Forced Entrepreneurs

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Abstract

How do labor market shocks impact the rate and quality of entrepreneurship? Analyzing the employment histories of 650,000 workers, we document graduating college during a period of high local unemployment increases entry to entrepreneurship. However, based on multiple measures of success, including survival, growth, innovation, and venture capital, recession-driven entrepreneurs are equal to or more capable than voluntary entrepreneurs. Directly surveying a representative sample of workers on lottery-choice preferences, we confirm labor shocks encourage risk-averse individuals towards entrepreneurship. By documenting a novel channel relating business cycle fluctuations to entrepreneurial activity, we find labor shocks unlock entrepreneurial potential among waged workers.

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"Nobody offered me a job, I was probably too proud to go look for one, and I said well why not start your own company." —Michael Bloomberg

1 Introduction

Declining labor market opportunities leave lasting scars on the workforce. Displaced workers are more likely to permanently exit the workforce (Yagan, 2019) and face lower wages even years after displacement (Jacobson et al., 1993); workers who enter the labor market during recessions experience long-term negative wage effects (Kahn, 2010). Distressed labor markets may then push job seekers to pursue alternative career paths such as entrepreneurship, as the opportunity cost to engage in entrepreneurial endeavors may fall during distressed times. This hypothesis has empirical support as one-quarter of Americans would create a new firm if not for the associated income risk (Gallup, 2014).

Perhaps less clear is whether workers forced into entrepreneurs by distressed labor create low- or high-quality firms. As the returns to entrepreneurship are highly-skewed to the superstar entrepreneurs,[1] understanding the relationship between labor market opportunities and firm creation ultimately depends on identifying *which* workers select into entrepreneurship during distressed times. When individuals enter entrepreneurship based on their expected performance, those with the greatest ability may have already selected into entrepreneurship prior to any labor shocks (Lucas Jr, 1978).[2] *Forced entrepreneurs* would then disproportionally lead to the creation of low-quality firms.

Alternatively, when individuals are unable to observe their potential as an entrepreneur,[3] local economic shocks may have a limited impact on the rate of entrepreneurial success. For instance, individuals may instead select into entrepreneurship based on risk preferences due to the risks intrinsic to entrepreneurial endeavors—including a significant failure rate

[1]For instance, Shane (2008) estimates over fifty percent of new firms fail within five years, while 0.03 percent achieved more than $100 million in sales.

[2]A separate view argues entrepreneurs who start during recessions are likely to face lower demand and experience lower growth (Parker, 2009)

[3]For instance, a large literature finds workers overstate their future abilities as an entrepreneur (Åstebro et al., 2007; Camerer and Lovallo, 1999; Holm et al., 2013)

(Hall and Woodward, 2010), low compensation compared to waged employment (Hamilton, 2000), and high exposure to nondiversified investments (Moskowitz and Vissing-Jørgensen, 2002). Assuming risk aversion is orthogonal to ability, declining labor opportunities will then increase the rate of entrepreneurship without any effects on the average quality of new firms (Kihlstrom and Laffont, 1979). Put simply, many individuals with great entrepreneurial potential may be currently employed as waged workers.

This paper evaluates whether labor market shocks impact the rate and composition of entrepreneurship. We find college educated individuals graduating in a weak local labor market are not only more likely to be underemployed, but also more likely to start a firm. We develop several measures of entrepreneurial success based on survival rates, employment size, and the likelihood of receiving venture capital funding, being acquired, producing patents, and successfully completing an IPO. Using these measures and their time series when available, we find that businesses formed by entrepreneurs entering weak labor markets perform identically, and sometimes better, than those who enter strong labor markets. By surveying a representative sample of individuals in our dataset on lottery-choices, we find that entrepreneurs graduating into a declining economy are more risk and ambiguity averse despite no difference in their actual quality. As a result, our findings support the Kihlstrom and Laffont (1979) view of entrepreneurship based on risk preferences, while rejecting the argument that workers select into entrepreneurship based on ability (Lucas Jr, 1978). Given innovative entrepreneurs have the potential to dramatically enhance the productivity of firms and, consequentially, economic growth (Aghion et al., 1998; Baumol, 1968; Lucas, 1988; Schoar, 2010), transitory labor shocks may have long-term effects on local economic growth through the entrepreneurship channel.

To date, a large-scale analysis of the workers entering the entrepreneurial sector in the U.S. has proved challenging due to a lack of high-quality data. Our particular analysis requires access to detailed work histories on both salaried employees and entrepreneurs, and measures of firm success over the life cycle of each new establishment, which have not previously been available. We overcome this obstacle by developing a new hand-collected dataset that merges individual employment histories obtained from LinkedIn with firm-level data from Crunchbase, LinkedIn, and the USPTO. LinkedIn includes employment histories for over 600 million users in over 200 countries.[4] The employment histories come from self-reported résumés that detail the career path of the individual and offer a snapshot of each worker in any given year.

Our data sample covers detailed profiles for roughly 640,000 skilled U.S. workers. While we collect workers from over 2,200 undergraduate institutions, we overdraw students from highly-selective colleges and universities to guarantee entrepreneurs across the distribution of talent, particularly those who have the potential to be superstar and transformational founders. For instance, Massachusetts Institute of Technology, Stanford University, Northwestern University, Cornell University, University of California at Berkeley, and University of Michigan each graduate one percent or more of the employee sample. Similar to panels of employee-employer linked data used in prior research, our data includes employment histories over long periods of time (Jacobson et al., 1993). However, in contrast to alternative datasets, LinkedIn includes information on small start-ups and self-employment (rather than exclusively incorporated firms) and occupation (necessary to identify firm founders).

Within our employee sample, we identify over 35,000 founders of firms. As our dataset covers individuals graduating from even the top undergraduate institutions, our sample includes highly-successful entrepreneurs including the co-founders of Dropbox, Yelp, Youtube, Khan Academy, Instagram, Square, Paypal, Airbnb, among others—141 startups in our sample completed successfully an IPO. For each entrepreneurial endeavor we develop a range of measures of entrepreneurial quality including (i) firm survival, (ii) current employment, (iii) innovation, (iv) access to venture capital financing, and (v) exiting the market through an acquisition or IPO. In addition, we directly survey a subset of the individuals graduating in both recession and non-recession periods to develop measures

[4] In contemporaneous work, Jeffers (2018) evaluates the effects of non-compete clauses on the rate of entrepreneurship, while Gupta and Hacamo (2018) examine whether the growth of the financial sector led to a reduction in the number of high-talent students starting firms.

of risk and ambiguity preferences based on lottery-choices, as well as alternate behavioral traits.

To study entry to entrepreneurship, our empirical design exploits exogenous time of entry in the labor market of individuals who follow a very similar academic path. Specifically, we compare a worker graduating from a U.S. undergraduate institution to a separate student of the same gender graduating from the same institution with the same major, but in the prior year. As college graduation dates are determined primarily based on the year when students were born, the characteristics of the student population are otherwise uncorrelated with the labor market opportunities at the time of graduation (Kahn, 2010); therefore, we are able to exploit time-series variation in the year of college graduation. In addition, as a large fraction of undergraduate students are in-state residents (Wozniak, 2018) and are employed in-state following graduation (Foote, 2019), we are able to exploit cross-sectional variation in the state-level labor markets—our identification assumption is that the variation in unemployment rates in two consecutive graduation years cannot be anticipated by students when they make their college choice.[5] Our framework is motivated by recent evidence demonstrating the cost of graduating in poor labor markets (Altonji et al., 2016; Bell and Blanchflower, 2011; Liu et al., 2016; Moreira, 2016; Oreopoulos et al., 2012; Oyer, 2006, 2008; Schoar and Zuo, 2017).[6] Lastly, to examine how labor shocks affect the composition of entrepreneurship, we compare the distribution of firm outcomes of those who entered the labor market in good versus bad times.

Turning to our data, we first demonstrate that a 10 percentage point increase in the state-level unemployment rate is associated with a (i) 4 percentage points decrease in likelihood of employment with a top consulting or finance firm, (ii) 10 percentage points

[5] As of 2018 the majority of students enrolled in four-year colleges in the US are within an hour's drive from home. In addition, the U.S. Census found 55% of recent graduates from the University of Wisconsin gained employment in state, compared to 66% of graduates from the University of Colorado and 80% of graduates from the University of Texas.

[6] For instance, Oyer (2008) evaluates Stanford MBA graduates and estimates that not entering the investment banking industry due to poor market conditions leads to a decrease in lifetime earnings of $1.5 - $5 million. Given nearly 100,000 of the workers in our sample graduates from a top twenty undergraduate institution, we believe this measure is applicable to our own sample.

decline in the likelihood of employment with a firm in the Russell 1000 Index, and (iii) 5 percentage points decrease in a high-wage industry. In addition, weak labor markets negatively impact all workers, including those who graduate from the most prestigious U.S. universities. We can therefore causally exploit differences in graduation year as a shock to labor market opportunities.

In our baseline analysis, we estimate a 10 percentage point increase in the state-level unemployment rate increases the likelihood of entering entrepreneurship by 2.1 percentage points compared to students of the same gender graduating from the same institution and major in the prior year. Given a baseline entrepreneurship rate of 2.2% at graduation, a ten percentage point increase in unemployment effectively doubles the rate of entrepreneurship despite these areas experiencing lower consumer demand and decreased access to financing (Hurst and Lusardi, 2004; Parker, 2009). In addition, as differences in entrepreneurship rates remain steady years after graduation, transitory labor shocks result in the creation of firms that would otherwise not exist in the economy. These results suggest that the declines in firm creation during recessions would have been even larger in the absence of this labor channel. Overall, our *pseudo difference-in-difference* strategy validates the role of labor market opportunities as a driver of entrepreneurship.

We next examine whether labor shocks affect the entry of *relevant* firms. For each entrepreneur in the sample, we collect firm-level information including industry, survival, and current employment from Linkedin.[7] Among the firms in our sample, 24% remain in business as of 2019; among the those still in business the average firm has 21 employees. We also match our new firms with venture capital data from Crunchbase and find 15% receive venture capital—a rate nearly five times higher than than the average new firm in the economy (Robb and Robinson, 2012)—and 4.5% were eventually acquired. We also merge our sample with data provided by the USPTO, and verify that 6% of the firms in our sample receive at least one patent. We return to our empirical framework and confirm that

[7] To measure current employment for a given firm, we count every user on Linkedin that reports to be working for the firm.

an increase in the local unemployment rate increases the rate of (i) large employer firms, (ii) venture-backed firms, (iii) patent-holding firms and (iii) acquired firms. Due to the size and survival of the firms in our sample, these results suggest that forced entrepreneurship may partially alleviate the initial job losses of economic recessions.

Given temporary shocks to the labor market increase the rate of entrepreneurship, the next question is *which* workers enter entrepreneurship. We hypothesize labor market shocks may lead to lower quality new firms when workers sort into entrepreneurship base on their actual or perceived entrepreneurial ability (Lucas Jr, 1978). To test this hypothesis, we compare the ex-post success of entrepreneurial endeavors across ten separate measures of firms as measured within 5 years after graduation from college or determined today. Compared to firms started during periods of low local unemployment, we find forced entrepreneurs have the same employment size, and identical probability of being acquired or successfully completing an IPO. Strikingly, firms started by entrepreneurs who entered the labor market during distressed labor markets are actually more likely to survive, obtain venture capital financing, or produce a patent. These results are similar for entrepreneurs starting a firm within two years of graduation, and also for those who started firms after 1998 and prior to 2005. All together, we find extremely limited evidence that workers facing poor labor opportunities start lower quality firms on average.

To better explain these findings, we replicate our analysis on a subset of workers especially capable of entrepreneurial success. Specifically, we focus on workers graduating from twenty of the most selective undergraduate institutions in the U.S. as we find entrepreneurs from these college are significantly more likely to start high-quality firms relative to the rest of the sample.[8] We offer four findings. First, analyzing nearly 100,000 *elite* workers, we find that individuals graduating from selective institutions continue to suffer increased rates of underemployment after declining labor markets. Second, in response to a local labor market, we find these workers are more likely to enter entrepreneurship than workers who

[8]Our sample of twenty most selective colleges include University of Chicago, Harvard University, Columbia University, Stanford University, Princeton, CalTech, UC Berkeley, MIT, Yale University, among others.

graduate from non-elite colleges. Third, graduates from the most prestigious universities are more likely to create successful firms as measured by employment, survival, VC funding, patent creation, and likelihood of being acquired. Fourth, we find no evidence that workers from top institutions start worse firms when graduating in poor labor markets. Overall, the results suggest that local labor shocks do not decrease the proportion of workers with high ex-ante potential from entering entrepreneurship.

According to our results, local labor shocks increase the rate of entrepreneurship with no effect on the rate of entrepreneurial quality. One possible explanation for this discrepancy is that rather than ability, workers sort into entrepreneurship based on risk-aversion or ambiguity aversion (Kihlstrom and Laffont, 1979). Under this hypothesis, local labor shocks will then promote entrepreneurship among more risk-averse individuals without reducing the likelihood of survival and growth. To test this prediction, we survey a representative sample of over 1,100 entrepreneurs and non-entrepreneurs from our dataset. Following the literature, we present lottery choices to participants and infer their risk- and ambiguity-aversion based on their answers. We also pose several questions to infer their overconfidence and optimism.

Analyzing these novel data, we present four findings. First, we confirm that even after controlling for observable differences of ability, an increase in the state unemployment rates increases the proportion of risk-averse and ambiguity-averse entrepreneurs.[9] Second, we argue the results on risk/ambiguity preferences are unique selection factor as we fail to find differences in other behavioral factors including confidence and optimism. Third, we argue risk-aversion is not impacted by graduating in a recession as we find no evidence that non-entrepreneurs graduating in poor labor markets hold a lower tolerance for risk and ambiguity. Fourth, we verify that on average entrepreneurs are more tolerant of risk and ambiguity compared to the non-entrepreneurs in the sample.

[9] In addition, we control for other behavioral characteristics of entrepreneurs, namely, entrepreneurial and non-entrepreneurial overconfidence, and economic and non-economic optimist.

Overall, our results detail the prolonged employment effects of transitory aggregate labor shocks on the rate and composition of entrepreneurship. While these findings suggest there is a supply of potential entrepreneurs in the workforce today, this does not imply policies should force workers out of waged employment and towards entrepreneurial endeavors. Rather, as workers forced into entrepreneurship due to declining job opportunities are not worse entrepreneurs, our results offer support for policies promoting entrepreneurship within economically-depressed communities. In particular, because workers appear to sort into entrepreneurship based on risk preferences, policies that minimize the downside of entrepreneurship may be particularly effective in facilitating the underemployed workforce towards firm creation.

2 Review of the Literature

Our paper contributes to four separate literatures: (i) the relationship between labor markets and entrepreneurship, (ii) the interaction between business cycles and entrepreneurship, (iii) the risk preferences of entrepreneurs, and (iv) the role of labor policies in promoting entrepreneurship. In regards to the first, Evans and Leighton (1989) and Evans and Leighton (1990) find that unemployed workers are twice as likely to transition to self-employment, while Farber (1999) argues individuals are less likely to enter into self-employment following a layoff. More recently, Babina (2015) evaluates linked employee-employer data from the Census to document that financially-distressed firms are at risk of losing workers to entrepreneurship or existing start-ups.[10] Although understanding the impact on the quality of entrepreneurship is the chief contribution of our paper, we contribute to this literature by (i) focusing on a sample of individuals who have the potential to start transformational and superstar firms, and (ii) considering an alternate identification strategy that exploits time-variation in the labor market facing recent college graduates. By directly comparing same-gender students graduating from the same institution and academic

[10] More generally, Baghai et al. (2015) argue that firms lose their most talented employees during periods of financial distress.

major, but in consecutive years, we show that adverse local labor markets increase the rate entrepreneurship.

A second literature studies the relationship between business cycles and entrepreneurship. Moscarini and Postel-Vinay (2012) documents that large firms exhibit a more pronounced negative correlation between net job creation and the unemployment rate. In contrast, Fort et al. (2013) claim that, since the gap between the net job creation rate of young (small) and old (large) businesses shrinks during downturns, younger (and smaller) businesses are more sensitive to business cycle shocks. In line with this evidence, Moreira (2016) shows that firms born in downturns start and remain small over their entire lifecycle.[11] Our paper contributes to this literature by offering an alternate channel relating business cycle fluctuations to entrepreneurial activity. Our findings suggest that the declines in firm creation during recessions would have been even larger in the absence of this labor channel.

A third literature examines the empirical link between risk or ambiguity preferences and firm creation (Hall and Woodward, 2010; Knight, 1921). To date, however, the empirical evidence that risk or ambiguity aversion is a primary determinant of entry to entrepreneurship is mixed and may depend on the particular methodology (Parker, 2009). For instance, Hvide and Panos (2014) find that individuals investing in the stock market are more likely to be entrepreneurs; similarly, Ahn (2010) and Cramer et al. (2002) estimate lower risk aversion predicts entrepreneurship. In contrast, (Holm et al., 2013) and Koudstaal et al. (2015) show that entrepreneurs are no more likely to make risky choices than other workers in an experimental setting.[12] By combining survey data with the empirical framework discussed above, we introduce a new methodology to confirm the relationship between risk/ambiguity aversion and entry to entrepreneurship. Our result are bolstered by our findings that employment shocks do not (i) impact the success rate of entrepreneurship,

[11] In related work, Decker et al. (2014) show a declining trend in the last three decades on the share of US employment accounted for by young firms.

[12] For a more complete discussion of the literature, we refer readers to Astebro et al. (2014).

(ii) lead less confident or optimistic individuals to enter entrepreneurship, or (iii) alter the risk preferences of workers.

By combining the three literatures above, we also contribute to a recent literature evaluating the impacts of labor policies on the level and composition of entrepreneurship. For instance, Gottlieb et al. (2016) find that a Canadian reform extending job-protected leave to recent mothers increased entrepreneurship by 1.9 percentage points. In another recent paper, Hombert et al. (2019) evaluate the implications of a French policy reform that provided downside insurance to eligible unemployed workers who enter entrepreneurship. They find the reform, which provides an insurance of 2000 euros a year for up to three years, significantly increases entrepreneurship, primarily self-employment, without worsening the quality of new entrants. However, whether policies impact the proportion of successful entrepreneurial endeavors is less clear from this analysis, as small financial incentives may not be enough to change the career paths of highly talented employees.[13,14] To overcome these limitations, we instead examine shocks to labor market opportunities, which can lead to a large and long-lasting negative effect on wages, among even highly skilled workers.[15] As we find no evidence that labor shocks impact the average quality of new firms, our findings offer new support for policies minimizing the downside of entrepreneurship even among the highly-talented workforce.

3 Data

We begin this section by detailing the data sources for our analysis, particularly the data from LinkedIn, Crunchbase, and USPTO. We then summarize: (i) the complete LinkedIn

[13]Specifically, while their paper focuses primarily on self-employment, we focus more on employer firms: thirteen percent of the firms in our sample receive venture capital financing, nearly five percent are acquired, and 0.4 percent enter an initial public offering.

[14]Our sample includes the co-founders of Dropbox, Yelp, Youtube, Khan Academy, Instagram, Square, Paypal, Airbnb, among others.

[15]Oyer (2008) illustrates how weak labor markets may have large effects on earned wages. He evaluates Stanford MBA graduates and estimates that not entering the investment banking industry due to poor market conditions leads to a decrease in lifetime earnings of $1.5 - $5 million. Given nearly 100,000 of the workers in our sample graduates from a top twenty undergraduate institution, we believe this measure is likely applicable to our own sample.

database, (ii) the subset of the workers included in our estimation, (iii) their prior undergraduate institutions including local economic conditions, (iv) the new firms founded by the workers in the sample, and (v) survey responses from a representative sample of the population.

