 0/1 indicator variables for the difference between the current year and year of graduation. *Current year trend* and *cohort trend*: current year variable and cohort variable.

Table 1.6: Cross-sectional Estimates of the Impact of Graduating Conditions on Entry into Invention

	5 Years		10 Years		15 Years	
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate	0.0017 (0.0011)	0.0015 (0.0010)	0.0024** (0.0011)	0.0022 (0.0014)	0.0006 (0.0013)	0.0004 (0.0015)
Characteristics	No	Yes	No	Yes	No	Yes
Cohort Trend	Yes	Yes	Yes	Yes	Yes	Yes
N	16,610	16,610	16,610	16,610	16,610	16,610

Notes: Person-level observation. All estimates are from ordinary-least-squares (OLS) models. Dependent variable is 0/1 indicator variable for becoming an inventor in 5 years (Column (1) and (2)), 10 years (Column (3) and (4)), or 15 years (Column (5) and (6)) after graduation. Sample includes all graduates from the 1980-1995 cohorts. Robust standard errors clustered at the cohort level are shown in parentheses. \* :  $p < 0.10$ ; \*\* :  $p < 0.05$ ; \*\*\* :  $p < 0.01$ . *Unemployment rate:* the national unemployment rate in the year of graduation. *Characteristics:* include age, cumulative GPA standardized by major and cohort, indicator variables for gender, race, engineering or science student, high school region. *Experience dummies:* 0/1 indicator variables for the difference between the current year and year of graduation. *Cohort trend:* cohort variable and its square.

Table 1.7: Cross-sectional Estimates of the Impact of Graduating Conditions on Inventor Characteristics, Long-term Sector, and Time to First Patent

<i>Panel A: Characteristics (N=2,828)</i>			
	(A1) GPA	(A2) Engineering	(A3) Science
Unemployment Rate	-0.0036 (0.0143)	0.0064 (0.0100)	-0.0032 (0.0071)
Cohort Trend	Yes	Yes	Yes
<i>Panel B: Technology Field (N=2,828)</i>			
	(B1) Computer & Communications	(B2) Electrical & Electronic; Mechanical	(B3) Chemical; Drugs & Medical
Unemployment Rate	0.003 (0.011)	0.001 (0.008)	-0.005 (0.004)
Characteristics	Yes	Yes	Yes
Cohort Trend	Yes	Yes	Yes
<i>Panel C: Currently Employed Sector (N=2,538)</i>			
	(C1) Tech. & Industrial	(C2) Academia	(C3) Non-SE
Unemployment Rate	0.004 (0.008)	-0.007 (0.005)	-0.001 (0.004)
Characteristics	Yes	Yes	Yes
Cohort Trend	Yes	Yes	Yes
<i>Panel D: Time to First Patent (N=2,828)</i>			
	(D1)	(D2)	(D3)
Unemployment Rate	-0.109* (0.052)	-0.111** (0.051)	-0.105** (0.048)
Cohort Trend	Yes	Yes	Yes
Tech. Field Dummies	No	Yes	Yes
Characteristics	No	No	Yes

**Notes:** Person-level observation. All estimates are from ordinary-least-squares (OLS) models. Sample includes graduates from the 1980-1995 cohorts who have produced at least one patent in the first 15 years after graduation. Dependent variable in Panel A is: GPA (A1), 0/1 indicator variable for being an engineering major (A2) or science major (A3). Dependent variable in Panel B is 0/1 indicator variable for being in one of the three technology fields listed in the column names. Dependent variable in Panel C is 0/1 indicator variable for being in one of the three currently employed sectors listed in the column names. Dependent variable in Panel D is the number of years between the year of graduation and the year of application for the first granted patent. Robust standard errors clustered at the cohort level are shown in parentheses. \* :  $p < 0.10$ ; \*\* :  $p < 0.05$ ; \*\*\* :  $p < 0.01$ . *Technology field*: the technology field in which the inventors patent the most. *Currently employed sector*: assigned from the current employer reported on Infinite Connection as of June 2011; missing values are excluded. *Time to First Patent*: the number of years between year of graduation and year of patent application for the first granted patent. *Unemployment rate*: the national unemployment rate in the year of graduation. *Characteristics*: include age, cumulative GPA standardized by major and cohort, indicator variables for gender, race, engineering or science student, high school region. *Cohort trend*: cohort variable and its square.

Table 1.8: Cross-sectional Estimates of the Impact of Graduating Conditions on Patent Characteristics

<i>Panel A: Inventor Characteristics</i>			
	(A1) GPA	(A2) Engineering	(A3) Science
Unemployment Rate	0.0061 (0.0198)	-0.0107 (0.0103)	0.0120 (0.0078)
Cohort Trend	Yes	Yes	Yes
<i>Panel B: Technology Field</i>			
	(B1) Computer & Communications	(B2) Electrical & Electronic; Mechanical	(B3) Chemical; Drugs & Medical
Unemployment Rate	0.006 (0.018)	0.005 (0.012)	-0.012 (0.012)
Unemployment*Science	-0.031 (0.023)	0.002 (0.027)	0.034*** (0.011)
Inventor Characteristics	Yes	Yes	Yes
Cohort Trend	Yes	Yes	Yes
Application Year Trend	Yes	Yes	Yes

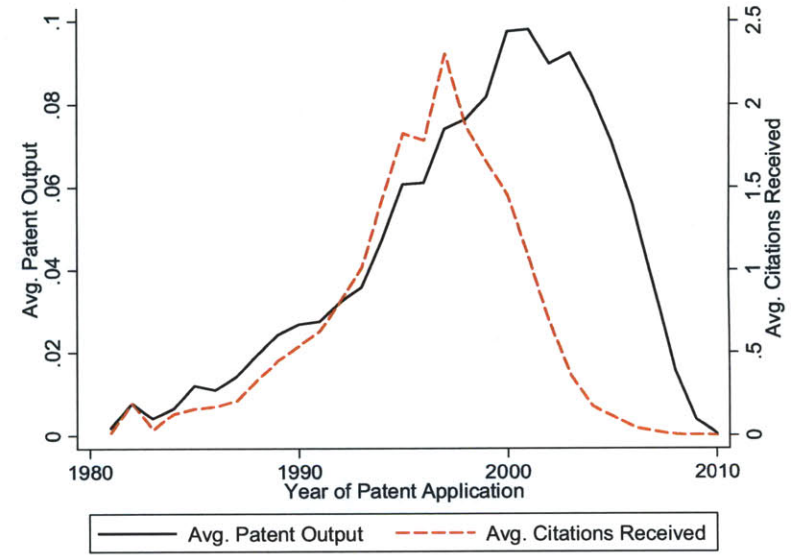
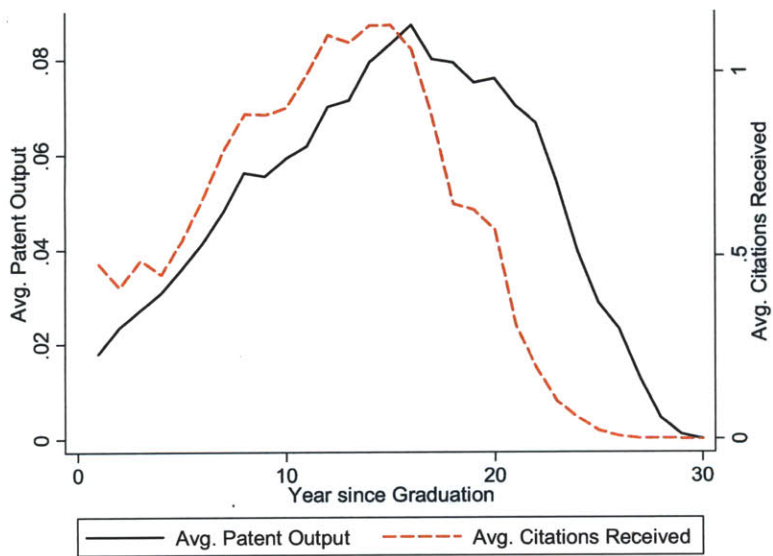
Notes: Patent-level observation (N=13,336). All estimates are from ordinary-least-squares (OLS) models. Sample includes all patents produced by the 1980-1995 cohorts in the first 15 years after graduation. Dependent variable in Panel A is: GPA (A1), 0/1 indicator variable for being an engineering major (A2) or science major (A3). Dependent variable in Panel B is 0/1 indicator variable for being in one of the three technology fields listed in the column names. Robust standard errors clustered at the cohort level are shown in parentheses. \* :  $p < 0.10$ ; \*\* :  $p < 0.05$ ; \*\*\* :  $p < 0.01$ . *Unemployment rate*: the national unemployment rate in the year of graduation. *Unemployment\*Science*: the interaction term of "unemployment rate" and the 0/1 indicator variable for being a science major. *Inventor Characteristics*: include age, cumulative GPA standardized by major and cohort, indicator variables for gender, race, engineering or science student, high school region. *Cohort trend*: cohort variable and its square. *Application year trend*: application year variable and its square.

Table 1.9: Cross-sectional Estimates of the Impact of Graduating Conditions on Patent Citations

	<i>Panel A: OLS</i>		
	(C1)	(C2)	(C3)
Unemployment Rate	-0.202 (0.694)	-0.672 (0.442)	-0.655 (0.415)
Application Year Dummies	No	Yes	Yes
Technology Field Dummies	No	Yes	Yes
Inventor Characteristics	No	No	Yes
Cohort Trend	Yes	Yes	Yes
	<i>Panel B: Median Regression</i>		
	(D1)	(D2)	(D3)
Unemployment Rate	-0.273 (0.182)	0.001 (0.084)	-0.139 (0.086)
Application Year Dummies	No	Yes	Yes
Technology Field Dummies	No	Yes	Yes
Inventor Characteristics	No	No	Yes
Cohort Trend	Yes	Yes	Yes

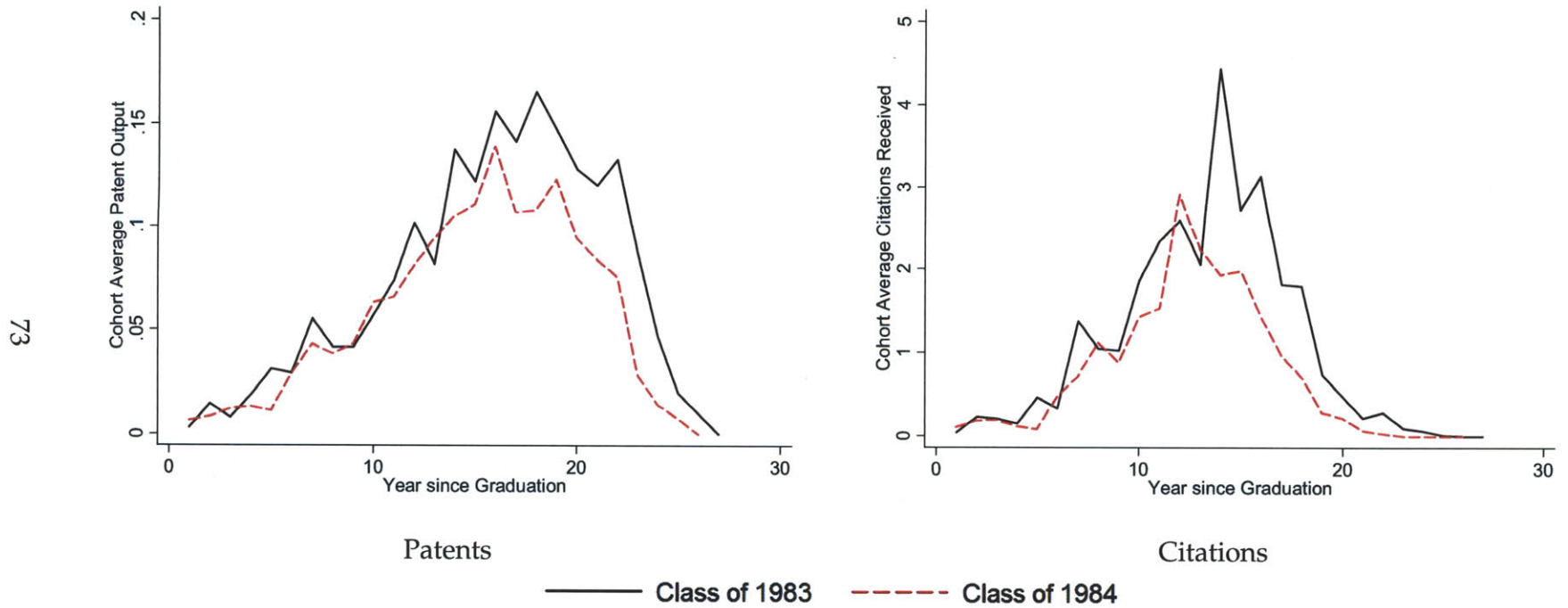
**Notes:** Patent-level observation (N=13,336). Estimates in Panel A are from ordinary-least-squares (OLS) models. Estimates in Panel B are from quantile regressions estimated at the median. Sample includes all patents produced by the 1980-1995 cohorts in the first 15 years after graduation. Dependent variable is the number of citations received by the end of 2010. Robust standard errors clustered at the cohort level are shown in parentheses.\* :  $p < 0.10$ ; \*\* :  $p < 0.05$ ; \*\*\* :  $p < 0.01$ . *Unemployment rate:* the national unemployment rate in the year of graduation. *Inventor Characteristics:* include age, cumulative GPA standardized by major and cohort, indicator variables for gender, race, engineering or science student, high school region. *Cohort trend:* cohort variable and its square. *Application year dummies:* the set of 0/1 indicator variables for each application year. *Technology field dummies:* the set of 0/1 indicator variables for each technology field.

Figure 1-1: By Year: Average Patents and Citations Per Person



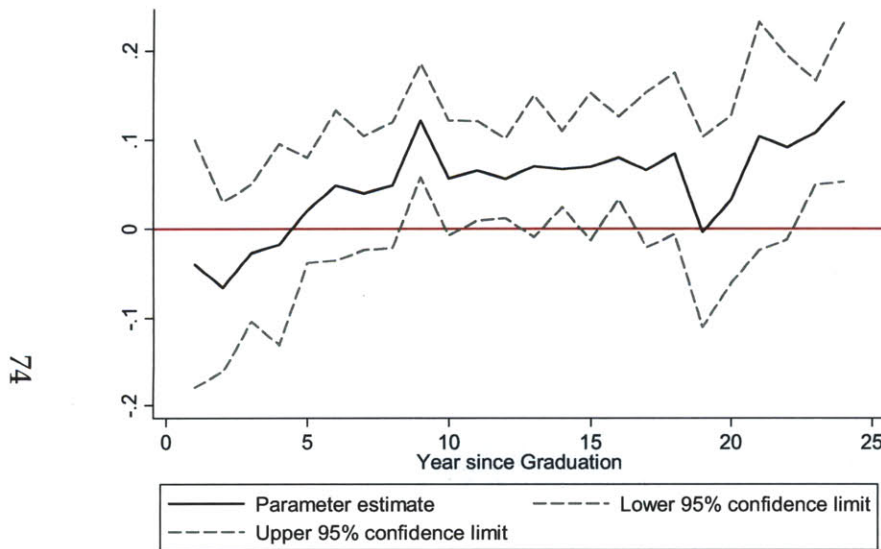
Notes: This figure plots the average patent output in the each year, by year since graduation (on the left) and year of patent application (on the right).

Figure 1-2: Classes of 1983 VS 1984: Patent Output by Year

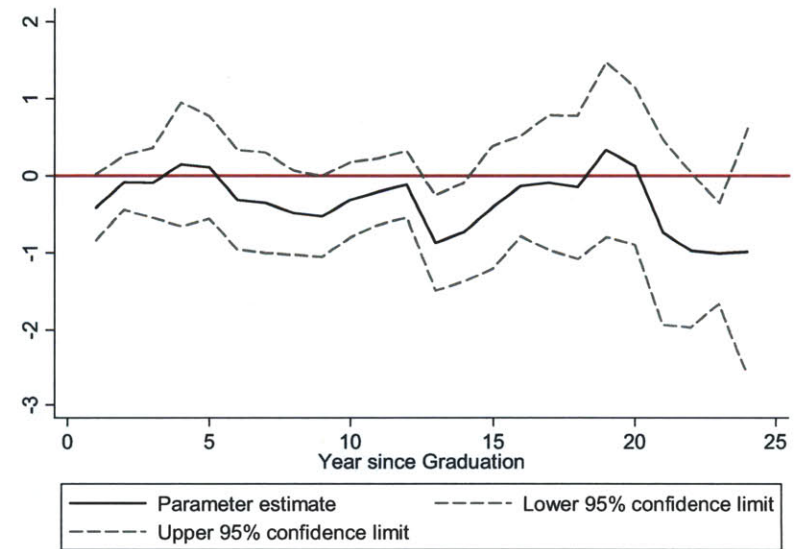


Notes: Outcome plotted is, by year since graduation, the average patent output in the each year (on the left) and the average citations received for patents produced in that year (on the right). The black line is Class of 1983, and the red dashed line is Class of 1984.

Figure 1-3: Persistent Effects of Graduating Conditions on Patent Output



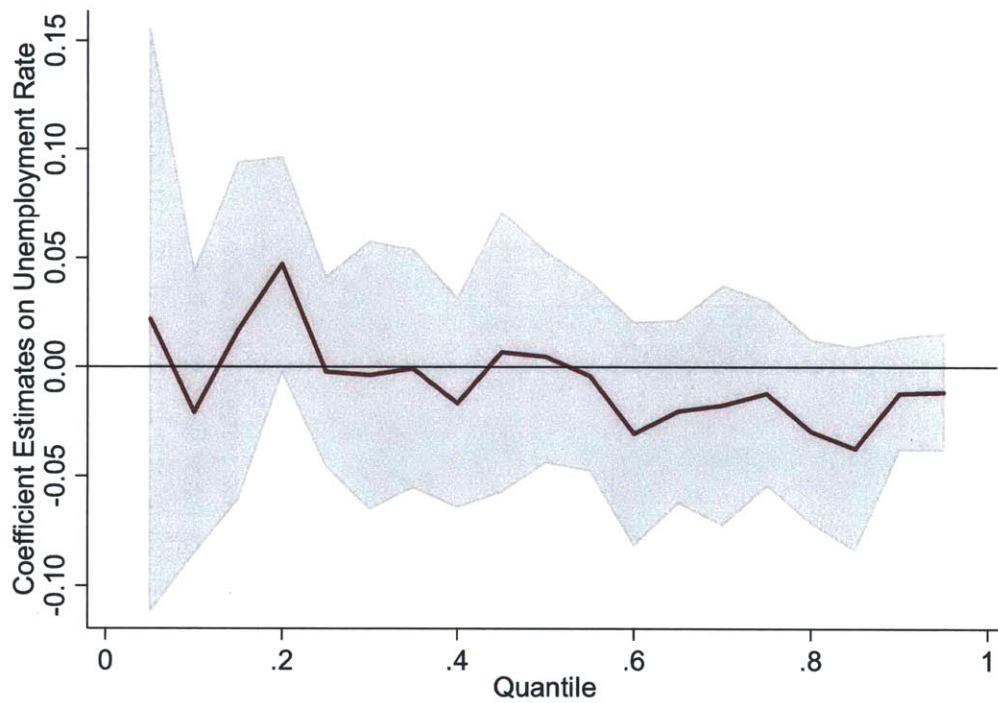
Unemployment Rate in the Year of Graduation



Stock Return during Sophomore and Junior Years

Notes: Person\*year-level observation. These figures plot the coefficient estimates and confidence interval of the interaction term between the shock and the dummy for each year since graduation from a quasi-ML Poisson model. Dep. Variable = Number of patents produced in a year. On the left: shock measured by unemployment rate in the year of graduation. On the right: shock measured by the stock return during the sophomore and junior years.

