The Journal of FINANCE
The Journal of THE AMERICAN FINANCE ASSOCIATION

THE JOURNAL OF FINANCE • VOL. , NO. 0 • XXXX 2021

Forced Entrepreneurs

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ABSTRACT

Conventional wisdom suggests that labor market distress drives workers into temporary self-employment, lowering entrepreneurial quality. Analyzing employment histories for 640,000 U.S. workers, we document that graduating college during a period of high unemployment does increase entry to entrepreneurship. However, compared to voluntary entrepreneurs, firms founded by *forced* entrepreneurs are more likely to survive, innovate, and receive venture backing. Explaining these results, we confirm that labor shocks disproportionately impact high earners, with these workers starting more successful firms. Overall, we document untapped entrepreneurial potential across the top of the income distribution and the role of recessions in reversing this missing entrepreneurship.

> "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

HOW RELEVANT ARE LABOR MARKET declines in driving workers to start highly successful businesses? Weak labor markets are known to leave lasting scars on the workforce: Displaced workers face lower wages even years after displacement and struggling job seekers are more likely to permanently exit the workforce (Jacobson, LaLonde, and Sullivan (1993), Yagan (2019)). Distressed labor markets may then push some to pursue entrepreneurship, as the

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We thank the Editor, Amit Seru; the anonymous associate editor and referees; discussants Hans Hvide, John McConnell, Paige Ouimet, Jessica Jeffers, Tolga Caskurlu, and Murat Tasci; as well as Heitor Almeida, Fernando Anjos, Brian Ayash, Matt Billett, Nicolas Bollen, Diana Bonfim, Igor Cunha, Andrew Ellul, Miguel Ferreira, Peter Haslag, Mathias Hoffmann, Benjamin Golez, Eitan Goldman, Nandini Gupta, Bharadwaj Kannan, Pedro Matos, Chris Parsons, Noah Stoffman, Antoinette Schoar, Scott Smart, Harry Turtle, Wenyu Wang, and Joshua T. White. We also thank seminar and conference participants at the Bank of Portugal, Cal Poly San Luis Obispo, Colorado State University, Darden Entrepreneurship and Innovation Conference, EFA, FDIC, FIRS, Indiana University, Innovation Workshop, ITAM Finance Conference, HEC Spring Finance Conference, Mitsui Finance Symposium, NOVA School of Business and Economics, University of Virginia, University of Zurich, Vanderbilt University, and Wabash River Finance Conference for their comments and suggestions. We have read *The Journal of Finance* disclosure policy and have no conflicts of interest to disclose.
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DOI: 10.1111/jofi.13097

opportunity cost to engaging in entrepreneurial endeavors may fall during distressed times (Babina (2020)).[1] However, assuming that individuals with the greatest ability enter entrepreneurship regardless of outside job opportunities, workers who start firms following unemployment may be less likely to achieve success, with their firms only transitory until the founder can rejoin the workforce. In this case, the entrance of *forced entrepreneurs* may lead to relatively few innovative and productive ventures.

In contrast to the rationale above, we demonstrate that labor market declines can lead to not only more firms, but also better firms.[2] Specifically, compared to voluntary entrepreneurs, firms founded by forced entrepreneurs are equally likely to grow in terms of employment, and are more likely to survive, innovate, receive venture capital (VC) financing, and be acquired. These results arise due to the highly cyclical wage patterns of the top earners (Parker and Vissing-Jorgensen (2010), Guvenen, Ozkan, and Song (2014), Guvenen et al. (2017)), potentially shifting high-skilled workers toward entrepreneurship following economic downturns.[3] As these same workers are also responsible for a disproportionate level of innovation and transformative entrepreneurship (Baumol, Schilling, and Wolff (2009), Bell et al. (2019)), declines in the labor market can increase the average quality of new ventures. By extending the standard theory of Lucas (1978) to include high- and low-wage workers, we formalize these arguments and develop testable hypotheses.

We compile a novel data set to conduct our analysis. Our data include profiles of 640,000 recent college graduates, representing 3% of all workers graduating from a U.S. college between 1996 and 2014. Although the workers from our sample graduate from over 2,200 undergraduate institutions, we overdraw graduates of highly selective universities since these colleges disproportionately graduate successful entrepreneurs.[4] For instance, Massachusetts Institute of Technology, Stanford University, Northwestern University, Cornell University, University of California at Berkeley, and University of Michigan each graduate 1% or more of the employee sample. We identify over 36,000 founders of firms and our sample include highly successful entrepreneurs such

[1] In line with this argument, policies reducing the income risk associated with entrepreneurship increase the rate of firm creation in the economy (Hombert et al. (2020), Gottlieb, Townsend, and Xu (2021)) and one-quarter of Americans would create a new firm if not for the associated income risk (Gallup (2014)).