3.1 Data Sources

Online Business Networking Service Data. Our dataset is constructed from LinkedIn, the largest online business networking service worldwide. LinkedIn includes employment histories for over 600 million users in over 200 countries, including 160 million U.S. users, suggesting that a large fraction of the U.S. workforce uses LinkedIn.[16] Individuals self-report their resumes, including educational background and employment history. Educational background includes information on each degree, school attended, and, for some users, their major. The history of employment includes the title, full name of the firm, start and end dates, and, in many cases, the detailed job description and location. All users report their current industry and current location. Users of this website have an incentive to keep their profiles up to date since the site is valuable for professional networking: many employers currently use it to recruit employees, either by posting job ads or through direct headhunting.

To document the coverage of the full sample of LinkedIn, we match LinkedIn industry categories to the industry definitions from the Bureau of Economic Analysis. We then determine which industries are overrepresented and underrepresented in the complete LinkedIn database. We find that all two-digit NAICS Industry Codes are represented in the database. According to Figure 1, most workers in (i) professional services, (ii) financial services, and (iii) information have a profile. In contrast, LinkedIn understates the employment size in (i) construction, (ii) trade, transportation, and utilities, and (iii) agriculture and mining. Importantly, more than 50% of the labor force in any industry uses LinkedIn.

[16]We note a portion of the 160 million US users may no longer, be in the labor force.

A separate concern is that workers may only periodically update LinkedIn profiles, leading to the overstatement of job spans in our data. To assess the validity of this concern, we compare in Figure A1 the average job tenure rates of workers in LinkedIn to all US workers. To measure job tenure for US workers, we collect data from the US Current Population Survey Job Tenure Supplement for respondents aged 15 years and older. To measure job tenure from LinkedIn profiles, we collect a random sample of one million workers employed at some point with a firm listed in the Russell 1000 Index. While this choice may bias the results towards workers employed in larger firms, it allows us to match the age distribution of workers surveyed by CPS, while excluding self-employed workers. We then plot the cumulative job tenure for each worker in each year from 1996 to 2014 for both data samples. We find minimal differences in job tenure rates, offering little evidence that LinkedIn profiles hold outdated (or overstated job tenure) information.

From the universe of worker resumes available in the online business networks service, we collect employment profiles for 641,144 workers graduating with a Bachelor's degree during the years 1998- 2012 from US universities. To create our dataset and to guarantee a certain degree of randomization, we sample LinkedIn using a tool available in most online search engines, such as Google and Yahoo. These websites allow search results to be restricted to a specific website. We make use of this feature to search for profiles of workers on LinkedIn. Specifically, we search for workers from a given college or university; in addition to the university name, we append a random alphanumeric character. This methodology generates a sample in which the degree of randomness depends on the webpage ranking ordering created by the search engine crawler. While search engines use sophisticated and non-random methods to order websites (i.e., linkedin.com versus facebook.com), it less clear how they order webpages of the same website, especially when random alphanumeric characters are added to the search term. Through this process we aim to generate a sample that is representative of the population of college educated workers.

First, we collect the employment history of each worker including: (i) firm name, (ii) job title, and (iii) skillsets. Second, we collect the educational history of each worker including (i) institution name, (ii) degree, and (iii) self-reported major. We then match each college major to a major category based on a natural language processing algorithm. We then compile the full worker employment history into a yearly panel dataset. An additional benefit of LinkedIn is that organizations also have profiles, which are typically maintained by firms (and institutions) themselves. After matching the names of each firm across workers, we collect characteristics for each firm from LinkedIn. For each firm, we collect (i) year founded, (ii) industry, (iii) description of firm activities, (iv) headquarters address, (v) company size (measured by employment bins), and (vi) whether the company is public or private.

For each educational institution mentioned in the resume data, we obtained information on (i) exact location, (ii) annual tuition, (iii) acceptance rate, (iv) total enrollment, (v) school website, (vi) type of institution (public or private), and (vii) founding year. However, Linkedin users use different names to refer to their undergraduate educational institution. For example, they may use different designations for the same university (M.I.T, MIT, Massachusetts Institute of Technology, etc.); or, instead, just refer to their college or department within the university (i.e., MIT School of Engineering, MIT Sloan, MIT Department of Mechanical Engineering, etc). To identify the main undergraduate institution, we first use a search engine (i.e., Google.com or Yahoo.com) to search for the institution name written on each employee's resume. Through this method, we obtain the website address of the university, school, or department. We then use the top domain of each school's (or department's) website to determine the top domain (i.e., mit.edu). From the top domain we identify the main undergraduate institution (i.e., MIT) as schools and departments within the same university institution share the same top domains.

We define firm creation using the following criteria. First, we include individuals that classify their job title as 'owner', 'co-owner', 'founder', 'co-founder', or 'entrepreneur' of a firm. Each firm's startup year is either directly observed in the firm's profile on the business networking website, or estimated using the earliest date any employee joined the firm (as observed on LinkedIn). From this data source, we develop two measures of entrepreneurial success. First, we calculate survival as the tenure of the entrepreneur at the firm. This assumption underestimates survival, since founders may transfer the ownership of their firms to other parties.[17] Second, for each new firm in the sample, we measure employment as the number of employees currently employed with the firm according to the firm's profile.

Overall, our data is similar to three related sources. First, it resembles the employee-employer linked data from the U.S. Census Longitudinal Employer-Household Dynamics or administrative datasets (Graham et al., 2013; Jacobson et al., 1993). These sources suffer from three primary disadvantages: (i) limited information on young and small firms, (ii) missing occupation information (further preventing the identification of firm founder), and (iii) imputed information on educational backgrounds (limiting our ability to identify college graduates).[18] Second, employment histories are frequently studied using either general datasets such as the Panel Study of Income Dynamics or more specialized sources including the Survey of Displaced Workers (Ruhm, 1991); however, there is no survey dataset that includes corresponding information on firm starts, limiting any analysis of entrepreneurial quality. Third, our data is most similar to online job search websites as discussed in Brown and Matsa (2012) and Agrawal and Tambe (2016). Yet, while (Agrawal and Tambe, 2016) covers approximately 13% of the U.S. workforce, we cover between 50% to 70%.

Entrepreneurial Financing Data. We obtain additional sources of information for the new firms in our sample. First, we match each firm to its respective profile on Crunchbase.com, an online data service. Crunchbase records information on founders and firms, venture capital funding, and exits through acquisitions and IPOs. Crunchbase is a crowd-sourced

[17] However, using the 2007 Survey of Business Owners (SBO) Public Use Microdata Sample (PUMS), we estimate that even five years after formation, ninety percent of all firms are still owned by the initial owner.

[18] Workers that leave the sample may have become unemployed, retired, or moved to another state. Therefore, most analyses of US data has had to focus solely on wages.

database and its main source of data is TechCrunch, an online publisher of technology industry news. For firms to be present on Crunchbase it is not required that they receive venture capital financing; hence, Crunchbase may include start-ups that are financed by angel investors or crowd-funding. Note that Crunchbase includes both self-reported information and data collected from TechCrunch and the greater web. From this data, we are able to observe whether a firm has received venture capital funding (VC), the money invested by each VC investor, whether the company has been acquired, and whether the firm has successfully completed an IPO.

Patent and Citations Data. We obtain patent data directly from the United States Patent and Trademark Office (USPTO). The USPTO maintains a permanent and historical record of all US patent applications and provides a search engine on their website. We search for the name of each company founded by an entrepreneur in our dataset. We opted to collect patents by firm instead of personal patents since (i) they account for patents created by other inventors besides the founder, and (ii) they are the property of the firm rather than the founder.

Local Data. In addition to the data sources summarized above, we collect annual data on the unemployment rate at the state-level. All measures are collected from the Bureau of Labor Statistics.

Survey Data of Workers. Compared to data sources analyzed in prior research, a unique feature of our environment is that we are able to directly contact the individuals in our sample. Therefore, for a subsample of the population, we e-message the users of LinkedIn with a request to respond to a quick survey on SurveyMonkey.com. Each survey response can be matched to the worker profile and added to the database. In total, we contact a total of approximately 4,000 entrepreneurs through the OBNS and receive 622 replies, resulting in a 16% response rate. While one might be concerned that the individuals who responded might misrepresent the sample of entrepreneurs in our sample, we confirm that the observable characteristics of the survey responded match the characteristics of the full sample of entrepreneurs in our sample, which contains over 35,000 entrepreneurs. We report this differences in Table A2 of the appendix. We also survey a total of 4,000 non-entrepreneurs within our sample, and received 508 responses.

The primary questions of the survey evaluate an individual's risk preferences based on prior evidence that entrepreneurs hold a higher tolerance for risk and ambiguity (Knight, 1921; Parker, 2009). In particular, the first question (Q1) measures *risk aversion*, defined as the willingness to accept risk for a potential reward. The second question (Q2) measures *ambiguity aversion*, defined as the willingness to accept ambiguity for a potential reward.

Q1: How much would you pay for a lottery ticket that gives you a 50% probability of winning $500 and 50% of winning nothing?

Q2: How much would you pay for a lottery ticket that gives you a x% probability of winning $500? (x is between 25% and 75%)

In regards to both the first and second question (Q1 and Q2), we offer six possible answers (i) Less than $50, (ii) $50-$100, (iii) $100-$150, (iv) $150-$200, (v) $200-$250, and (vi) more than $250. We then create a binary variable equal to one for those individuals who are in the top quartile of our risk (ambiguity) aversion categorical measure. This approach divides individuals into two groups, those who are risk averse and those are less risk-averse, neutral, or risk seeking. According to this definition, we classify individuals who are willing to pay less than $50 as the most risk (ambiguity) averse, and those who are willing to pay more than $50 as the least risk (ambiguity) averse. The classification implies that 35 (40%) of the sample is classified risk (ambiguity) averse.

In addition, measures of risk and ambiguity tolerance, we include six other questions in the survey; each question is a binary measure and answers are provided in more detail in the appendix. These questions evaluate the confidence and optimism of the workers in the sample. First, our focus on entrepreneurial confidence as a predictor of entry is based on a significant literature including (Holm et al., 2013). The third question (Q3) develops a measure of entrepreneurial confidence based on the likelihood of being acquired, while the fourth question (Q4) measures confidence in employing at least ten workers. Second, prior research including Åstebro et al. (2007) argues that an individual's general confidence is a primary predictor into entrepreneurship. Therefore, question five (Q5) measures an individual's confidence in their future salary growth. Question six (Q6) instead develops an indirect measure of confidence based on their willingness to compete based on the findings of Camerer and Lovallo (1999). Third, we attempt to measure a worker's optimism. While optimism and confidence are related, confidence is concerned with ability, as opposed to luck. Question seven (Q7) develops a measure of economic optimism based on the findings of Bengtsson and Ekeblom (2014), while the eighth question (Q8) considers the role of non-economic optimism (Puri and Robinson, 2007). We provide the questions below and the possible answers for each question in the appendix.

Q3: Among firms started by college graduates, 5% are eventually acquired by a larger firm. If you started a company today, what is the likelihood your firm would eventually be acquired?

Q4: Among firms started by college graduates, 12% grow to employ ten or more workers within five years. If you started a company today, what is the likelihood your firm would employ ten or more workers within five years?

Q5: What is the likelihood your salary doubles in the next five years?

Q6: Do you view yourself as a competitive person?

Q7: Over the past 90 years, the US stock market has observed an average return of 9% a year. What will be the average annual US stock market return over the next ten years?

Q8: Among people born in the US in 1919, 1.4% are still alive in 2019. What is the likelihood you live to age 100?

We create binary measures that aggregate the answers similarly to our procedure for risk and ambiguity aversion. For Q3 and Q4, we create a binary variable equal to one for respondents who are in the top quartile in their belief of entrepreneurial success. For Q5, we create a binary equal to one for individuals in the top quartile of expectations of salary growth. For Q6, we compute a binary variable equal to one for those who are in the top quartile in their willingness to compete. For Q7, we generate a binary variable that equals one for individuals in the top quartile in their expectations of highest stock market return growth. And lastly, for Q8, we create a binary variable equal to one for individuals who are in the top quartile in their belief that they will live until age 100. We use these binary variables in our analysis.

3.2 Data Summary

Summary of Workers. From the universe of worker resumes available on LinkedIn, we collect employment profiles for 641,144 workers graduating with a Bachelor's degree during the years 1998- 2012 from US universities. We first compare our data sample to the full set of college graduates. According to data from the National Center for Education Statistics (National Center for Education Statistics, 2018), a total of 21.7 million students graduated from an undergraduate institution between 1998-2012, leading to a mean of 1.45 million students annually. Therefore, our sample includes information on 3% of the entire sample of college graduates during this time period. Comparing the national data to our own sample in Figure 2, we note our data over-represents the earlier years in the sample and under-reports the later years of the sample. Specifically, our sample covers roughly 3.5% of all college graduates between 1998 and 2009, but closer to 2% of graduates between 2010-2012.

Panel A in Table 1 reports the average probability that a student in our sample becomes an entrepreneur. We estimate 2.2% of students found a new firm directly after graduation, 2.8% within two years, 3.3% within three years, and 3.9% within four years. For comparison, the Kauffman Foundation estimates that on average, between 1998 and 2018, only 0.32% of the U.S. population started a business every year. In line with our hypothesis, we note entrepreneurship rates are counter-cyclical: for instance, over five percent of workers graduating in 2010 enter entrepreneurship within two years of graduation.

We also summarize the worker characteristics in our sample. Recall all students included in our sample have earned a Bachelor's degree;[19] in addition, 20% of our sample obtains a graduate degree within 5 after graduation. For comparison, according to 2014 estimates from the National Center for Education Statistics, 22% of the US population aged 25-29 with a Bachelor's degree also hold a graduate degree. To ensure we include entrepreneurs in the top of the talent distribution, we over-select from the top undergraduate institutions; in our data, 18% of workers graduate from a top twenty institution based on U.S. News and World Report Rankings.

To measure gender, we match names from GenderCheck: 36% of the sample is female. Given our interest in entrepreneurship, we also focus on two fields that may offer particular skillsets to facilitate firm creation. We estimate 16% of the sample graduates with a degree in business or economics, while 27% of students graduated with a degree in engineering, computer science, or mathematical sciences.

We develop three measures to assess the quality of employment at graduation. First, we estimate the likelihood of obtaining a job at a top consulting or finance firm at graduation. Our list of top finance firms include Goldman Sachs, Morgan Stanley, JPMorgan Chase, Citigroup, and Credit Suisse;[20] while our list of top consulting firms only includes five firms: McKinsey & Company, The Boston Consulting Group, Booz Allen Hamilton, Bain & Company, and A.T. Kearney. Second, we estimate the likelihood of joining a firm listed in the Russell 1000. Third, we compute the likelihood that a worker joins a high wage industry after graduating from college.

To define a high-wage industry, we first estimate the hourly wage for each industry in the following top occupations: Top Executives, Management Occupations, and Architecture

[19] For comparison, 34% of the US population aged 25-29 had completed a Bachelor's degree

[20] The full list of top finance firms are Goldman Sachs, Morgan Stanley, JPMorgan Chase, Citigroup, Credit Suisse, Wells Fargo, Merrill Lynch, Deutsche Bank, Lehman Brothers, Capital One, BlackRock, Bloomberg, and Barclays Capital.

and Engineering Occupations. We focus on these occupations as all workers in our sample are college graduates, over a quarter acquire graduate degrees, and 18% graduate from a top twenty undergraduate institution. We then define high wage industries as those above the median in income within the three occupations listed above. Following graduation from college, 5% of workers in our sample join a top finance or consulting, and 25% join a firm listed in the Russell 1000. The average worker in our sample joins an industry where the mean wage in top occupations is $61.80 per hour.[21]

Last, we match each institution to the corresponding zip code to determine the local economic conditions facing workers in the sample. Workers face a mean state-level unemployment rate of 6.3% at the time of graduation. We document both time-series and cross-sectional variation in unemployment rates during our period. For instance, unemployment was measured at 4% in 2000, but 10% at the start of 2010. However, even in 2010 we note significant variation: Nevada suffered a rate of 15%, while North Dakota remained below 4%. We exploit these differences across both time and space in our empirical framework.

Summary of Undergraduate Institutions and Local Economies. As discussed above, all workers in our data graduated from an undergraduate institution between 1998 and 2012. Therefore, we next summarize the set of undergraduate institutions represented in the data in Panel B of Table 1. In total, the workers in our sample have graduated from over 2200 different institutions. Individuals in our sample graduated from an institution with an average acceptance rate of 51% and average total enrollment of 30,327 students. On average, the institution was founded in 1889 and annual tuition was $22,269. Last, 75% are public institutions.

For additional information, in Table A1 of the online appendix we list the institutions composing the largest proportion of our sample. In order, we find that the University of California at Berkeley and the University of Illinois at Urbana-Champaign each compose

[21] We define the following as top occupations: "Top Executives", "Management Occupations", "Architecture and Engineering Occupations"

3.11% of the entire sample, University of Texas at Austin composes 2.92%, University of California in Los Angeles is fourth at 2.67% and the University of Wisconsin rounds out the top five at 2.49%. Combined, these five institutions graduate 11.82% of the entire sample, while the ten largest compose a total of 22.8%.

Summary of Entrepreneurs. We summarize data on the new firm demographics in Panel A of Table 2. Our analysis includes a total of 36,316 entrepreneurs. Compared to the full sample of workers, we note three differences. First, entrepreneurs are twice as likely to graduate from a top twenty undergraduate institution. Second, entrepreneurs are more likely to study engineering and computer-related fields. Third, entrepreneurs are significantly less likely to be female.

By focusing our analysis on workers with college degrees (especially degrees from selective institutions), a significant proportion of these firms are particularly successful. We estimate 24% remain in business as of 2019, while 14% also employ at least ten workers. In addition 9.4% (5.1%) currently employ at least twenty (fifty) workers. We estimate at least 6% of the firms created at least one patent, our measure of innovation, including 2.5% that patent within five years of establishment. Turning to our data on financing, we estimate 15% received venture capital funding throughout their firm life, and 12% receive venture capital funding within five years of establishment; additionally, we estimate that 4.5% were acquired by a separate firm. Lastly, 141 startups in our sample completed successfully an Initial Public Offering (IPO), representing 5.7% of all startups that completed an IPO between 1999 and 2012.[22]

Finally, we also match each new firm to a two-digit NAICS code and present the results in Figure 3. New firms predominantly arise in the industries: Professional, Scientific, and Technical Services (33%), Information (27%), Manufacturing (12%), and Finance and Insurance (9%). In Table A7 of the online appendix, we distinguish the sample between firms started by workers during periods of high local unemployment (defined as a rate above the sample median) and firms started by workers in low unemployment markets (defined as

[22] According to Statista.com, 2462 startups successfully completed an IPO between 1999 and 2012.

a rate below the sample median). We find almost no differences in the industry breakdown. In addition, we compare these estimates to the industry breakdown of all new firms founded by college graduates according to the 2007 Census Survey of Business Owners. We note our sample of new firms is biased towards firms in Information, Manufacturing, and Professional, Scientific, and Professional Services; in contrast, the firms under-represent the proportion of new firms in Trade (both retail and wholesale), Administrative Services, and Accommodation and Food Services.