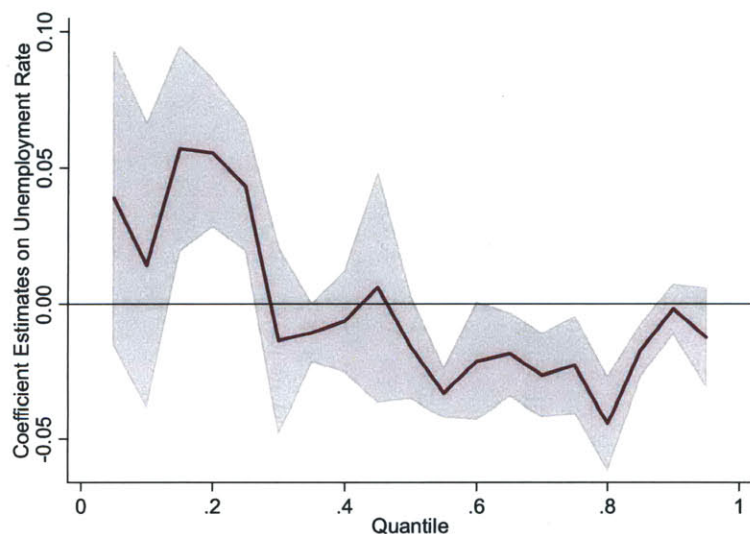
Figure 1-4: Balanced Panel: Initial Conditions And Inventors' GPA<sup>†</sup>



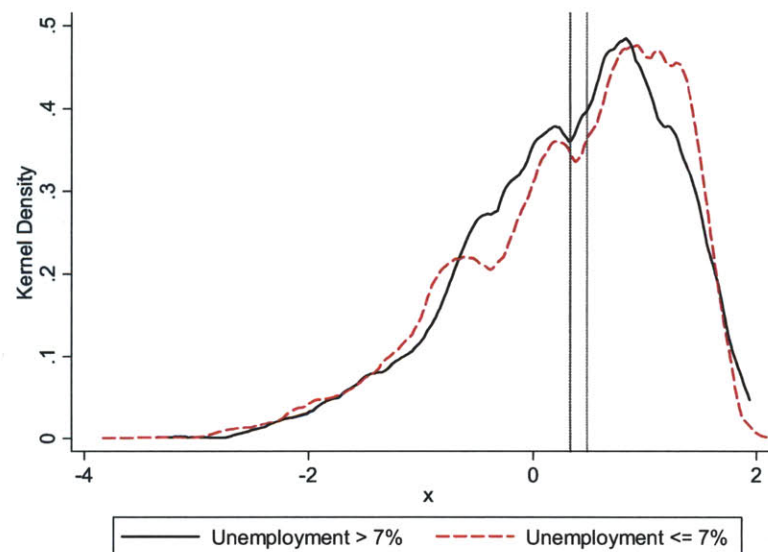
Notes: Person-level observation. This figure plots the coefficient estimates and 95% CI from the Quantile regression. Dep. Var. = GPA. Independent variable plotted: national unemployment rate in the year of graduation. Standard errors are bootstrapped with 2000 repetitions. Sample includes all the individuals from the 1980-1995 cohorts that have produced at least one patent within 15 years after graduation.

Figure 1-5: Balanced Panel: Initial Conditions and Patent-Weighted Inventors' GPA

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(A) Quantile coefficient estimates

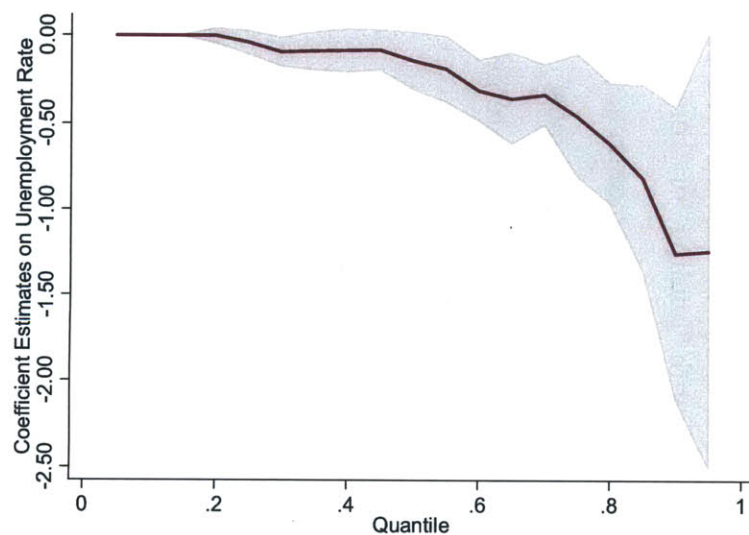


(B) Kernel density

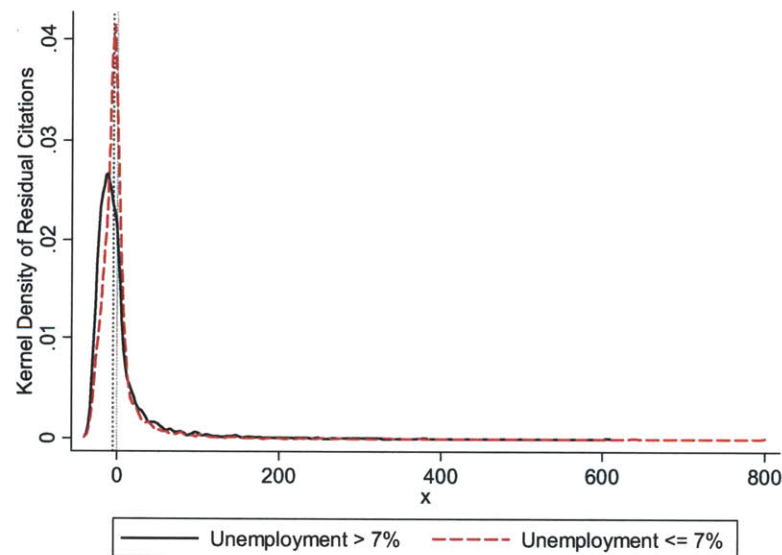
Notes: Patent-level observation. Sample includes all the patents produced by the 1980-1995 cohorts within 15 years after graduation. On the left: the coefficient estimates from the Quantile regression. Dependent variable is the (patent-weighted) GPA of the inventor. Independent variable plotted: national unemployment rate in the year of graduation. Standard errors are bootstrapped with 2000 repetitions. On the right: the kernel density of inventor's GPA. Black line: the sample of patents produced by the inventors who graduated with the national unemployment higher than 7%. Red dashed line: the sample of patents produced by the inventors who graduated with the national unemployment rate lower than 7%. The two gray vertical lines are the mean and median of the whole sample.

Figure 1-6: Balanced Panel: Initial Conditions and the Distribution of Citations<sup>†</sup>

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(A) Quantile coefficient estimates



(B) Kernel density of Residual Citations

Notes: Patent-level observation. Sample includes all the patents produced by the 1980-1995 cohorts within 15 years after graduation. On the left: the coefficient estimates from the Quantile regression. Dependent variable is the number of citations. Independent variable plotted: national unemployment rate in the year of graduation. Standard errors are bootstrapped with 2000 repetitions. On the right: the kernel density of residual citations. Residual citations are the residuals from regressing citations on cohort trend, inventor characteristics, application year dummies and technology field dummies. Black line: the sample of patents produced by the inventors who graduated with the national unemployment higher than 7%. Red dashed line: the sample of patents produced by the inventors who graduated with the national unemployment rate lower than 7%. The two gray vertical lines are the mean and median of the whole sample.

## 1.8 Appendix

### 1.8.1 Assigning Sector based on Employer

Based on the employer reported on Infinite Connection, I assign the graduates to three sectors: technology and industrial (anything that generally involves patent production); academia; and non-science and non-engineering ("non-SE", including finance, consulting, law, real estate, and government). I determine the sector in two ways. The first is by firm. For instance, Google is in the first group whereas Goldman Sachs is in the third group. However, this is only plausible for large firms. Since the graduates work for a very wide range of firms (more than 10,000 unique names), it would be too time consuming to go through all the firms and determine their sectors. Thus, the second way to assign sector is based on keywords. For instance, any firm with "semiconductors" or "pharma" in its names is assigned to the first group; any employer with "university" or "college" is assigned to the second group; any firm with "holding" or "consult" is assigned to the third group. Although doing so inevitably allows more measurement errors than assigning sector by firm, it is more efficient and covers most of the sample. Only 13% of the reported employers are unassigned. They are generally small firms such as start-ups.

Samples of keywords used to identify each sector are:

1. Technology & Industrial: tech machine syst dynamics scien research commu-  
nication devic wire manufact telecom syst soft defense instrument engineer  
space material equipment aircraft energ motor electr industri robot network  
chemical conduct comput auto mobile product info elevat data design media  
petro oil enrg solution innovat power metal analysis utilit diagnosti metric  
engine digita activ internet intranet atomic aviation cemex cement oceano-

graph analyt telegraph nuclear pharma therapeut molecu biomed cure cancer;

2. Academia: universi college "medical school" "business school;"
3. Non-SE: consult capital trading asset invest securitie bank venture finance financial wealth holding fund insurance broker architect hotel society foundation entertain picture embassy community school academy ministry teach healthcare airline proptert program practice clinic attorney realestate marketing adverti realty.

## 1.8.2 Patent Matching

My matching procedure has two steps. In the first step, I match the alumni to the inventors that have the same first and last names, and drop those with different non-missing middle names or initials. It is possible that this first step could drop a small set of patents produced by the alumni, if a) the names are misspelled on the patent grants, or b) the alumni use new names on the patents but have not reported the name change to the Alumni Association.

In the second step, I assign each alumnus-inventor pair an integer score out of 10 based on a) how well the middle names match, b) how well the locations match, and c) how rare the first and/or last names are. Table A1.1 provies a summary of the score assignment. In the middle score category, the full score, 3, is when the full middle names, including when there are no middle names, are matched between the alumnus and the inventor. A score of 2 is when the initials match or when the middle name is missing for the inventors but not the alumni. Since it is not required for inventors to report their full names, not having a middle name listed on the patent does not imply there is no middle name. A score of 1 is when the

middle name is missing for the alumnus but not the inventor. It is less likely but still possible that some alumni do not report their middle names to the Registrar's Office and the Alumni Association. It is also possible that the alumnus has added a middle name since graduation and listed it on the patents. In the location category, the full score, 4, is when one of the work or home city-level addresses reported by the alumnus perfectly matches the city of the inventor. 3 is when the states match, and 1 is when the countries match. In the name rarity category, there are two sub-criteria: how rare the names are among the MIT population (full score 2), and how rare the names are among the inventors population (full score 1). On the first criterion, the full score 2 is when the first or last name is very rare (less than 10 people with the same first or last name); 1 is when the first or last name is fairly rare (less than 100 people with the same first or last name); the rest are 0. On the second criterion, 1 is when there are less than 15 unique inventors with the same first and last name, and 0 otherwise.

A higher score implies a greater likelihood that the matching is correct. For example, an alumnus-inventor pair scores 10 when the graduate and the inventor have a rare first or last name and are exactly matched on middle name and city of residence. A score of 3 means the two have common names, live in different states, and the middle name is missing in the alumni records. Since an inventor may provide different information across patents, the matching score could also differ across patents. In this case I use the highest score for each alumnus-inventor pair. In the very few cases where two alumni are matched to the same inventor, I look both up on Google or LinkedIn and determine the correct match based on their years of graduation and where they have worked.

The matching score is not a perfect criteria due to obvious data limitations. If an alumni inventor has moved many times, then the location match would not

be perfect. On the other hand, even within a city, there are people with the same names. A score lower than 6 means the alumnus-inventor pair fails to fully satisfy at least two out of the three criteria listed above. In this case, it is hard to distinguish whether the low score is from not observing the correct address or the match is a false positive. A score above 8 means that the alumnus-inventor pair is a perfect match by multiple criteria, but not all the correctly matched pairs would score this high. Thus, scores that are sufficiently low should be dropped, but there is a trade-off between Type I and Type II errors. I use 6 as the main threshold to gain more statistical power in my analysis, but I also use 8 as a robustness check. After dropping all the pairs that score below 6, the final sample includes over 4,500 alumni inventors with more than 25,000 total patents granted by the end of 2010. These patents have received over 300,000 citations in total by the end of 2010. Restricting to those scoring above 8 still leaves over 3,400 alumni and 19,300 patents with nearly 250,000 citations. I exclude all the patents that were applied for before and during the year of graduation. Figure (A1.1) shows that the variations in the cohort-level patent production do not depend on the score.<sup>51</sup>

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<sup>51</sup>Since the later cohorts have less time to invent, there is a natural downward slope in both patent and citation output.

### 1.8.3 Additional Tables and Figures

Table A1.1: Assigning Matching Score

	<b>Strong</b>	<b>Medium</b>	<b>Weak</b>
<i>Middle Name</i>	[3] Exact match	[2] Initial; Inventor missing	[1] Alumnus missing
<i>Location</i>	[4] City	[3] State	[1] Country
<i>Name Rarity</i>	[3] Very rare	[2] Rare	[1] or [0] Not rare

Table A1.2: Mean Characteristics of Classes of 1983 and 1984<sup>†</sup>

Class	1983	1984
Female	0.2091	0.215
Age at Graduation	22.677	22.576
Inventor	0.251	0.251
<i>Ethnicity/Citizenship</i>		
White	0.797	0.773
Asian Am.	0.044**	0.068
Other Minorities (US)	0.092	0.073
International	0.068	0.086
<i>Highschool Region</i>		
Northeast	0.504*	0.465
Midwest	0.137	0.127
South	0.151	0.146
West	0.101	0.112
International	0.108***	0.151
<i>Field of Study</i>		
Engineering	0.683	0.701
Science	0.208	0.223
Non-SE	0.109**	0.077
N (Person)	1033	1065
<i>Current Sector</i>		
Tech. and Industrial	0.520	0.500
Academia	0.131*	0.161
Non-SE	0.186	0.202
Unassigned	0.163	0.138
N (Person)	861	908

Notes: Statistical significance reported for the T-test of equal means. \* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

Table A1.3: Baseline Coefficient Estimates: Characteristics

Female	-1.129*** (0.044)	Asian American	0.199*** (0.041)
Age at Graduation	-0.022*** (0.008)	International	-0.083* (0.047)
Engineering	1.431*** (0.072)	Other Minorities	-0.380*** (0.058)
Science	1.042*** (0.075)	HS Midwest	0.063 (0.042)
GPA*Engineering	0.378*** (0.068)	HS South	-0.100*** (0.035)
GPA*Science	0.339*** (0.069)	HS West	-0.055 (0.035)
GPA (Non-SE)	-0.043	HS International	0.068* (0.041)

Notes: Coefficients reported from Column (7) of Table 1.4. Base groups are: non-SE; white; northeast highschool. \* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

Table A1.4: Robustness Checks: The Impact of Graduating Conditions on Patent Production

<i>Panel A: OLS &amp; 2SLS</i>				
	OLS		2SLS	
	(A1)	(A2)	(A3)	(A4)
Unemployment Rate	0.004*** (0.001)		0.003*** (0.001)	
2 Year Market Return		-0.015*** (0.004)		-0.021*** (0.005)
N	475,636	475,636	475,636	475,636
<i>Panel B: Balanced Panel</i>				
	Sample I		Sample II	
	(B1)	(B2)	(B3)	(B4)
Unemployment Rate	0.042*** (0.014)		0.069*** (0.018)	
2 Year Market Return		-0.436*** (0.085)		-0.410*** (0.124)
N	249,150	249,150	182,710	182,710
<i>Panel C: Excluding Top Inventors</i>				
	Dependent: (Pat>0)		Top Inventors Excluded	
	(C1)	(C2)	(C3)	(C4)
Unemployment Rate	0.039*** (0.008)		0.060*** (0.009)	
2 Year Market Return		-0.129*** (0.053)		-0.309*** (0.082)
N	474,588	474,588	474,763	474,763

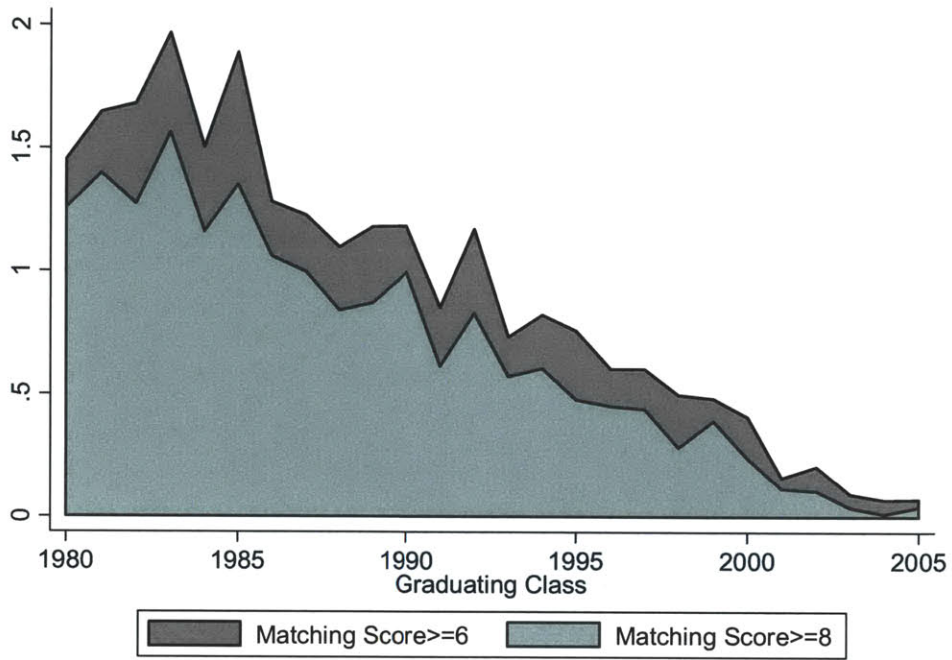
Notes: Person-year-level observations. Dependent variable is number of patents produced in a year except for (C1) and (C2). Robust standard errors are corrected clustered at the cohort-year level are shown in parentheses. \* :  $p < 0.10$ ; \*\* :  $p < 0.05$ ; \*\*\* :  $p < 0.01$ . Panel A: Estimates in (A1) and (A2) are from ordinary-least-squares (OLS) models. Estimates in (A3) and (A4) are from two-stage-least-squares (2SLS) models. Sample includes the 1980-2005 cohorts observed for years between the year after graduation and 2010. Panel B: Estimates are from quasi-maximum likelihood (QML) Poisson models. Sample I includes 1980-1995 cohorts observed for the first 15 years after graduation; Sample II includes 1980-1995 cohorts observed between 2000 and 2010. Panel C: Estimates in (C1) and (C2) are from Logistic regressions. Estimates in (C3) and (C4) are from QML Poisson models. Dependent variable in (C1) and (C2) is 0/1 indicator variable for positive patent production. Sample in (C3) and (C4) excludes the most productive inventors with more than 50 lifetime patents. *Unemployment rate*: the annual unemployment rate in the year of graduation. *2 year market return*: the CSRP market return during the sophomore and junior years. All the regressions include the following controls: the log of federal R&D expenditure as a ratio of U.S. GDP in the year of graduation; age, cumulative GPA standardized by major and cohort, indicator variables for gender, race, engineering or science student, high school region; 0/1 indicator variables for the difference between the current year and year of graduation; and 0/1 indicator variables for the current year.

Table A1.5: Robustness Checks: The Impact of Graduating Conditions on Selection into Majors

<i>Dependent</i>	<i>Engineering=1</i>		<i>Science=1</i>	
	(1)	(2)	(3)	(4)
Unemployment	0.004 (0.004)	0.003 (0.004)	-0.004 (0.003)	-0.002 (0.003)
Characteristics	No	Yes	No	Yes
Cohort Trend	Yes	Yes	Yes	Yes
N	27,145	27,145	27,145	27,145

Notes: Person-level observations. Coefficients reported are marginal effects from Logistic models. Dependent variable is 0/1 indicator variable for being an engineering major ((1) and (2)) or science major ((3) and (4)). Robust standard errors are corrected clustered at the cohort level are shown in parentheses. \* $p < 0.10$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ . *Unemployment rate*: the annual unemployment rate in the year of graduation. *Characteristics*: include age, cumulative GPA standardized by major and cohort, indicator variables for gender, race, engineering or science student, high school region. *Cohort trend*: cohort variable.

Figure A1.1: Average Patent Output by Cohort



Patent

Notes: This figure plots, by cohort, the number of patents produced per person since the year after graduation.