[2] We note that our focus on labor market effects differs from Moreira (2016) and Sedláček and Sterk (2017), who illustrate that firms started during recessions are smaller in initial size and experience limited growth due to decreased customer demand and access to capital.

[3] For example, Guvenen et al. (2017) estimate the correlation between growth in earnings and growth in GDP across earnings percentile bins. The authors estimate a GDP-beta of 2 for male workers in the top 1 percentile of wage earnings and over 3.5 for male workers in the top 0.1 percentile. For comparison, workers at the 75$^{\text{th}}$ percentile of earnings have a beta below one.

[4] Based on our own analysis, we estimate that (i) 15% of Fortune 500 firms are created by alumni of top-20 colleges and (ii) these firms represent 30% of Fortune 500 employment. Our findings are additionally supported by evidence from Black (2020) that over 20% of all VC funding is given to graduates of top-20 universities. Finally, Bhagat, Bolton, and Subramanian (2010) estimate that over 15% of all public firm CEOs completed an undergraduate degree at a top-20 university.

as the co-founders of Airbnb, Dropbox, Instagram, Khan Academy, Paypal, Square, Yelp, and Youtube, among others. In total, 141 of the startups in our sample completed successfully an initial public offering (IPO).

To identify the causal effect of job opportunities on selection into entrepreneurship, we exploit the exogenous time of entry in the labor market of individuals who follow similar academic paths. Specifically, we compare a worker graduating from a U.S. undergraduate institution to a worker of the same gender graduating from the same institution with the same major, but in the two previous years. As graduation dates are determined primarily by the year of birth, the characteristics of the student population are uncorrelated with the labor market opportunities at the time of graduation (Kahn (2010)). In addition, because labor market conditions at the time of graduation have long-term effects on wages, even for students attending the most prestigious academic institutions (Oyer (2008)), we identify a large-scale shock to highly skilled young workers.[5] In support of these arguments, we demonstrate that a 1 percentage point increase in the national unemployment rate is associated with a (i) 0.5 percentage point decrease in the likelihood of employment with a top consulting, finance, or technology firm; (ii) 0.4 percentage point decline in the likelihood of employment with a firm in the Russell 1000 Index; and (iii) 0.3 percentage points decrease in a high-wage industry.[6]

In our baseline analysis, we estimate that a 1 percentage point increase in the national unemployment rate increases the likelihood of entering entrepreneurship by 0.2 percentage points compared to individuals 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 one-standard-deviation increase in unemployment increases entrepreneurship by 15% relative to the mean. Since differences in entrepreneurship rates continue to persist three years after graduation, transitory labor shocks result in the creation of firms that otherwise would not exist in the economy. Last, we find that the majority of these firms are in the Financial, Professional, Business, and Technical Services Sector, with this industry composition explained largely by the skillsets of the founding entrepreneurs.

Startups in our sample are more successful than average startups in the economy. We find that 15% of our startups receive VC funding, 4.5% are

[5] Oyer (2008) illustrates that 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 to $5 million. Given undergraduate students of highly ranked institutions also routinely join the financial sector (for instance, Goldin and Katz (2008) estimate that 28% of Harvard College students enter banking following graduation), we can expect similar earnings declines among the students in our sample.

[6] The magnitude of the shock is a primary difference from Hombert et al. (2020), who evaluate the implications of a French policy reform that provided downside insurance to eligible unemployed workers who enter entrepreneurship. They find that the reform, which provides insurance of 2,000 euros a year for up to three years, significantly increases entrepreneurship, primarily self-employment, without worsening the quality of new entrants. We instead focus more on employer firms: 13% of the firms in our sample receive VC financing, nearly 5% are acquired, and 0.4% enter an IPO.

eventually acquired, and 6% receive at least one patent.[7] Confirming labor shocks impact the entry of successful and innovative ventures, we show that an increase in the unemployment rate increases the rate of (i) large employer firms, (ii) venture-backed firms, (iii) patent-holding firms, and (iv) acquired firms.

We next evaluate *which* workers enter entrepreneurship. We compare the ex post success of entrepreneurial endeavors across 10 separate firm measures as evaluated (i) within the five years after graduation from college or (ii) determined at the time of this study. Compared to firms started during periods of low unemployment, we find that forced entrepreneurs have the same employment size and identical probability of 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 VC financing, produce a patent, or be acquired. These results are similar for entrepreneurs starting a firm within two years of graduation, hold across different subsample periods, and are not driven by workers entering graduate school. Taken together, the evidence suggests that workers facing poor labor opportunities start high-quality firms on average.