Summary of Survey Responses from Entrepreneurs. We summarize the survey responses in Panel A of Table 3. We identify 35% of the respondents as highly risk-averse and 40% highly ambiguity-averse. In addition, we develop two measures of confidence in entrepreneurial abilities: conditional on founding a new firm, 31% of respondents believe there is a significant chance in the likelihood of starting a firm that is ultimately acquired, while 44% believe there is a significant chance of employing at least ten workers. Next, we develop two definitions of general confidence based on (i) future expected salary growth and (ii) preference for competition. Based on these measures, 41% of respondents are confident in their salary growth and 27% hold a preference for competitive environments. Third, we consider two definitions of optimism based on (i) life expectancy and (ii) future stock market returns. We find 41% of entrepreneurs are defined as optimistic about the future stock market and 10% are optimistic about their life expectancy.

As we are not able to survey the full population, a primary concern is that entrepreneurs answering the survey differ from the other entrepreneurs in the sample.[23] Therefore in Table A2 of the online appendix, we confirm the entrepreneurs in our survey sample start similar firms to those in the larger sample; the only exception is that the surveyed population is 1.9% more likely to found a firm with at least one patent and this difference is statistically significant at the ten percent level. As a result, we believe the entrepreneurs included in the survey are representative of the larger set of entrepreneurs.

[23] To overcome this concern, we control for personal and firm characteristics in our regression analysis of the survey data.

Summary of Survey Responses from Non-Entrepreneurs. For comparison, we also survey a set of 508 workers from our full sample that have not entered entrepreneurship. This data provides two benefits. First, we can test whether risk and ambiguity preferences predict entry to entrepreneurship. Second, we can verify non-entrepreneurs graduating during periods of poor labor opportunities are not more risk or ambiguity-averse. We summarize the data in Panel B of Table 3.

4 Methodology

In this section we first outline our three hypotheses and then describe the empirical framework to test each hypothesis.

4.1 Empirical Setting

This paper tests three hypotheses. First, we analyze how job market opportunities impact the rate and composition of entrepreneurship in the economy. The argument that local labor markets are related to entry to entrepreneurship is straightforward: sudden increases in local unemployment creates an excess supply of labor. Job searches impose heavy constraints on time (Aguiar et al., 2013), and the mismatch between vacancies and job seekers across sectors might affect the likelihood of finding a job (Sahin et al., 2012). Past research has also demonstrated the long-term costs of unemployment: for instance, job displacement is followed by a long-term decrease in wages as well as an increase in wage volatility (Jacobson et al., 1993). Since prospective entrepreneurs weigh employment risks against entrepreneurship risks (Hamilton, 2000; Hombert et al., 2019; Scott et al., 2015), local employment shocks may potentially impact the rate of new firm creation.

Though this argument relating labor market conditions and entrepreneurship may be quite convincing, macroeconomic research offers little evidence of this channel. For instance, as the unemployment rate rose from under four percent in 2006 to peak at ten percent by 2010, the number of new firms declined by twenty-two percentage points and has failed to return to pre-recession levels as of 2019. One likely explanation for this discrepancy is that areas suffering from poor labor market conditions are also more likely to suffer from decreased access to entrepreneurial finance (Hurst and Lusardi, 2004) and decreased customer demand (Fort et al., 2013; Parker, 2009). Assuming these channels are more relevant than the labor market channel discussed above, it is not surprising that recessions decrease the overall rate of entrepreneurship in the economy.

Second, we analyze how local employment opportunities impact the quality of entrepreneurs. The standard argument in the literature is that individuals with the greatest ability have already chosen to enter entrepreneurship prior to changes in local employment opportunities (Lucas Jr, 1978). Any firms created due to local employment shocks will therefore instead be a stop-gap measure until the founder can rejoin the workforce (Delmar and Davidsson, 2000), resulting in few implications for long-term entrepreneurial dynamics. Based on these arguments, we expect that increases in the local unemployment rate lead workers with lower entrepreneurial ability to start firms. While direct evidence supporting this hypothesis is limited, Moreira (2016) illustrates that firms started during recessions are smaller in initial size and experience limited growth compared to firms founded in more favorable environments. However, the precise channel is again not obvious as the effects may instead be driven by decreased customer demand and lack of financing supply.

Third, we examine the relationship between opportunities in the labor market and risk preferences of entrepreneurs. Based on Kihlstrom and Laffont (1979), workers may sort into entrepreneurship based on risk or ambiguity aversion. In this environment, individuals with the greatest risk tolerance enter entrepreneurship regardless of the local employment opportunities; as a result, entrepreneurs entering the market during periods of high unemployment will be more risk-averse on average. Past empirical research has found evidence that entrepreneurs are more tolerant of risk (Ahn, 2010; Cramer et al., 2002; Hvide and Panos, 2014); however, no paper has previously evaluated whether entrepreneurs entering the market during recessions are more risk or ambiguity-averse.

Based on the arguments above, our analysis requires a setting where individuals are directly impacted by fluctuations in labor market opportunities. We follow a notable literature including Altonji et al. (2016); Bell and Blanchflower (2011); Kahn (2010); Liu et al. (2016); Oreopoulos et al. (2012); Oyer (2006, 2008); and Schoar and Zuo (2017). As such, we exploit exogenous time of entry in the labor market among individuals with very similar academic paths.[24] More concretely, we compare a worker graduating from a U.S. undergraduate institution to a separate student of the same gender graduating from the same institution with the same major, but in the prior year. We believe this setting provides three primary advantages.

First, the time of initial enrollment is unlikely to be correlated with local economic conditions at the time of graduation. According to the National Center for Education Statistics (NCES), ninety percent of students enrolled in a Bachelor's program at four-year public institutions are under 25 years of age; the number decreases slightly to 87% of students at non-profit four year private institutions (National Center for Education Statistics, 2017). Therefore, the timing of college entrance is not dependent on local economic conditions, but rather their year of birth. By comparing two same-gender workers who graduate from the same undergraduate institution with the same major, but in consecutive years, we are able to identify the impact of local economic conditions on entrepreneurship.

Second, past research has found shocks to labor market opportunities have significant and persistent implications on graduating students. For instance, Oreopoulos et al. (2012) estimate that students graduating during a recession earn nine percent less than other student; Altonji et al. (2016) estimate a similar ten percent decline, though the effect is two to three times larger during the Great Recession. Oyer (2008) evaluates Stanford MBA

[24] At first, it may seem desirable to analyze workers facing turnover. However, it is generally difficult to distinguish between unforced turnover (i.e. worker quits) and forced turnover due to worker ability (i.e. worker firings).

To identify the effect of job displacement on the propensity of starting a new firm, one then needs to address several endogeneity concerns. In particular, it is necessary to distinguish worker displacement from voluntary exit or personal firings. Workers that voluntarily exit a firm have a reason for the decision: a preferable job opportunity, retirement, family needs, etc. Similarly, workers that exit a firm due to a firing are different from workers that stay: in particular, they are likely to be worse employees.

graduates and estimates that not entering the investment banking industry due to poor market conditions leads to a decrease in lifetime earnings of $1.5 - $5 million. Liu et al. (2016) argues these losses are driven primarily by a thirty percent increase in the rate of job mismatch as students are unable to find employment in their field of study. Therefore, this setting allows us to isolate the impact of a decline in job opportunities on entrepreneurship.

Third, young and college-educated workers are critical to the entrepreneurial sector. For instance, past research has found a positive correlation between city-level education and entrepreneurship rates, as well as entrepreneurial success (Doms et al., 2010). One potential explanation is that education is associated not only with greater knowledge and training, but also a higher income (Grogger and Eide, 1995) and greater access to family wealth (Belley and Lochner, 2007). In addition, prior evidence has found that start-ups disproportionately employ younger workers due to both their skillsets and risk tolerance (Ouimet and Zarutskie, 2014).

4.2 Framework

We outline the empirical methodology to test the three hypotheses outlined above. To test the first hypothesis, we estimate the impact of changes in the state-level unemployment rate on the likelihood that worker i graduating from an undergraduate institution in year t enters entrepreneurship with x years of graduation. Specifically, we estimate the following linear probability cross-sectional model:

$$\begin{aligned} \text{Entrepreneur}_{i,t}^{x} &= \beta \times \text{Local Unemployment}_{i,t \to t+1} \\ &+ \text{University} \times \text{Cohort FE} \times \text{Gender FE} + \eta_{i,t} \end{aligned} \tag{1}$$

The dependent variable $\left(Entrepreneur_{i,t}^{x}\right)$ is a binary variable denoting individual i graduating in year t entered entrepreneurship within x years after graduation. We focus on entering entrepreneurship within 1 to 4 years following graduation. The independent variable of interest is $Local\ Unemployment_{i,t \rightarrow t+1}$, and measures the average unemployment rate in years t and $t+1$ in the state where the college of individual i is located. We focus on multiple years as a portion of workers in our sample are likely graduating at the end of the calendar year and searching for positions in the beginning of the following year; as we are not able observe the month of graduation within our data, we are not able to differentiate these students.[25] We focus on state-level conditions as the majority of undergraduate students are in-state residents (Wozniak, 2018) and are employed in-state following graduation (Foote, 2019).[26]

The regressions include a set of fixed effects that interact university, graduation cohort, and gender. The cohort is defined as a two-year rolling window; for instance workers graduating in 1998 and 1999 and in the same academic major compose a cohort.[27] These set of fixed effects ensures that we only compare individuals who graduate from the same university, major, and gender, but in consecutive years. As a result, our inferences remain valid even if colleges are not equally represented in each year of the sample. The coefficient β then measures the impact of the local employment shock on entry to entrepreneurship; according to our hypothesis, $\beta > 0$. We cluster standard errors at the state-year level.

To test this second hypothesis, we use a strategy that directly measures the quality of firms founded by the workers in the sample and estimates whether mean quality declines following increases in the local unemployment rate. In contrast to the prior test, we start by estimating our specification with no fixed effects, and then introduce the full battery of fixed effects introduced above. We follow this approach to compare the full distribution of individuals who become entrepreneurs during good and bad labor markets. We therefore estimate the linear probability model:

[25] In robustness tests, we also test the model with the unemployment rate in year t and $t+1$ separately.

[26] The results similarly hold if we define local unemployment at the county-level or the national level.

[27] The results remain quantitatively similar if we instead include three-year or four-year rolling windows.

$$\begin{aligned}\text{Firm Quality}_{i,t} &= \beta \times \text{Local Unemployment}_{i,t\to t+1} \qquad (2)\\ &+ \text{University} \times \text{Cohort FE} \times \text{Gender FE}\\ &+ \text{Industry FE} + \eta_{i,t}\end{aligned}$$

where $FirmQuality_{i,t}$ is a binary variable measuring the success of the given entrepreneurial venture started by student i graduating in year t. We develop multiple measures of entrepreneurial quality based on: (i) firm survival, (ii) firm employment size, (iii) patent creation, (iv) access to venture capital financing, (v) acquisition by another firm, and (vi) successful Initial Public Offering (IPO). As before, the independent variable of interest is $Local\ Unemployment_{i,t\to t+1}$, and measures the average unemployment rate in year t and $t+1$ in the state where the college of individual i is located. The coefficient β then measures the impact of the local employment shock on the mean quality of entrepreneurship; according to our hypothesis, $\beta < 0$. As in the prior specification, we include a university fixed effect interacted with a cohort fixed effect and a gender fixed effect. We now also include an industry fixed effect for each two-digit NAICS code. Finally, we cluster standard errors at the state-year level.

We follow a similar framework to test our third hypothesis: focusing on a subset of entrepreneurs in the sample that responded to an online survey, we evaluate whether the proportion of risk (or ambiguity) averse entrepreneurs declines following increases in the local unemployment rate. We therefore estimate the linear probability model:

$$\begin{aligned}\text{Risk-Averse Entrepreneur}_{i,t} &= \beta \times \text{Local Unemployment}_{i,t\to t+1} \qquad (3)\\ &+ \text{University FE} + \text{Cohort FE} + \text{Gender FE}\\ &+ \theta \times \text{Worker Controls}_i\\ &+ \phi \times \text{Firm Controls}_i + \text{Industry FE} + \eta_{i,t}\end{aligned}$$

where $Risk - Averse\ Entrepreneur_{i,t}$ is a binary variable denoting whether worker i graduating in year t is risk-averse. We consider a related measure of ambiguity preferences. The independent variable of interest is again $Local\ Unemployment_{i,t\rightarrow t+1}$, and measures the average unemployment rate in year t and $t+1$ in the state where the college of individual i is located. The coefficient β then measures the impact of the local employment shock on the mean level of risk-aversion; according to our hypothesis, $\beta > 0$. In contrast to before, we no longer interact fixed effects due to the smaller sample size; instead we include cohort, university, and gender fixed effects independently. As before, we include industry fixed effects for the industry of the start-up. In addition, we now control for other behavioral characteristics, namely the confidence and optimism of each worker. We also control for the firm's characteristics as risk and ambiguity aversion may be driven by the entrepreneurial experiences of the workers in the sample. Finally, we cluster standard errors at the state-year level.

5 Results

We divide the discussion of our results into four parts. First, we confirm an increase in local unemployment leads to an increased likelihood of underemployment among workers in the sample. Second, we estimate the impact of labor market shocks on firm creation. Third, we evaluate whether these shocks also impact the quality of entrepreneurship. Fourth, we consider the relationship between the risk aversion of entrepreneurs and local unemployment shocks.

5.1 Local Employment Shocks and Labor Outcomes

The underlying assumption motivating our empirical framework is that labor market outcomes impact the job outcomes of recent college graduates. Therefore, we first offer empirical evidence of this assumption within our student population. Our primary measure defines underemployment based on the percent of workers entering top financial and consulting firms. We have two motivations for this measure. First, evaluating the labor market of Stanford MBA graduates, Oyer (2008) estimates that not entering the financial sector due to poor market conditions leads to a decrease in lifetime earnings of $1.5 - $5 million. Given nearly 100,000 of the workers in our sample graduates from a top twenty undergraduate institution, we believe this measure is applicable to our own sample and highlights the cost imposed on high-skill workers. Second, recent evidence by Gupta and Hacamo (2018) argues that the rise of the financial and consulting sector had a significant impact on the rate of entrepreneurship and innovation among workers completing engineering degrees at high-ranking institutions.

In addition, we offer two alternative definitions of underemployment. Our second measure is based on prior evidence that recessions lead college graduates to join less desirable employers even within the same occupation (Oreopoulos et al., 2012; Oyer, 2006; Schoar and Zuo, 2017). We identify desirable employers in our setting as firms listed in the Russell 1000 Index, which allows for employers across a variety of industries and occupations. Motivated by Kahn (2010) and Bell and Blanchflower (2011), our third measure focuses directly on the wage impacts of graduating in a poor labor market. Though we cannot directly observe individual-level wages in our setting, we develop proxies based on mean salary in top occupations at the industry-level.[28] These estimates are based on data available from the Bureau of Labor Statistics.

We present our findings in Panel A of Table 4. The independent variable is the unemployment rate at the time of graduation and located in the state of the undergraduate institution. In the odd columns, we include university fixed effects, gender, and cohort fixed effects separately; in the even columns, we interact university, gender, and cohort fixed effects. Recall a cohort fixed effect is a fixed effect for all students in the same academic major and graduating within a two-year window. Across all measures, we find significant evidence that local unemployment shocks lead to lower job quality among college graduates. Specifically, a ten percentage point increase in the local unemployment rate decreases the likelihood of employment in the finance or consulting sector by 3.5%, the likelihood

[28] We provide additional details concerning these occupations in the data section.

of a job in a desirable firm (defined as employers in the Russell 1000 Index) by 9.8%, and the chance of joining a high-wage industry by 4.6%. The results offer strong support our empirical setting.

5.2 Local Employment Shocks and Entrepreneurship

Linear Specification. Panel A of Table 5 reports the linear relationship between local unemployment and entry to entrepreneurship. Our dependent variable is a binary variable taking a value of one when the student becomes an entrepreneur within a certain number of years following graduation. The first two columns consider firms started within one year of graduation from the Bachelor's Degree, while the following columns consider firms started within two, three, and four years post graduation. We consider two specifications. The specifications in the odd columns include a fixed effect for each academic institution, gender, and cohort; the specification in the odd columns interacts these fixed effects. This way we only compare graduates from consecutive years with the same major and of the same gender. For example, we only compare a female Stanford engineering graduate from the class of 1998 with a female Stanford engineering graduate from the class of 1999. Within our more restrictive specification, 9,004 observations (out of 641,144) are absorbed by the fixed effects, and the average comparison group contains 17.54 individuals.

According to the first and second column, a 10 percentage point increase in the unemployment rate increases the rate of entrepreneurship by 2.14 percentage points in the year following graduation and the coefficient is statistically significant at the one percent level. Relative to a baseline entrepreneurship rate of 2.2% within the year following graduation, we observe the entrepreneurship rate nearly doubles following a 10 percentage point increase in unemployment. For comparison, Evans and Leighton (1989) and Evans and Leighton (1990) find that unemployed workers are twice as likely to transition to self-employment.[29]

One potential concern is that unemployment shocks alter the timing of firm creation; in other words, poor labor market opportunities may encourage future entrepreneurs to start their firm right after graduation. To address this issue, we evaluate whether the relationship between unemployment shocks and entrepreneurship decreases as the time horizon increases. According to Panel A of Table 5, a 10 percentage point increase in the unemployment rate increases the cumulative rate of entrepreneurship by 2.36 percentage points within two years, 2.37 percentage points within three years, and 2.4 percentage points within four years. Therefore, we document that unemployment shocks lead to a permanent increase in the rate of entrepreneurship as the non-treated group fails to catch up with the treated group.

Nonlinear Specification. Given the likelihood of firm creation within four years of graduation is only 3.9% according to Table 1, the binary dependent variable takes a value of one for only a small set of students. This potentially raises concerns that the linear probability model is a misfit for this application. To mitigate these concerns, we also estimate our results under a probit regression model to ensure the results are robust to the modeling choice in the baseline estimation. Table A3 of the online appendix reports these estimates. We confirm that an increase in the state unemployment rate increases the rate of entrepreneurship within the year following graduation; in addition, this effect continues to hold through the four years after graduation. The results suggest our prior estimates under the linear probability model do not depend on the particular empirical specification.

Robustness to Sample. In Table A4 of the online appendix, we also evaluate whether the results are driven by a small sample of the workers in our data. We test this in four ways. First, we exclude workers graduating in the peak of the two recessions in our

[29] In unreported results we also find female workers are 1.4% less likely to enter entrepreneurship than comparable men in the first year following graduation and 2.1% less likely within four years. Our results reinforce prior evidence of low rates of female entrepreneurship (Fairlie and Robb, 2009; Jennings and Brush, 2013).

period: 2002 and 2010. Second, we exclude workers graduating in California. Third, we exclude workers employed in the technology industry. Fourth, we impose the last three conditions simultaneously; that is, we exclude workers graduating in the two recessions, graduating from California schools, or employed in the technology industry. Acrsso the specifications, we estimate a 10 percentage point increase in the local unemployment rate increases the four-year entrepreneurship rate by 2.1-2.34 percentage points (compared to the 2.4 percentage point increase with the full sample of observations). Our results do not appear to depend on any specific industry, geography, or year.

In addition, a separate concern is that the students entering entrepreneurship were not necessarily intending to enter the workforce following graduation. Instead, these students would have entered graduate school if only they graduated during a period of low local unemployment. While this offers an alternative counterfactual to our hypothesis, we provide two arguments against this opposing narrative. First, according to Panel A of Table 4, we document that college graduates are more, rather than less, likely to enter a graduate program when graduating in a poor labor market, confirming the findings of Johnson (2013) for our own sample. Second, Table A4 excludes all workers that entered a graduate program within the four years following college graduation. We confirm that a negative local labor shocks increases the rate of entrepreneurship by 2.5 percentage points.