## Chapter 2

# Self-Selection into Finance and Implications for Talent Allocation<sup>1</sup>

### 2.1 Introduction

Over the last three decades, the wage gap between financiers and engineers in the Current Population Surveys has grown from less than 5% to over 30% (Philippon and Reshef, 2009). Today, finance has become one of the industries with the highest earnings potential.<sup>2</sup> It is thus not surprising that the proportion of bachelor's graduates who became financiers has grown steadily at elite schools such as MIT and Harvard (Figure A2.1; Goldin and Katz, 2008). Before the onset of

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<sup>1</sup>I thank David Autor, Daron Acemoglu, and Scott Stern for their generous support and guidance on this project. Pierre Azoulay, Panle Barwick, Mihir Desai, JB Doyle, Michael Greenstone, John S. Reed, Attoinette Schoar, Jialan Wang, Heidi Williams, and numerous seminar participants at the Massachusetts Institute of Technology and Harvard Business School have provided helpful comments and suggestions. I am grateful to Suzanne Berger, Maggy Bruzelius, Claude Canizares, Daniel Hastings, 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. This project was supported by the Kauffman Foundation. All errors are my own.

<sup>2</sup>Oyer (2008) shows that for Stanford MBA graduates, the expected difference in cumulative income between investment bankers and non-financiers is millions of dollars during the first 20 years after graduation. Kaplan and Rauh (2010) find that in 2004 the top-25 hedge fund managers together earned more than all of the CEOs of Standard & Poor's 500 companies combined.

the recent financial crisis in 2008, finance was attracting between 20% and 40% of top college graduates who entered the labor force (Hastings et al., 2010; Rampell, 2011).

To some, the raising popularity of finance is disconcerting, as the high wages in finance might be luring away young talent from sectors where they would have produced more value to society. For example, Kedrosky and Stangler (2011) make the alarming observation that the increase in financial employment over the last several decades parallels the decline in new firm founding activities in America. Wadhwa (2011) articulates the concern that engineering students are increasingly likely to choose a career in finance over engineering. Macroeconomic theory suggests that talent allocation is strongly responsive to a society's reward structure and that allocating talent from productive to rent-seeking activities hurts economic growth (Baumol, 1990; Murphy et al., 1991; Acemoglu, 1995).<sup>3</sup> However, there exists little empirical work on whether financiers would have been productive engineers, scientists, or entrepreneurs in a counterfactual world with low relative wages in finance.

Using data on MIT bachelor's graduates between 2006 and 2010, I provide some of the first empirical evidence on talented college graduates' self-selection into different career paths. I find that finance and graduate school are the main competitors for the students with the most observed academic talent and skills coming out of MIT. At the time of college entrance, students with higher raw academic talent are only slightly more likely to go to graduate school after graduation than go into finance. However, at the time of graduation, students who enter grad-

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<sup>3</sup>The existing literature has not reached a consensus on whether the recent rise in financial wages represents booming productivity or increasing opportunities in rent seeking. For example, Philippon and Reshef (2009) argue that the financial deregulation of the early 1980s has driven the increase in skill intensity and thus wages in finance. In contrast, Bolton et al. (2011) suggest that the growth of information technology has lowered the costs of exchanging financial information and has allowed financiers to extract more rents.

uate school have much higher grade point averages (GPAs), in both magnitude and statistical significance, than those who enter finance, especially among the engineering and science majors. This suggests that students with different career paths in mind specialize in developing different skills during college. Students who aspire to go to graduate school are likely to focus on developing academic skills and their efforts are reflected in their GPAs. In contrast, students who are interested in finance may spend time practicing skills that are not captured by GPAs (e.g., social skills such as networking and communications). As a result, the two populations do not appear to be substitutable in their skills when they graduate from MIT.

To understand the nature of the self-selection into finance, I analyze the impact of the recent financial crisis, which exogenously and dramatically decreased the proportion of financiers in the 2009 and 2010 cohorts. I show that when finance is no longer a viable option, the most likely alternative career for financiers with engineering and science degrees is graduate school. Under the assumption that entry-level base salaries in finance are sticky, I use the crisis as an instrument to estimate the return to having higher academic talent and skills. Although having greater academic talent is positively and significantly associated with a higher wage in finance, additional academic skills learned in engineering and science coursework are not rewarded. Marginal financiers, who did not enter finance because of the crisis, have significantly lower base salaries than average financiers. These results suggest that students who enter finance are positively sorted based on their skills as valued in finance, but it is unclear whether finance and science and engineering graduate programs value the same set of the skills. Furthermore, limiting the number of entry-level jobs in finance in the case of a financial crisis does not make the sector less attractive to graduates but, rather, makes it more

competitive.

Few studies analyze the sorting of college graduates into different initial careers or majors based on ability, despite the vast literature that has established the importance of self-selection in understanding various labor market outcomes such as labor force participation, educational attainment, and immigration (Heckman, 1979; Willis and Rosen, 1979; Borjas, 1987; Heckman and Honore, 1990; Arcidiacono, 2004; Mulligan and Rubinstein, 2008; Bayer et al., 2011; Maurel and D'Haultfoeuille, 2011; Boehm and Watzinger, 2011).<sup>4</sup> Arcidiacono (2004) finds large differences in ability sorting across majors that cannot be explained by earnings premiums, which he attributes to unobserved preferences. Turner and Bowen (1999) show that ability sorting based on SAT scores can only explain a small part of the growing gender gap in choices of majors. Compared to previous studies, I focus on a relatively homogeneous sample, MIT bachelor's graduates. This allows me to observe refined measures of academic talent and skills with approximately uniform scales. My results are likely informative for other top engineering and science undergraduate programs, but they may not be generalizable to the entire engineering and science population.

The rest of this chapter is organized as follows. Section 2.2 discusses my conceptual framework in the context of a modified Roy model. Section 2.3 describes the data and summary statistics. Sections 2.4 and 2.5 present the empirical strategy and results, respectively. Section 2.6 concludes the paper.

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<sup>4</sup>Previous studies on college graduates' choices of majors and careers have mostly focused on the impact of monetary incentives. They find that students' choices are sensitive to potential future payoffs (Berger, 1988; Keane and Wolpin, 1997; Ryoo and Rosen, 2004; Majumdar and Shimotsu, 2006; Boudarbat, 2008).

## 2.2 Conceptual Framework

Based on the intuition developed in Roy (1951), individuals self-select into the sector with the highest potential payoff. While financiers are likely to possess the skills valued in finance, they may not necessarily have the potential or ability to become successful engineers or scientists. In a static framework without skill development, this would be the case where financiers do not have the innate talent for science and engineering. However, in a dynamic framework it is also possible that financiers choose not to develop engineering and science skills even if they have the potential to do so. This section first formalizes this intuition in a two-period Roy-style model for skill development and career choice. It then discusses its implications and extensions for empirical analysis.

### 2.2.1 A Modified Roy Model

#### Model Set-up

I consider a two-period Roy-style model with two sectors and two skills in which individuals choose which skill to develop based on the sector they would like to enter in the future. I denote the two sectors "SE" for Science and Engineering and "F" for Finance. Each sector values a different skill, denoted  $h_{SE}$  or  $h_F$ . In the first period, individual  $i$  chooses to allocate time between developing skills subject to

$$1 = \frac{1}{\alpha_i} h_{SE}^i + \frac{1}{\beta_i} h_F^i,$$

where  $\frac{1}{\alpha_i}$  and  $\frac{1}{\beta_i}$  are the individual costs of developing  $h_{SE}$  and  $h_F$ , respectively.

In the second period, individual  $i$  chooses which sector to enter based on the

payoffs to his or her skills:

$$W_{SE}^i = k_{SE}h_{SE}^i; W_F = k_F h_F^i + x^i,$$

where  $W_{SE}$  and  $W_F$  are wages inclusive of non-pecuniary preferences,  $k_{SE}$  and  $k_F$  are the returns to skills, and  $x^i$  is a preference parameter that captures the taste differential between the two sectors without loss of generality. Let  $k = \frac{k_F}{k_{SE}}$ .

**Proposition 2.2.1.** *Individual  $i$  develops  $h_{SE}^i = \alpha_i$  and enters sector SE if and only if  $\alpha_i \geq k\beta_i + \frac{x^i}{k_{SE}}$ . Otherwise, individual  $i$  develops  $h_F^i = \beta_i$  and enters sector F.*

*Proof.* The maximal payoff to individual  $i$  for entering sector SE is  $k_{SE}\alpha_i$  and the maximal payoff for entering F is  $k_F\beta_i + x^i$ . Since there is no uncertainty, individual  $i$  simultaneously chooses which skill to develop and which sector to enter based on the higher payoff. □

Since each sector only values one skill in the model, an individual would not develop both skills. Thus, individuals with high potential payoffs ( $\alpha_i$ ) in SE do not necessarily end up with a high  $h_{SE}$ . If their payoff for going into Finance is higher, they would choose to develop  $h_F$  instead. Conceptually,  $\alpha$  and  $\beta$  represent the potential talent in each sector, while  $h_{SE}$  and  $h_F$  are the observed skills.

### Self-Selection of Talent

It follows directly from Proposition 2.2.1 that the average observed  $h_{SE}$  of individuals going into F is lower than that of those going into SE. However, this does not imply that the financiers would not have been productive workers in sector SE in the absence of sector F, as they would have followed a different path of skill development. To study sorting into finance, I compare individuals based

on their raw talents instead of observed skills. I make the following normality assumption to derive an explicit expression:

$$\begin{pmatrix} \alpha \\ \beta \end{pmatrix} \sim N \begin{pmatrix} \mu_\alpha & \sigma_\alpha^2 & \rho\sigma_\alpha\sigma_\beta \\ \mu_\beta & \rho\sigma_\alpha\sigma_\beta & \sigma_\beta^2 \end{pmatrix}.$$

I also assume that  $x^i = x$  is constant across individuals so that the focus is on sorting based on ability. Let  $x_k = \frac{x}{k_{SE}}$ .

**Proposition 2.2.2.**  $E[\alpha|SE] > E[\alpha|F]$  if and only if  $\rho < \frac{\sigma_\alpha}{k\sigma_\beta}$ .

*Proof.* We have

$$E[\alpha|SE] = E[\alpha_i | \alpha_i - k\beta_i \geq x_k] = \mu_\alpha + \rho_{\alpha 0} \sigma_\alpha \lambda\left(\frac{\mu_0 - x_k}{\sigma_0}\right)$$

and

$$E[\alpha|F] = E[\alpha_i | \alpha_i - k\beta_i < x_k] = \mu_\alpha - \rho_{\alpha 0} \sigma_\alpha \lambda\left(-\frac{\mu_0 - x_k}{\sigma_0}\right),$$

where  $\alpha_i - k\beta_i \sim N(\mu_0, \sigma_0^2)$  and  $\rho_{\alpha 0} = \text{corr}(\alpha_i, \alpha_i - k\beta_i)$ .

Thus,  $E[\alpha|SE] > E[\alpha|F]$  if and only if  $\rho_{\alpha 0} > 0$  and

$$\rho_{\alpha 0} > 0 \Leftrightarrow \text{cov}(\alpha_i, \alpha_i - k\beta_i) = \sigma_\alpha^2 - k\rho\sigma_\alpha\sigma_\beta > 0 \Leftrightarrow \rho < \frac{\sigma_\alpha}{k\sigma_\beta}.$$

□

**Proposition 2.2.3.**  $E[\beta|F] > E[\beta|SE]$  if and only if  $\rho < \frac{k\sigma_\beta}{\sigma_\alpha}$ .

*Proof.* We have

$$E[\beta|SE] = E[\beta_i | \alpha_i - k\beta_i \geq x_k] = \mu_\beta + \rho_{\beta 0} \sigma_\beta \lambda\left(\frac{\mu_0 - x_k}{\sigma_0}\right)$$

and

$$E[\beta|F] = E[\beta_i | \alpha_i - k\beta_i < x_k] = \mu_\beta - \rho_{\beta 0} \sigma_\beta \lambda\left(-\frac{\mu_0 - x_k}{\sigma_0}\right),$$

where  $\rho_{\beta 0} = \text{corr}(\beta_i, \alpha_i - k\beta_i)$ .

Thus,  $E[\beta|F] > E[\beta|SE]$  if and only if  $\rho_{\beta 0} < 0$  and

$$\rho_{\beta 0} < 0 \Leftrightarrow \text{cov}(\beta_i, \alpha_i - k\beta_i) = \rho \sigma_\alpha \sigma_\beta - k \sigma_\beta^2 < 0 \Leftrightarrow \rho < \frac{k \sigma_\beta}{\sigma_\alpha}.$$

□

Proposition 2.2.2 shows that whether individuals who enter sector SE have above average talent in SE depends on the correlation between the two types of talent. When this correlation is sufficiently low, finance does not attract the top talent away from engineering and science. I call this “positive sorting in SE.” Similarly, Proposition 2.2.3 shows that positive sorting in sector F, where the average individuals entering F have greater talent in F than the average individuals entering SE, also occurs when the correlation between the two talents is sufficiently low. Thus, we have three scenarios:

1. Positive sortings in both sectors, where the better financial talent enters sector F and the better SE talent enters sector SE:  $\rho < \min\left(\frac{\sigma_\alpha}{k\sigma_\beta}, \frac{k\sigma_\beta}{\sigma_\alpha}\right)$ .
2. Positive sorting in SE but not in F, where the better of both talents enter sector SE:  $\rho > \frac{k\sigma_\beta}{\sigma_\alpha}$  and  $\sigma_\alpha > k\sigma_\beta$ .
3. Positive sorting in F but not in SE, where the better of both talents enter sector F:  $\rho > \frac{\sigma_\alpha}{k\sigma_\beta}$  and  $\sigma_\alpha < k\sigma_\beta$ .

Note that it is impossible to have negative sortings in both sectors since that requires  $\rho > \max\left(\frac{\sigma_\alpha}{k\sigma_\beta}, \frac{k\sigma_\beta}{\sigma_\alpha}\right) \geq 1$ . Scenarios 2 and 3 suggest that when the correlation between the two types of talent is high, positive sorting occurs in the sector with

the higher return to skill (measured by  $\sigma_\alpha$  and  $k\sigma_\beta$ ). Following the same derivation, one can show that if  $x^i$  varies across individuals, then sorting would depend on the correlation between talent in SE and a combination of talent in F and taste. For instance, if  $\alpha^i$  and  $-x^i$  are proportional, that is, individuals with high  $\alpha^i$  also have a strong preference for sector SE, then even when the correlation between the two types of talent is high, the best talent in SE may still go into SE instead of F.

### 2.2.2 Interpreting the Model in the Empirical Context

Empirically, the first period of the model corresponds to the four years during college when students take courses, participate in different activities, and develop a set of hard analytical skills as well as soft social skills. The second period corresponds to the years after graduation when students enter graduate school or different sectors in the labor market. In the previous section my model makes several simplifying assumptions. First, individuals may not always stay in the same sector. In contrast, Chapter 1 considers a model where some individuals have incentive to switch sectors. Here, however, one can think of the wages in the model as the life-time utility, inclusive of non-pecuniary returns, of career paths with different starting points. Thus, this assumption is without loss of generality for the purposes of this chapter. Second, there is no uncertainty in the model, but individuals may learn more about their talents and preferences over time. Third, the skills valued in different sectors are not one dimensional and are likely to include an array of hard and soft skills. Financiers are unlikely to have zero skills relevant to working in the science and engineering sectors as predicted in the model. Finally, one could generalize the model to multiple sectors. However, none of these limitations affects the key intuitions derived from the model as long as the financial sector values a different set of skills from the science and engineering sectors

and individuals do not randomly develop their skills. In particular, it remains true that individuals with different career paths in mind would develop different sets of skills during college and that those entering the science and engineering sectors are more suited to do so than financiers *at the time of graduation*, though not necessarily in terms of their potential talent.

The rise of finance manifests in the model in two ways. First, as the earnings of financiers grow, the return to skill in finance increases, which is equivalent to an increase in  $k$ . Thus, holding tastes constant, more students would choose to develop finance-related skills and would enter finance as a result of the increased expected payoff in that sector. This is the “size effect,” which is even larger if there is also a growing taste for finance, for example, as finance is increasingly perceived as more prestigious. Moreover, as Propositions 2.2.2 and 2.2.3 show,  $k$  also affects sorting in both sectors. An increase in  $k$  would decrease the degree of positive sorting into the SE sector, change the sorting from positive or negative, or increase the degree of negative sorting.<sup>5</sup> Increasing  $k$  would also affect the degree of sorting in the F sector in the opposite way. These are the “sorting effects.” Second, Philippon and Reshef (2009) argue that there is increasing demand in finance for quantitative and analytical skills that are traditionally valued in the engineering and science sectors. This is equivalent to an increase in  $\rho$  and decreases the likelihood of positive sortings in both sectors.

### 2.2.3 Using the Financial Crisis to Identify Sorting

One can think of  $\alpha$  and  $\beta + x_k$  as the potential payoffs in SE and F, respectively, inclusive of preferences. Thus, the correlation between the two payoffs, which determines the sorting of talent into finance, depends on two factors: how skills

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<sup>5</sup>Mulligan and Rubinstein (2008) make a similar observation in the context of women’s labor force participation.

are valued in each sector and how individual preferences correlate with skills. Both of these are ultimately empirical questions.

My data provide measures of raw academic talent, academic skills developed in college, and wages in finance. In the following empirical sections, I first show how financiers differ from others in their observed talent and skills. I then use fluctuations in the stock market, which are driven in my sample primarily by the recent financial crisis, to identify how academic talent and skills are valued by the financial sector in terms of base salaries. I make two identifying assumptions. First, the financial crisis is a negative and exogenous shock to the number of entry-level positions available in the financial sector. Second, the base salaries of entry-level positions in finance are sticky, so the crisis only affects observed salaries by changing the composition of financiers. Given these assumptions, I can estimate the wage equation in the financial sector using a Heckman selection model in which stock returns are an instrument. Furthermore, I follow the methodology in Gruber et al. (1999) and Chandra and Staiger (2007) and compare the characteristics of marginal financiers, whose entry into finance is sensitive to market conditions, to those of average financiers.

Since my measures of talent and initial wages are only available for recent cohorts, I cannot study the change in the nature of sorting into finance over the last several decades. However, the model suggests that my results should provide a lower (upper) bound for the degree of positive (negative) sorting in the science and engineering sectors for the earlier cohorts. In addition, I observe the choices of majors for the earlier cohorts. Consistent with the model, I show in the Appendix that a size effect exists, that is, an increasing tendency to major in finance-related fields (i.e., economics and management), controlling for demographics.

## 2.3 Data

### 2.3.1 Sample

In collaboration with the Institutional Research section of MIT's Office of the Provost, I collected data on gender, ethnicity, and high school state, as well as educational information such as major(s) and cumulative GPA, for all graduates who received a bachelor's degree from MIT between 1980 and 2010.<sup>6</sup> Based on their majors, I group graduates into three fields of study: economics and management, engineering and science, and others.<sup>7</sup>

My analysis focuses on the classes of 2006–2010, whose initial career choices and salaries are given in the Graduating Student Surveys (GSS) from the MIT Careers Office.<sup>8</sup> I determine the initial sector of employment based on post-graduation plans and employers. I classify the graduates into five sectors: 1) finance, 2) consulting, 3) technology and industrial,<sup>9</sup> 4) graduate school, and 5) other (e.g., law, real estate, and travel).<sup>10</sup> Only a sub-sample of the bachelor's graduates have valid employer or graduate school information that I can use to determine their sector, and the total response rate is approximately 64%.<sup>11</sup> For this sample, I also observe the amount of financial aid received in one's senior year, adjusted for inflation and used as a control for family income.

I rely on two sets of measures for ability and skills. First, the admission nu-

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<sup>6</sup>My data come from various offices at MIT, and Table A2.1 provides an overview of the variables and their sources.

<sup>7</sup>For students with two majors, around 10% of the sample, I assign the major first declared as the primary major. See the Appendix for the lists of majors assigned to each field.

<sup>8</sup>The GSSs started in 1999 but had no individual identifiers before 2006.

<sup>9</sup>The technology and industrial category includes research assistant positions in universities and institutes.

<sup>10</sup>See the Appendix for more details.