A potential explanation of the results above is that workers with the greatest entrepreneurial potential are disproportionately exposed to labor shocks. To test this argument, we focus on the workers in our sample with the greatest ex ante likelihood of becoming top earners: those graduating from the 20 (or 10) most selective undergraduate institutions in the United States.[8] Analyzing over 115,000 *elite* workers, we find that labor shocks on graduates from selective institutions disproportionately increase the likelihood of underemployment. Moreover, in response to a labor market shock, we find these workers are more likely to enter entrepreneurship relative to other graduates. We also confirm that entrepreneurs from the most selective institutions are significantly more likely to start high-quality firms relative to the rest of the sample.[9] These findings provide a simple explanation for our results: Top earners are more likely to become entrepreneurs following a decline in labor market opportunities and make better entrepreneurs on average.

To be clear, our results do not imply that recessions increase the level and quality of entrepreneurship. Indeed, the overall effect of recessions on the rate and composition of entrepreneurship is negative (Moreira (2016), Sedláček and Sterk (2017)). Rather, our findings provide the best evidence to date that a supply of potential entrepreneurs are employed in the workforce today,

[7] The VC funding rate of our startups is nearly five times higher than that for the average new firm in the economy (Robb and Robinson (2012))

[8] For instance, we define the 10 most selective colleges as University of Chicago, Harvard University, Columbia University, Stanford University, Princeton, CalTech, UC Berkeley, MIT, Yale University, and University of Pennsylvania.

[9] Relative to the rest of the sample, we find that top 20 (10) graduates are 2% (7%) more likely to start a firm with 20 or more employees, 5% (13%) more likely to receive VC funding, 2% (3%) more likely to be acquired, and 1% (3%) more likely hold at least one patent.

especially in the top finance, consulting, and technology firms.[10] Assuming that innovative entrepreneurs have the potential to boost firm productivity and, in turn, economic growth, there are potential benefits to policies that encourage entrepreneurship and discourage joining rent-seeking occupations (Murphy, Shleifer, and Vishny (1991), Baumol (1996)).

The paper is organized as follows. Section I outlines our theoretical framework. Section II introduces and summarizes our data set. Section III describes the empirical methodology. Section IV discusses our empirical results. Section V concludes.

I. Theory

We first determine the theoretical conditions necessary for labor market declines to increase not only the level but also average quality of entrepreneurship. Under the canonical model of Lucas (1978), agents face the decision of either joining the workforce or entering entrepreneurship. The model assumes that while all workers receive the same wage, entrepreneurs are compensated based on their entrepreneurial ability. Under this framework, shocks to technology ultimately have no impact on the level of entrepreneurship: While a positive technology shocks makes entrepreneurship more desirable, it also leads to higher wages in equilibrium. These effects exactly offset one another such that the level of entrepreneurship in the economy remains constant.[11]

Due to this limitation, we augment the Lucas (1978) model to allow for heterogeneous workers. Specifically, we consider two types of agents: high-type, agents who have a higher marginal productivity of labor and are compensated for this productivity, and low-type agents, who have lower productivity and wages. We also allow productivity in the wage workforce to be correlated with entrepreneurship. Importantly, we do not require high- and low-type agents to be equally exposed to technology shocks in the economy; Instead, the key to the model's implication will depend on which agents are more exposed to technology shocks. When high-type agents are disproportionately exposed to the technology shock, we find that a negative shock leads to (i) an increase in the proportion of high-wage agents selecting into entrepreneurship and (ii) an increase in mean entrepreneurial ability (under two additional assumptions). We provide details of the model below.

We consider an economy with two types of agents: high (H) and low (L) type. High-type individuals differ from low-type individuals as they have a larger

[10] For example, Goldin and Katz (2008) estimate 28% of Harvard College graduates enter the financial services industries as of 2008. In our own sample, we estimate that 17% (21%) of the graduates from top 20 (10) undergraduate institutions joined a prestigious finance/consulting/tech firm following graduation.

[11] Alternatively, we could analyze models in which agents select into entrepreneurship based on risk tolerance (Kihlstrom and Laffont (1979)) or wealth (Rampini (2004)). However, these models generally find that a positive technology shock increases, rather than decreases, the level of entrepreneurship as agents bear less risk following the shock. Our empirical results reject this outcome.

marginal product of labor as defined below. All individuals may become entrepreneurs and each are endowed with an entrepreneurial ability $G(x)$, where

$$G(x) = \begin{cases} \zeta x^{1-\alpha} & \text{if high-type agent} \\ x^{1-\alpha} & \text{if low-type agent.} \end{cases} \tag{1}$$