Alternate Definitions of Entrepreneurship. To identify firm creation, we require (i) the individual is identified as the founder of the firm, and (ii) no other employees joined the firm prior to the individual. One concern with this definition is that employment shocks may only influence the creation of small and unsuccessful firms. Assuming the economic value of firm creation is contingent on the likelihood of survival and growth, we should instead evaluate whether economic conditions impact the rate of successful firm creation in our setting. To this end, we tighten the definition of an entrepreneur based on reaching a particular threshold of entrepreneurial success. In Panel A of Table 6 we require the firm (i) remains in business as of 2019, (ii) currently employs at least 10 workers, (iii) currently employs at least 20 workers, and (iv) currently employs at least 50 workers. In Panel B, we instead require the firm (i) developed at least one patent, (ii) received venture capital funding, (iii) was acquired, or (iv) successfully completed an Initial Public Offering.

In the first and second columns of Panel A of Table 6, we estimate the impact of peers on establishing firms still present in 2019. Combined with the results from Table 5, these estimates find that 23% of the firms started due to heightened unemployment risk remain in business today. In the third and fourth columns we require the firm is still in business and employs at least ten employees. In the fifth and sixth (seventh and eighth) columns we require the firm is still in business and employs at least twenty (fifty) employees. Among the firms created due to weak labor markets, nearly 5% employ at least fifty employees today.

In the first and second column of Panel B of Table 6, we estimate that 5% of the firms founded due to local labor shocks in our sample hold at least one patent. In the third and fourth column, we estimate 15% of the firms founded in the sample due to depressed labor opportunities receive venture funding. In the fifth and sixth column, we estimate that 3.3% of the firms created during distressed labor markets are acquired by other firms. In sum, local labor opportunities influence the likelihood of significant and resilient firms, highlighting the potential for real effects on the economy.

5.3 Local Employment Shocks and Entrepreneurial Quality

Cross-Sectional Comparison of Entrepreneurial Quality. The results above confirm our first hypothesis: decreased employment opportunities lead to increased entry to entrepreneurship among recent college graduates. We next evaluate the second hypothesis: local employment shocks impact the relative quality of entrepreneurial firms. Testing this hypothesis depends on directly observing the success of entrepreneurial endeavors. Similar to Table 6, we measure quality across several measures: (i) remains in business as of 2019, (ii) currently employs at least x workers, (iii) developed a new patent, (iv) received venture capital financing, (v) was acquired, or (vi) completed an Initial Public Offering. We define each measure as a binary variable.

We first present a simple comparison of firm outcomes in Panel A of Figures 6 through 8. For each year of graduation, we split students based on whether the state experiences unemployment above or below the median state. We then classify entrepreneurs graduating in states with above median unemployment in that year as "forced" and other entrepreneurs as "voluntary". In Figure 6 we estimate the percent of firms still in business separately for each year t following establishment from year one to year ten. In Figure 7 we estimate the cumulative percent of firms creating at least one patent by year t following establishment; in Figure 8 we estimate the cumulative percent of firms that received venture capital by year t.[30]

First, in Panel A of Figure 6 we estimate largely identical survival rates for both "forced" entrepreneurs and "voluntary" entrepreneurs; in other words, the local unemployment rate has little explanatory power in the survival of the entrepreneurial endeavor. Second, in Panel A of Figure 7 we find similar patenting rates across both sets of entrepreneurs. Third, in Panel A of Figure 8 we actually find evidence that entrepreneurs graduating in a poor local labor market are roughly two percent more likely to obtain venture capital financing relative to entrepreneurs graduating in the same year in a better local labor market and this difference holds across the lifecycle of the firm.

Regression Analysis of Entrepreneurial Quality. The figures discussed above offer little evidence that workers entering entrepreneurship during periods of high local unemployment are worse entrepreneurs. However, the downside with this analysis is that systematic differences across states may confound the comparison between "force" and "voluntary" entrepreneurs. To offer a comparison free of selection biases, we compare same gender entrepreneurs who graduated from the same university and major, but in consecutive years. Specifically, we estimate the regression model introduced in Equation 2 of section

[30] We acknowledge we are not able to conduct this analysis for employment as we are only able to observe the employment of the firm as of 2019. While we are able to conduct this analysis for the acquisition and IPO rate; only a few firms in our sample undergo an acquisition or IPO within the first several years after establishment, dramatically lowering the power of the statistical test.

4.2. Within this restrictive specification we have 2,567 observations absorbed by the fixed effects; on average, the comparison group contains 2.81 entrepreneurs.

We present the results in Table 7. As we limit this analysis to entrepreneurs founding firms within five years of graduation, our sample drops to 12,059 total observations. We consider two separate specifications. In the odd columns, we only include cohort fixed effects; in the even columns we interact cohort, university, and gender fixed effects and separately include industry fixed effects. In contrast with the tests for the first hypothesis, it is necessary to estimate our regressions without any fixed effects before saturating the regression with fixed effects. If one of the characteristics absorbed by the fixed effects explains entrepreneurial success, we might find a spurious null result. For example, some universities may equip individuals to be become better entrepreneurs. In such case, university fixed effects would absorb important variation as it would not allow us to learn whether negative labor shocks push less of these individuals into entrepreneurship. The inclusion of university fixed effects would then incorrectly lead us to conclude that there is no difference in quality between *force* and *voluntary* entrepreneurs.

Across both Panel A and B, we find limited statistical evidence that local employment shocks decrease the quality of entrepreneurship. In contrast to the hypothesis, we estimate a 10 percentage point increase in unemployment leads to a 12-16 percentage point increase in likelihood of survival, an 11-14 percentage point increase in the likelihood of receiving venture capital within five years of establishment, and a 1-2 percentage point increase in the likelihood of patent creation within five years of establishment. In addition, we find no relationship between the unemployment rate and (i) employment, (ii) acquisition, or (iii) an initial pubic offering. Taken together, this evidence refutes the hypothesis that individuals sort into entrepreneurship based on entrepreneurial ability.

The results are in contrast to recent evidence by Moreira (2016), who offers convincing evidence that firms started during recessions are both small in initial size and experience limited growth compared to firms founded in more favorable environments. One likely explanation for this discrepancy is that by (i) focusing exclusively on firms founded by recent college graduates and (ii) more cleanly isolating the effect of labor market shocks, we are able to better analyze the implications of job market opportunities as opposed to decreased demand and financing.[31]

Quality across the Firm Lifecycle. Overall, the results highlight limited differences in entrepreneurial quality between entrepreneurs graduating in weak and tight local labor markets. A potential downside of the specification above is that we cannot easily compare differences in entrepreneurial quality across the lifecycle of the firm. For instance, entrepreneurs graduating in a weak labor market may start smaller firms upon establishment; however, these firms grow more quickly and eventually reach the employment size of their competitors. In this section we compare firm quality across multiple points in time. Specifically, we estimate the relationship between the state-unemployment rate and firm outcomes for each year since establishment. As before, compare firms within the same industry and year of establishment. We also continue to interact university fixed effects with cohort fixed effects.

We present the findings in Panel B of Figures 6 through 8. In Figure 6 we estimate the percent of firms still in business in year t, where $t = 1, .., 10$. In Figure 7 we estimate the cumulative percent of firms creating at least one patent by year t; in Figure 8 we estimate the cumulative percent of firms that received venture capital by year t. We plot both the estimated coefficient along with the 95% confidence intervals.

First, in Panel B of Figure 6 we estimate that graduating during a period of high local unemployment decreases the likelihood of surviving for the first four years following establishment, slightly increases the likelihood of surviving to years five through seven, and then has limited effects on surviving eight years of more. Given the lack of any specific pattern, we find limited evidence labor market opportunities decrease the rate of survival. Second, in Panel B of Figure 7 we find evidence that graduating during a poor labor market leads to higher rates of patent creation, though the results are not always statistically

[31] Note that in our setting we exploit variation in unemployment rates even during non-recession periods at the national level.

significant at the 5% level. Third, according to Panel B of Figure 8 entrepreneurs graduating during a period of high local unemployment are more likely to receive venture capital for every year after establishment. Across the lifecycle of the firm, we find no evidence that local labor market opportunities lead to a decline in average entrepreneurial quality.

Entrepreneurs Entering within Two Years of Graduation. In Table 7 we include all firms founded by workers within five years of college graduation. However, if the costs of graduating during a recession decline over time, workers entering entrepreneurship several years following graduation may no longer be limited by labor market opportunities. To overcome this concern, we augment the analysis above by considering only firms started within two years following graduation in Table 8, reducing the sample to 6,335 observations. Within this subsample of workers, we continue to find evidence that unemployment rate increases (rather than decreases) the likelihood of survival and venture-capital funding; however, we no longer document any effect on patent creation. Other measures are not statistically different from zero. Overall, we again find no support of a decrease in entrepreneurial quality.

Entrepreneurs Graduating prior to 2005. A separate concern with our empirical framework is that graduating in a poor labor market will encourage potential entrepreneurs to more quickly start a new firm; these workers will then have more time to expand the business and reach significant milestones. Given this concern, we next consider the subset of workers graduating in the first half of the sample (prior to 2005) to allow all entrepreneurial ventures the time necessary to access financing, innovate, and grow. We present the results in Table 9: again, poor labor market opportunities do not appear to impact the mean quality of new firms.

Entrepreneurs without Graduate Degrees (MS, JD, MBA and PhD). We have previously confirmed that students facing a tough labor market are more likely to apply and enter graduate programs according to Panel A of Table 4. If these programs increase human capital and improve the entrepreneurial ability of the student, firms founded by workers graduating during a period of high unemployment may actually have a greater chance of success. While this does not necessarily disqualify the results, it does limit the external validity of the results for older workers. Therefore in Table A6, we exclude all workers holding a graduate degree (i.e., Masters, MBA, JD, and PhD); we then include all firms founded within five years following the entrepreneur's graduation from college. After this restriction, we are left with 9,296 new firms. We find evidence that workers graduating in a weak labor market start firms that are more likely to survive and receive venture capital funding. We find no other evidence that the labor market impacts alternative measures of success.

5.4 Local Employment Shocks and Ex-Ante Entrepreneurial Ability

Identifying Ex-Ante Entrepreneurial Ability. Overall, we find limited evidence that workers select into entrepreneurship based on potential ability. A potential explanation of our findings is that even workers with the greatest entrepreneurial skills are impacted by local employment shocks, leading to increased rates of entrepreneurship without any decline in average quality. Testing this argument directly is challenging as it requires identifying ex-ante predictors of entrepreneurial ability across all workers, not just those entering entrepreneurship. In this section, we replicate our analysis on a subset of workers especially likely to hold significant entrepreneurial abilities.

Specifically, we focus on the 115,249 workers in our sample that graduated from a top twenty institution as defined by U.S. News and World Report. Our focus on workers graduating from top institutions is motivated by prior evidence that city-level education predicts both the rate and quality of entrepreneurship (Doms et al., 2010) as well as worker-level results confirming entrepreneurial quality is related to academic achievement (Gupta and Hacamo, 2018; Walsh and Nagaoka, 2009). In addition, we offer our own evidence that successful entrepreneurs disproportionately graduate from one of these highly-selective institutions. In Table 10, we analyze the set of all entrepreneurs in the sample. Across all measures of entrepreneurial quality—survival, employment growth, access to venture-capital, exit through acquisition, entering an IPO, and patent creation—we estimate that entrepreneurs graduating from one of the top-ranked institutions are more likely to achieve success. For instance, relative to firms created by entrepreneurs from non-elite universities, these firms are 9% more likely to survive, 7% more likely to be financed through venture-capital, 3% more likely to employ at least fifty workers, 2% more likely be acquired, and 2% more likely to develop a patent.

Impact of Local Employment Shocks. Next, in Panel B of Table 4 we estimate the impact of local employment opportunities on the underemployment rate of workers graduating from selective institutions. We estimate that a 10 percentage point increase in the local unemployment rate decreases the rate of employment with top finance or consulting firm by 5 percentage points; in comparison, we estimate a 3 percentage points decline for all other workers, and this difference is statistically significant at the one percent level. In addition, we estimate a 10 percentage point decrease in the likelihood of joining a Russell 100 employer (compared to a similar 10 percentage point decline for all other workers) and a 5 percentage point decrease in employment within a high-wage industry (compared to a 4 percentage point decrease for other workers). The results offer no evidence that employment shocks are less costly for graduates of high-ranked undergraduate institutions.

Given the results above, we expect these workers may be more likely to enter entrepreneurship when graduating into a poor labor market. In Panel B of Table 5, we estimate a 10 percentage point increase in the local unemployment rate leads to a 3.1 percentage point increase in the rate of entrepreneurship among workers graduating from top-ranked institutions. For comparison, we estimate a 1.9 percentage point increase among all other workers in the sample, and this difference is statistically significant at the one percent level. In addition, we confirm the effect remains greater among graduates of high-ranked undergraduate institutions four-years after graduation (3.6 percentage points compared to 2.1 percentage points). Therefore, we find no evidence that increasing unemployment rates decrease the proportion of high-performing students entering entrepreneurship.

Finally, in Table A5 of the online appendix, we examine whether local employment opportunities decrease the average quality of firms founded by workers graduating from top-ranked institutions. We consider the set of entrepreneurs starting a firm within five years of graduation, though the results are similar if we do not place a restriction on the time until firm creation. Across all specifications, we find graduating in a poor labor market is associated with a greater rate of survival and venture capital, but a lower rate of acquisition. By all other measures, we find no statistically significant effects. The results help further confirm that local unemployment shocks have limited impacts on the quality of entrepreneurship in the economy.

The value of this analysis is to compare workers across different institutions. Our empirical framework explicitly compares workers graduating from the same institution, but in the prior year. While this allows us to isolate the impact of an employment shock, it also excludes the possibility of comparing workers across institutions. For instance, as we have just illustrated, highly selective institutions disproportionately graduate workers with high entrepreneurial potential; in this environment, local employment opportunities may still reduce average entrepreneurial quality if workers from these institutions are less impacted by the cost of employment shocks. As evidence against this argument, we have found that workers graduating from highly-selective institutions are equally affected by local labor market shocks and slightly more likely to enter entrepreneurship following these shocks relative to other workers in the sample. Therefore, we find no evidence that local employment shocks impact the entrepreneurship rates across institutions.

5.5 Local Employment Shocks and the Risk Preferences of Entrepreneurs

Risk And Ambiguity Aversion. When workers enter entrepreneurship based on their known entrepreneurial ability, decreased labor market opportunities lower the quality of entrepreneurship in the economy. However, the results above offer little evidence of this hypothesis. The purpose of this next section of the paper is to offer evidence for an alternate theory of entrepreneurship. Specifically, we test whether the decision to enter entrepreneurship may depend on an individual's risk or ambiguity preferences as opposed to known abilities. Testing this relationship is challenging as measures of risk preferences are generally difficult to directly observe. Due to these obstacles, we directly survey a representative sample of the entrepreneurs included in our analysis.

We present the initial results of the survey in Panel A of Figure 5. For each year of graduation, we plot the percent of surveyed entrepreneurs reporting high risk aversion. In line with our hypothesis, we find entrepreneurs graduating during periods of high unemployment (in particular 2002 and 2010) are more risk averse than entrepreneurs graduating during other years. The results support the argument that workers sort into entrepreneurship based on risk preferences.

For a more careful examination of the survey responses, we analyze the data under three separate regression specifications in Table 11. First, we include separate fixed effects for each cohort and university. In the second specification, we add fixed effects for gender and industry. We also control for the workers general confidence, confidence in entrepreneurship, and optimism, as these traits may predict a worker's inclination towards entrepreneurship and be correlated with risk aversion. In the final specification, we also control for the characteristics of the new firm as entrepreneurs graduating during a recession may be more risk and ambiguity averse due to their entrepreneurial experience.

The first, second, and third column consider the responses concerning risk aversion (Q1), while fourth through sixth columns consider ambiguity aversion (Q2). According to our findings, an increase in the state unemployment rate leads to an increase in the rate of risk-averse entrepreneurs. Across all three specifications, the result is statistically significant at the one percent level. We also estimate an increase in unemployment increases the rate of ambiguity averse entrepreneurs and the result is statistically significant at the five percent level.

One possible concern is that risk and ambiguity aversion are not static measures, but instead driven by entrepreneurial experiences. If this is the case, then successful entrepreneurs may be less risk and ambiguity averse. However, we find no evidence that an entrepreneur's risk aversion or ambiguity aversion is correlated with the success of the new venture across any definition of success. The results helps support our argument these preference measures are unique to the individual and do not vary across time.

Risk Tolerance of Non-Entrepreneurs. As we acknowledge above, we are only able to observe risk and ambiguity tolerance as of 2019, rather than prior to entry into the workforce. This is a potential concern if risk and ambiguity vary across time (Cohn et al., 2015; Guiso et al., 2018); in our setting, workers graduating in a period of weak labor market opportunities may then develop a preference against risk and ambiguity. This will lead all workers, including entrepreneurs, to report higher risk and ambiguity aversion. This can offer an alternative explanation of Table 11.

To overcome this concern, we also survey 508 workers that have never started a firm. We argue that if risk and ambiguity preferences are influenced by business cycle dynamics, this effect will likely be present among both entrepreneurs and non-entrepreneurs. According to Figure 4, we estimate a higher rate of risk and ambiguity-aversion of non-entrepreneurs compared to entrepreneurs. In particular, we estimate 46% of non-entrepreneurs are defined as risk-averse according to our measure (compared to 35% of entrepreneurs). Similarly, we estimate 53% of non-entrepreneurs have are ambiguity-averse (compared to 40% of entrepreneurs). As these differences are statistically different, the results further support the argument that workers sort into entrepreneurship based on risk preferences.

We offer two pieces of evidence that non-entrepreneurs graduating in a poor labor market are not more risk or ambiguity-averse. First, we plot the proportion of risk-averse non-entrepreneurs by year of graduation in Panel B of Figure 5. According to the figure, we first note a high percentage of non-entrepreneurs are risk-averse compared to entrepreneurs graduating in the same year. Second, we note the risk-aversion of non-entrepreneurs does not increase during periods of high unemployment; if anything, we estimate risk-aversion is greatest among workers graduating during a period of low unemployment.

Second, we present these results in regression-form in Table 12. In the first and second column we evaluate risk-aversion, while the third and fourth column evaluate ambiguity-aversion. In addition, we include cohort fixed effects in all specifications as well as university fixed effects in the second and fourth column. We estimate that an increase in the local unemployment rate decreases the proportion of risk-aversion and ambiguity-averse workers, though the result is not statistically significant once we include university fixed effects. This is at odds with prior arguments that risk aversion increases following periods of poor labor market opportunities. Overall, we find limited evidence that recessions lead to more risk-averse workers in our sample.

Alternate Behavioral Explanations. Confirming that workers select into entrepreneurship based on risk and ambiguity tolerance is difficult as we are not able to observe and control for all other selection factors, especially behavioral factors. To partially alleviate this concern, we next verify that the workers in our sample do not appear to select into entrepreneurship based on alternative behavioral characteristics. In Panel A and B of Table 13 we examine the relationship between local employment opportunities and the behavioral traits of entrepreneurs. In contrast with our hypothesis, we find a positive relationship between local unemployment rates and future salary expectations. Across all other measures, we find no evidence that entrepreneurs graduating in poor labor markets are less confident in their entrepreneurial abilities, less confident in their general abilities, or less optimistic. The results offer an additional confirmation that risk and ambiguity aversion are unique and valid predictors of entry to entrepreneurship.