<sup>11</sup>MIT grants degrees in June, September, and February. The survey is only for June graduates, which comprises the vast majority of the students. The response rate is calculated based on all graduates.

meric index provides a proxy for a student's raw academic ability before entering MIT.<sup>12</sup> Based on college applications, the index score is a weighted average of objective measures such as standardized test scores, high school grades, and the difficulty of high school courses. It does not measure subjective qualities or soft skills. I normalize the admission index within each cohort so the reported statistics are measured in standard deviations from the cohort means. Second, the field of study at MIT and the cumulative GPA measure the field-specific skills developed at MIT. As for the admission index, I normalize the GPA by cohort and major so that its unit is the number of standard deviations from the mean in one's major and cohort. I use these two sets of variables together to measure the general and specific *academic* human capital accumulated by graduation. In Chapter 1, I find that normalized GPAs positively and significantly predict the long-run production of patents for the engineering and science students from the 1980–2005 cohorts. Thus, I consider my measures to be a reasonable proxy for the potential productivity in the engineering and science sectors. However, they do not necessarily provide a comprehensive picture of all the skills that determine future career success in finance. For instance, soft skills such as networking and communication abilities are likely to matter for salaries but have no direct measures. To understand sorting, however, it is still important to know the return to academic skills in finance.

### 2.3.2 Descriptive Statistics

Table 2.1 reports the mean characteristics for the 2006–2010 cohorts by their initial career choices. Among all graduates who received a bachelor's degree from MIT between 2006 and 2010, around 44% were female and the average age at grad-

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<sup>12</sup>Both are available for around 95% of the sample. The admission index does not apply to transfer students.

uation was 22.56. The vast majority of students, around 86% of the sample, chose an engineering or science major, whereas around 9.4% majored in economics or management. Nearly 70% of the students received financial aid in their senior year and around 34% received more than \$20,000 that year. Approximately 37% of the students were Caucasian Americans, 28% were Asian Americans, 27% were other minorities, including Hispanic, African, and Native American, and 9% were international students. Nearly 33% of the graduates between 2006 and 2010 went to a high school in the northeast region and nearly 12% went to a high school outside the United States.

The term “N/A” indicates that initial placement data are missing for students who did not respond to the GSS or did not answer the relevant questions. Those students, overall, had a similar demographic composition as the rest except they were less likely to be female. They also had lower than average admission index scores and GPAs. Among the students with valid placement records, around 44.4% were going to graduate school immediately after graduating from MIT.<sup>13</sup> Conditional on not entering graduate school, 16.4% of the graduates were going to work for a financial firm, 33% were starting in the technology and industrial sector, and 9.5% were going to consulting firms. Although the number of graduates going into the “Other” sector is larger than any of the aforementioned three sectors, it is because this sector includes a wide range of post-graduate plans, from working for firms that do not belong to the previous three sectors to taking non-working positions such as a traveling fellowship.

Financiers are less likely to be female and more likely to be Asian American. Since the overwhelming majority of graduates from MIT are engineering and sci-

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<sup>13</sup>In 2010, almost 90% of those going to graduate school in 2010 were entering a master’s or PhD program in science and engineering. Data on the type of graduate program are not available for earlier cohorts.

ence majors, it is not surprising that over 60% of financiers come from engineering and science majors. Financiers also have the highest average base salary among graduates entering the labor market. The average base salaries in the consulting and technology and industrial sectors are similar, both around 14% lower than in finance. This is likely to underestimate the earnings gap between finance and other sectors since finance also has tremendous potential for bonus earnings and future wage growth (Oyer, 2008), which is unobserved here. Compared to their working peers, financiers also, on average, have higher signing bonuses, including add-on benefits such as reimbursements for relocation costs. Signing bonuses, however, are a one-time transfer, so I do not include them as part of annual income.

Ranked by the average normalized admission index score, the order of sectors is finance, graduate school, consulting, technology and industrial, and other. The average normalized admission index scores of the first two sectors are positive, meaning that students going into those sectors are likely to have admission index scores above the mean of their cohorts. However, the ranking is different if I use normalized GPAs. Students going to graduate school have, on average, much higher GPAs than the rest. The average normalized GPA of financiers is still positive, but it is also lower than the average in consulting. Figure 2.1 presents a graphical illustration of these relations by separately plotting the distributions of admission index scores and GPAs in different sectors for the economics and management majors and the engineering and science majors. The contrast between GPAs and admission index scores is particularly sharp among the engineering and science majors. For economics and management majors, the distributions of admission index scores and GPAs are similar across different sectors.

Figure 2.2 shows the clear impact of the 2008 financial crisis on the initial placements of the MIT bachelor's graduates. According to the plot on the left,

the proportion of graduates entering finance took a large dip in 2009 and did not recover in 2010, similar to the two-year stock market return.<sup>14</sup> The plot on the right shows that other sectors, including consulting, as well as technology and industrial experience similar trends as finance, whereas the pattern of graduate school enrollment is the opposite. Figure 2.3 plots the distributions before and after the financial crisis of admission indices, GPAs, and real annual salaries for financiers from different fields of study. The average admission index score, GPA, and real salary are all higher in the post-crisis cohorts.

## 2.4 Financiers' Raw Academic Talent and Skill Development at MIT

This section shows how financiers differ from others in their raw academic talent and skills developed at MIT. Raw talent is measured before students enter MIT. Meanwhile, students develop more specialized skills at MIT based on their chosen career paths.<sup>15</sup> Thus, I compare raw talent and skill development in different equations.

### 2.4.1 Selection into Finance Based on Raw Talent

I run the following logit regressions at the individual level:

$$Pr(Sector_i = l) = G(\beta X_i + \delta \Pi_i + \theta(\Sigma^J)_j + \epsilon_i), \quad (2.1)$$

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<sup>14</sup>The two-year stock return is calculated as the Center for Research in Security Prices (CRSP) market return during an individual's sophomore and junior years.

<sup>15</sup>I assume that individuals' career interests do not affect their academic performance in high school since college admission is the main incentive for performing well.

where  $i$  denotes the graduate;  $k$  denotes the field;  $j$  denotes the cohort;  $X$ , the raw academic talent, is measured by the normalized admission index score;  $\Pi$  is the set of demographics; and  $\Sigma^J$  are cohort dummies.

Equation (2.1) compares how individuals who end up in different career paths differ in these observed characteristics, including raw academic talent, which are mostly determined upon entrance to MIT.<sup>16</sup> Table 2.2 reports the estimated marginal effects. Without controlling for demographics or cohort dummies, a one standard deviation increase in the admission index score is associated with a 1.9% increase in the likelihood of becoming a financier. However, the effect disappears once controls are included. On the other hand, the relation between the admission index score and the tendency to go to graduate school is robust to the inclusion of controls. Conditional on observed demographics, a student whose admission index score is one standard deviation higher has a 7.6% higher likelihood of entering graduate school, a 0.9% lower likelihood of going into consulting, and a 2.5% lower likelihood of working for a technology or industrial firm. All of these coefficient estimates are statistically significant at the 1% level. These results suggest that graduate school is the most attractive destination for students with high raw academic talent, but finance is also a strong contender. Consistent with the summary statistics, female students are significantly less likely to work in finance, consulting, or technology and industrial sectors and significantly more likely to go to graduate school. Compared to the Caucasian American students, Asian Americans are significantly more likely to work in finance. Receiving financial aid does not correlate with the tendency to go into finance.

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<sup>16</sup>Although I observe only the amount of financial aid received in students' senior year, conversations with Student Financial Services indicate that it is a good proxy of student aid received throughout college.

## 2.4.2 Skill Development at MIT

To receive a bachelor's degree from MIT, a student must satisfy the requirements for the core curriculum (the General Institute Requirements) as well as for the departmental program(s) of his or her choice.<sup>17</sup> The core curriculum requires students to take courses in a wide range of subjects, from science to humanities. In the first and second years, students usually take general courses in the core curriculum and introductory courses in the majors of their choice. By the end of the second year, all students are required to declare at least one major. They then focus on field-specific courses in their junior and senior years.

Being an economics or management major is not a prerequisite to getting a job in finance. As seen in Table 2.1, over half of the financiers are engineering and science majors. However, it is reasonable to think that students may allocate their time differently based on their career interests and the costs of developing different skills. For instance, someone set on entering a top doctoral program may work hard to achieve the best grades, whereas students interested in finance may spend more time attending networking events, developing soft skills such as communications, or even practicing trading stocks and derivatives. To see the differences in students' skill development, I run the following regressions:

$$Skill_i = \alpha D_i^{Sec} + \beta X_i + \delta \Pi_i + \theta(\Sigma^J)_j + \epsilon_i, \quad (2.2)$$

where  $D^{Sec}$  is a set of dummies indicating student  $i$ 's initial sector and  $X$ ,  $\Pi$ , and  $\Sigma^J$  are the same as in Equation (2.1).

Equation (2.2) is a descriptive regression showing how students with different career interests differ in their skill development at MIT. However, it should

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<sup>17</sup>See the 2011–2012 MIT Course Catalog for more information.

not be interpreted as causal, since students' skill development could also influence their career interests. Table 2.3 reports the results for two measures of skill: whether one majors in engineering or science and a normalized GPA. Compared to financiers, students who end up going to graduate school are significantly more likely to major in engineering and science at MIT. Among engineering and science majors, those going to graduate school also have significantly higher GPAs than financiers and the average difference is over half a standard deviation, even after controlling for raw academic talent and other observables. This is consistent with Figure 2.1, which shows that between financiers and those entering graduate school, the difference in average normalized GPAs is substantially larger than the difference in raw academic talent.

For economics and management majors, those going to graduate school have similar GPAs as those entering finance. Students entering other sectors are also more likely to major in engineering and science, but their GPAs are generally not significantly different from those of financiers. The normalized admission index positively and significantly predicts the likelihood of majoring in engineering and science. As expected, it is also positively and significantly associated with normalized GPA, although the relation is not one to one. A one standard deviation increase in the admission index score is associated with a 0.3 standard deviation increase in the cumulative GPA at MIT. Since the admission index score can be thought of as a measure of the potential for developing academic skills in the Roy model, the empirical results on talent would develop different skills, depending on their career interests.

In Chapter 1, I show that engineering and science majors have significantly higher patent production in the long term than their MIT classmates. Furthermore, normalized GPAs also positively and significantly predict patent production. Since

engineering and science majors with high GPAs are likely to enter graduate school, part of these relations could be driven by the causal impact of a science and engineering graduate program on patent productivity. Nevertheless, it is reasonable to assume that such talents and skills are also highly valued in the engineering and science sectors. Thus, the results here suggest positive sorting into graduate programs in science and engineering.

However, it is still unclear whether there is positive sorting in finance. Both possibilities could be consistent with the finding that financiers do not necessarily have the best academic potential. On one hand, it could be that the financial sector does not value GPAs as much as graduate schools do. In that case, it would make sense for potential financiers to develop other skills—such as networking and communications—during college, which are valued at a relative premium in finance. In other words, the skills valued in finance are sufficiently different from those valued in science and engineering sectors, so there is positive sorting in both sectors. On the other hand, it is possible that finance also highly values engineering and science skills, but those with high academic skills have a particular inclination to stay in engineering and science. In that case, there would be negative sorting into finance. Stern (2004), for instance, shows that scientists are willing to take a pay cut for the freedom to pursue their own research agenda and publish in research journals. There is also anecdotal evidence from MIT where top students in mathematics, physics, electrical engineering, and computer science turn down highly lucrative job offers from financial firms to pursue doctoral degrees in their fields.

## 2.5 The Financial Crisis as a Natural Experiment

This section uses the recent financial crisis to study the return to academic skills in finance as well as the nature of sorting.

### 2.5.1 Impact on Entry into Finance

To see how the financial crisis affects the probability of going into finance, I run the following logistic regression:

$$Pr(\text{Sector}_i = \text{Fin}) = G(\beta_l R_j + \gamma_l \Gamma_i + \epsilon_{ij}), \quad (2.3)$$

where  $Pr(\text{Sector}_i = \text{Fin})$  is one if graduate  $i$  from cohort  $j$  works in finance after graduation,  $R_j$  is the two-year stock return from December of year  $j - 3$  to December of year  $j - 1$  (i.e., the return during the student's sophomore and junior years),<sup>18</sup> and  $\Gamma_i$  is the set of controls, including demographics and a linear cohort trend. Since  $R_j$  varies by cohort, I can no longer control for cohort dummies. Controlling for a linear cohort trend is likely to underestimate the effect on entry into finance since identification comes mainly from the market crash in 2008. Thus, I view those estimates as conservative.

Table 2.4 presents the coefficient estimates separately for all students, economics and management students, and engineering and science students. Since the crisis could also affect the choice of major, I report the results with and without dummies for fields of study. For all students, a one standard deviation decrease in the stock return, which is around 24 percentage points,<sup>19</sup> decreases the probability

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<sup>18</sup>Since the recruiting season usually starts in the fall of the senior year, I use the stock market return during the two previous years so that it is fully determined by then. The results change little if I use the return between September  $j-3$  and September  $j-1$ .

<sup>19</sup>Between 2008 and 2009, the difference in the two-year stock returns is around 60 percentage points, or around 2.5 standard deviations.

of entering finance by around 2.5 percentage points, without controlling for a linear cohort trend or fields of study. Controlling only for a linear cohort trend, the same change in the stock return decreases the probability of entering finance by around 2 percentage points, which is a 21.5% drop relative to the base probability of 9.13%. Since the financial crisis is a particularly strong shock to the industry, it is reasonable that the magnitudes of my findings are higher than what Oyer (2008) finds, namely, that a one standard deviation increase in the stock return increases the likelihood of entering investment banking by around 14% for Stanford MBA graduates. Controlling for fields of study decreases the estimated impact of the stock return, suggesting that the crisis is likely to have a small but noticeable impact on the choices of majors. For economics and management majors, a one standard deviation drop in the stock return increases the likelihood of going into finance by 5.3 percentage points, or around 14% of their base probability. In contrast, for engineering and science majors, the same shock decreases the likelihood of financial employment by roughly 20%.

The following multinomial logit model estimates how the stock market return affects relative selection into finance as opposed to other sectors:

$$\text{Log} \left( \frac{\text{Pr}(\text{Sector}_i = l)}{\text{Pr}(\text{Sector}_i = \text{Fin})} \right) = \beta_l R_j + \gamma_l \Gamma_i + \epsilon_{ij}, \quad (2.4)$$

where  $l$  denotes the non-financial sector,  $j$  is the cohort,  $R_j$  is the two-year stock return, and  $\Gamma_i$  is the set of controls, as in Equation (2.3). Thus,  $\beta_l$  captures how the relative sizes of the sectors change with job market conditions.

Table 2.5 presents the coefficient estimates. Overall, a one standard deviation increase in the stock market return around the mean increases the likelihood of going into finance by around 2.1% and decreases the likelihood of going to graduate school by 3.4%. Both the consulting and technology and industrial sectors also

boom when the stock return is high, although to a much less degree than finance. These results are driven mainly by the engineering and science majors. For economics and management majors, the two-year stock return does not significantly affect the relative margin of going to graduate school. Overall, I find that a financier's alternative sector is likely to be graduate school for an engineering and science major and other non-consulting firms for an economics and management major.

## 2.5.2 Base Salary in Finance

To show the value of academic talent and skills in finance, I estimate the following wage equation:

$$G(\text{Salary}_i) = \alpha X_i + \beta W_i + \delta \Pi_i + \theta(\Sigma^J)_j + \epsilon_i, \quad (2.5)$$

where the dependent variable is the real annual base salary in finance, or its logarithm;  $X$  is raw academic talent, measured by the normalized admission index;  $W$  is field-specific skill, measured by field of study and GPA;  $\Pi$  is the set of demographic variables; and  $\Sigma^J$  are the cohort dummies. Although employers do not directly observe the admission index score, they may indirectly observe raw academic talent through interviews. The coefficients of  $X$  and  $W$  also capture the return to other unobserved characteristics that are correlated with observed skills and talent and valued in finance (e.g., diligence).

Since selection into finance is non-random, ordinary least squares (OLS) estimates of Equation (2.5) may be biased, depending on the nature of sorting (Heckman, 1979). To correct for any selection bias, I rely on the assumption that entry-level base salaries and the nature of sorting in finance are not affected by short-term

fluctuations in the stock market. Although the crisis may affect financiers' year-end bonuses, the base salaries of entry-level positions are likely to be sticky. For instance, the median annual initial base salary in nominal terms among MIT graduates working for JP Morgan, Goldman Sachs, and Morgan Stanley was \$60,000 U.S. dollars before the crisis (2006–2008) and \$70,000 after. However, since the growth in nominal wages in finance may not exactly follow the Consumer Price Index, I need to include cohort dummies to control for measurement errors in real salaries. Thus, the stock market return by itself can no longer be an instrument since it is fully absorbed by the cohort dummies. Instead, I use the stock return interacted with the field of study and exploit the differential effects of stock market returns across different fields of study, as in Section 2.5.1.

Table 2.6 reports the estimates using both OLS and full information maximal likelihood (FIML) with Heckman correction. Using the linear salary and log salary gives qualitatively similar results with different statistical significance. A Wald test does not reject the null hypothesis that there is no bias from selection at the 10% level in the linear specification, but it rejects it in the log specification. There is supporting evidence that students with higher admission index scores end up with higher salaries in finance. A one standard deviation increase in the admission index score is associated with around \$5700 more, or a 4.6% increase, in the annual base salary. The effect is significant across all specifications except the FIML specification with log salaries. The coefficient estimates for being an engineering and science major and having a higher GPA in engineering and science are both positive, but the standard errors are also large. These results suggest that, conditional on raw academic talent, the marginal return as a financier to having extra engineering and science skills may not be high for MIT graduates. Since the core curriculum requires all MIT graduates to accumulate at least some skills in engi-

neering and science, this does not mean that finance does not value engineering and science skills at all. The marginal return may be very high for having some minimum of training in engineering and science, but such variations may not exist within the MIT population.

### 2.5.3 Comparing Marginal and Average Financiers

Since I do not observe all the skills valued in finance, it is difficult to study the nature of sorting into finance based on the wage equation above. Instead, I use the financial crisis to identify sorting. The significant impact of the financial crisis on entry into finance implies that some students did not become financiers *because* of the shock. I call those individuals whose career choices are sensitive to this shock “marginal financiers.” In contrast, “infra-marginal financiers” work in finance, regardless of graduating economic conditions. Following Gruber et al. (1999) and Chandra and Staiger (2007), I develop an empirical test to determine how marginal financiers differ from average financiers:

$$Y_i = \alpha + \delta \ln(S_j) + \epsilon, \quad (2.6)$$

where  $Y$  is an outcome variable of interest (e.g., admission index score),  $S_j$  is the share of financiers in cohort  $j$ , and the regression is run on the *sample of financiers only*.

Intuitively,  $\delta$  measures how much the average characteristic changes when there are more financiers. As the proportion of financiers increases, their average outcome changes based on how each additional financier differs from the average. A negative  $\delta$  implies that each additional financier decreases the mean outcome of

the entire group of financiers. Mathematically, the relation is

$$\delta = \frac{\partial Y/S}{\partial \ln(S)} = \frac{\partial Y}{\partial S} \frac{1}{S} + \frac{\partial \frac{1}{S}}{\partial \ln(\frac{1}{S})} Y = \frac{\partial Y}{\partial S} - \frac{Y}{S}.$$

This shows that  $\delta$  measures the difference between a marginal financier's outcome ( $\frac{\partial Y}{\partial S}$ ) and the average outcome ( $\frac{Y}{S}$ ). To isolate the effect of the financial crisis, I instrument  $\ln(S_j)$  with the two-year stock market return.

Given a measure of the "fit for finance," the difference between marginal and average financiers reveals the nature of sorting into finance. The assumption is that the nature of sorting does not change within the sample period. For instance, it cannot be the case that finance becomes disproportionately less attractive to individuals with higher skills. If there is positive selection into finance, marginal financiers should be less qualified to enter finance than the average financiers, while negative sorting into finance would imply the opposite.

Table 2.7 reports the results for two measures of fit: the observed log real salary and the predicted log salary. The predicted log salary is derived from the FIML estimates of Equation (2.5), calculated using only individual characteristics and excluding cohort effects. In addition, I compare the observed academic talents and skills of marginal and average financiers. The results suggest that marginal financiers earn almost 16% less, according to their observed base salary, than average financiers. Although their predicted log salary, normalized admission index, and GPA are also lower, the differences are not statistically significant. Since the predicted salary does not account for unobserved skills valued in finance, which financiers are likely to have developed in college, it is likely to underestimate the degree of positive sorting. At the same time, the observed log real salary may have measurement errors that are correlated with entry into finance, for instance, if nominal growth in financial salary is higher than for the Consumer Price Index.

However, controlling for a linear trend in the observed salary almost doubles the estimated effect. Conditional on a linear cohort trend, marginal financiers earn almost 30% less than average financiers.