We assume that x is uniformly distributed between zero and one, and that $\zeta \geq 1$ to allow for a positive correlation between worker productivity and entrepreneurial ability. We also make the standard assumption $0 < \alpha < 1$. If an individual decides to become an entrepreneur, her firm produces

$$f(x, n_L, n_H) = G(x)\left(A^{\theta}\delta n_H^{\alpha} + A n_L^{\alpha}\right), \tag{2}$$

where A is total factor productivity, n_L and n_H are the labor inputs of low- and high-type individuals, δ allows for different marginal products of labor between high- and low-type individuals, and θ is a cyclicality parameter. An entrepreneur's profits are given by

$$\pi(x, n_L, n_H) = G(x)\left(A^{\theta}\delta n_H^{\alpha} + A n_L^{\alpha}\right) - w_L n_L - w_H n_H, \tag{3}$$

where w_H and w_L are the equilibrium wages of high- and low-type individuals. We start by assuming that both high- and low-type individuals may become entrepreneurs. Given that a firm's output increases with x, there is a cutoff, $0 \leq z_s \leq 1$, $s \in \{H, L\}$, above which individuals become entrepreneurs, similar to Lucas (1978). Since the marginal product of labor and entrepreneurial ability differs between high- and low-type individuals, we allow z_H to differ from z_L. Similar to the Lucas model, these cutoffs can be obtained from the break-even condition for the marginal entrepreneur,

$$\pi(z_H, n_L(z_H), n_H(z_H)) = w_H \quad \text{and} \quad \pi(z_L, n_L(z_L), n_H(z_L)) = w_L. \tag{4}$$

The demand for high- and low-type labor can be derived from first-order conditions of the profit function—we derive these conditions in the Internet Appendix.[12] Finally, market-clearing conditions determine market wages for high- and low-type workers according to

$$z_s = \int_{z_H}^{1} n_s' dx + \int_{z_L}^{1} n_s'' dx, \quad \text{with} \quad s \in \{L, H\}, \tag{5}$$

where n_s' is the demand from firms created by high-type individuals and n_s'' is the demand from firms created by low-type individuals. We provide more details on the derivation of the model in the Internet Appendix.

By solving this model, we pin down the level of entrepreneurship among both high- and low-type agents, and, in turn, capture the rate of entrepreneurship

[12] The Internet Appendix may be found in the online version of this article.

among high-type agents relative to low-type agents, $\frac{z_H}{z_L}$, which is given by

$$\frac{z_H}{z_L} = \left(\frac{A^{\theta-1}\delta}{\zeta^{\frac{1}{1-\alpha}}}\right)^{\frac{1}{2-\alpha}}. \tag{6}$$

We present details on the derivation in the Internet Appendix. Equation (6) provides the bounds necessary for the average quality of entrepreneurship among high-wage agents to be greater than the average quality of entrepreneurship among low-wage agents (i.e., $z_H \geq z_L$). This bound requires that $\zeta \leq (\delta A^{1-\theta})^{1-\alpha}$, or alternatively, that δ be sufficiently large relative to ζ. Intuitively, when the marginal product of labor is sufficiently high relative to entrepreneurial returns for high-type agents, only those with very large entrepreneurial ability choose to become entrepreneurs. Put differently, many high-type agents with high entrepreneurial ability choose to be wage workers.

The model provides us a simple framework to understand the theoretical impact of a recession on entry to entrepreneurship across types of individuals, and on entrepreneurial quality. Within our model, a recession (or a negative shock to earnings) is defined as a decrease in total factor productivity, A. We can therefore examine how a recession affects entry to entrepreneurship of high types relative to low types. This leads to our first proposition.

PROPOSITION 1: *If $\theta > 1$, a decline in A causes a disproportional number of high-wage agents to become entrepreneurs relative to low-wage agents, or*

$$\frac{\partial}{\partial A}\left(\frac{z_H}{z_L}\right) < 0. \tag{7}$$

It is trivial to prove Proposition 1 using equation (6). In our setting, Proposition 1 implies that declines in productivity shocks will lead agents with high labor productivity to select entrepreneurship compared to agents with lower labor productivity.

While Proposition 1 is valuable, it remains unclear whether the average quality of entrepreneurship will increase or decrease. This is because the quality of new firms in the economy depends not only on the proportion of marginal high- and low-type agents selecting into entrepreneurship, but also the entrepreneurial ability function $G(x)$. Therefore, the total quality of entrepreneurship in the economy can be defined as

$$Q(z_H, z_L) = \int_{z_H}^{1} \zeta x^{1-\alpha} dx + \int_{z_L}^{1} x^{1-\alpha} dx. \tag{8}$$

How this function depends on the parameter space then leads us to the second proposition.

PROPOSITION 2: *If $\theta > 1$, there exists $\zeta > 1$ and $\delta > 1$ such that total average entrepreneurial quality increases when A decreases.*

We provide the proof to this proposition in the Internet Appendix. In this scenario, a decline in total factor productivity disproportionately reduces the benefits of wage work among high-type agents. In equilibrium, this leads to a sufficiently high rate of entrepreneurial entry among these individuals relative to low-type agents, so that the average entrepreneurial quality in the economy increases after a negative shock. Intuitively, this occurs when (i) agents with greater labor productivity are most exposed to a negative productivity shock, (ii) entrepreneurial ability is sufficiently correlated with the marginal product of labor of high-skill individuals, and (iii) wages of high-skill individuals are sufficiently high in the workforce. The propositions above therefore provide sufficient conditions for a negative productivity shock to lead to an increase in (i) the proportion of agents with high labor productivity entering entrepreneurship and (ii) the average quality of entrepreneurial endeavors. As both outcomes ultimately depend on the parameter space, the model cannot provide clear answers to these questions. We must therefore turn to empirical analysis.