6 Conclusion

This paper evaluates whether local labor market opportunities impact the rate and composition of entrepreneurship. We find individuals graduating in a weak local labor market are not only more likely to be underemployed, but also more likely to start a firm. However, developing multiple measures of entrepreneurial success, we find no evidence that business formed during recession years perform worse than non-recession firms. Instead, entrepreneurs graduating during a recession are more risk and ambiguity averse despite no difference in their actual quality. As a result, our findings support the (Kihlstrom and Laffont, 1979) view of entrepreneurship based on risk preferences, while rejecting the argument that workers select into entrepreneurship based on ability (Lucas Jr, 1978).

More broadly, this paper highlights the current data limitations researchers face when studying firm creation. Current datasets lack detailed information on both founder characteristics (such as occupation and education) as well as the attributes of small firms (employment size, revenue, financial access). By relying on newly hand-collected data from LinkedIn, we have developed a unique dataset covering over 640,000 college graduates across the United States. This dataset represents over 3% of all students graduating from an undergraduate institution during this period. We then combine this data with worker-level surveys detailing behavioral preferences not otherwise observable. Collectively, this paper illustrates the value of this data for research purposes, especially to understand dynamics and preferences of workers entering entrepreneurship.

References

P. Aghion, P. Howitt, M. Brant-Collett, and C. Garcia, D.a-Penalosa. *Endogenous growth theory*. MIT press, 1998.

A. Agrawal and P. Tambe. Private equity and workers' career paths: the role of technological change. *The Review of Financial Studies*, 29(9):2455–2489, 2016.

M. Aguiar, E. Hurst, and L. Karabarbounis. Time use during the great recession. *The American Economic Review*, 103(5):1664–1696, 2013.

T. Ahn. Attitudes toward risk and self-employment of young workers. *Labour Economics*, 17(2):434–442, 2010.

J. G. Altonji, L. B. Kahn, and J. D. Speer. Cashier or consultant? Entry labor market conditions, field of study, and career success. *Journal of Labor Economics*, 34(S1):S361–S401, 2016.

T. Åstebro, S. A. Jeffrey, and G. K. Adomdza. Inventor perseverance after being told to quit: The role of cognitive biases. *Journal of Behavioral Decision Making*, 20(3):253–272, 2007.

T. Astebro, H. Herz, R. Nanda, and R. A. Weber. Seeking the roots of entrepreneurship: Insights from behavioral economics. *Journal of Economic Perspectives*, 28(3):49–70, 2014.

T. Babina. Destructive creation at work: How financial distress spurs entrepreneurship. *Available at SSRN*, 2015.

R. Baghai, R. Silva, V. Thell, and V. Vig. Talent in distressed firms: Labor fragility and capital structure. Technical report, Working paper, Stockholm School of Economics and London Business School, 2015.

W. J. Baumol. Entrepreneurship in economic theory. *The American Economic Review*, pages 64–71, 1968.

D. N. Bell and D. G. Blanchflower. Young people and the great recession. *Oxford Review of Economic Policy*, 27 (2):241–267, 2011.

P. Belley and L. Lochner. The changing role of family income and ability in determining educational achievement. Technical report, National Bureau of Economic Research, 2007.

O. Bengtsson and D. Ekeblom. The bright but right view? A new type of evidence on entrepreneurial optimism. 2014.

J. Brown and D. A. Matsa. Boarding a sinking ship? An investigation of job applications to distressed firms. Technical report, National Bureau of Economic Research, 2012.

C. Camerer and D. Lovallo. Overconfidence and excess entry: An experimental approach. *American Economic Review*, 89(1):306–318, 1999.

A. Cohn, J. Engelmann, E. Fehr, and M. A. Maréchal. Evidence for countercyclical risk aversion: An experiment with financial professionals. *American Economic Review*, 105(2):860–85, 2015.

J. S. Cramer, J. Hartog, N. Jonker, and C. M. Van Praag. Low risk aversion encourages the choice for entrepreneurship: An empirical test of a truism. *Journal of Economic Behavior & Organization*, 48(1):29–36, 2002.

R. Decker, J. Haltiwanger, R. Jarmin, and J. Miranda. The role of entrepreneurship in US job creation and economic dynamism. *The Journal of Economic Perspectives*, pages 3–24, 2014.

F. Delmar and P. Davidsson. Where do they come from? Prevalence and characteristics of nascent entrepreneurs. *Entrepreneurship & regional development*, 12(1):1–23, 2000.

M. Doms, E. Lewis, and A. Robb. Local labor force education, new business characteristics, and firm performance. *Journal of Urban Economics*, 67(1):61–77, 2010.

D. S. Evans and L. S. Leighton. Some empirical aspects of entrepreneurship. *The American Economic Review*, pages 519–535, 1989.

D. S. Evans and L. S. Leighton. Small business formation by unemployed and employed workers. *Small business economics*, 2(4):319–330, 1990.

R. W. Fairlie and A. M. Robb. Gender differences in business performance: Evidence from the characteristics of business owners survey. *Small Business Economics*, 33(4):375, 2009.

H. S. Farber. Alternative and part-time employment arrangements as a response to job loss. Technical report, National Bureau of Economic Research, 1999.

A. Foote. Where do college graduates go for jobs? *U.S. Census Bureau America Counts; Behind the Numbers*, 2019.

T. C. Fort, J. Haltiwanger, R. S. Jarmin, and J. Miranda. How firms respond to business cycles: The role of firm age and firm size. *IMF Economic Review*, 61(3):520–559, 2013.

Gallup. Many potential entrepreneurs aren't taking the plunge. *Business Journal*, 2014.

J. D. Gottlieb, R. R. Townsend, and T. Xu. Experimenting with entrepreneurship: The effect of job-protected leave. 2016.

J. R. Graham, H. Kim, S. Li, and J. Qiu. Human capital loss in corporate bankruptcy. *Available at SSRN 2276753*, 2013.

J. Grogger and E. Eide. Changes in college skills and the rise in the college wage premium. *Journal of Human Resources*, pages 280–310, 1995.

L. Guiso, P. Sapienza, and L. Zingales. Time varying risk aversion. *Journal of Financial Economics*, 128(3): 403–421, 2018.

N. Gupta and I. Hacamo. Superstar (and entrepreneurial) engineers in finance jobs. Technical report, Kelley School of Business, Indiana University, 2018.

R. E. Hall and S. E. Woodward. The burden of the nondiversifiable risk of entrepreneurship. *American Economic Review*, 100(3):1163–94, 2010.

B. H. Hamilton. Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy*, 108(3):604–631, 2000.

H. J. Holm, S. Opper, and V. Nee. Entrepreneurs under uncertainty: An economic experiment in china. *Management Science*, 59(7):1671–1687, 2013.

J. Hombert, A. Schoar, D. A. Sraer, and D. Thesmar. Can unemployment insurance spur entrepreneurial activity? Evidence from france. *HEC Paris Research Paper No. FIN-2013-1020*, 2019.

E. Hurst and A. Lusardi. Liquidity constraints, household wealth, and entrepreneurship. *Journal of Political Economy*, 112(2):319–347, 2004.

H. K. Hvide and G. A. Panos. Risk tolerance and entrepreneurship. *Journal of Financial Economics*, 111(1): 200–223, 2014.

L. S. Jacobson, R. J. LaLonde, and D. G. Sullivan. Earnings losses of displaced workers. *The American Economic Review*, pages 685–709, 1993.

J. Jeffers. The impact of restricting labor mobility on corporate investment and entrepreneurship. *Working Paper*, 2018.

J. E. Jennings and C. G. Brush. Research on women entrepreneurs: challenges to (and from) the broader entrepreneurship literature? *The Academy of Management Annals*, 7(1):663–715, 2013.

M. T. Johnson. The impact of business cycle fluctuations on graduate school enrollment. *Economics of education review*, 34:122–134, 2013.

L. B. Kahn. The long-term labor market consequences of graduating from college in a bad economy. *Labour Economics*, 17(2):303–316, 2010.

R. E. Kihlstrom and J.-J. Laffont. A general equilibrium entrepreneurial theory of firm formation based on risk aversion. *Journal of political economy*, 87(4):719–748, 1979.

F. H. Knight. Cost of production and price over long and short periods. *Journal of Political Economy*, 29(4): 304–335, 1921.

M. Koudstaal, R. Sloof, and M. Van Praag. Risk, uncertainty, and entrepreneurship: Evidence from a lab-in-the-field experiment. *Management Science*, 62(10):2897–2915, 2015.

K. Liu, K. G. Salvanes, and E. Ø. Sørensen. Good skills in bad times: Cyclical skill mismatch and the long-term effects of graduating in a recession. *European Economic Review*, 84:3–17, 2016.

R. E. Lucas. On the mechanics of economic development. *Journal of monetary economics*, 22(1):3–42, 1988.

R. E. Lucas Jr. On the size distribution of business firms. *The Bell Journal of Economics*, pages 508–523, 1978.

S. Moreira. Firm dynamics, persistent effects of entry conditions, and business cycles. 2016.

G. Moscarini and F. Postel-Vinay. The contribution of large and small employers to job creation in times of high and low unemployment. *American Economic Review*, 102(6):2509–39, 2012.

T. J. Moskowitz and A. Vissing-Jørgensen. The returns to entrepreneurial investment: A private equity premium puzzle? *American Economic Review*, 92(4):745–778, 2002.

National Center for Education Statistics. Characteristics of postsecondary students. *The Condition of Education*, 2017.

National Center for Education Statistics. Digest of education statistics, 2018.

P. Oreopoulos, T. Von Wachter, and A. Heisz. The short-and long-term career effects of graduating in a recession. *American Economic Journal: Applied Economics*, 4(1):1–29, 2012.

P. Ouimet and R. Zarutskie. Who works for startups? the relation between firm age, employee age, and growth. *Journal of Financial economics*, 112(3):386–407, 2014.

P. Oyer. Initial labor market conditions and long-term outcomes for economists. *Journal of Economic Perspectives*, 20(3):143–160, 2006.

P. Oyer. The making of an investment banker: Stock market shocks, career choice, and lifetime income. *The Journal of Finance*, 63(6):2601–2628, 2008.

S. C. Parker. *The economics of entrepreneurship*. Cambridge University Press, 2009.

M. Puri and D. T. Robinson. Optimism and economic choice. *Journal of Financial economics*, 86(1):71–99, 2007.

A. M. Robb and D. T. Robinson. The capital structure decisions of new firms. *Review of Financial Studies*, pages 153–179, 2012.

C. J. Ruhm. Are workers permanently scarred by job displacements? *The American Economic Review*, pages 319–324, 1991.

A. Sahin, J. Song, G. Topa, and G. L. Violante. Mismatch unemployment. 2012.

A. Schoar. The divide between subsistence and transformational entrepreneurship. *Innovation policy and the economy*, 10(1):57–81, 2010.

A. Schoar and L. Zuo. Shaped by booms and busts: How the economy impacts ceo careers and management styles. *The Review of Financial Studies*, 30(5):1425–1456, 2017.

E. L. Scott, P. Shu, R. M. Lubynsky, et al. Are better ideas more likely to succeed? An empirical analysis of startup evaluation. *Harvard Business School Technology & Operations Mgt. Unit Working Paper*, 45(16-013), 2015.

S. Shane. *Fool's Gold?: The truth behind angel investing in America*. Oxford University Press, 2008.

J. P. Walsh and S. Nagaoka. Who invents? Evidence from the Japan & US inventor survey. *RIETI Discussion papers*, 2009.

A. Wozniak. Going away to college? School distance as a barrier to higher education. *Econofact*, 2018.

D. Yagan. Employment hysteresis from the great recession. *Journal of Political Economy*, 2019.

Figure 1: LinkedIn Coverage across Industries

This figure presents the industry composition of (i) the U.S. workforce and (ii) U.S. Linkedin users. We use data from LinkedIn's website as of October 2019 to estimate the employment figures in each industry for all users on the platform. The industry distribution for the U.S. workforce is estimated using the BEA employment data in 2018. The x-axis plots the 2-digit NAICS industry classifications, and the y-axis reports the employment numbers in millions.

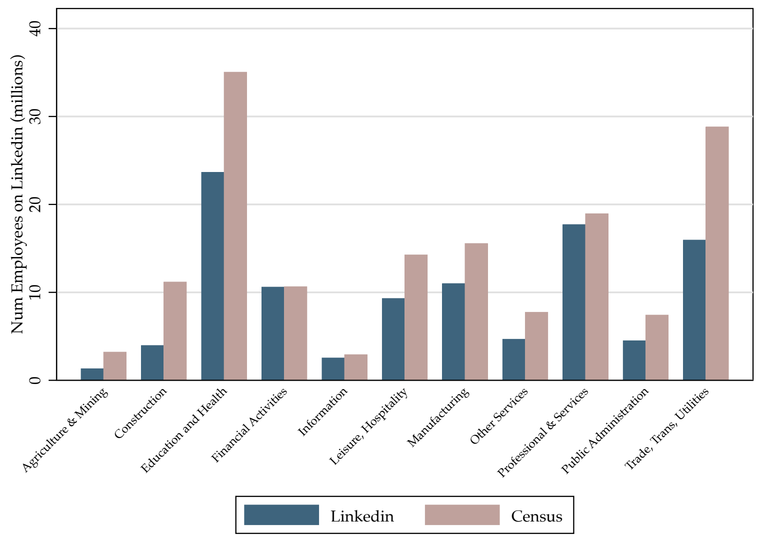


Figure 2: Coverage of US College Graduates

This figure reports the fraction of all students graduating from a U.S. undergraduate institution covered by our sample in each year between 1998 and 2012. The figures for the population of U.S. college graduates are collected from National Center for Education Statistics. The y-axis reports the coverage ratio in percentages.

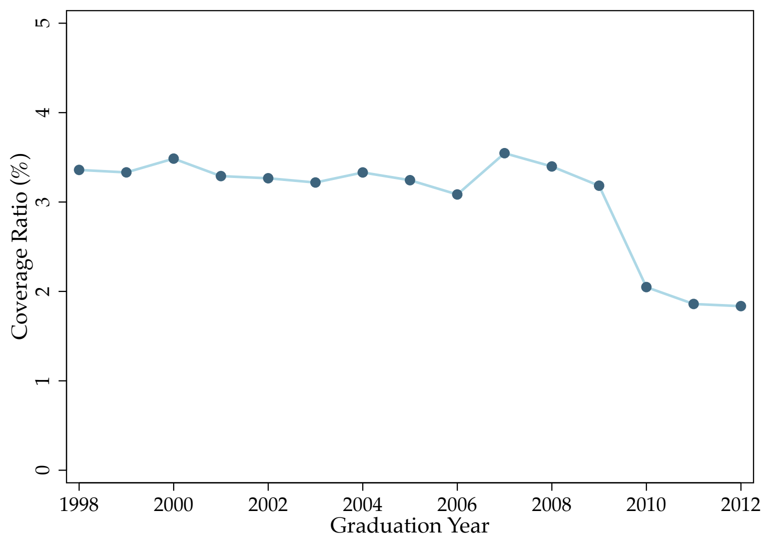


Figure 3: Industry Composition of New Firms

This figure compares the industry composition of firms founded by individuals in our sample to firms founded by U.S. college graduates. We obtain data on firms created by US college graduates from the 2007 Census Survey of Business Owners. For our sample, we consider all firms in the sample started between 1998 and 2012. The x-axis plots 2-digit NAICS industries, and the y-axis corresponds to the fraction of total firms in each industry code, presented in decimals.

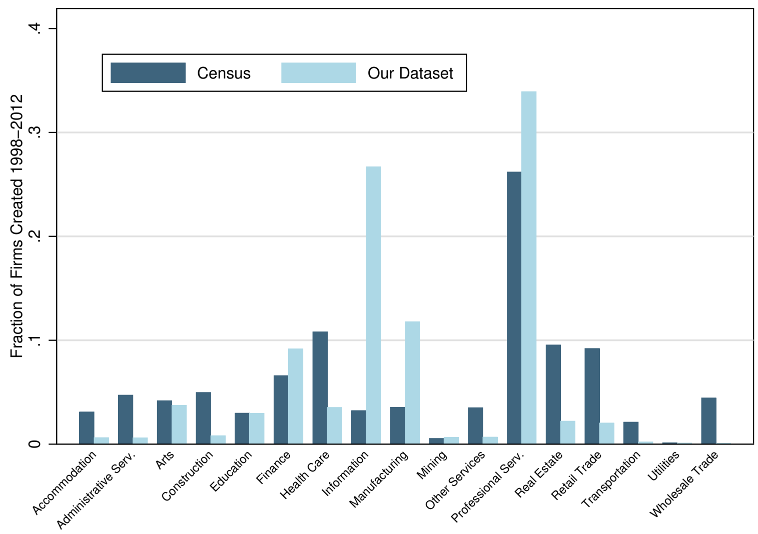


Figure 4: Risk Preferences of Entrepreneurs and Waged Workers

This figure presents the fraction of entrepreneurs and waged workers classified as risk-averse and ambiguity-averse. Individuals are classified as risk- and ambiguity-averse according to their response to survey questions as described in the Data section. Entrepreneurs and waged workers workers included in the survey are a subsample of workers in the full dataset. The figure also includes the 95% confidence intervals.

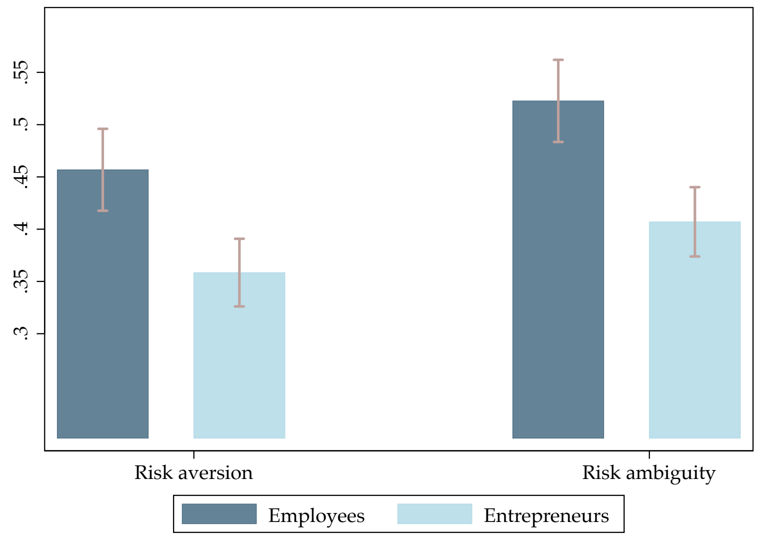
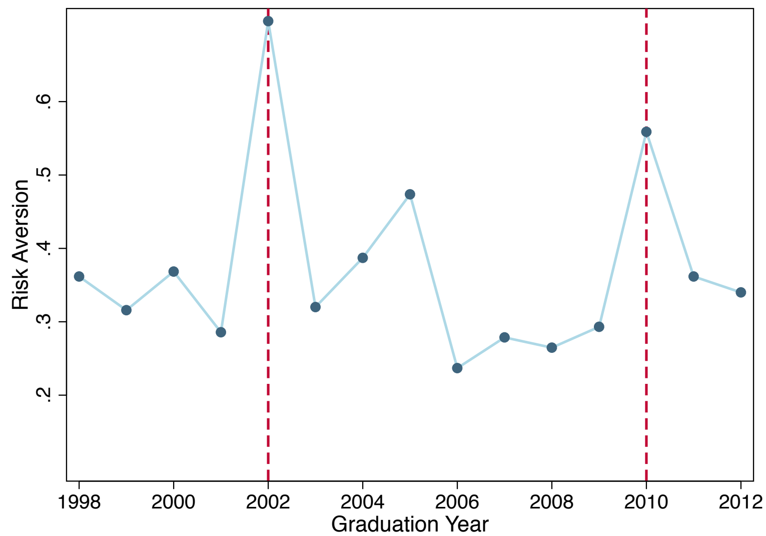


Figure 5: Risk Aversion of Entrepreneurs and Waged Workers by Graduation Year

This figure provides the percentage of entrepreneurs and waged workers reporting high risk-aversion according to survey responses. We estimate the risk aversion of each individual according to the criteria discussed in the Data section. We plot this percentage across each graduation year.