It is also possible that the crisis changed the nature of sorting into finance. In particular, one may suspect that the sector has become less attractive if society perceives a career in finance to be riskier or more rent seeking. Thus, it is possible that the return to skill inclusive of taste has decreased, resulting in a decrease in the degree of positive sorting into finance. In this case, my finding is a lower bound of the positive sorting into finance. Overall, this section provides two findings that are consistent with each other and with the predictions in the conceptual framework. First, finance does not value extra science and engineering skills as much as science and engineering graduate programs. Second, positive sorting into finance likely exists.

## 2.6 Conclusions

This paper presents three key results on the self-selection of MIT bachelor's graduates in their initial career choices. First, finance is competing against science and engineering graduate programs for the very best talent from MIT. Second, there is positive sorting into graduate school, in that students pursuing a graduate degree are better in their observed academic talents and skills, which are highly valued in the academic sector. Third, there is also positive sorting into finance. Finance does not value academic skills as much as graduate school and, as a result, students interested in finance are likely to develop a different set of skills that are unobserved here. Although the recent financial crisis, as an exogenous shock, has pushed some engineering and science majors out of finance and into graduate school, financiers and students entering graduate school are not substitutable in

their skills, since they followed different paths of skill development at MIT. Therefore, in the case when it is socially optimal to encourage or discourage entry into finance, policies that affect the relative payoffs of different career paths at the time of graduation may be too late, since students have already specialized in their skill development.

By providing evidence of self-selection, this paper builds toward an understanding of the welfare implications of the growing financial sector in the United States. However, it is important to note the differences between MIT bachelor's graduates and the national science and engineering population. As the top-ranked engineering school ranked by the U.S. News, MIT is likely to attract students who are best suited for engineering and science in terms of both their talents and tastes. Thus, even though a marginal financier from MIT may not have been the most productive engineer or scientist from MIT, he or she may still have above-average talent compared to the broader population. Furthermore, most MIT graduates have at least some skills in engineering and science. While the marginal return to engineering and science skills for someone with no such skills may be high, there are no variations in my sample to identify the effect. An important direction for future research would be to generalize the methodology developed in this paper to study a more representative sample of engineering and science students.

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## 2.7 Tables and Figures

Table 2.1: By Initial Career: Mean Characteristics (2006–2010)

	All	Finance	Grad. Sch.	Consult.	Tech.	Other	N/A
N	4,936	286	1,391	166	576	712	1,805
Initial Annual Salary	–	72,967	–	64,083	63,770	51,536	–
Signing bonus	–	12,315	–	7,942	4,716	263.9	–
Measures of Skills							
Norm. Adm. Index	-0.005	0.190	0.153	-0.028	-0.129	-0.236	-0.027
Normalized GPA	-0.007	0.061	0.442	0.116	-0.217	-0.247	-0.213
Engr. & Science	0.859	0.619	0.946	0.735	0.938	0.810	0.835
Econ & Management	0.094	0.371	0.027	0.247	0.038	0.100	0.103
Other Majors	0.047	0.010	0.027	0.018	0.024	0.090	0.062
Demographics							
Proportion Female	0.442	0.367	0.498	0.440	0.462	0.525	0.371
Age at Graduation	22.56	22.34	22.25	22.28	22.47	22.43	22.93
Financial Aid > 0	0.698	0.703	0.733	0.663	0.733	0.770	0.634
Fin. Aid > 20,000/yr	0.357	0.350	0.341	0.319	0.385	0.406	0.303
Ethnicity/Citizenship							
Caucasian American	0.369	0.339	0.386	0.355	0.418	0.389	0.338
Asian American	0.278	0.402	0.298	0.361	0.255	0.236	0.259
International	0.086	0.080	0.091	0.072	0.059	0.056	0.104
Other Minorities	0.267	0.178	0.225	0.211	0.267	0.319	0.299
High School Region							
Northeast	0.327	0.353	0.334	0.307	0.335	0.332	0.316
Midwest	0.126	0.136	0.142	0.108	0.127	0.131	0.110
South	0.245	0.231	0.222	0.283	0.260	0.256	0.252
West	0.187	0.171	0.180	0.199	0.184	0.204	0.187
International	0.116	0.080	0.122	0.102	0.094	0.079	0.104

Notes: This table reports the means of individual characteristics by initial sector, including individuals with missing information (under the N/A column). *Initial Annual Salary*, *Signing Bonus*, and *Financial Aid* are in 2010 dollars. Normalized Admission Index and SAT scores are missing for around 5% of the sample.

Table 2.2: Cross-Sectional Estimates of Selection into Initial Sectors

Dep. Var.	Finance		Graduate School		Consulting	Tech.
	(1)	(2)	(3)	(4)	(5)	(6)
Norm. Adm. Index	0.019** (0.009)	0.007 (0.010)	0.072*** (0.011)	0.076*** (0.011)	-0.009*** (0.003)	-0.024*** (0.008)
Female		-0.047*** (0.006)		0.043*** (0.010)	-0.017** (0.007)	-0.013** (0.006)
Age at Graduation		-0.001 (0.007)		-0.046*** (0.008)	-0.002 (0.004)	0.020** (0.009)
Asian American		0.053*** (0.019)		-0.031 (0.019)	0.023 (0.020)	-0.023** (0.011)
International		0.013 (0.026)		0.044 (0.049)	0.009 (0.029)	-0.071** (0.029)
Other Minorities		-0.014 (0.015)		0.006 (0.009)	-0.010 (0.013)	-0.025** (0.012)
Aid $\in(0, 20000/\text{year}]$		-0.019 (0.013)		0.034* (0.020)	-0.015* (0.009)	-0.014 (0.024)
Aid > 20,000/year		-0.004 (0.010)		0.008 (0.017)	-0.023** (0.010)	-0.003 (0.014)
HS Region Dummies	No	Yes	No	Yes	Yes	Yes
Cohort Dummies	No	Yes	No	Yes	Yes	Yes
N	3,013	3,013	3,013	3,013	3,013	3,013

Notes: Person-level observations. The coefficients reported are marginal effects from logistic models. The dependent variable is a 0/1 indicator variable for (Columns (1) and (2)) working for a financial firm after graduation, (Columns (3) and (4)) entering a graduate program, (Column (5)) going into consulting, or (Column (6)) going into technology and industrial. Robust standard errors clustered at the cohort level are shown in parentheses. The superscripts \*, \*\*, and \*\*\* indicate  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$ , respectively. The sample includes the 2006–2010 cohorts with valid responses on the GSSs (64% of the total sample). *Normalized Admission Index*: see text for the definition. Caucasian American is the omitted group for race. *Aid $\in(0, 20000/\text{year}]$*  and *Aid > 20,000/year*: indicator variables for whether the amount of support received in the senior year in 2010 dollars is positive and below 20,000 or above 20,000, respectively. *HS Region Dummies* and *Cohort Dummies*: indicator variables for high school regions and cohorts, respectively.

Table 2.3: Skill Development and Career Choices

Dep. Var.	Engr. & Science	Normalized GPA		
	All	All	Engr. & Scien.	Econ. & Mgmt.
Sample	(1)	(2)	(3)	(4)
Graduate School	0.212*** (0.010)	0.388*** (0.075)	0.559*** (0.088)	0.051 (0.090)
Consulting	0.046*** (0.013)	0.121 (0.084)	0.213 (0.105)	0.149 (0.081)
Tech. & Industrial	0.124*** (0.001)	-0.134 (0.064)	0.020 (0.078)	-0.105 (0.144)
Other	0.080*** (0.009)	-0.132 (0.096)	-0.013 (0.117)	-0.204*** (0.040)
Normalized Adm. Index	0.030*** (0.004)	0.284*** (0.011)	0.297*** (0.013)	0.330*** (0.052)
Demographics	Yes	Yes	Yes	Yes
Cohort Dummies	Yes	Yes	Yes	Yes
N	3,013	3,013	2,627	271

Notes: Person-level observations. The coefficients reported are the marginal effects from the logistic models for Column (1) and for OLS for Columns (2)–(4). The dependent variable is a 0/1 indicator variable for (Column (1)) majoring in engineering and science or (Columns (2)–(4)) the normalized grade point average. Robust standard errors clustered at the cohort level are shown in parentheses. The superscripts \*, \*\*, and \*\*\* indicate  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$ , respectively. The sample includes the 2006–2010 cohorts with valid responses on the GSSs (64% of the total sample). *Normalized Admission Index*: see text for the definition. All the regressions control indicator variables for demographics and indicator variables for cohorts.

Table 2.4: The Impact of the Financial Crisis on Entry into Finance

Sample	All			Engr. & Scien.	Econ. & Mgmt.
	(1)	(2)	(3)	(4)	(5)
Stock Return	0.105*** (0.012)	0.084*** (0.010)	0.068*** (0.006)	0.064*** (0.014)	0.225*** (0.044)
Field-Specific Skills	No	No	Yes	No	No
Linear Cohort	No	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes
N	3,013	3,013	3,013	271	2,627

Notes: Person-level observations. The coefficients reported are marginal effects from logistic models. The dependent variable is a 0/1 indicator variable for going to work for a financial firm after graduation. Robust standard errors corrected and clustered at the cohort level are shown in parentheses. The superscripts \*, \*\*, and \*\*\* indicate  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$ , respectively. The samples include (Columns (1)–(3)) all majors in the 2006–2010 cohorts, (Column (4)) engineering and science majors, and (Column (5)) economics and management majors. Individuals with missing initial sector data are excluded (36% of the population). *Stock Return*: the CRSP market return during the sophomore and junior years. *Field-Specific Skills*: includes indicator variables for the field of study, the normalized GPA interacted with each indicator for fields. All the regressions include the following controls: age at graduation; indicator variables for gender, race, and high school region; indicator variables for whether the amount of support received in the senior year in 2010 dollars is positive and below 20,000 or above 20,000; and the normalized admission index.

Table 2.5: Relative Selection into Sectors

	Finance	Grad. School	Consulting	Tech. & Industrial	Other
Panel A: All Students (N = 3,013)					
Stock Return	–	-1.353***	-0.389***	-0.850***	-1.116***
	–	(0.088)	(0.150)	(0.238)	(0.105)
$\Delta Pr$	0.021	-0.034	0.008	0.009	-0.004
Panel B: Engr. & Science (N = 2,627)					
Stock Return	–	-1.483***	-0.756**	-0.891**	-1.337***
	–	(0.204)	(0.374)	(0.371)	(0.255)
$\Delta Pr$	0.016	-0.031	0.005	0.016	-0.006
Panel C: Econ. & Mgmt. (N = 271)					
Stock Return	–	0.148	0.075	-3.359***	-1.509**
	–	(0.396)	(0.428)	(1.017)	(0.678)
$\Delta Pr$	0.053	0.022	0.022	-0.042	-0.055

Notes: Person-level observations. All estimates are from multinomial logistic models. The dependent variable is the initial sector, with five categories listed in the column names. Finance is the base category. Robust standard errors clustered at the cohort level are shown in parentheses. The superscripts \*, \*\*, and \*\*\* indicate  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$ , respectively. The samples include all majors in the 2006–2010 cohorts (Panel A), the engineering and science majors (Panel B), and the economics and management majors (Panel C). Individuals with missing initial sector are excluded (36% of the population). *Stock Return*: the CRSP market return during the sophomore and junior years.  $\Delta Pr$ : the change in the probability of going into a sector calculated from a one standard deviation increase in *Stock Return* around the mean, that is, from 0.5 standard deviation below the mean to 0.5 standard deviation above. All the regressions include the following controls: age at graduation; indicator variables for gender, race, and high school region; indicator variables for whether the amount of support received in the senior year in 2010 dollars is positive and below 20,000 or above 20,000; the normalized admission index, and linear cohort.

Table 2.6: Return to Skills in Finance

Dep. Var.	Salary		Log(Salary)	
	(1) OLS	(2) FIML	(3) OLS	(4) FIML
Norm. Adm. Index	5760.234*	5640.419**	0.069**	0.046
	(2305.842)	(2361.202)	(0.023)	(0.033)
Engr. & Science	1468.525	2493.624	0.033	0.239
	(3938.788)	(5628.569)	(0.051)	(0.164)
Other Majors	1574.949	2713.810	0.055	0.282
	(4878.151)	(6569.189)	(0.065)	(0.206)
GPA * Econ. & Mgmt.	-3703.925	-3683.553*	-0.021	-0.020
	(2035.316)	(1963.239)	(0.028)	(0.026)
GPA * Engr. & Science	609.163	759.917	0.013	0.043
	(2841.072)	(2723.436)	(0.033)	(0.036)
GPA * Other Majors	37855.613	37980.951**	0.401	0.451**
	(17763.712)	(16903.153)	(0.202)	(0.190)
N	261	3,002	261	3,002

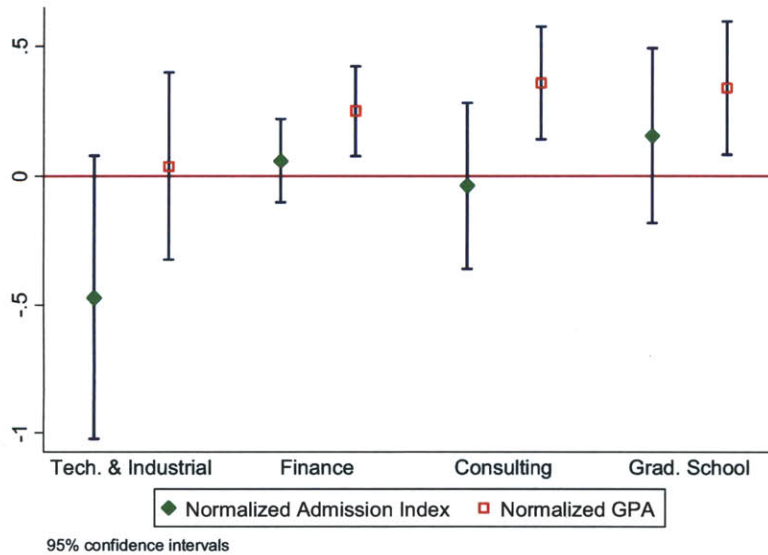
Notes: Person-level observations. The coefficients reported are from the OLS for Columns (1) and (3) and from the FIML for Columns (2) and (4). The dependent variable is the real annual base salary in 2010 dollars or its logarithm. Robust standard errors clustered at the cohort level are shown in parentheses. The superscripts \*, \*\*, and \*\*\* indicate  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$ , respectively. The samples include (Columns (1) and (3)) the 2006–2010 cohorts who are going to work for a financial firm and (Columns (2) and (4)) the 2006–2010 cohorts with valid responses on the GSSs. The instruments in Columns (2) and (4) include *Stock Return* interacted with being an engineering & science major or another major. *Normalized Admission Index*: see text for definition. Economics and management majors are the omitted group. Controls include age at graduation; indicator variables for gender, race, and high school region; indicator variables for whether the amount of support received in the senior year in 2010 dollars is positive and below 20,000 or above 20,000, and cohort dummies.

Table 2.7: Differences between Marginal and Average Financiers

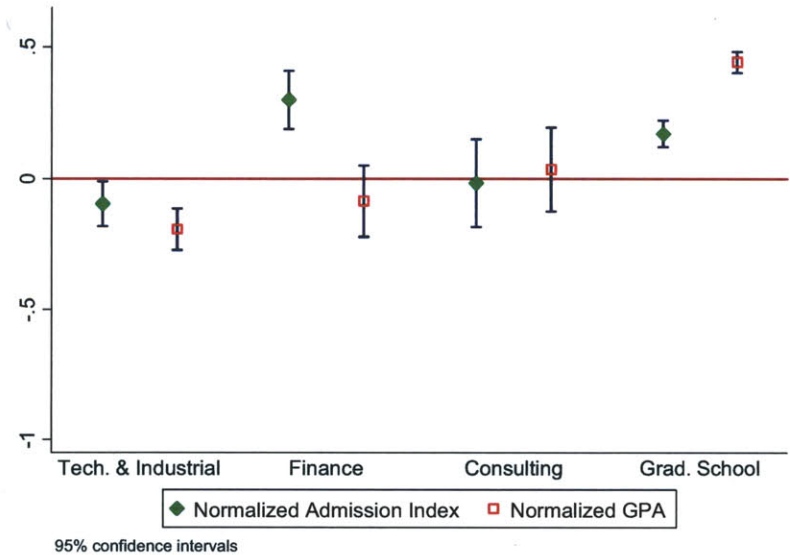
Dep. Var.	Log(Sal)	$\widehat{\text{Log}}(\widehat{\text{Sal}})$	Adm. Ind.	GPA	Log(Sal)
Panel A: OLS					
	(A1)	(A2)	(A3)	(A4)	(A5)
Log(Financiers Share)	-0.130* (0.059)	-0.041 (0.022)	-0.403 (0.353)	-0.203 (0.234)	-0.260** (0.076)
Linear Cohort	No	No	No	No	Yes
Panel B: IV					
	(B1)	(B2)	(B3)	(B4)	(B5)
Log (Financiers Share)	-0.157** (0.055)	-0.045 (0.026)	-0.423 (0.357)	-0.308 (0.218)	-0.292** (0.078)
Linear Cohort	No	No	No	No	Yes
N	275	272	272	286	275

Notes: Person-level observations. All estimates are from OLS in Panel A or instrumental variables (IV) models in Panel B. Robust standard errors corrected and clustered at the cohort level are shown in parentheses. The superscripts \*, \*\*, and \*\*\* indicate  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$ , respectively. The samples include all financiers from the 2006–2010 cohorts. The dependent variables are explained in the text. *Log (Financiers Share)*: the logarithm of the proportion of financiers in the cohort. The instrumental variable in the IV specifications is the CRSP market return during the sophomore and junior years.