II. Data

A. Data Sources

A.1. Online Business Networking Service Data

We construct a novel data set 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.[13] Users of this website have an incentive to keep their profiles current since the site is valuable for professional networking: Many employers use it to recruit employees, either by posting job ads or through direct headhunting.

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 to 2012 from U.S. universities. We collect the employment history and educational history of each worker included and compile the full worker employment history into a yearly panel data set. Organizations also have profiles, which are typically maintained by the firms (or institutions) themselves. After matching the names of each firm across workers, we collect characteristics for each firm from LinkedIn.[14] Finally, we obtain information for each educational institution mentioned in the resume data.[15]

[13] We note that a portion of the 160 million U.S. users may no longer be in the labor force.

[14] For each firm, we collect year founded, industry, description of firm activities, headquarters address, company size (measured by employment bins), and whether the company is public or private.

[15] We obtain information on exact location, annual tuition, acceptance rate, total enrollment, school website, type of institution (public or private), and founding year.

A.2. Entrepreneurial Financing and Patent Data

To identify new firms, 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 construct two measures of entrepreneurial success. First, we measure survival as the tenure of the entrepreneur at the firm. This assumption underestimates survival, since founders may transfer firm ownership to other parties.[16] 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.

We next obtain additional information for the new firms in our sample. First, we match each firm to its respective profile on Crunchbase.com, an online data service. From these data, we are able to observe whether a firm has received VC funding, the amount invested by each VC investor, whether the company has been acquired, and whether the firm has successfully completed an IPO. We also obtain patent data directly from the United States Patent and Trademark Office (USPTO). We search for the name of each company founded by an entrepreneur in our data set. We choose to collect patents by firm instead of personal patents because (i) doing so accounts for patents created by other inventors at the firm and (ii) such patents are the property of the firm rather than the founder.

B. Data Summary

B.1. Summary of Workers and Undergraduate Institutions

We first compare our data sample to the full set of college graduates. According to data from the National Center for Education Statistics (NCES) (National Center for Education Statistics (2018)), a total of 21.7 million students graduated from an undergraduate institution between 1998 and 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 period. Comparing the national data to our own sample in Figure IA.3 of the Internet Appendix, we note our data overrepresent earlier years in the sample and underreport later years of the sample.

Panel A of Table I reports the average probability that a student in our sample becomes an entrepreneur. We estimate that 2.2% of students found a new firm directly after graduation, 2.8% within two years, and 3.3% within three years.[17] In line with our hypothesis, we find that entrepreneurship rates

[16] However, using the 2007 Survey of Business Owners (SBO) Public Use Microdata Sample (PUMS), we estimate that even five years after formation, 90% of all firms are still owned by the founder.

[17] For comparison, the Kauffman Foundation estimates that on average, each year between 1998 and 2018, only 0.32% of the U.S. population started a business. Our rates of entrepreneurship

Table I

Data Summary of Workers

This table reports summary statistics for all individuals in our sample. Panel A summarizes individual-level characteristics. Panel B summarizes individual's undergraduate institutions. Panel C summarizes the subset of entrepreneurs in the sample. In Panel C, the first and second rows present summary statistics for the individuals who became entrepreneurs, while the remainder of the rows present summary statistics for the firms created by those individuals.

Panel A: Summary statistics, All individuals

	N	Mean	Std	50th	90th
Unemployment at Graduation	641,144	0.052	0.016	0.047	0.087
Graduation Year	641,144	2004.9	4.11	2005	2011
Top 20 College	641,144	0.19	0.40	0	1
Female	641,144	0.36	0.48	0	1
Grad. School within 5 Years	641,144	0.20	0.40	0	1
Prestigious Finance/Consulting/Tech Job	641,144	0.088	0.28	0	0
Russell 1000 Job	641,144	0.25	0.44	0	1
Avg Industry Wage	617,714	61.8	9.97	65.2	69.1
Founder within 1 Year	641,144	0.022	0.15	0	0
Founder within 2 Years	641,144	0.028	0.16	0	0
Founder within 3 Years	641,144	0.033	0.18	0	0

Panel B: Summary statistics, Undergraduate institutions

	N	Mean	Std	50th	90th
Annual Tuition in USD	639,782	22,269.2	16,352.6	13,509	50,494.8
Year Founded	638,142	1,889.1	97.2	1,885.0	1,944.4
Total Enrollment	632,803	30,327.4	24,556.3	25,006.8	65,085.2
Acceptance Rate (%)	633,383	50.8	24.1	53.3	80.2
Public University	641,144	0.75	0.43	1	1