Panel A: Entrepreneurs



Panel B: Employees

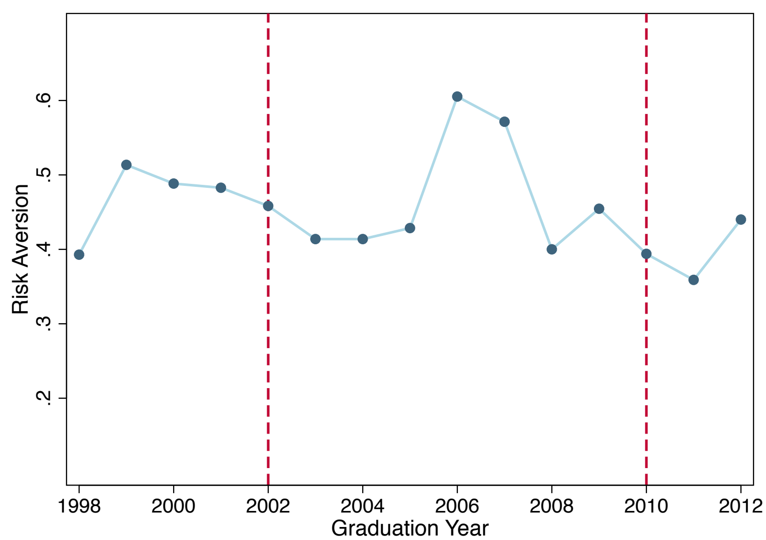


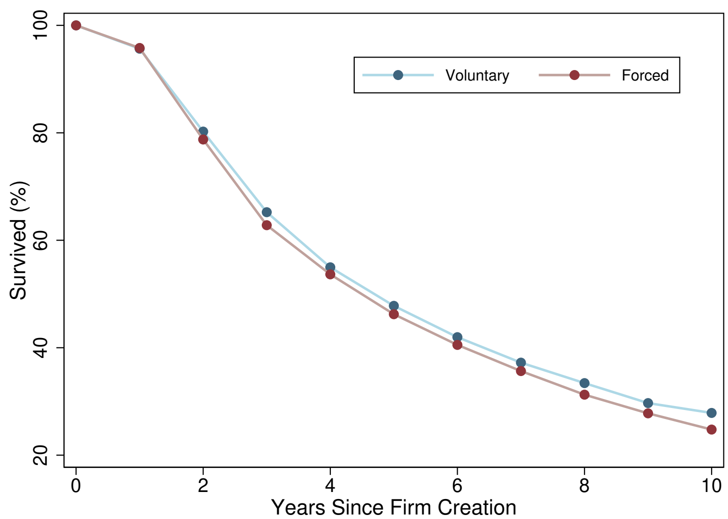
Figure 6: Survival Rate of New Firms

In Panel A, we compare survival rates for firms created by "voluntary" and "forced" entrepreneurs. For each year of graduation, we split workers based on whether the U.S. state where their undergraduate institution is located experienced unemployment above or below the median across all U.S. states in that year. We classify entrepreneurs graduating in states with above median unemployment as "forced" and those below the median unemployment rate as "voluntary". We then estimate the mean survival rate for each group at each point in the firm lifecycle. In Panel B, we plot the estimated regression coefficients of local labor market opportunities on the firm survival rate. We estimate this relationship separately for each year x following firm establishment:

$$\text{Survival Rate}^{x}_{i,t} = \beta \times \text{Unemployment}_{i,t \rightarrow t+1} + \text{University} \times \text{Gender} \times \text{Cohort FE} + \text{Industry FE} + \eta_{i,t}$$

Unemployment measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for gender. *Industry FE* is a fixed effect for the industry of the new firm. We cluster standard errors at the state-year level and we provide the 95% confidence intervals.

Panel A: Cross-Sectional Means Comparison



Panel B: Regression Coefficients

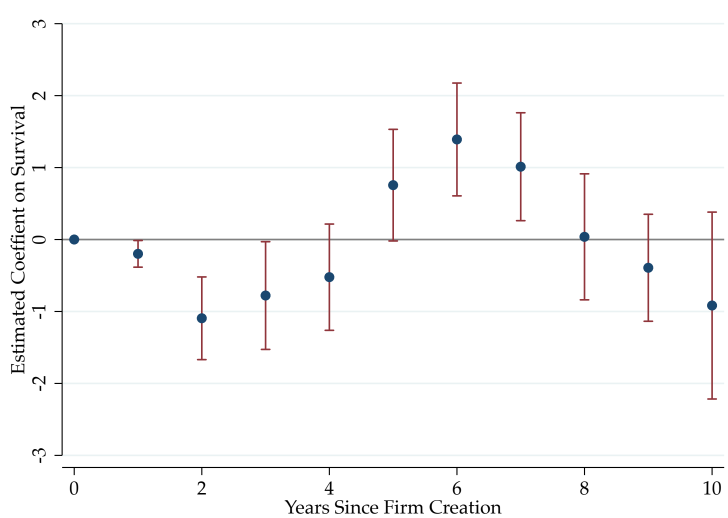


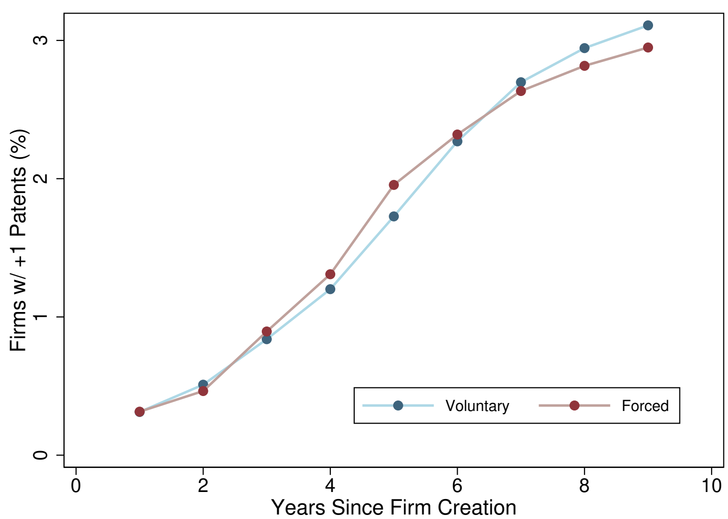
Figure 7: Patent Creation of New Firms

In Panel A, we compare patent creation rates for firms created by "voluntary" and "forced" entrepreneurs. For each year of graduation, we split workers based on whether the U.S. state where their undergraduate institution is located experienced unemployment above or below the median across all U.S. states in that year. We classify entrepreneurs graduating in states with above median unemployment as "forced" and those below the median unemployment rate as "voluntary". We then estimate the mean patent creation rate for each group at each point in the firm lifecycle. In Panel B, we provide estimated regression coefficient of local labor market opportunities on the firm's patent creation rate. We estimate this relationship separately for each year x following firm establishment:

$$\text{Patent Rate}^{x}_{i,t} = \beta \times \text{Unemployment}_{i,t\to t+1} + \text{University} \times \text{Gender} \times \text{Cohort FE} + \text{Industry FE} + \eta_{i,t}$$

Unemployment measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for gender. *Industry FE* is a fixed effect for the industry of the new firm. We cluster standard errors at the state-year level and we provide the 95% confidence intervals.

Panel A: Cross-Sectional Means Comparison



Panel B: Regression Coefficients

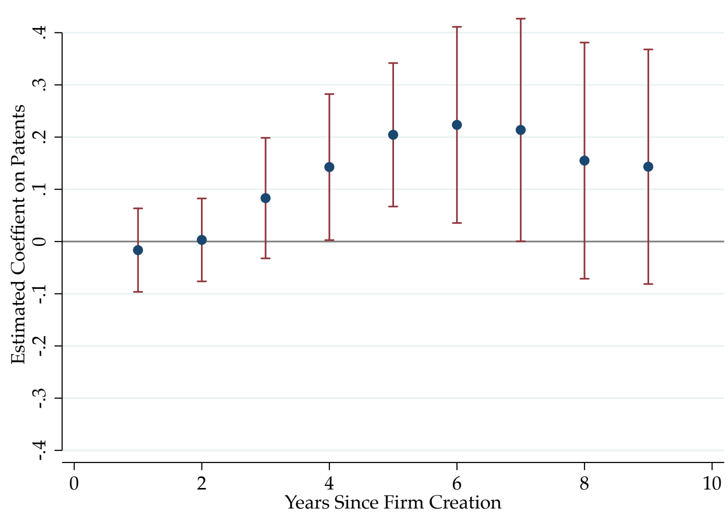


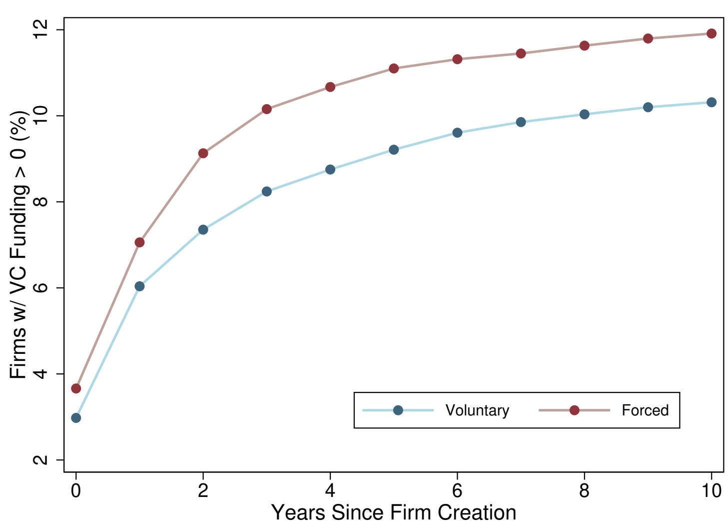
Figure 8: Venture Capital Financing of New Firms

In Panel A, we compare access to venture capital between "voluntary" and "forced" entrepreneurs". For each year of graduation, we split workers based on whether the U.S. state where their undergraduate institution is located experienced unemployment above or below the median across all U.S. states in that year. We classify entrepreneurs graduating in states with above median unemployment as "forced" and those below the median unemployment rate as "voluntary". We then estimate the mean access to venture capital for each group at each point in the firm lifecycle. In Panel B, we provide estimated regression coefficient of local labor market opportunities on the likelihood of receiving venture capital financing. We estimate this relationship separately for each year x following firm establishment:

$$\text{VC Funding Rate}^{x}_{i,t} = \beta \times \text{Unemployment}_{i,t\to t+1} + \text{University} \times \text{Gender} \times \text{Cohort FE} + \text{Industry FE} + \eta_{i,t}$$

Unemployment measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for gender. *Industry FE* is a fixed effect for the industry of the new firm. We cluster standard errors at the state-year level and we provide the 95% confidence intervals.

Panel A: Cross-Sectional Means Comparison



Panel B: Regression Coefficients

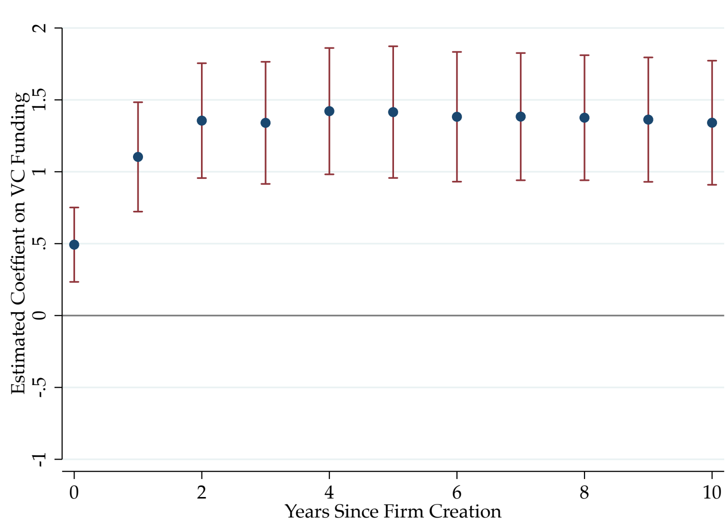


Table 1: Data Summary of Workers

This table reports the summary statistics of all individuals in our sample. Panel A summarizes the individual-level characteristics. Panel B summarizes their undergraduate institutions.

Panel A: Summary Statistics of All Individuals

	N	Mean	Std	50th	90th
Unemployment at Graduation	641144	0.063	0.021	0.057	0.095
Graduation Year	641144	2004.9	4.11	2005	2011
Top 20 College	641144	0.18	0.38	0	1
Female	641144	0.36	0.48	0	1
Engineering Major	641144	0.27	0.44	0	1
Business/Econ Major	641144	0.16	0.36	0	1
Grad. School within 5 years	641144	0.20	0.40	0	1
Top Finance/Consulting Job	641144	0.049	0.22	0	0
Russell 1000 Job	641144	0.25	0.44	0	1
Avg Industry Wage	617714	61.8	9.97	65.2	69.1
Founder within 1 Year	641144	0.022	0.15	0	0
Founder within 2 Years	641144	0.028	0.16	0	0
Founder within 3 Years	641144	0.033	0.18	0	0
Founder within 4 Years	641144	0.039	0.19	0	0

Panel B: Summary Statistics of Undergraduate Institutions

	N	Mean	Std	50th	90th
Annual Tuition in USD	639782	22269.2	16352.6	13509	50494.8
Year Founded	638142	1889.1	97.2	1885.0	1944.4
Total Enrollment	632803	30327.4	24556.3	25006.8	65085.2
Acceptance Rate (%)	633383	50.8	24.1	53.3	80.2
Public University	641144	0.75	0.43	1	1

Table 2: Data Summary of Entrepreneurs

This table reports the summary statistics for all entrepreneurs in the sample. The first four rows present characteristics of the individuals who became entrepreneurs, while the remainder of the rows present properties of the firms created by them.

	N	Mean	Std	50th	90th
Top 20 College	36316	0.36	0.48	0	1
Engineering Major	36316	0.35	0.48	0	1
Business/Econ Major	36316	0.16	0.37	0	1
Female	36316	0.21	0.41	0	1
Firm Survival to 2019	36316	0.24	0.42	0	1
$>$ 10 Employees	36316	0.14	0.35	0	1
$>$ 20 Employees	36316	0.094	0.29	0	0
$>$ 50 Employees	36316	0.051	0.22	0	0
Log(# Current Employees)	36316	0.78	1.41	0	2.89
Log(VC Funding)	36316	1.80	4.97	0	12.7
VC Funding $>$ 0	36316	0.15	0.36	0	1
VC Funding $>$ 0 in 5 years	36316	0.12	0.33	0	1
Num Patents $>$ 0	36316	0.060	0.24	0	0
Patents $>$ 0 in 5y	36316	0.025	0.16	0	0
Acquired	36316	0.045	0.21	0	0
Initial Public Offering	36316	0.0039	0.062	0	0

Table 3: Data Summary of Survey Responses

This table reports the summary statistics of all survey responses. Panel A summarizes the survey responses of the 622 entrepreneurs surveyed. Panel B summarizes the survey responses of the 508 non-entrepreneurs surveyed. The survey questions are detailed in the Data section. Panel B also provides individual characteristics observed in our dataset. Table A2 presents the characteristics of firms created by the surveyed entrepreneurs and compares them to the full population of entrepreneurs in our sample.

Panel A: Survey Responses of Entrepreneurs

	N	Mean	Std	50th	90th
Risk Aversion	622	0.35	0.48	0	1
Ambiguity Aversion	622	0.40	0.49	0	1
Entre. Overconfidence (Acquired)	622	0.31	0.46	0	1
Entre. Overconfidence (Employment)	622	0.44	0.50	0	1
Salary Overconfidence	622	0.41	0.49	0	1
Preference for Competition	622	0.27	0.45	0	1
Stock Market Optimism	622	0.41	0.49	0	1
Life Expectancy Overoptimism	622	0.10	0.31	0	1

Panel B: Survey Responses of Non-Entrepreneurs

	N	Mean	Std	50th	90th
Top 20 College	508	0.21	0.41	0	1
Female	508	0.27	0.45	0	1
Engineering Major	508	0.25	0.43	0	1
Business/Econ Major	508	0.19	0.39	0	1
Risk Aversion	508	0.46	0.50	0	1
Ambiguity Aversion	508	0.53	0.50	1	1

Table 4: Do Labor Shocks Impact the Rate of Underemployment?

This table reports the impact of a change in the local unemployment rate on the job outcomes of college graduates. Panel A analyzes the set of all workers in our sample. Panel B separately analyzes the subset of workers graduating from a top twenty ranked undergraduate institution, and workers graduating from all other institutions. The dependent variable is a binary variable measuring career outcomes following graduation. We examine four career outcomes. First, *Top Finance/Consulting* measures the percent of workers gaining employment with a top finance or consulting firm; second, *Russell 1000* measures the percent of workers gaining employment with a firm listed in the Russell 1000 Index; third, *High-wage Industry* measures the percent of workers gaining employment within a high-wage industry; and *Graduate School* measures the percent of workers entering a graduate program (MS, MBA, JD, or PhD) following college graduation. *Unemployment at Graduation* measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution.*Gender FE* is a fixed effect for each gender. The variable *diff* in Panel B corresponds to the difference between the estimated coefficients in the two subsamples (Top-20 versus Non-Top 20). We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

Panel A: All Workers

	Top Finance/Consulting		Russell 1000		High-wage Industry		Graduate School	
Unemployment at Graduation	-0.294***	-0.350***	-0.861***	-0.976***	-3.850***	-4.581***	0.801***	0.845***
	(-8.47)	(-10.70)	(-10.98)	(-13.49)	(-3.59)	(-4.85)	(9.48)	(9.70)
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	Yes	No	Yes	No	Yes	No	Yes	No
University FE	Yes	No	Yes	No	Yes		Yes	No
University × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes
N	641144	641144	641144	641144	617714	617714	641144	641144
R-squared	.062	.12	.031	.087	.062	.12	.035	.094

Panel B: Workers from Top-20 Schools versus Non Top-20 Universities

	Top Finance/Consulting			Russell 1000			High-wage Industry			Graduate School		
	Top 20	Non-Top 20	diff	Top 20	Non-Top 20	diff	Top 20	Non-Top 20	diff	Top 20	Non-Top 20	diff
Unemployment at Graduation	-0.532***	-0.299***	-0.233***	-0.960***	-0.981***	0.020	-5.131***	-4.427***	-0.704	0.929***	0.821***	0.108
	(-6.38)	(-8.98)	(-2.71)	(-8.41)	(-12.64)	(0.17)	(-3.70)	(-3.65)	(-0.35)	(5.07)	(10.71)	(0.68)
University × Gender × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	115249	525895	641144	115249	525895	641144	111089	506625	617714	115249	525895	641144
R-squared	.09	.12	.12	.048	.096	.087	.049	.13	.12	.038	.11	.094

Table 5: Do Labor Shocks Impact the Rate of Entrepreneurship?