Figure 2.1: Mean and 95% Confidence Intervals of Skills by Field and Initial Career:



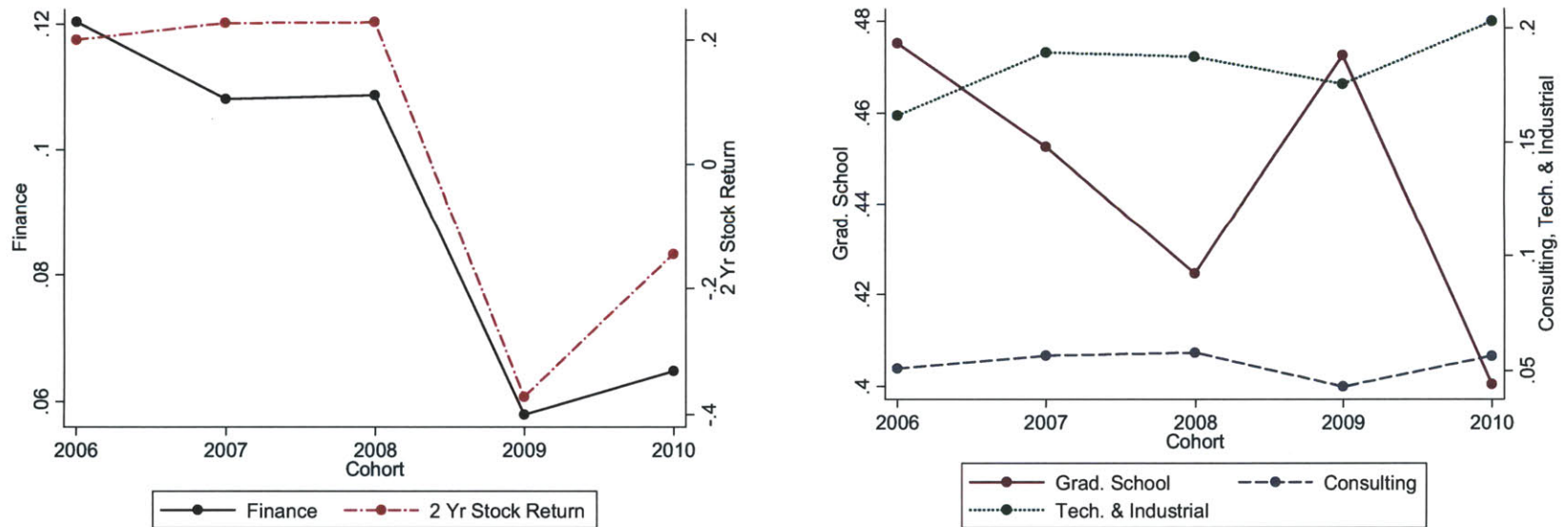
Economics & Management (N=206)



Engineering & Science (N=2,155)

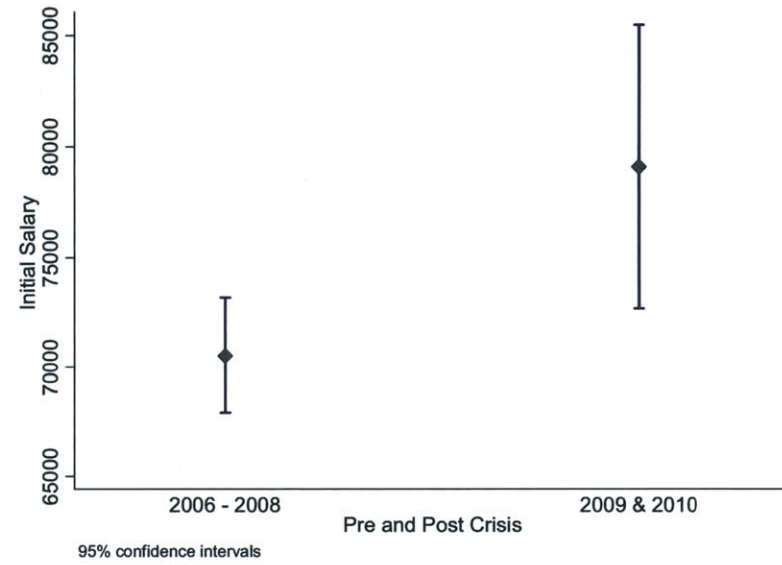
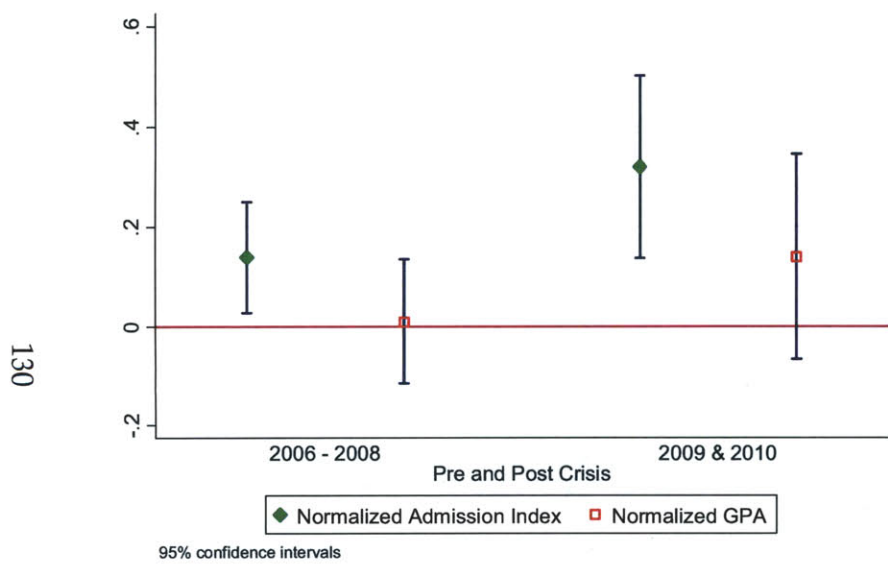
Notes: Person-level observations. This figure plots, by major, the mean and 95% confidence intervals of the normalized admission index and GPA for economics and management majors (on the left) and engineering and science majors (on the right). The sample includes the individuals in the 2006–2010 cohorts who are going to either the technology and industrial, finance, or consulting sectors or to graduate school.

Figure 2.2: Distribution of Sectors by Cohort



Notes: Person-level observations. This figure plots, by cohort, the proportion of students going into finance against the two-year stock return (on the left) and the proportions of students going to graduate school, consulting, or the technology and industrial sector (on the right). The sample includes the 2006–2010 cohorts with valid responses on the GSSs, around 64% of the total sample. *Stock Return:* the CRSP market return during the sophomore and junior years.

Figure 2.3: Pre- and Post-Crisis Financiers: Mean and 95% Confidence Intervals of Skills and Salaries



Admission Index and GPA

Real Salary

Notes: Personal-level observations. This figure plots the mean and 95% confidence intervals of the normalized admission index and GPA of students who entered finance before and after the 2008 financial crisis (on the left) and their initial annual salaries in 2010 dollars (on the right).

## 2.8 Appendix

### 2.8.1 Assigning Field

Based the 2011–2012 MIT Course Catalog, I denote majors under the School of Engineering as “engineering” majors and majors under the School of Science as “science” majors. More specifically, the engineering majors include Aeronautics and Astronautics (Course 16), Biological Engineering (Course 20), Chemical Engineering (Course 10), Civil and Environmental Engineering (Course 1), Electrical Engineering and Computer Science (Course 6), Materials Science and Engineering (Course 3), Mechanical Engineering (Course 2), Nuclear Science and Engineering (Course 22), and Ocean Engineering (Course 13).<sup>20</sup> The science majors include include Biology (Course 7), Brain and Cognitive Sciences (Course 9), Chemistry (Course 5), Earth, Atmospheric, and Planetary Sciences (Course 12), Mathematics (Course 18), and Physics (Course 8). Economics and management majors are from Courses 14 and 15, respectively. The rest of the majors include all unassigned majors, such as architecture, political science, and literature.

### 2.8.2 Assigning Sector

I assign the initial sectors using the GSSs. There are five sectors: 1) finance, 2) consulting, 3) technology and industrial, 4) graduate school, and 5) others. First, students self-report whether they are going to work or to graduate school. Then, based on their employers, I determine the working graduates in the first three sectors. The last sector includes students who are neither working nor going to graduate school (e.g., taking a traveling fellowship) as well as those working in other sectors, such as law and real estate.

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<sup>20</sup>Course 13 has been merged into Course 2.

Similar to Chapter 1, I first rely on common knowledge about the firms to assign employers to finance, consulting, and technology and industrial. For instance, financial firms include investment banks such as Goldman Sachs and JP Morgan, as well as hedge funds, such as D. E. Shaw and Renaissance Technologies. Consulting firms include Boston Consulting Group, McKinsey, and so forth. Google, Facebook, Raytheon, IBM, and Intel are some examples of firms in the technology and industrial sector. I also use keyword matching, where firms with certain keywords are assigned to a certain sector. Firms that are unassigned after these two steps are looked up on the Internet and assigned a sector based on their core business.

Samples of keywords used to identify each sector are as follows.

- Technology and industrial: tech machine syst dynamics scien research communication devic wire manufact telecom syst soft defense instrument engineer space material equipment aircraft energ motor electr industri robot network chemical comput auto mobile.
- Finance: fund capital trading asset securities venture wealth holding bank invest.
- Consulting: consult.

### **2.8.3 Decomposing the Trend in Majoring in Economics and Management**

As Figure A2.2 shows, the proportion of students majoring in economics and management has increased over the last three decades. Part of this increase may be due to the growing diversity among the undergraduate population at MIT. Compared to the summary statistics in Chapter 1, which studies earlier cohorts of MIT

bachelor’s graduates, the sample in this chapter has more female and non-white students. I perform a Oaxaca-style decomposition to determine the relative contributions of compositional changes in student demographics versus the increasing tendency to major in economics and management, conditional on demographics:

$$\overline{\Delta Pr(Field = EM)} = \delta^{pre} * \Delta \bar{\Pi} + \Delta \delta * \bar{\Pi}^{pre} + \Delta \delta * \Delta \bar{\Pi}, \quad (2.7)$$

where, conditional on a cutoff cohort  $J$ ,  $\overline{\Delta Pr(Field = EM)}$  is the change in the proportion of economics and management majors before and after  $J$ ,  $\delta^{pre}$  are the regression coefficients for demographics before and including  $J$ , and  $\bar{\Pi}^{pre}$  is the set of average demographic compositions before and including year  $J$ . The regressions are estimated using a logit model. Thus, the change in the proportion of economics and management majors can be broken down into three parts: the “endowment effect”, due to changes in student demographics; the “coefficient effect”, due to changes in the tendency to major in economics and management, conditional on demographics; and the interaction of the two.

Table A2.2 reports the results for using different years as the cutoff. For example, the first column shows that 8.7% of the graduates in the 1991–2010 cohorts major in economics and management, which is 3.8% more than the graduates in the 1980–1990 cohorts. Out of the 3.8% difference, 2.6% is due to the coefficient effect, whereas only 0.5% is due to the endowment effect. The results are similar using 1995, 2000, and 2005 as the cutoff years. Depending on the cutoff, changes in the tendency to major in economics and management conditional on demographics could explain between 58% and 75% of the overall increase in the proportion of economics and management majors. Changes in demographic composition, in contrast, could only account for between 13% and 33%. Thus, there has been a clear increase in the tendency to major in economics and management at MIT over

the past three decades, controlling for student demographics. This is consistent with the observation of Philippon and Reshef (2009) that the relative wage gap of an average financier over an average engineer has grown from less than 10% in the early 1980s to over 30% in the early 2000s.

## 2.8.4 Additional Tables and Figures

Table A2.1: Data Overview: Variables and Sources

Variables	Cohorts	Source
Demographics and Academic Records	1980–2010	MIT Registrar’s Office
Admission Index and SAT Scores	2004–2010	MIT Admissions Office
Amount of Support from MIT	1994–2010	MIT Student Financial Services
Initial Placement and Salary	2006–2010	MIT Career Services

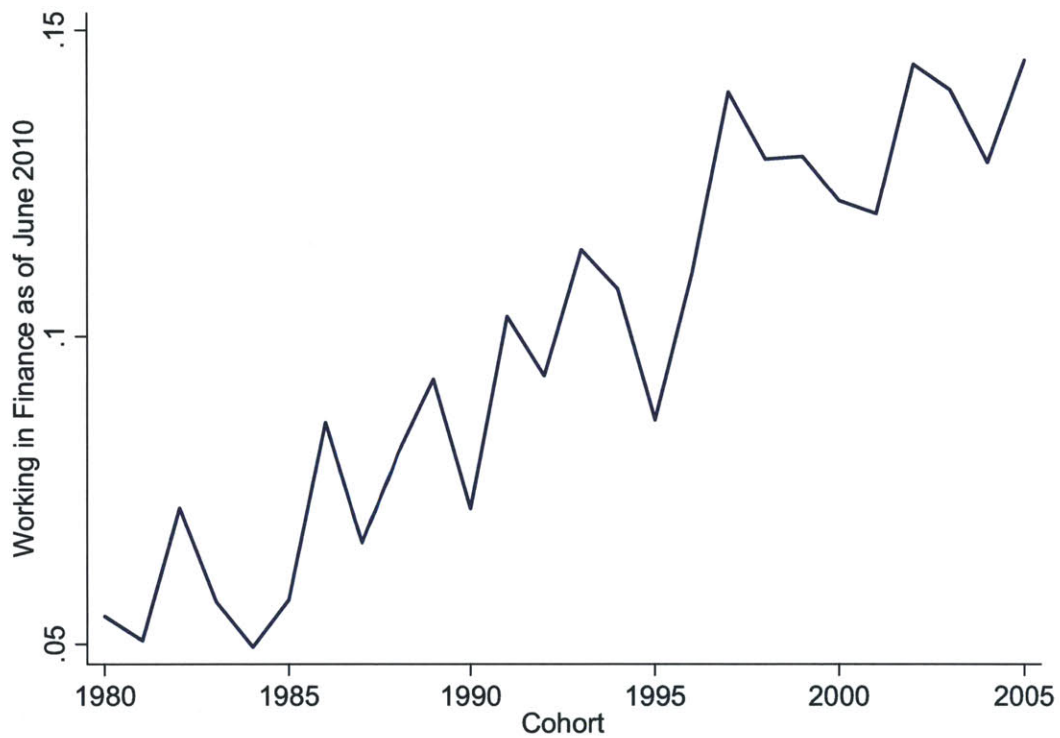
Notes: This provides an overview of the data. Demographics and academic records are available for everyone who received Admission index and SAT scores are available for around 95% of the sample between 2004 and 2010. The amount of support from MIT is calculated during the senior year and is available for the 1994–2010 cohorts. Initial placement and salary are self-reported on the GSSs, where the information is missing for 36% of the sample.

Table A2.2: Decomposition of Trends in Majoring in Economics and Management (1980–2010)

Year	1990	1995	2000	2005
<b>Means</b>				
Before	0.049*** (0.003)	0.055*** (0.003)	0.061*** (0.003)	0.070*** (0.004)
After	0.087*** (0.004)	0.094*** (0.004)	0.100*** (0.003)	0.094*** (0.003)
Difference	0.038*** (0.005)	0.039*** (0.005)	0.039*** (0.004)	0.024*** (0.005)
<b>Decomposition</b>				
△Endowments	0.005** (0.002)	0.007*** (0.002)	0.008*** (0.001)	0.008*** (0.001)
△Coefficients	0.026*** (0.005)	0.028*** (0.005)	0.029*** (0.005)	0.014** (0.006)
Interaction	0.007*** (0.003)	0.004* (0.002)	0.001 (0.002)	0.002 (0.003)

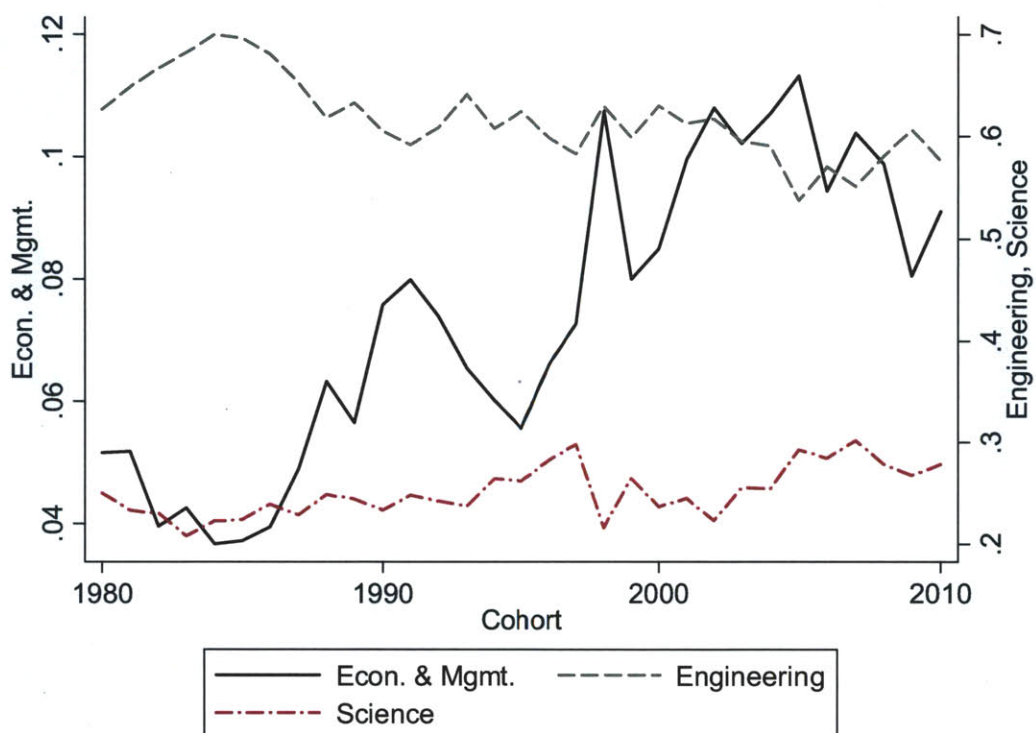
Notes: Person-level observations. Here N=32,059. This table reports the Oaxaca decomposition results from logistic models using different years as the cutoff. The superscripts \*, \*\*, and \*\*\* indicate  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$ , respectively. See the text for details.

Figure A2.1: Proportion of Financiers by Cohort (1980–2005)



Notes: Person-level observations. This figure plots, by cohort, the proportion of graduates working in finance in June 2011, based on self-reported employment information from Infinite Connection. The sample includes the 1980–2005 cohorts.

Figure A2.2: Proportions of Bachelor's Graduates by Field and by Cohort (1980–2010)



Notes: Person-level observations. This figure plots, by cohort, the proportions of students majoring in economics and management (left scale), engineering (right scale), and science (right scale). The sample includes the 1980–2010 cohorts.

# Chapter 3

## Asset Accumulation and Labor Force Participation of Disability Insurance Applicants<sup>1</sup>

### 3.1 Introduction

Designed to protect the working population from the risk of total disability, the Social Security Disability Insurance (SSDI) is one of the largest income transfer programs in the United States. In December 2010, the program paid 9.6 billion U.S. dollars in benefits to over 9.4 million people, including 8.2 million disabled workers (Social Security Social Security Administration, 2010). To qualify for SSDI, a worker must be younger than the full retirement age and have worked enough in recent years.<sup>2</sup> In addition, the worker must pass the screening for “total disability,” which the Social Security Administration defines as the inability to work due to

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<sup>1</sup>I thank David Autor for his detailed feedback on this project. I also appreciate helpful comments from Leila Agha, Peter Diamond, JB Doyle, Amy Finkelstein, Jon Gruber, Jon Skinner, and numerous seminar participants at Colgate University and the Massachusetts Institute of Technology. I acknowledge support from the Kauffman Foundation. All errors are my own.

<sup>2</sup>The exact length and timing requirements for employment vary by person.

medical conditions that are expected to result in death or to last for at least one year. Since the program intends to cover workers with long-term disabilities, few beneficiaries exit voluntarily by becoming employed again. The two main reasons for leaving SSDI are reaching the full retirement age<sup>3</sup> and death, which together account for 86% of the exits in 2004 (Autor and Duggan, 2006).

Because receiving disability benefits is almost an absorbing state, mistakenly accepting work-capable individuals into disability insurance could generate additional financial burdens to taxpayers, as well as productivity losses to society. The current SSDI application review process is likely imperfect since it is based on a mixture of objective and subjective criteria intended to evaluate an applicant's medical impairments and ability to work. Certain medical conditions, such as back pain and depression, are difficult to verify, making the award decision more susceptible to personal judgment. Maestas et al. (2011) show that disability examiners vary in their stringency and, as a result, applicants with similar characteristics may receive benefits under some examiners but get rejected by others.

Previous empirical studies show that an imperfectly screened disability insurance can discourage work in two ways. First, receiving disability benefits may cause work-capable recipients to stay away from the labor force (Chen and van der Klaauw, 2008; Maestas et al., 2011; von Wachter et al., 2011; Borghans et al., 2012). Second, the presence of an imperfectly screened disability insurance program may induce work-capable individuals to drop out of the labor force to apply for disability insurance, especially when they face adverse labor market conditions (Gruber and Kubik, 1997; Gruber, 2000; Autor and Duggan, 2003; Autor et al., 2012). This paper considers a dynamic type of work disincentive effect that has not been explored in the empirical literature. Under a disability insurance program with im-

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<sup>3</sup>The disability benefits become retirement benefits at the full retirement age.

perfect screening, individuals with a sufficiently high work disutility may *plan* to drop out of the labor force in the future and apply for disability insurance, regardless of their future health status. As a result, the current literature focusing on the contemporaneous impact of disability insurance on labor force participation may underestimate the magnitude of the total work disincentive effect, since disability insurance not only affects current labor supply but may also affect the labor supply in the future. I develop a modified two-period version of the model of Golosov and Tsyvinski (2006) showing that it is utility maximizing for certain individuals to plan for their future disability insurance application. Since they intend to retire sooner, on average, these individuals choose to accumulate more assets than those who would only apply for disability insurance if disabled.

I present empirical support for the model using the RAND Health and Retirement Study (HRS) panel data. Using quantile regressions, I show that, conditional on observed characteristics—including income, labor force participation, and health status—rejected applicants have more liquid assets than accepted applicants at the time of their disability insurance application. The effect is increasing in applicants' asset levels and statistically significant for the 50% to 80% quantiles. Furthermore, rejected and accepted applicants have similar levels of liquid assets in the several years before their application, suggesting that the divergence at the time of the disability insurance application is unlikely to have been driven by any unobserved differences in the applicants' inherent tendency to save. Consistent with the model, I also find evidence that the rejected applicants display significantly lower attachment to the labor force prior to their application, implying that they may have a lower desire to work than the accepted applicants. Although rejected and accepted applicants are similar in their self-reported levels of health at the time of application, accepted applicants are significantly less healthy than re-

jected applicants in the few years after application. Taken together, these results suggest that some rejected applicants have accumulated their assets in a way that is consistent with the planning story. However, the current screening system is sufficiently effective at detecting at least some of these work-capable applicants, even without relying on assets as a criterion.<sup>4</sup> Thus, it is unclear whether imposing an asset-based criterion on top of the current system, as suggested by Golosov and Tsyvinski (2006), would increase the efficacy of screening.