Panel C: Summary statistics, Entrepreneurs and new ventures

	N	Mean	Std	50th	90th
Top 20 College	36,316	0.39	0.49	0	1
Female	36,316	0.21	0.41	0	1
Firm Survival to 2019	36,316	0.23	0.42	0	1
> 10 Employees	36,316	0.14	0.35	0	1
> 20 Employees	36,316	0.094	0.29	0	0
> 50 Employees	36,316	0.051	0.22	0	0
Log(# Current Employees)	36,316	0.78	1.41	0	2.89
Log(VC Funding)	36,316	1.80	4.96	0	12.6
VC Funding > 0	36,316	0.15	0.36	0	1
VC Funding > 0 in 5 Years	36,316	0.12	0.33	0	1
Num Patents > 0	36,316	0.060	0.24	0	0
Patents > 0 in 5 Years	36,316	0.025	0.16	0	0
Acquired	36,316	0.045	0.21	0	0
Initial Public Offering	36,316	0.0038	0.062	0	0

are countercyclical, with over 5% of workers graduating in 2010 entering entrepreneurship within two years of graduation.

Panel B of Table I details the 2,200 different institutions that our sample workers have graduated from. To ensure we include entrepreneurs in the top of the talent distribution, we overselect from the top undergraduate institutions—19% of the workers in our data graduate from a top-20 institution. We list the institution that comprise the largest proportion of our sample in Table IA.I of the Internet Appendix.[18]

B.2. Summary of Entrepreneurs

According to Panel C of Table I, our analysis covers 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-20 undergraduate institution. Second, entrepreneurs are more likely to study engineering and computer-related fields. And third, entrepreneurs are significantly less likely to be female.

Focusing our analysis on workers with college degrees (especially from selective institutions), we find that a significant proportion of startup firms are particularly successful. First, as of 2019, 23% startups continue to be in business and 9.4% (5.1%) employ at least 20 (50) workers. Second, at least 6% of sample firms have created at least one patent, with 2.5% patenting within five years of establishment. We further find that 15% have received VC funding, with 12% receiving VC backing within five years of establishment, and that 4.5% were acquired by a separate firm. Finally, we find that 141 startups successfully completed an IPO, representing 5.7% of all IPOs between 1999 and 2012.[19]

According to Table IA.II and Figure IA.4 of the Internet Appendix, new firms predominantly arise in the Professional, Scientific, and Technical Services (33%), Information (27%), Manufacturing (12%), and Finance and Insurance (9%) industries. Compared to the 2007 Census SBO, our sample of new firms is biased toward firms in Information, Manufacturing, and Professional, Scientific, and Technical Services, while our startups underrepresent the proportion of new firms in trade (both retail and wholesale), Administrative Services, and Accommodation and Food Services.

are likely higher as the majority of college graduates do not already hold full-time employment and are searching for a job. In line with this argument, Evans and Leighton (1990) estimate a rate of entrepreneurship of 2.9 to 4.5% among unemployed individuals.

[18] In order, we find that the University of California at Berkeley and the University of Illinois at Urbana-Champaign each account for 3.11% of our sample of workers, University of Texas at Austin (2.92%), University of California in Los Angeles (2.67%), and the University of Wisconsin (2.49%). Combined, these five institutions graduate 11.82% of our entire sample, while the 10 largest institutions account for 22.8% of our sample.

[19] According to Statista.com, 2,462 startups successfully completed an IPO between 1999 and 2012.

C. Entrepreneurship Potential across the Distribution of Workers

A primary advantage of collecting data from LinkedIn is that profiles are available for workers with the potential to start highly successful entrepreneurial ventures, which allows us to understand the effects of labor market shocks on entrepreneurial quality. We conclude this section by verifying this argument. To ex ante identify entrepreneurs, we focus on the 124,919 (41,881) workers in our sample that graduated from a top-20 (10) institution as defined by *U.S. News and World Report*. This choice is motivated by our findings that (i) 15% of Fortune 500 firms are created by alumni of top 20 colleges and (ii) these firms represent 30% of Fortune 500 employment.[20] Our findings are additionally supported by evidence from Black (2020) that over 20% of all VC funding is given to graduates of top-20 universities.[21] Finally, Bhagat, Bolton, and Subramanian (2010) estimate that over 15% of all public firm CEOs completed an undergraduate degree at a top-20 university.

We present our findings in Table II. Even after controlling for gender and major, we find that (i) graduates of top-20 institutions are better entrepreneurs than other graduates and (ii) graduates of the top-10 institutions are more successful entrepreneurs than graduates of the next 10 institutions. Relative to the rest of the sample, graduates from top-20 (10) institutions are 2% (7%) more likely to start a firm with 20 or more employees, 5% (13%) more likely to receive VC funding, 2% (3%) more likely to be acquired, and 1% (3%) more likely to hold at least one patent. These results confirm that our data include a wide distribution of ex ante entrepreneurial talent.