This table reports the impact of a change in the local unemployment rate on the likelihood that individuals become entrepreneurs. Panel A analyzes the set of all workers in our sample. Panel B separately analyzes the subset of workers graduating from a top twenty ranked undergraduate institution, and workers graduating from all other institutions. The dependent variable is a binary variable measuring whether the worker founded a firm with x years following graduation. We examine x varying from 1 to 4 years after graduation. *Unemployment at Graduation* measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for each gender. The variable *diff* in Panel B corresponds to the difference between the estimated coefficients in the two subsamples (Top-20 versus Non-Top 20). We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

Panel A: All Workers

	1-y post college		2-y post college		3-y post college		4-y post college	
	(i)	(ii)	(i)	(ii)	(i)	(ii)	(i)	(ii)
Unemployment at Graduation	0.183***	0.214***	0.199**	0.236***	0.194**	0.237***	0.194**	0.240***
	(3.13)	(4.23)	(2.88)	(3.91)	(2.47)	(3.43)	(2.47)	(3.23)
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	Yes	No	Yes	No	Yes	No	Yes	No
University FE	Yes	No	Yes	No	Yes	No	Yes	No
University × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes
N	641144	641144	641144	641144	641144	641144	641144	641144
R-squared	.014	.071	.014	.072	.014	.07	.014	.069

Panel B: Workers from Top-20 vs Non-Top 20 Universities

	1-y post college			2-y post college			3-y post college			4-y post college		
	Top 20	Non-Top 20	diff	Top 20	Non-Top 20	diff	Top 20	Non-Top 20	diff	Top 20	Non-Top 20	diff
Unemployment at Graduation	0.313***	0.186***	0.127***	0.303***	0.217***	0.086**	0.314***	0.215***	0.099*	0.358***	0.207***	0.151**
	(6.34)	(3.66)	(4.46)	(4.14)	(3.82)	(2.53)	(3.28)	(3.50)	(2.08)	(3.25)	(3.22)	(2.51)
University × Gender × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	115249	525895	641144	115249	525895	641144	115249	525895	641144	115249	525895	641144
R-squared	.019	.086	.071	.02	.087	.072	.019	.084	.07	.021	.083	.069

Table 6: Do Labor Shocks Impact the Rate of (Good) Entrepreneurship?

This table reports the impact of a change in the local unemployment rate on the likelihood that individuals create *good* firms. Relative to the previous table, we restrict the definition of entrepreneurship to exclude self-employment and firms that are small, subsistence, and non-transformational. In Panel A, we measure whether a firm is *good* based on firm survival and current employment of at least x workers. More concretely, the first and second columns define success based on survival; the third and fourth columns measure success as currently employing at least 10 workers; the fifth and sixth columns measure success as currently employing at least 20 workers; the seventh and eighth columns measure success as currently employing at least 50 workers. In Panel B, we assess whether a firm is *good* based on patent creation, access to capital through venture-capital and public offerings, exit through acquisition, and exit through successful completion of an IPO. Specifically, in the first and second columns, we measure success as creating at least one patent within five years of founding; in the third and fourth columns, we measure success based on access to venture capital funding within five years of founding; in the fifth and sixth columns, we measure success as exit through acquisition; and, in the seventh and eighth columns, we measure success as entering an initial public offering. *Unemployment at Graduation* measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for each gender. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

Panel A: Survival and Employment

	Survived		> 10 emp		> 20 emp		> 50 emp	
Unemployment at Graduation	0.043***	0.048***	0.012**	0.015**	0.010**	0.011**	0.007**	0.009***
	(3.39)	(4.33)	(2.19)	(2.86)	(2.55)	(2.97)	(2.82)	(3.74)
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	Yes	No	Yes	No	Yes	No	Yes	No
University FE	Yes	No	Yes	No	Yes	No	Yes	No
University × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes
N	641144	641144	641144	641144	641144	641144	641144	641144
R-squared	.0075	.038	.0061	.033	.0046	.027	.0032	.027

Panel B: Patents, Access to Financing, Acquisition, and IPO

	Patents > 0		VC Funding > 0		Acquired		IPO	
Unemployment at Graduation	0.008*	0.010**	0.027***	0.029***	0.007**	0.007**	0.000	0.001
	(2.08)	(2.58)	(3.19)	(3.39)	(2.75)	(2.73)	(0.60)	(0.98)
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	Yes	No	Yes	No	Yes	No	Yes	No
University FE	Yes	No	Yes	No	Yes	No	Yes	No
University × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes
N	641144	641144	641144	641144	641144	641144	641144	641144
R-squared	.0044	.043	.0057	.031	.0028	.024	.0018	.028

Table 7: Do Labor Shocks Impact Entry of Low-quality Firms Founded Within 5 years?

This table reports the impact of a change in the local unemployment rate on the proportion of new firms that are ultimately successful. The sample includes all firms founded within *five years* following the entrepreneur's graduation from college. The dependent variable is a binary variable measuring whether the worker founded a firm following graduation that ultimately achieved success. In Panel A, we measure firm success based on firm survival, current employment of at least x workers, and acquisition. The first and second columns define success based on survival. The third and fourth columns measure success as currently employing at least 10 workers. The fifth and sixth columns measure success as currently employing at least 20 workers. The seventh and eighth columns measure success as currently employing at least 50 workers. The ninth and tenth columns measure success as whether the startup was ultimately acquired by an established firm. In Panel B, we measure success based on patent creation, access to capital through venture-capital, and likelihood of completing an IPO. In the first and second columns, we measure success as access to venture capital funding within five years of founding. In the third and fourth columns, we measure success as total venture capital funding received until 2019. In the fifth and sixth columns, we measure success at creating at least one patent within five years of founding. In the seventh and eighth columns, we measure success as the total number of patents created until 2019. In the ninth and tenth column, we measure success as the likelihood of successfully completing an initial public offering. *Unemployment at Graduation* measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for each gender. *Industry FE* is a fixed effect for the industry of the new firm. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

Panel A: Survival, Employment, and Acquired

	Survival		10+ Employees		20+ Employees		50+ Employees		Acquired	
Unemployment at Graduation	1.207***	1.638***	-0.075	-0.066	-0.016	-0.086	0.029	0.031	0.122	-0.031
	(4.56)	(5.57)	(-0.39)	(-0.30)	(-0.11)	(-0.44)	(0.28)	(0.23)	(0.95)	(-0.28)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	No	No	No	No	No	No	No	No	No	No
University FE	No	No	No	No	No	No	No	No	No	No
Univ. $\times$ Gender $\times$ Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	12059	12059	12059	12059	12059	12059	12059	12059	12059	12059
R-squared	.0096	.34	.00064	.32	.0004	.3	.00045	.29	.0017	.26

Panel B: Financing, Patents, and IPO

	VC in 5y $>$ 0		VC in '19 $>$ 0		Patent 5y $>$ 0		Patent in '19 $>$ 0		IPO	
Unemployment at Graduation	1.126***	1.415***	1.030***	1.414***	0.124***	0.204***	0.213*	0.317*	0.005	-0.018
	(5.87)	(5.37)	(5.21)	(6.14)	(2.66)	(2.59)	(1.74)	(1.86)	(0.18)	(-0.43)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	No	No	No	No	No	No	No	No	No	No
University FE	No	No	No	No	No	No	No	No	No	No
Univ. $\times$ Gender $\times$ Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	12059	12059	12059	12059	12059	12059	12059	12059	12059	12059
R-squared	.014	.3	.0097	.32	.0021	.27	.0024	.32	.0008	.4

Table 8: Do Labor Shocks Impact Entry of Low-quality Firms Founded Within 2 years?

This table reports the impact of a change in the local unemployment rate on the proportion of new firms that are ultimately successful. The sample includes all firms founded within *two years* following the entrepreneur's graduation from college. The dependent variable is a binary variable measuring whether the worker founded a firm following graduation that ultimately achieved success. In Panel A, we measure firm success based on firm survival, current employment of at least x workers, and acquisition. The first and second columns define success based on survival. The third and fourth columns measure success as currently employing at least 10 workers. The fifth and sixth columns measure success as currently employing at least 20 workers. The seventh and eighth columns measure success as currently employing at least 50 workers. The ninth and tenth columns measure success as whether the startup was ultimately acquired by an established firm. In Panel B, we measure success based on patent creation, access to capital through venture-capital, and likelihood of completing an IPO. In the first and second columns, we measure success as access to venture capital funding within five years of founding. In the third and fourth columns, we measure success as total venture capital funding received until 2019. In the fifth and sixth columns, we measure success at creating at least one patent within five years of founding. In the seventh and eighth columns, we measure success as the total number of patents created until 2019. In the ninth and tenth column, we measure success as the likelihood of successfully completing an initial public offering. *Unemployment at Graduation* measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for each gender. *Industry FE* is a fixed effect for the industry of the new firm. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

Panel A: Survival, Employment, and Acquired

	Survival		10+ Employees		20+ Employees		50+ Employees		Acquired	
Unemployment at Graduation	1.053***	2.025***	-0.153	0.133	-0.032	0.052	0.046	0.286	0.206	0.108
	(3.44)	(5.67)	(-0.66)	(0.39)	(-0.19)	(0.16)	(0.36)	(1.29)	(1.15)	(0.57)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	No	No	No	No	No	No	No	No	No	No
University FE	No	No	No	No	No	No	No	No	No	No
Univ. × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	6335	6335	6335	6335	6335	6335	6335	6335	6335	6335
R-squared	.0095	.43	.00083	.42	.0012	.39	.0015	.38	.0022	.34

Panel B: Financing, Patents, and IPO

	VC in 5y > 0		VC in '19 > 0		Patent 5y > 0		Patent in '19 > 0		IPO	
Unemployment at Graduation	0.842***	1.294***	0.692***	1.341***	0.028	0.008	-0.012	0.155	-0.044	-0.050
	(3.33)	(4.19)	(2.68)	(3.96)	(0.34)	(0.05)	(-0.09)	(0.46)	(-1.02)	(-0.65)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	No	No	No	No	No	No	No	No	No	No
University FE	No	No	No	No	No	No	No	No	No	No
Univ. × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	6335	6335	6335	6335	6335	6335	6335	6335	6335	6335
R-squared	.014	.37	.0086	.4	.0023	.4	.0029	.41	.0016	.57

Table 9: Do Labor Shocks Impact Entry of Low-quality Firms Founded Prior to 2005?

This table reports the impact of a change in the local unemployment rate on the proportion of new firms that are ultimately successful. The sample includes the subset of workers graduating prior to 2005 and includes all firms founded following the entrepreneur's graduation from college. The dependent variable is a binary variable measuring whether the worker founded a firm following graduation that ultimately achieved success. In Panel A, we measure firm success based on firm survival, current employment of at least x workers, and acquisition. The first and second columns define success based on survival. The third and fourth columns measure success as currently employing at least 10 workers. The fifth and sixth columns measure success as currently employing at least 20 workers. The seventh and eighth columns measure success as currently employing at least 50 workers. The ninth and tenth columns measure success as whether the startup was ultimately acquired by an established firm. In Panel B, we measure success based on patent creation, access to capital through venture-capital, and likelihood of completing an IPO. In the first and second columns, we measure success as access to venture capital funding within five years of founding. In the third and fourth columns, we measure success as total venture capital funding received until 2019. In the fifth and sixth columns, we measure success at creating at least one patent within five years of founding. In the seventh and eighth columns, we measure success as the total number of patents created until 2019. In the ninth and tenth column, we measure success as the likelihood of successfully completing an initial public offering. *Unemployment at Graduation* measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for each gender. *Industry FE* is a fixed effect for the industry of the new firm. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

Panel A: Survival, Employment, and Acquired

	Survival		10+ Employees		20+ Employees		50+ Employees		Acquired	
Unemployment at Graduation	0.327	2.732**	-0.586	-0.477	-0.357	0.382	-0.436*	0.135	0.289	0.598
	(0.55)	(2.09)	(-1.53)	(-0.55)	(-1.10)	(0.48)	(-1.70)	(0.20)	(1.32)	(0.91)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	No	No	No	No	No	No	No	No	No	No
University FE	No	No	No	No	No	No	No	No	No	No
Univ. × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	20497	20497	20497	20497	20497	20497	20497	20497	20497	20497
R-squared	.0018	.24	.00035	.22	.00029	.2	.00049	.2	.00014	.18

Panel B: Financing, Patents, and IPO

	VC in 5y $>$ 0		VC in '19 $>$ 0		Patent 5y $>$ 0		Patent in '19 $>$ 0		IPO	
Unemployment at Graduation	0.219	1.676*	0.255	1.669	0.140	-0.262	-0.397	-0.525	-0.004	0.035
	(0.58)	(1.96)	(0.61)	(1.44)	(1.05)	(-0.41)	(-1.41)	(-0.45)	(-0.06)	(0.17)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	No	No	No	No	No	No	No	No	No	No
University FE	No	No	No	No	No	No	No	No	No	No
Univ. × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	20497	20497	20497	20497	20497	20497	20497	20497	20497	20497
R-squared	.0012	.2	.0013	.22	.00044	.22	.00069	.27	.0002	.23

Table 10: Are Graduates from Elite Universities Better Entrepreneurs?

This table shows whether entrepreneurs graduating from top-ranked undergraduate institutions are more likely to reach benchmarks of entrepreneurial success. In the first column, the outcome variable is a binary indicating whether the firm remains in business as of 2019. In the second, third, and fourth columns, the outcome variable is a binary indicating whether the firm currently employs at least 10, 20, or 50 employees, respectively. In the fifth column, the outcome variable is a binary indicating whether the firm ever received venture capital financing as of 2019. In the sixth column, the outcome variable is a binary indicating whether the firm was eventually acquired by an established firm. In the seventh column, the outcome variable is a binary indicating whether the firm successfully completed an IPO. In the last column, the outcome variable is a binary indicating whether the firm developed at least one patent as of 2019. *Time FE* is a fixed effect for each year of graduation. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

	Survival	10+ Emp	20+ Emp	50+ Emp	VC in '19 >0	Acquired	IPO	Patent in '19 > 0
Top 20 College	0.090***	0.056***	0.042***	0.025***	0.073***	0.023***	0.001	0.018***
	(12.46)	(11.64)	(10.29)	(8.72)	(14.49)	(10.15)	(1.38)	(4.82)
Female	-0.072***	-0.032***	-0.024***	-0.013***	-0.047***	-0.025***	-0.000	-0.020***
	(-14.08)	(-6.82)	(-6.21)	(-4.90)	(-11.32)	(-11.51)	(-0.27)	(-6.03)
Engineering Major	0.086***	0.019***	0.017***	0.014***	0.075***	0.028***	-0.000	0.037***
	(14.64)	(4.37)	(4.41)	(4.81)	(15.55)	(11.22)	(-0.20)	(9.10)
Business/Econ Major	0.034***	0.031***	0.024***	0.017***	0.021***	0.004	0.002*	-0.005
	(4.96)	(5.73)	(5.22)	(4.75)	(3.95)	(1.18)	(1.82)	(-1.09)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	36467	36467	36467	36467	36467	36467	36467	36467
R-squared	.031	.01	.0088	.0062	.028	.013	.00054	.011

Table 11: Do Labor Shocks Encourage Risk-Averse Workers into Entrepreneurship?

This table reports the impact of a change in the local unemployment rate on the proportion of risk-averse and ambiguity-averse entrepreneurs. The dependent variable in the first through third columns is a binary variable indicating high risk-aversion; the dependent variable in the fourth through sixth columns is a binary variable indicating high ambiguity-aversion. Risk and ambiguity aversion are defined according to the survey questions introduced in the Data section. *Unemployment at Graduation* measures the unemployment rate in the state hosting the undergraduate institution. *Behavioral Controls* are the behavioral characteristics of the worker including (i) two measures of entrepreneurial confidence, (ii) two measures of general confidence, and (iii) two measures of optimism. These measures are defined using the survey questions introduced in the Data section. *Industry FE* is a fixed effect for the industry of the new firm. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *Gender FE* is a fixed effect for gender. *University FE* is a fixed effect for each undergraduate institution. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

	Risk Aversion			Ambiguity Aversion		
Unemployment at Graduation	6.057**	5.860**	5.854**	4.396*	4.237*	4.326*
	(2.54)	(2.53)	(2.54)	(1.70)	(1.79)	(1.84)
Log(# Current Employees)			0.002			0.002
			(0.11)			(0.12)
Firm Survival to 2019			-0.050			-0.078
			(-0.64)			(-1.08)
Initial Public Offering			0.051			0.084
			(0.36)			(0.54)
VC Funding $>$ 0 in 5 years			-0.042			0.023
			(-0.48)			(0.30)
Patents $>$ 0 in 5y			0.138			0.157
			(0.99)			(1.10)
Acquired			0.033			-0.011
			(0.35)			(-0.12)
Industry FE	No	Yes	Yes	No	Yes	Yes
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Gender FE	No	Yes	Yes	No	Yes	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes
Behavioral Controls	No	Yes	Yes	No	Yes	Yes
N	622	622	622	622	622	622
R-squared	.51	.58	.58	.52	.57	.58

Table 12: Do Labor Shocks Impact the Risk-Aversion of Waged Workers?

This table reports the impact of the local labor market on the risk- and ambiguity-aversion of non-entrepreneurs. The dependent variable in the first and second column is a binary variable indicating high risk-aversion; the dependent variable in the third and fourth column is a binary variable indicating high ambiguity-aversion. These measures are defined using the survey questions introduced in the Data section. *Unemployment at Graduation* measures the unemployment rate in the state hosting the undergraduate institution. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for each gender. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

	Risk Aversion		Ambiguity Aversion	
Unemployment at Graduation	-2.022*	-1.367	-2.433**	-3.542
	(-1.92)	(-0.63)	(-2.31)	(-1.52)
Cohort FE	Yes	Yes	Yes	Yes
University FE	No	Yes	No	Yes
N	508	508	508	508
R-squared	.015	.53	.014	.52

Table 13: Do Labor Shocks Encourage Less Confident Workers into Entrepreneurship?

This table reports the impact of a change in the local unemployment rate on the proportion of confident and optimistic entrepreneurs. In Panel A, the dependent variable is a binary variable denoting confidence in founding a firm that is acquired (first and second column) or confidence in starting a firm employing at least ten workers (third and fourth column). In Panel B, the dependent variable is a binary variable denoting confidence in future salary growth (first and second column), willingness to compete (third and fourth column), optimism about life expectancy (fifth and sixth column), and optimism about future stock returns (seventh and eighth column). *Unemployment at Graduation* measures the unemployment rate in the state hosting the undergraduate institution. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for gender. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

Panel A: Entrepreneurial Confidence

	Entrepreneurial Confidence			
	Acquir.	Acquir.	Emp.	Emp.
Unemployment at Graduation	1.761	1.923	0.088	0.505
	(0.81)	(0.76)	(0.04)	(0.22)
Cohort FE	Yes	Yes	Yes	Yes
Gender FE	No	Yes	No	Yes
University FE	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes
N	622	622	622	622
R-squared	.49	.62	.44	.6

Panel B: General Confidence and Optimism

	General Confidence				Optimism			
	Salary	Salary	Compet.	Compet.	Life	Life	Stock	Stock
Unemployment at Graduation	4.514*	5.355*	0.328	1.675	0.081	0.591	-1.413	-1.373
	(1.92)	(1.73)	(0.17)	(0.74)	(0.06)	(0.35)	(-0.62)	(-0.50)
Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender FE	No	Yes	No	Yes	No	Yes	No	Yes
University FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
N	622	622	622	622	622	622	622	622
R-squared	.45	.63	.46	.59	.46	.6	.44	.6

ONLINE APPENDIX

Figure A1: Job Tenure of Workers on LinkedIn and the U.S. Labor Force

This figure compares the average length of job tenure for workers on Linkedin versus all workers in the U.S. labor force. The set of workers from Linkedin consists of a random sample of one million individuals who work for firms in the Russell 1000. Job tenure for workers in LinkedIn is measured using the start- and end- dates of employment spells listed on worker profiles. Job tenure for workers in the U.S. labor force is measured using the U.S. Current Population Survey (CPS) Job Tenure Supplement for respondents aged 15 years and older. The y-axis reports the average length of job tenure in years.