By comparing the rejected and accepted applicants, my methodology follows the literature that attempts to identify the causal impact of receiving disability benefits on future labor force participation. One of the earliest studies taking this approach is that of Bound (1989), who argues that since the rejected applicants are on average healthier, their post-application labor force participation should serve as an upper bound for the counterfactual labor force participation of the accepted applicants. Although the author finds a low labor force participation rate among the rejected applicants in his sample, his methodology is criticized for not carefully controlling for the differences between the rejected and accepted applicants. Follow-up studies improve upon Bound's work by either conditioning on observables (von Wachter et al., 2011) or exploring features of SSDI that generate different award decisions to otherwise similar applicants (Chen and van der Klaauw, 2008; Maestas et al., 2011).<sup>5</sup> In contrast to this literature, I explore the differences between the rejected and accepted applicants rather than assuming the two groups are similar or constructing a comparable sample. Giertz and Kubik (2011) use a similar approach, also with the HRS data, to compare the labor force participation of re-

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<sup>4</sup>At the same time, it is not effective enough to deter their applications.

<sup>5</sup>These studies provide evidence that receiving SSDI benefits has a negative impact on beneficiaries' tendency to return to work. For instance, Maestas et al. (2011) show that applicants who receive SSDI benefits due to being randomly assigned to more lenient disability examiners are significantly less likely to work than those whose applications were rejected by stricter examiners.

jected and accepted applicants. However, they do not study asset accumulation or test a model similar to mine.

The rest of this chapter is organized as follows. Section 3.2 explains the conceptual framework and its link to empirical analysis. Section 3.3 discusses the RAND HRS data and my sample construction. Section 3.4 presents the empirical strategies and results. Section 3.5 concludes the paper.

## 3.2 Conceptual Framework

Following the framework in Diamond and Mirrlees (1978) and Golosov and Tsyvinski (2006), I develop a two-period model to illustrate how agents simultaneously determine their asset accumulation and future labor force participation. The goal of the model is to show that under an imperfectly screened disability insurance program, it could be optimal for agents to plan for their exit out of the labor force in the future and apply for disability insurance regardless of whether they will be truly disabled.

### 3.2.1 Assumptions

The model has two periods. In the first period, all agents are able. In the second period, each agent faces a probability of being disabled, that is, unable to work. Thus, the only source of uncertainty in this model is the disability status in the second period. If working in either period, the agent will supply one unit of labor inelastically and receive wage  $w$ , which is assumed to be uniform across individuals. All agents start with zero assets in the first period. Let  $\beta$  be the discount rate and  $R$  be the interest rate. To simplify the math, without loss of generality, I assume that  $\beta R = 1$ .

I allow the agents to differ on two parameters:  $\theta_i$ , the probability of being totally disabled in the second period, and  $x_i$ , the disutility of work in each period. An agent derives utility  $u(c_i) - x_i$  in a period if working and  $u(c_i)$  if not, where  $c_i$  is consumption. Following the standard assumptions,  $u(\cdot)$  is increasing, concave, and  $u(0) = -\infty$ . By distinguishing the disutility of work from the probability of total disability, I conceptually separate being *unwilling* to work from being *unable* to work. Empirically, the former is an unobserved preference, whereas the latter can be partially observed based on health. However, from the perspective of designing optimal disability insurance, some argue that it is unnecessary to separate the two (Diamond and Sheshinski, 1995).

### 3.2.2 Utility Maximization without Disability Insurance

As a starting point, I assume there is no disability insurance. Let  $k_i$  be individual  $i$ 's asset accumulated by the end of the first period. Thus, if the agent becomes disabled in the second period or chooses not to work, she consumes  $Rk_i$ . If the agent works, she consumes  $Rk_i + w$ . The agent's utility maximization problem is as follows:

$$V = \max_{k_i} u(w - k_i) + \beta V_2(k_i), \text{ where}$$

$$V_2(k_i) = \max \{ \theta_i u(Rk_i) + (1 - \theta_i)(u(w + Rk_i) - x_i), u(Rk_i) \}$$

$$= \begin{cases} u(Rk_i) & \text{if } u(w + Rk_i) - u(Rk_i) < x_i; \\ \theta_i u(Rk_i) + (1 - \theta_i)(u(w + Rk_i) - x_i) & \text{otherwise.} \end{cases}$$

Since everyone works in the first period,  $x_i$  drops out of the problem in the first period. The choice parameter  $k_i$  affects the incentive compatibility constraint

in the second period. Thus, workers simultaneously decide in the first period how much to save and whether to work (if able) in the second period. Time consistency requires that a worker who decides not to work in the second period will not work in the second period, regardless of disability realization.

**Proposition 3.2.1.** *Given  $\theta$ , there exists a cutoff  $\tilde{x}$  such that, for all  $x_i \leq \tilde{x}$ , the agent will work in the second period if able (“working path”) and save  $k_i = k^\alpha$  and, for all  $x_i > \tilde{x}$ , the agent will not work in the second period (“non-working path”) and save  $k_i = k^\beta$ , where  $k^\alpha$  and  $k^\beta$  solve the following first-order conditions, respectively:*

$$u'(w - k^\alpha) = \theta u'(Rk^\alpha) + (1 - \theta)(u'(w + Rk^\alpha)), \quad (3.1)$$

$$\text{and } u'(w - k^\beta) = u'(Rk^\beta). \quad (3.2)$$

*Proof.* See Section 3.7.1 in the Appendix. □

**Proposition 3.2.2.**  $k^\alpha < k^\beta$ .

*Proof.* We have

$$\begin{aligned} u'(w - k^\alpha) - u'(Rk^\alpha) &= (1 - \theta)(u'(w + Rk^\alpha) - u'(Rk^\alpha)) < 0, \\ u'(w - k^\beta) - u'(Rk^\beta) &= 0. \end{aligned}$$

Since  $u''(\cdot) < 0$ ,  $u'(w - k) - u'(Rk)$  is increasing in  $k$ . Thus,  $u'(w - k^\alpha) - u'(Rk^\alpha) < u'(w - k^\beta) - u'(Rk^\beta)$  implies that  $k^\alpha < k^\beta$ . □

Propositions 3.2.1 and 3.2.2 suggest that, conditional on the probability of being disabled in the second period, agents with a sufficiently high disutility of work will decide not to work in the future, regardless of their disability realization, even

in the absence of a disability insurance system. Since the expected income is zero in the second period, these agents would save more than those who decide to work in the second period.

### 3.2.3 Utility Maximization with Disability Insurance

I now introduce disability insurance into the model but start with the simple case with no screening. The disability insurance program exists in the second period through imposing a labor tax ( $\tau$ ) on the working population and transferring benefits ( $T$ ) to the recipients. Since there is no screening, anyone who applies for the insurance is accepted. An agent receiving disability insurance cannot work. The parameters  $(\tau, T)$  are chosen such that total transfers equal total tax payments; there is no need to explicitly specify the rules here.

Given  $(\theta, x)$  and  $k$ , the utility in the second period becomes

$$(1 - \theta) [u(w(1 - \tau) + Rk) - x] + \theta u(Rk + T)$$

for the working path and  $u(Rk + T)$  for the non-working path. Following the same derivation as in Section 3.2.2, one can show that there are two levels of assets for each of the working and non-working paths and workers with a disutility of work lower than a certain cutoff  $\tilde{x}'$  would choose the working path. The disability transfer makes the non-working path more attractive than before and the labor tax makes the working path less attractive. Thus, the new cutoff  $\tilde{x}'$  is lower than the original cutoff  $\tilde{x}$ . In other words, given  $\theta$ , people with  $x$  slightly below the original cutoff  $\tilde{x}$  now have the incentive to switch to not working in the second period and become disability recipients regardless of disability realization.

For agents choosing the non-working path, the expected income in the second

period is positive and thus their new optimal level of asset would be lower than  $k^\beta$  in Equation (3.2). However, since  $w(1 - \tau) > T$ ,<sup>6</sup> their expected income in the second period is still lower than that for agents who choose the working path. As a result, agents choosing the non-working path still accumulate more assets than those choosing the working path.

### 3.2.4 Utility Maximization with Imperfectly Screened Disability Insurance

While previous studies such as that of Golosov and Tsyvinski (2006) do not explicitly include screening in similar models, screening could affect both the labor force participation and asset accumulation of potential disability applicants. To see this, suppose the program makes both Type I and Type II errors and let  $p$  be the probability that the disability insurance program accepts an able worker and  $q$  be the probability that it rejects a disabled worker. Furthermore, I assume that a rejected applicant earns zero income in the second period. This is consistent with the empirical observation that to qualify for disability insurance, an applicant needs to be out of the labor force for a sufficiently long period (five months) before applying for disability as well as during the entire time of the application, which can take up to several years. As a result, a rejected disability insurance applicant may have a difficult time getting back into the labor force afterward (Parsons, 1991).

Given  $(\theta, x)$  and  $k$ , the utility in the second period for the working path is

$$(1 - \theta) [u(w(1 - \tau) + Rk) - x] + \theta(1 - q)u(Rk + T) + \theta qu(Rk)$$

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<sup>6</sup>Otherwise there would be no incentive to work.

and the utility in the second period for the non-working path is

$$[\theta(1 - q) + (1 - \theta)p]u(Rk + T) + [(1 - \theta)(1 - p) + \theta q]u(Rk).$$

As long as  $p$  is strictly positive, able agents who have chosen the non-working path would always apply for disability insurance in the second period. Because of screening, the non-working path becomes less attractive than in Section 3.2.3 but it is still better than the case with no disability insurance in Section 3.2.2. Thus, given  $\theta$ , the threshold for the disutility of work between agents choosing the working path and those choosing the non-working path,  $\tilde{x}^*$ , is between  $\tilde{x}$  and  $\tilde{x}'$ . The same intuition holds that the optimal level of asset accumulation in the non-working path is higher than for the working path, since an agent's expected income in the former path in the second period is lower.

### 3.2.5 Asset Accumulation of Rejected and Accepted Applicants

In the second period, able agents who have chosen the working path would always work in the second period and not apply for disability insurance. The disability applicant pool consists of three groups: disabled agents who have chosen the working path, disabled agents who have chosen the non-working path, and able agents who have chosen the non-working path. Because of imperfect screening, both rejected and accepted applicants include a mixture of all three groups.

**Proposition 3.2.3.**  $E(k|\theta, \text{rejected}) - E(k|\theta, \text{accepted}) > 0$  if and only if  $1 - p > q$ .

*Proof.* See Section 3.7.2 in the Appendix. □

Proposition 3.2.3 shows that the expected assets of a rejected applicant are higher than those of an accepted applicant as long as screening is sufficiently effective so that an able agent is more likely to be rejected than a disabled agent.

Furthermore, the  $\tau$ th quantile of the asset of an accepted applicant is

$$Q_k(\tau|\theta, \text{accepted}) = \begin{cases} k^{\alpha^*} & \text{for } \tau < \frac{\theta(1-q)F_\theta(\tilde{x}^*)}{\theta(1-q)+p(1-\theta)(1-F_\theta(\tilde{x}^*))} = \tau_1; \\ k^{\beta^*} & \text{otherwise.} \end{cases}$$

And the  $\tau$ th quantile of the asset of a rejected applicant is

$$Q_k(\tau|\theta, \text{rejected}) = \begin{cases} k^{\alpha^*} & \text{for } \tau < \frac{\theta q F_\theta(\tilde{x}^*)}{\theta q + (1-p)(1-\theta)(1-F_\theta(\tilde{x}^*))} = \tau_2; \\ k^{\beta^*} & \text{otherwise.} \end{cases}$$

Thus, the difference between the two is

$$Q_k(\tau|\theta, \text{rejected}) - Q_k(\tau|\theta, \text{accepted}) = \begin{cases} k^{\beta^*} - k^{\alpha^*} & \text{for } \tau_2 < \tau < \tau_1; \\ 0 & \text{otherwise.} \end{cases} \quad (3.3)$$

Note that  $\tau_1 - \tau_2 = \theta(1-\theta)(1-F_\theta(\tilde{x}^*))F_\theta(\tilde{x}^*)(1-q-p) > 0$  if and only if  $1-p > q$ . Thus, rejected and accepted applicants have similar assets at the lowest and highest quantiles, but rejected applicants have higher assets in between the two extremes.

### 3.2.6 Identification

The theoretical model implies that, conditional on observing wage and health, the level of assets at the time of SSDI application is indicative of whether one has chosen a working path or a non-working path. However, empirically linking the observed asset level to a certain path is extremely challenging, if not impossible. Not only are there many more factors that affect individuals' asset accumulation, but also the observations of wage and health are imperfect. Thus, in order to test

whether certain SSDI applicants planned for their application, I rely on the observation that the current SSDI system does not use an asset test and the identifying assumption that the screening rejects some of the work-capable applicants who have taken the non-working path.<sup>7</sup> As long as rejected applicants have a higher proportion of individuals who have chosen the non-working path, I expect them to have a higher level of assets than accepted applicants at the time of SSDI application, both in expected value and at certain quantiles. To control for any unobserved differences in individuals' tendency to save, I also compare their asset levels in the years leading up to their application. Since it is less likely that individuals start planning for the SSDI application well in advance, I do not expect to find much difference in their asset levels several years before the application.

Since rejected applicants are expected to be healthier, if they were all to take the working path, their asset levels would have been *lower* than the accepted applicants', controlling for wages. This is because healthier agents have a higher expected income if they decide to work. Thus, any unobserved differences in health should bias against finding any effect.

### 3.3 Data

#### 3.3.1 The RAND HRS Data

To compare rejected and accepted applicants at the time of application, the data for my empirical analysis require observing the timing and outcome of disability application, as well as the path of asset accumulation. The publicly available data that best satisfy these requirements are the RAND HRS panel data. A clean, compiled version of the original HRS, the data follow five cohorts of individuals

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<sup>7</sup>At the same time, screening is also imperfect, so that these applicants have the incentive to apply.

born between 1931 and 1953, with observations every two years since 1992.<sup>8</sup> In addition to disability insurance application and wealth, the data also provide information on demographics, health, employment, retirement, and income. RAND (2011) provides the details on the construction of the RAND HRS panel data.

### 3.3.2 Sample Construction

I use two criteria to select my sample of disability insurance applicants:

- An individual must have applied for SSDI but not Supplemental Security Income (SSI) between ages 44 and 65.<sup>9</sup>
- An individual must have non-missing asset data between the year of SSDI application and three years prior. Since the HRS survey takes place in even years, I observe SSDI applicants either zero and two years before application or one and three years before application. Thus, I define the time of the SSDI application to be zero or one year before the application and use observations in the two and three years before the application as controls.

The resulting sample includes 172 rejected SSDI applicants and 422 accepted applicants who applied for disability benefits between 1994 and 2010. The ratio of rejected to accepted applicants is similar for those who applied in odd years and for those who applied in even years. The overall acceptance rate is around 71%, which is comparable to other studies that use the HRS to study SSDI and SSI applicants (Benitez-Silva et al., 1999, 2004; Giertz and Kubik, 2011) as well as the 1% Files of Social Security administrative data used by von Wachter et al. (2011). It is

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<sup>8</sup>There is a sixth cohort, the “Mid Baby Boomer” cohort, which was first interviewed in 2010. However, data on the sixth cohort are not available yet.

<sup>9</sup>SSI imposes a limit on “countable resources” such as cash and bank accounts. As of 2012, the limit is \$2000 for an individual and \$3000 for a couple (SSA, 2012). Thus, I do not expect to find significant differences among the asset levels of SSI applicants.

higher, however, than the national acceptance rates between 1992 and 2009 (SSA, 2010), which are usually less than 60%.

## **3.4 Empirical Results**

To establish that there is enough power to detect any significant difference, my analysis needs to a) distinguish between rejected and accepted applicants based on ex ante observable characteristics used in the SSDI evaluation (e.g., health) to show that screening is sufficiently effective and b) distinguish between applicants based on ex ante characteristics unobserved by SSDI but that might affect asset accumulation (e.g., work disutility). Thus, I first present the results comparing the mean characteristics of the rejected and accepted applicants. I then discuss the regression analysis.

### **3.4.1 Mean Comparisons**

#### **Demographics and Labor Force Participation**

Panel A in Table 3.1 compares the demographics of the rejected and accepted applicants. It also reports the t-statistics from a two-sample T-test of equal means. Overall, the two groups are similar. The only two variables that are significantly different based on the T-test are birth year and household size at the time of SSDI application. The rejected applicants are less likely to be male and white (at 38.4% and 43.4%, respectively) and, on average, have slightly fewer years of education (around 11.76 years). Although the rejected applicants are younger in the same calendar year, their average age at the time of application is similar to that of the accepted applicants. At the time of application, the rejected applicants are slightly less likely to be married, but their household size is larger. The rejected applicants

are more likely to live in the south and the west and less likely to live in the north-east and midwest. The differences in their geographic distributions, however, are not significant.

Similar to Giertz and Kubik (2011) and von Wachter et al. (2011), I find that the rejected applicants show significantly less attachment to the labor force immediately before their SSDI application. According to Panel B in Table 3.1, 40.1% of the rejected applicants report that they were at least partially retired at the time of application, compared to 34.6% among the accepted applicants. Only 40.7% and 34.5% of the rejected applicants were in the labor force or working for pay, respectively. In contrast, 59.7% and 54.3% of the accepted applicants were in the labor force or working for pay. The differences in both variables are large and statistically significant. The rejected applicants are not only less likely to have been working at the time of SSDI application, but also have worked for significantly fewer years during the years that they were eligible to work (calculated as age minus the sum of six and years of education). The rejected applicants, on average, had worked for 77.9% of the years that they were eligible to work, whereas the accepted applicants, on average, had worked for 84.3% of the years. Given that the average number of eligible working years is around 40, the 5% difference is equivalent to two years of employment. Conditional on being employed in the year of SSDI application or the year before, the rejected applicants, on average, worked five hours fewer per week, though both groups worked for a similar number of weeks per year. Taken together, the results are consistent with two possibilities that are not mutually exclusive: The rejected applicants face worse labor market conditions and/or they have a higher disutility of work. Panel A shows that the rejected and accepted applicants have similar education levels, demographics, and geographic distributions. Furthermore, both groups of applicants are similarly likely

to have had blue collar jobs, such as construction workers, for the occupation with the longest tenure. Thus, it is unlikely that adverse labor market conditions alone could drive the stark difference in the applicants' attachment to the labor force, both at the time of application and over their lifetime. Since preference is unobserved, these results are suggestive but not definitive evidence that the rejected applicants have, on average, a higher disutility of work.

### **Health before and after Application**

Table 3.2 compares the health of the rejected and accepted applicants at the time of their SSDI application (Panel A) and immediately after (Panel B), using both subjective and objective measures. The subjective measures include self-reported health and its first difference, as well as answers as to whether health is limiting work and whether one is having back pain<sup>10</sup> or feeling depressed. The objective measures include whether one has stayed overnight in a hospital or visited a doctor in the past two years and out-of-pocket medical expenses. In the year of SSDI application or the year before, the average health of the rejected applicants appears slightly worse based on subjective measures, but better based on objective measures. None of the differences, however, are statistically significant except for whether health is limiting work. Around 69% of the rejected applicants reported that their health was limiting them from working at the time of application, which is around 10% more than the proportion among the accepted applicants.

However, one or two years after the SSDI application the rejected applicants were significantly healthier by both subjective and objective measures. Compared to the accepted applicants, the rejected applicants were significantly less likely to report having fair or poor health or having stayed at a hospital or visited a doc-

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<sup>10</sup>Whether one is having back pain is surveyed every other wave, so around 41% of the observations are missing.

tor in the last two years. They also spent less in out-of-pocket medical expenses but the difference is not significant. Before and after the application, the average self-reported health level stays fairly constant for the rejected applicants but deteriorates for the accepted applicants. In one or two years after the application, nearly 95% of the accepted applicants' reported that health was limiting them from working, now 5% more than for the rejected applicants, and the difference is statistically significant. The only exception is that the rejected applicants were significantly more likely to report having back pain. The two groups are also similar in their likelihood of having depression. Since the application review process takes up to several years, the results suggest that the SSA screening process distinguishes the more healthy applicants from the less healthy ones at least by the time of the award decision.