III. Methodology

Our analysis requires a setting in which individuals are exogenously impacted by fluctuations in labor market opportunities. As such, we exploit the labor market conditions in the year in which a worker first enters the labor market. Prior work documents significant costs to entering the labor market during a period of distress: Oreopoulos, Von Wachter, and Heisz (2012) and Altonji, Kahn, and Speer (2016) estimate that students graduating during a recession earn 9% to 10% less than comparable students, although the effect was considerably larger during the Great Recession. In our specification, we compare a worker graduating from a U.S. undergraduate institution to a student of the same gender graduating from the same institution and with the same major, but during the prior two years.[22]

[20] We constructed these statistics by collecting data from alumni wiki pages (e.g., https://en.wikipedia.org/wiki/List_of_Massachusetts_Institute_of_Technology_alumni#Business_and_entrepreneurship Link to MIT Alumni webpage or https://en.wikipedia.org/wiki/List_of_Duke_University_people#Business Link to Duke Alumni webpage).

[21] This observation is based on the 2020 Pitchbook Universities Report.

[22] A potential concern with this empirical strategy is that students may time their graduation year based on labor market opportunities. However, Oreopoulos, Von Wachter, and Heisz (2012) find little evidence in support of this argument as a 5 percentage point increase in the unemploy-

Table II

Are Graduates from Selective Universities Better Entrepreneurs?

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

	Survival	10+ Emp	20+ Emp	50+ Emp	VC > 0	Acquired	IPO	Patent > 0
Top 10 College	0.078***	0.054***	0.048***	0.031***	0.065***	0.017***	0.003**	0.021***
	(7.93)	(7.63)	(8.45)	(6.33)	(7.44)	(3.59)	(2.50)	(3.71)
Top 20 College	0.060***	0.036***	0.024***	0.014***	0.047***	0.016***	−0.001	0.013***
	(7.24)	(7.85)	(6.54)	(4.74)	(8.22)	(5.33)	(−0.78)	(3.26)
Female	−0.070***	−0.033***	−0.026***	−0.014***	−0.045***	−0.024***	−0.000	−0.019***
	(−13.95)	(−7.41)	(−7.24)	(−5.64)	(−11.24)	(−11.13)	(−0.33)	(−6.00)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Major FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	36,316	36,316	36,316	36,316	36,316	36,316	36,316	36,316
R^2	0.039	0.014	0.012	0.0088	0.034	0.018	0.001	0.015

We first develop an empirical framework to test whether weak labor markets increase entry to entrepreneurship. We estimate the impact of changes in the national unemployment rate on the likelihood that worker i graduating from an undergraduate institution in year t enters entrepreneurship within x years of graduation using the linear probability cross-sectional model

$$\begin{aligned} Entrepreneur^{x}_{i,t} = \beta \times Unemployment_{i,t\to t+1} \\ + University \times CohortFE \times GenderFE + \eta_{i,t}. \end{aligned} \quad (9)$$

The dependent variable ($Entrepreneur^{x}_{i,t}$) is an indicator variable denoting whether individual i graduating in year t entered entrepreneurship within x years after graduation. We focus on entering entrepreneurship within one to three years following graduation. The independent variable of interest, $Unemployment_{i,t\to t+1}$, measures the average national unemployment rate in years t and $t+1$. We focus on multiple years as some of workers in our sample graduate at the end of the calendar year and start searching for positions in the beginning of the following year.[23] The coefficient β thus captures the effect of the unemployment shock on entry to entrepreneurship; according to our hypothesis, $\beta > 0$.

The regressions include fixed effects that interact university, graduation cohort, and gender. Each cohort is defined as a three-year window and each individual belongs to a single cohort; for instance, workers graduating in 1998, 1999, and 2000 with the same academic major compose a cohort.[24] These fixed effects ensure that we only compare workers with individuals of the same gender, from the same university, with the same major, but in the two prior years. We define 10 separate majors in our analysis: (i) Arts, (ii) Biology and Health, (iii) Business, (iv) Communications and Education, (v) Computer Science, (vi) Engineering, (vii) Humanities, (viii) Science, (ix) Social Science and Economics, and (x) Unclassified. We outline the distribution of majors in Panel A of Table IA.5 in the Internet Appendix. The largest majors are Business (20% of the sample), Social Science and Economics (16%), and Engineering (15%), while the smallest major is Arts and Architecture (4%). As illustrated in Panel B, roughly 6% of students are not categorized in our classification and this rate is roughly constant throughout the sample period. As a result of these fixed effects, our inferences remain valid even if colleges are not equally represented in each year of the sample. We cluster standard errors at the state-year level.

ment rate increases time in college by only three weeks on average. Instead, graduation timing appears to be driven primarily by year of birth. According to the NCES, 90% of students enrolled in a bachelor's program at four-year public institutions are under 25 years of age; this number decreases slightly to 87% of students at nonprofit four-year private institutions (National Center for Education Statistics (2017)).