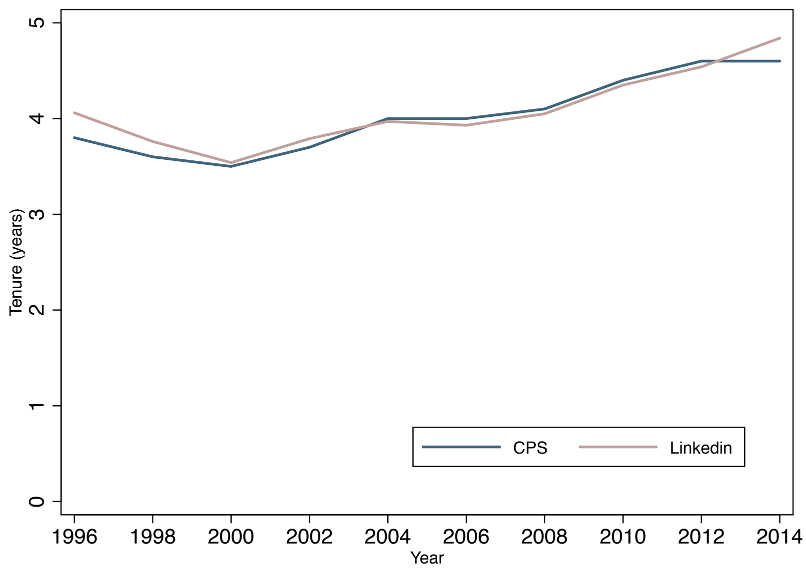


Table A1: List of Undergraduate Institutions

This table lists the set of undergraduate institutions graduating at least 0.4% of our worker sample. The list shows the breakdown of the most represented universities in our dataset. In total, this list comprises over 40% of the sample of universities in our dataset. The first column of the list reports the abbreviated institution name, the second column reports the website of the institution, and the third column reports the number of workers in our sample that graduated from these institutions. The fourth column reports the fraction of sample of workers that graduated from the institution, and the last column reports the cumulative percentage.

School Name	Website	Count	Fraction (%)	Cumulative (%)
UC Berkeley	berkeley.edu	19971	3.11	3.11
UIUC	illinois.edu	19950	3.11	6.23
U of Texas	utexas.edu	18693	2.92	9.14
UCLA	ucla.edu	17140	2.67	11.82
U of Wisconsin	wisc.edu	15953	2.49	14.3
Cornell University	cornell.edu	14819	2.31	16.61
Georgia Tech	gatech.edu	14074	2.2	18.81
Stanford	stanford.edu	9142	1.43	20.24
Northerwestern U	northwestern.edu	8269	1.29	21.53
U of Michigan	umich.edu	8148	1.27	22.8
Phoenix	phoenix.edu	8077	1.26	24.06
Carnegie Mellon	cmu.edu	7328	1.14	25.2
MIT	mit.edu	7324	1.14	26.34
Purdue U	purdue.edu	7029	1.1	27.44
Texas A and M	tamu.edu	6595	1.03	28.47
PennState	psu.edu	5452	0.85	29.32
UCSD	ucsd.edu	5355	0.84	30.15
Upenn	upenn.edu	4804	0.75	30.9
NYU	nyu.edu	4519	0.7	31.61
MSU	msu.edu	4152	0.65	32.25
Harvard U	harvard.edu	4042	0.63	32.88
USC	usc.edu	3796	0.59	33.48
ASU	asu.edu	3716	0.58	34.06
U of Minnesota	umn.edu	3689	0.58	34.63
OSU	osu.edu	3427	0.53	35.17
U of Florida	ufl.edu	3390	0.53	35.69
U of Maryland	umd.edu	3331	0.52	36.21
Princeton	princeton.edu	3133	0.49	36.7
Rutgers U	rutgers.edu	3125	0.49	37.19
BYU	byu.edu	3032	0.47	37.66
Virginia Tech	vt.edu	2952	0.46	38.12
CUNY	cuny.edu	2910	0.45	38.58
UC at Santa Barbara	ucsb.edu	2910	0.45	39.03
Washington U	washington.edu	2845	0.44	39.48
UVA	virginia.edu	2830	0.44	39.92
Indiana U	indiana.edu	2748	0.43	40.35
Columbia U	columbia.edu	2636	0.41	40.76
Boston U	bu.edu	2617	0.41	41.16
Duke U	duke.edu	2562	0.4	41.56

Table A2: Are Surveyed Entrepreneurs Representative?

This table reports the summary statistics for the firms created by entrepreneurs in the full dataset and the summary statistics for the firms created by the surveyed entrepreneurs. The eighth column compares the differences in means and the last column reports the t-statistic evaluating whether these means are statistically different from each other.

	All Entrepreneurs				Surveyed			Difference	
	N	Mean	Std	90th	N	Mean	Std	Diff	t-stat
Firm Survival to 2019	36316	0.24	0.42	1	622	0.24	0.43	-0.0010	(-0.058)
$>$ 10 Employees	36316	0.14	0.35	1	622	0.13	0.34	0.0061	(0.44)
$>$ 20 Employees	36316	0.094	0.29	0	622	0.087	0.28	0.0070	(0.61)
$>$ 50 Employees	36316	0.051	0.22	0	622	0.040	0.20	0.011	(1.41)
Log(# Current Employees)	36316	0.78	1.41	2.89	622	0.74	1.31	0.033	(0.63)
Log(VC Funding)	36316	1.80	4.97	12.7	622	1.67	4.74	0.14	(0.72)
VC Funding $>$ 0	36316	0.15	0.36	1	622	0.14	0.35	0.0040	(0.28)
VC Funding $>$ 0 in 5 years	36316	0.12	0.33	1	622	0.12	0.32	0.0077	(0.59)
Num Patents $>$ 0	36316	0.060	0.24	0	622	0.079	0.27	-0.019	(-1.74)
Patents $>$ 0 in 5y	36316	0.025	0.16	0	622	0.024	0.15	0.00090	(0.15)
Acquired	36316	0.045	0.21	0	622	0.035	0.18	0.010	(1.35)
Initial Public Offering	36316	0.0039	0.062	0	622	0.0032	0.057	0.00071	(0.31)

Table A3: Do Labor Shocks Impact the Rate of Entrepreneurship?

This table reports the impact of a change in the local unemployment rate on the likelihood of becoming an entrepreneur under a probit model. In first through the fourth columns, the outcome variable is the likelihood of creating a firm from one to four years after college graduation. *Unemployment at Graduation* measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

	1-y post coll.	2-y post coll.	3-y post coll.	4-y post coll.
Unemployment at Graduation	2.981***	2.693***	2.313***	2.177***
	(3.20)	(2.98)	(2.73)	(2.98)
Cohort FE	Yes	Yes	Yes	Yes
Gender FE	Yes	Yes	Yes	Yes
University FE	No	No	No	No
N	641144	641144	641144	641144
R-squared	.019	.016	.014	.012

Table A4: Is the Impact of Labor Shocks on the Rate of Entrepreneurship Robust?

This table reports the impact of a change in the local unemployment rate on the likelihood of becoming an entrepreneur across several subsamples of the data. The sample in the first column excludes workers graduating in 2002 and 2010, the second column excludes workers graduating from colleges located in California, and the third column excludes workers and entrepreneurs in the tech industry. The fourth column estimates our baseline model in a sample that excludes workers who (i) graduated in 2002 and 2010, (ii) graduated from a California school, or (iii) work in the tech industry. The fifth column excludes all workers that entered a graduate program within four years following graduation. The dependent variable is a binary variable measuring whether the worker founded a firm within 4 years following graduation. *Unemployment at Graduation* measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

	Exclude '02 & '10	Exclude CA	Exclude Tech	Exclude All	No Graduate School
Unemployment at Graduation	0.234**	0.218**	0.210***	0.202**	0.254***
	(3.00)	(2.61)	(3.18)	(2.66)	(3.48)
Cohort FE	No	No	No	No	No
Gender FE	No	No	No	No	No
University FE	No	No	No	No	No
University × Gender × Cohort FE	Yes	Yes	Yes	Yes	Yes
N	565663	546192	532765	406122	512217
R-squared	.073	.073	.077	.086	.079

Table A5: Do Labor Shocks Impact Entry of Low-quality Firms for Elite Workers?

This table reports the impact of a change in the local unemployment rate on the proportion of new firms that are ultimately successful. The sample includes the subset of workers graduating form a top twenty undergraduate institution and includes all firms founded within five years following the entrepreneur's graduation from college. The dependent variable is a binary variable measuring whether the worker founded a firm following graduation that ultimately achieved success. In Panel A, we measure firm success based on firm survival, current employment of at least x workers, and acquisition. The first and second columns define success based on survival. The third and fourth columns measure success as currently employing at least 10 workers. The fifth and sixth columns measure success as currently employing at least 20 workers. The seventh and eighth columns measure success as currently employing at least 50 workers. The ninth and tenth columns measure success as whether the startup was ultimately acquired by an established firm. In Panel B, we measure success based on patent creation, access to capital through venture-capital, and likelihood of completing an IPO. In the first and second columns, we measure success as access to venture capital funding within five years of founding. In the third and fourth columns, we measure success as total venture capital funding received until 2019. In the fifth and sixth columns, we measure success at creating at least one patent within five years of founding. In the seventh and eighth columns, we measure success as the total number of patents created until 2019. In the ninth and tenth column, we measure success as the likelihood of successfully completing an initial public offering. *Unemployment at Graduation* measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for each gender. *Industry FE* is a fixed effect for the industry of the new firm. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

Panel A: Survival, Employment, and Acquired

	Survival		10+ Employees		20+ Employees		50+ Employees		Acquired	
Unemployment at Graduation	0.676**	1.094***	-0.154	0.006	0.043	0.165	0.125	0.160	-0.145	-0.293**
	(2.38)	(2.62)	(-0.47)	(0.02)	(0.16)	(0.55)	(0.70)	(0.85)	(-0.79)	(-2.33)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	No	No	No	No	No	No	No	No	No	No
University FE	No	No	No	No	No	No	No	No	No	No
Univ. × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	4336	4336	4336	4336	4336	4336	4336	4336	4336	4336
R-squared	.016	.2	.0015	.15	.0015	.15	.0016	.14	.0012	.13

Panel B: Financing, Patents, and IPO

	VC in 5y $>$ 0		VC in '19 $>$ 0		Patent 5y $>$ 0		Patent in '19 $>$ 0		IPO	
Unemployment at Graduation	0.955***	1.412***	0.818**	1.264***	-0.011	-0.063	0.166	0.207	0.009	-0.035
	(3.09)	(4.14)	(2.52)	(4.49)	(-0.09)	(-0.49)	(0.86)	(0.93)	(0.16)	(-0.77)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	No	No	No	No	No	No	No	No	No	No
University FE	No	No	No	No	No	No	No	No	No	No
Univ. × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	4336	4336	4336	4336	4336	4336	4336	4336	4336	4336
R-squared	.021	.2	.016	.2	.0044	.16	.0034	.18	.002	.1

Table A6: Do Labor Shocks Impact Entry of Low-quality Firms due to Graduate Degrees?

This table reports the impact of a change in the local unemployment rate on the proportion of new firms that are ultimately successful. The sample includes the subset of workers without graduate degrees (i.e., Masters, MBA, JD, and PhD) and includes all firms founded within five years following the entrepreneur's graduation from college. The dependent variable is a binary variable measuring whether the worker founded a firm following graduation that ultimately achieved success. In Panel A, we measure firm success based on firm survival, current employment of at least x workers, and acquisition. The first and second columns define success based on survival. The third and fourth columns measure success as currently employing at least 10 workers. The fifth and sixth columns measure success as currently employing at least 20 workers. The seventh and eighth columns measure success as currently employing at least 50 workers. The ninth and tenth columns measure success as whether the startup was ultimately acquired by an established firm. In Panel B, we measure success based on patent creation, access to capital through venture-capital, and likelihood of completing an IPO. In the first and second columns, we measure success as access to venture capital funding within five years of founding. In the third and fourth columns, we measure success as total venture capital funding received until 2019. In the fifth and sixth columns, we measure success at creating at least one patent within five years of founding. In the seventh and eighth columns, we measure success as the total number of patents created until 2019. In the ninth and tenth column, we measure success as the likelihood of successfully completing an initial public offering. *Unemployment at Graduation* measures the unemployment rate in the state where the undergraduate institution is located. *Cohort FE* is a fixed effect for all students graduating in the same major and in a two-year span. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for each gender. *Industry FE* is a fixed effect for the industry of the new firm. We use * to denote significance at the 10% level, ** to denote significance at the 5% level, and *** to denote significance at the 1% level. We cluster standard errors at the state-year level.

Panel A: Survival, Employment, and Acquired

	Survival		10+ Employees		20+ Employees		50+ Employees		Acquired	
Unemployment at Graduation	1.090***	1.382***	-0.117	-0.198	-0.074	-0.163	-0.041	0.138	0.130	0.036
	(4.32)	(4.04)	(-0.59)	(-0.64)	(-0.47)	(-0.57)	(-0.32)	(0.69)	(1.16)	(0.27)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	No	No	No	No	No	No	No	No	No	No
University FE	No	No	No	No	No	No	No	No	No	No
Univ. × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	9296	9296	9296	9296	9296	9296	9296	9296	9296	9296
R-squared	.01	.41	.00078	.38	.00039	.36	.0007	.35	.0016	.32

Panel B: Financing, Patents, and IPO

	VC in 5y $>$ 0		VC in '19 $>$ 0		Patent 5y $>$ 0		Patent in '19 $>$ 0		IPO	
Unemployment at Graduation	1.106***	1.426***	1.032***	1.373***	-0.011	-0.031	0.094	0.184	-0.000	-0.008
	(6.39)	(5.28)	(5.51)	(5.04)	(-0.18)	(-0.24)	(0.84)	(0.87)	(-0.00)	(-0.12)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	No	No	No	No	No	No	No	No	No	No
University FE	No	No	No	No	No	No	No	No	No	No
Univ. × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
N	9296	9296	9296	9296	9296	9296	9296	9296	9296	9296
R-squared	.016	.36	.012	.37	.0016	.36	.0018	.38	.0012	.39

Table A7: What is the Industry Composition of New Firms?

This table reports the industry composition of all new firms in the sample. Panel A focuses on one-digit NAICS and Panel B focuses on three-digit NAICS within the 500-599 NAICS range. Forced Entrepreneurs are defined as all workers graduating in a state above the median unemployment rate in the given year; Voluntary Entrepreneurs are defined as all workers graduating in a state below the median unemployment rate in the given year.

Panel A: Composition of All Firms

	(1)		(2)		(3)	
	All Entrep.		Forced Entrep.		Voluntary Entrep.	
NAICS 1-dig	#Firms	Fraction	#Firms	Fraction	#Firms	Fraction
Agriculture	1026	2.81	533	3.08	493	2.57
Mining, Utilities, and Construction	568	1.56	262	1.51	306	1.60
Manufacturing	4180	11.46	1996	11.53	2184	11.40
Trade and Transportation	834	2.29	379	2.19	455	2.38
Information, Finance, and Professional Serv.	25752	70.62	12162	70.24	13590	70.95
Education and Health	2311	6.34	1123	6.49	1188	6.20
Arts, Accommodation, and Food	1553	4.26	742	4.29	811	4.23
Other Services	243	0.67	117	0.68	126	0.66
Total	36467	100.00	17314	100.00	19153	100.00

Panel B: Breakdown of Firms in the *Information, Finance, and Professional Services Industries*

	(1)		(2)		(3)	
	All Entrep.		Forced Entrep.		Voluntary Entrep.	
NAICS 3-dig	#Firms	Fraction	#Firms	Fraction	#Firms	Fraction
Publishing	7879	30.60	3915	32.19	3964	29.17
Motion Picture and Sound Recording	305	1.18	172	1.41	133	0.98
Broadcasting	82	0.32	42	0.35	40	0.29
Telecommunications	300	1.16	130	1.07	170	1.25
Data Processing and Hosting	890	3.46	385	3.17	505	3.72
Other Information Services	8	0.03	4	0.03	4	0.03
Credit Intermediation	1631	6.33	764	6.28	867	6.38
Securities and Investments	1548	6.01	633	5.20	915	6.73
Insurance	75	0.29	32	0.26	43	0.32
Real Estate	596	2.31	243	2.00	353	2.60
Rental and Leasing	192	0.75	95	0.78	97	0.71
Professional, Scientific, and Technical	12027	46.70	5632	46.31	6395	47.06
Administrative and Support Services	219	0.85	115	0.95	104	0.77
Total	25752	100.00	12162	100.00	13590	100.00

Survey to Entrepreneurs

- How important is it for you to be in control of your daily schedule?
  - 1 (Not at all important)
  - 2 (A little important)
  - 3 (Somewhat important)
  - 4 (Important)
  - 5 (Very Important)
- How important is it for you to have a job providing a variety of different tasks?
  - 1 (Not at all important)
  - 2 (A little important)
  - 3 (Somewhat important)
  - 4 (Important)
  - 5 (Very Important)
- Do you view yourself as a competitive person?
  - 1 (Not at all competitive)
  - 2 (A little competitive)
  - 3 (Somewhat competitive)
  - 4 (Competitive)
  - 5 (Very competitive)
- Over the past 90 years, the US stock market has observed an average return of 9% a year. What will be the average annual US stock market return over the next ten years?
  - 2-4% each year
  - 4-6% each year
  - 6-8% each year
  - 8-10% each year

  - 10-12% each year
  - 12-14% each year
  - 14-16% each year
  - above 16% each year

- Among people born in the US in 1919, 1.4% are still alive in 2019. What is the likelihood you live to age 100?
  - 0-1%
  - 1-2%
  - 2-5%
  - 5-10%
  - 10%-15%
  - 15-20%
  - 20-30%
  - 30-50%
  - >50%

- What is the likelihood your salary doubles in the next five years?
  - 0-1%
  - 1-2%
  - 2-5%
  - 5-10%
  - 10%-15%
  - 15-20%
  - 20-30%
  - 30-50%
  - >50%

- Among firms started by college graduates, 15% grow to employ ten or more workers within five years. If you started a company today, what is the likelihood your firm would employ ten or more workers within five years?

  - 0-1%
  - 1-2%
  - 2-5%
  - 5-10%
  - 10%-15%
  - 15-20%
  - 20-30%
  - 30-50%
  - >50%

- Among firms started by college graduates, 5% are eventually acquired by a larger firm. If you started a company today, what is the likelihood your firm would eventually be acquired?
  - 0-1%
  - 1-2%
  - 2-4%
  - 4-6%
  - 6%-8%
  - 8-10%
  - 10-15%
  - 15-20%
  - >20%

- How much would you pay for a lottery ticket that gives you a 50% probability of winning $500 and 50% of winning nothing?
  - Less than $50
  - 50-$100
  - 100-$150
  - 150-$200
  - 200-$250

- More than $250

- How much would you pay for a lottery ticket that gives you an x% probability of winning $500? (x is between 25% and 75%)
  - Less than $50
  - 50-$100
  - 100-$150
  - 150-$200
  - 200-$250
  - More than $250

- How much would you pay for a lottery ticket that gives you a 50% probability winning $500 and a 50% probability of losing $250?
  - Less than $50
  - 50-$100
  - 100-$150
  - 150-$200
  - 200-$250
  - More than $250