There are several possibilities why the rejected applicants appear to have health similar to that of the accepted applicants at the time of application. The rejected applicants may underreport their health levels to the HRS at the time of SSDI application, since they may feel obliged to justify their application or doubt the confidentiality of the study (Benitez-Silva et al., 2004). Alternatively, some of rejected applicants may actually become healthier after the application, which leads to their rejection. For the purpose of this study, it is not necessary to distinguish between these hypotheses, since both suggest that the SSA's screening process is effective at least to some degree.

### **Wealth and Income**

Table 3.3 compares the wealth and income of the accepted and rejected applicants at the time of application. My main measure of liquid assets is the level of household non-housing financial assets. Since asset distribution is highly skewed

(see Table A3.1 in the Appendix), I report both the mean and the median. Panel A shows the comparison at the time of application, while Panel B reports the statistics two or three years before the application. Overall, the accepted applicants have higher personal earnings and total household income, which is consistent with the observation that they work significantly more than the rejected applicants. Two or three years before application, the accepted applicants have a higher median of liquid assets, but the rejected applicants' median asset level surpasses that of the accepted applicants at the time of application. Since many factors could affect the level of liquid assets, I use regression analysis to formally estimate the differences between the two groups, controlling for observables.

### 3.4.2 Regression Analysis

Since ordinary least squares (OLS) regressions are sensitive to the inclusion of outliers, my preferred specification uses quantile regressions to estimate the following equation:

$$A_{it} = \alpha + \beta_0 Rejected_i \times T_1 + \beta_1 Rejected_i \times T_2 + \beta_3 I_{it} + \Phi \cdot \Sigma_{it} + \varepsilon, \quad (3.4)$$

where  $i$  denotes an applicant;  $t$  denotes a period;  $A_{it}$  is a household's liquid asset level of person  $i$  in period  $t$ ; "Rejected" is one if an applicant is ultimately rejected and zero otherwise;  $I_{it}$  is the household's total income two years before  $t$ ; and  $\Sigma_i$  includes a set of controls, such as demographics, labor force participation, health, out-of-pocket medical expenses, calendar year dummies, and years to application dummies.

I estimate the effect of being a rejected applicant at the asset level separately

for two time periods: zero or one year before the time of SSDI application and two or three years before the application. I include only observations that are in these two time periods to ensure a balanced panel.<sup>11</sup> Since the HRS survey is conducted every other year, this means I have two observations for each applicant. Note that  $\beta_0$  and  $\beta_1$  are not the causal impact of SSDI rejection on asset accumulation but, instead, represent the differences between the two groups, controlling for other observables.

Columns (1) to (4) in Table 3.4 report the estimates from quantile regressions at the median and 25th and 75th percentiles, with standard errors bootstrapped with 1000 repetitions. Controlling for income, the rejected applicants have around \$3300 more in median liquid assets than the accepted applicants at the time of SSDI application and the results are robust to having different controls. The difference is positive but not significant at the 25% quantile. However, at the 75% quantile, the coefficient estimate is large and highly significant. In contrast, two or three years before the application, the difference in the asset levels of the rejected and accepted applicants is small and insignificant across all quantiles. Figure 3.1 plots the coefficient estimates and the 90% confidence intervals from Equation (3.4). The coefficient estimate is increasing in the applicants' asset level and is especially large and significant after the 60% quantile. Two or three years before the application, all the estimates are close to zero and statistically insignificant. The OLS results in Columns (5) and (6) also suggest that the rejected applicants accumulate more assets prior to the application, but the estimates are highly sensitive to the inclusion of controls.

Overall, the regression results suggest a significant difference in the asset levels of the rejected and accepted applicants at the time of their SSDI application.

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<sup>11</sup>Some of the applicants' asset information is missing for earlier periods, so including earlier periods would result in an unbalanced panel.

Such a difference does not appear in the two or three years before the application, suggesting that it is unlikely to be driven by any inherent and unobserved differences in the applicants' tendency to save. Since the observations of health and income are not perfect, there are likely to be other unobserved factors that affect assets. For instance, the rejected applicants could be healthier and expect a higher probability of rejection from the SSDI program. However, in the absence of the non-working path, these differences should lead to the rejected applicants having a *lower* level of assets controlling for their income, in theory, since they have a higher probability of returning to work and earning income. Thus, both the regression results and the mean comparisons are consistent with the predictions that the rejected applicants are more likely to have planned their exit from the labor force as a result of having a higher disutility of work.

### 3.5 Conclusion

This paper develops and empirically tests a model that predicts the asset accumulation and labor force participation of SSDI applicants. An applicant with a high disutility of work plans to apply for disability insurance in the future, regardless of whether or not the applicant becomes disabled. A person with such a plan would have more assets at the time of her disability application than if she had planned to only apply when truly disabled. Using the RAND HRS data, I find that rejected applicants are significantly healthier shortly after their application and display significantly lower labor force attachment prior to their application. This suggests that rejected applicants are more likely to be work-capable individuals with a high disutility of work, but the SSDI screening is effective enough to detect them. Consistent with the theory's predictions, my quantile regressions show that rejected applicants have more liquid assets at the time of their applications

and the difference is especially large for applicants in higher asset quantiles. These findings are unlikely to be driven by any unobserved differences in preferences or health.

My results suggest that there is an additional channel through which SSDI discourages labor force participation. In particular, it encourages people to plan for their future exit from the labor force. Without accounting for the intertemporal effect of disability insurance on the future labor supply, the current literature focusing on the contemporaneous relation likely underestimates the associated productivity losses. Not only does disability insurance function as long-term unemployment insurance for individuals facing adverse labor market conditions (Autor and Duggan, 2003, 2006), but it is also possible that individuals with a high disutility of work consider SSDI to be a form of early retirement insurance. However, this paper does not directly calibrate the degree of the dynamic work disincentive effect. Given the suggestive evidence of rejected applicants' high disutility of work, it is unclear what proportion of them would have stayed in the labor force longer in the absence of a disability insurance program. Understanding the magnitude of the dynamic work disincentive effect is a promising direction for future research.

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## 3.6 Tables and Figures

Table 3.1: Mean Characteristics of Rejected and Accepted SSDI Applicants at the Time of Application

	Rejected (N=172)	Accepted (N=422)	—t—
Panel A: Demographics			
Male	0.384	0.434	1.12
White	0.709	0.749	0.99
Years of education	11.759	11.953	0.73
Year of birth	1943.95	1942.52	2.80***
Age at application	58.180	58.438	0.77
Married	0.692	0.723	0.75
Household size	2.692	2.465	1.90*
Northeast	0.116	0.166	1.53
Midwest	0.238	0.256	0.45
South	0.477	0.434	0.96
West	0.169	0.145	0.74
Panel B: Employment			
Considers self partly/completely retired	0.401	0.346	1.25
In the labor force	0.407	0.597	4.28***
Currently working for pay	0.345	0.543	4.43***
Self-reported total years working	0.779	0.843	2.45**
Eligible working years			
Hours worked per week if employed	33.828	38.284	2.42**
Weeks worked per year if employed	50.036	50.000	0.04
Blue collar occupations	0.352	0.364	0.27

Notes: This table reports the mean statistics of individual characteristics for the rejected and accepted SSDI applicants in my sample. Here “—t—” is the t-statistic from a two-sample t-test for equal means; the superscripts \*, \*\*, and \*\*\* indicate  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$ , respectively; *Married*, *Household size*, *Northeast*, *Midwest*, *South*, *West* and variables in Panel B are determined the year of or one year before the application; *Eligible working years* is calculated as (age - years of education - 6); *Blue collar occupations* represents a blue collar job in the occupation with the longest tenure.

Table 3.2: Mean Health Status of Rejected and Accepted SSDI Applicants

	Rejected (N=172)	Accepted (N=422)	—t—
Panel A: 0 or 1 year before application			
Self-reported health: fair or poor	0.587	0.559	0.62
Change in self-reported health	0.512	0.511	0.01
Health limiting work	0.691	0.598	2.10**
Has back pain	0.564	0.498	1.09
Has depression	0.329	0.280	1.17
Stayed at a hospital in the last 2 years	0.390	0.419	0.67
Visited a doctor in the last 2 years	0.959	0.976	1.11
Out-of-pocket medical expenses	3.535	4.358	0.99
Panel B: 1 or 2 years after application			
Self-reported health: fair or poor	0.589	0.691	2.23**
Change in self-reported health	0.021	0.327	2.79***
Health limiting work	0.895	0.945	1.96*
Has back pain	0.650	0.533	1.79*
Has depression	0.292	0.294	0.05
Stayed at a hospital in the last 2 years	0.452	0.535	1.71*
Visited a doctor in the last 2 years	0.944	0.980	2.18*
Out-of-pocket medical expenses	6.323	9.480	0.60

Notes: This table reports the mean statistics of health-related variables for the rejected and accepted SSDI applicants in my sample. Here “—t—” is the t-statistic from a two-sample t-test for equal means; the superscripts \*, \*\*, and \*\*\* indicate  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$ , respectively; *Self-reported health*: an integer between one and five, with five being poor and one being excellent; *Self-reported health: fair or poor* is 0/1 indicator variable for self-reported health being fair or poor; *Change in self-reported health*: the first difference in self-reported health between the two survey years; and *Out-of-pocket medical expenses* is in thousands of real dollars, with 2000 being the base year.

Table 3.3: Earnings and Assets of Rejected and Accepted SSDI Applicants

	Rejected (N=172)		Accepted (N=422)	
	Mean	Median	Mean	Median
Panel A: 0 or 1 year before application				
Household non-housing financial assets	34.085	2.138	28.000	1.085
Last year's personal earnings	15.878	3.145	21.174	15.378
Last year's household capital income	11.160	0.034	9.750	0.031
Last year's household total income	50.834	35.710	55.271	38.641
Panel B: 2 or 3 years before application				
Household non-housing financial assets	59.047	2.018	44.690	2.840
Last year's personal earnings	22.797	12.723	24.380	19.794
Last year's household capital income	7.866	0.039	9.583	0.040
Last year's household total income	54.158	38.343	56.315	39.482

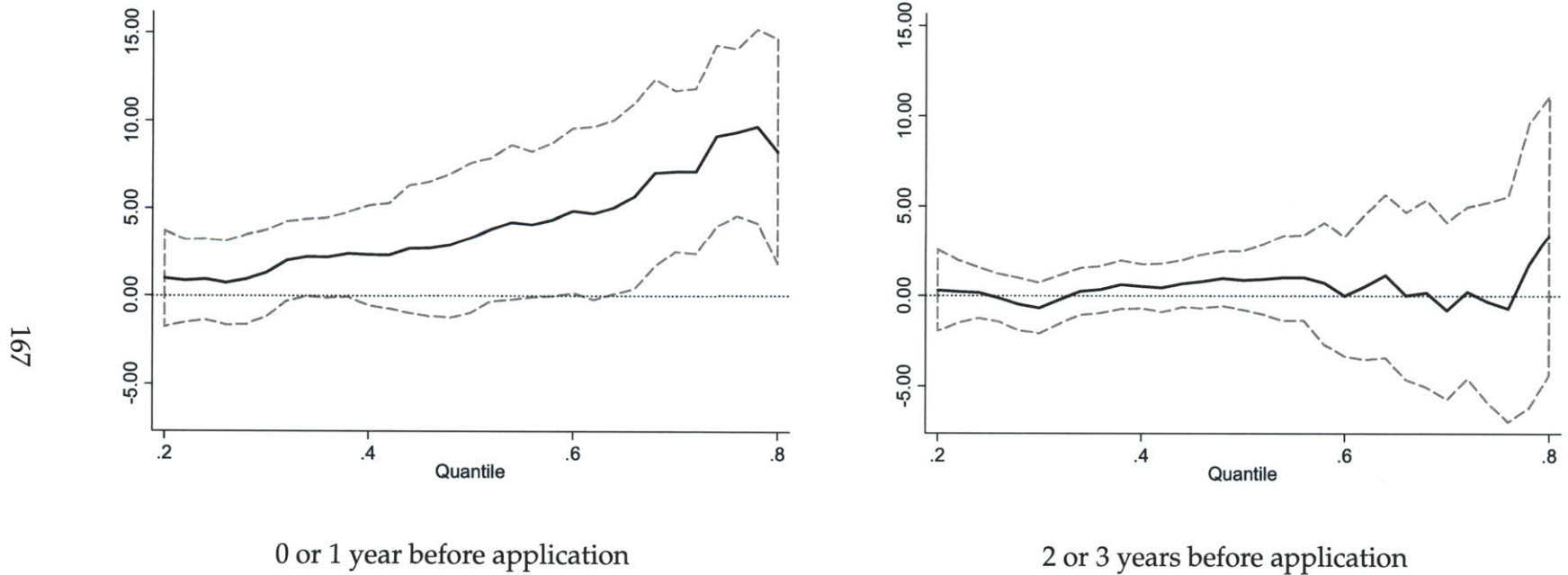
Notes: This table reports the mean and median statistics of the wealth-related variables for the rejected and accepted SSDI applicants in my sample. All variables are in thousands of real dollars, with 2000 being the base year.

Table 3.4: Panel Estimates of the Differences in Assets between Rejected and Accepted Applicants (Dep. Var. = Household Non-Housing Financial Assets)

	Quantile				OLS	
	(1) 50%	(2) 50%	(3) 25%	(4) 75%	(5)	(6)
Rejected × (0 or 1 yr before app.)	2.420** (1.160)	3.314* (1.925)	0.949 (1.205)	9.524*** (3.314)	2.088 (7.372)	8.954 (10.852)
Rejected × (2 or 3 yrs before app.)	0.907 (1.321)	0.847 (1.406)	-0.015 (1.072)	-0.665 (4.378)	24.135** (5.247)	15.826 (7.072)
Household Income	0.293*** (0.052)	0.331*** (0.059)	0.086** (0.035)	0.862*** (0.108)	0.877** (0.195)	0.857** (0.197)
Controls	No	Yes	Yes	Yes	No	Yes
N	1,188	1,188	1,188	1,188	1,188	1,188

Notes: This table reports the quantile and OLS regression estimates. The dependent variable is the amount of household non-housing financial assets in thousands of real dollars, with 2000 being the base year. Standard errors in the quantile regressions are bootstrapped with 1000 repetitions. Standard errors in the OLS regressions are robust and clustered by year of application. The superscripts \*, \*\*, and \*\*\* indicate  $p < 0.10$ ,  $p < 0.05$ , and  $p < 0.01$ , respectively. The controls include variables for gender, age, white, and household size; geographic region dummies; an indicator variable for being in the labor force; and indicator variable for self-reported health being fair or poor; out-of-pocket medical expenses in the last two years; survey year dummies; and years to application dummies.

Figure 3.1: Quantile Estimates of Being a Rejected Applicant at the Level of Liquid Assets



Notes: This figure plots the estimates and 90% confidence intervals of the quantile regression coefficients from Equation (3.4) between the 20% and 80% quantiles. Standard errors are bootstrapped with 1000 repetitions. The figure on the left plots the coefficient estimates of being a rejected applicant interacted with it being zero or one year before the SSDI application. The figure on the right plots the coefficient estimates of being a rejected applicant interacted with it being two or three years before the SSDI application.

## 3.7 Appendix

### 3.7.1 Proof of Proposition 3.2.1

*Proof.* The agent solves the utility maximization in two steps. First, the agent determines how many assets to accumulate based on whether he or she works in the second period. Second, the agent compares the lifetime utility of each path and picks that with the higher utility. If the agent works in the second period if able, the solution  $k^\alpha$  must satisfy the following first-order condition:

$$u'(w - k^\alpha) = \theta u'(Rk^\alpha) + (1 - \theta)(u'(w + Rk^\alpha))$$

for  $x_i \leq u(w + Rk^\alpha) - u(Rk^\alpha)$ .

Similarly, if the agent does not work in the second period regardless of disability realization, the solutions  $k^\beta$  must satisfy the following first-order condition:

$$u'(w - k^\beta) = u'(Rk^\beta)$$

for  $x_i > u(w + Rk^\beta) - u(Rk^\beta)$ .

Because the disutility of work and consumption enter the utility function separately,  $x_i$  does not enter the first-order conditions. For now, I assume incentive compatibility constraints hold. Thus an agent chooses the working path if and only if

$$x_i < \frac{u(w - k^\alpha) + \beta [\theta u(Rk^\alpha) + (1 - \theta)u(w + Rk^\alpha)] - (u(w - k^\beta) + \beta u(Rk^\beta))}{\beta(1 - \theta)}. \quad (3.5)$$

The right-hand side of Equation (3.5) is the explicit expression for  $\tilde{x}$ . To see

that  $\tilde{x}$  satisfies the incentive compatibility constraints, we have

$$\begin{aligned} \tilde{x} - [u(w + Rk^\alpha) - u(Rk^\alpha)] &= \\ \frac{u(w - k^\alpha) + \beta u(Rk^\alpha) - [u(w - k^\beta) + \beta u(Rk^\beta)]}{\beta(1 - \theta)} &< 0, \end{aligned}$$

since  $k^\beta$  maximizes  $u(w - k) + \beta u(Rk)$ .

Similarly, since  $k^\alpha$  maximizes  $u(w - k^\alpha) + \beta [\theta u(Rk^\alpha) + (1 - \theta) u(w + Rk^\alpha)]$ ,

$$\begin{aligned} \tilde{x} - [u(w + Rk^\beta) - u(Rk^\beta)] &= \\ \frac{u(w - k^\alpha) + \beta [\theta u(Rk^\alpha) + (1 - \theta) u(w + Rk^\alpha)]}{\beta(1 - \theta)} & \\ - \frac{u(w - k^\beta) + \beta [\theta u(Rk^\beta) + (1 - \theta) u(w + Rk^\beta)]}{\beta(1 - \theta)} &> 0. \end{aligned}$$

□

### 3.7.2 Proof of Proposition 3.2.3

*Proof.* Let  $F_\theta(x)$  be the conditional cumulative distribution function of  $x$  given  $\theta$ .

Thus

-  $F_\theta(\tilde{x}^*)$  is the proportion of agents taking the working path and accumulating  $k^{\alpha*}$ , while  $1 - F_\theta(\tilde{x}^*)$  is the proportion of agents taking the non-working path and accumulating  $k^{\beta*}$ ,

-  $\theta + (1 - \theta)(1 - F_\theta(\tilde{x}^*))$  is the proportion of SSDI applicants,

-  $\theta(1 - q) + p(1 - \theta)(1 - F_\theta(\tilde{x}^*))$  is the proportion of accepted applicants, and

$\theta q + (1 - p)(1 - \theta)(1 - F_\theta(\tilde{x}^*))$  is the proportion of rejected SSDI applicants.

The expected assets accumulated by an accepted applicant are

$$E(k|\theta, \text{accepted}) = \frac{\theta(1-q)F_\theta(\tilde{x}^*)k^{\alpha^*} + (\theta(1-q) + p(1-\theta))(1-F_\theta(\tilde{x}^*))k^{\beta^*}}{\theta(1-q) + p(1-\theta)(1-F_\theta(\tilde{x}^*))};$$

and the expected assets accumulated by a rejected applicant are

$$E(k|\theta, \text{rejected}) = \frac{\theta q F_\theta(\tilde{x}^*) k^{\alpha^*} + (\theta q + (1-p)(1-\theta))(1-F_\theta(\tilde{x}^*)) k^{\beta^*}}{\theta q + (1-p)(1-\theta)(1-F_\theta(\tilde{x}^*))}.$$

Since  $k^{\alpha^*} > k^{\beta^*}$ , this implies that

$$\begin{aligned} & E(k|\theta, \text{accepted}) - E(k|\theta, \text{rejected}) \\ &= \theta(1-\theta)(1-F_\theta(\tilde{x}^*))F_\theta(\tilde{x}^*)(k^{\alpha^*} - k^{\beta^*})(1-q-p) \\ &> 0 \text{ if and only if } 1-q-p > 0. \end{aligned}$$

□

### 3.7.3 Additional Tables and Figures

Table A3.1: Distribution of Household Non-Housing Financial Asset at the Time of Application

Sample	Rejected	Accepted
Min.	-50.652	-1500.369
25%	0	0
50%	2.135	1.085
75%	28.360	25.006
Max.	528	1338.773

Notes: This table reports the household non-housing financial asset (in thousands of real dollars, with base year 2000) for the rejected and accepted applicants at the 0%, 25%, 50%, 75%, and 100% quantiles.