[23] The results remain quantitatively similar if we measure unemployment rate in year t.

[24] The results remain quantitatively similar if we instead include two-year or four-year windows.

Moving to our central hypothesis, we use a strategy that directly measures the quality of firms founded by our sample workers and estimates whether mean quality improves following increases in the unemployment rate. In contrast to the prior test, here we start by estimating our specification with no fixed effects; we 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. Specifically, we estimate the linear probability model

$$\begin{aligned} FirmQuality_{i,t} = {} & \beta \times Unemployment_{i,t\rightarrow t+1} \\ & + University \times CohortFE \times GenderFE \\ & + IndustryFE + \eta_{i,t}, \end{aligned} \tag{10}$$

where $FirmQuality_{i,t}$ is a binary variable measuring the success of the 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 VC financing, (v) acquisition by another firm, and (vi) successful IPO. As before, the independent variable of interest is $Unemployment_{i,t\rightarrow t+1}$, which measures the average unemployment rate in year t and $t+1$. The coefficient β thus measures the impact of the 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 cohort and gender fixed effects. We now also include an industry fixed effect for each two-digit NAICS code given there are likely differences in entrepreneurial ventures across industries. Finally, we cluster standard errors at the state-year level.

IV. Results

We divide discussion of our results into six parts. First, we confirm that an increase in the unemployment rate 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 examine what types of firms and entrepreneurs are missing during periods of strong labor markets. Fourth, we show that labor market shocks have limited impacts on the quality of entrepreneurship. Fifth, we provide an explanation for these findings. Finally, we discuss alternative explanations.

A. *Employment Shocks and Labor Outcomes*

The underlying assumption motivating our empirical framework is that labor market declines impact the job outcomes of recent college graduates. Therefore, we begin by testing this assumption empirically in our sample. We use three measures of employment. Our primary measure defines underemployment based on the percent of the sample obtaining employment with prestigious firms within the financial, consulting, and technology sectors.[25] Our second measure is based on prior evidence that recessions lead college graduates to join less desirable employers even within the same occupation (Oreopoulos, Von Wachter, and Heisz (2012)). 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 Oyer (2008), our third measure focuses on employment across any firm in (i) Finance and Real Estate (NAICS Code 52/53) or (ii) Professional and Business Services (NAICS Code 54). According to Panel A in Table I, 8.8% of workers in our sample join a top finance, consulting, or technology firm, and 25% join a firm listed in the Russell 1000.

We present our findings in Panel A of Table III. Across all measures, we find significant evidence that unemployment shocks lead to lower job quality among college graduates. Specifically, a 1 percentage point increase in the unemployment rate decreases the likelihood of employment in a top finance, consulting, or technology firm by 0.46%; the likelihood of a job in a desirable firm (defined as employers in the Russell 1000 Index) by 0.43%; and the likelihood of joining a high-wage industry by 0.26%. The results offer strong support for our empirical setting.

B. Employment Shocks and Entrepreneurship

B.1. Linear Specification

Panel A of Table IV reports the linear relationship between unemployment and entry to entrepreneurship. According to the first and second columns, a 1 percentage point increase in the unemployment rate increases the entrepreneurship rate by 0.2 percentage points in the year following graduation, with the coefficient statistically significant at the 1% level. As entrepreneurship is relatively rare, our effects are quite large relative to the mean. Specifically, 2.2% of our sample enters entrepreneurship within one year of graduation, and thus a one-standard-deviation increase in the unemployment rate (1.6%) leads to a 15% increase in entrepreneurship relative to the mean. We can also measure these effects in the aggregate. Given our sample includes 641,000 graduates, a one-standard-deviation increase in unemployment results in over 2,000 new firms in our sample. In addition, 21.7 million workers graduated from a four-year college between 1998 and 2012. Assuming that our sample is representative of all college graduates, a one-standard-deviation increase in unemployment would lead to over 70,000 more firms.

[25] The 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. The top consulting firms include McKinsey & Company, The Boston Consulting Group, Booz Allen Hamilton, Bain & Company, and A.T. Kearney. The top technology firms include Amazon, Apple, Cisco, Facebook, Google, IBM, Intel, Microsoft, Oracle, and Yahoo!.

Table III

Do Labor Shocks Impact the Rate of Underemployment?

This table reports the effect of a change in the unemployment rate on the job outcomes of college graduates. Panel A analyzes the set of all workers in our sample. Panel B separately analyzes workers graduating from a top-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, *Prestigious Firms* measures the percent of workers who gain employment with a top finance, consulting, or technology firm; second, *Russell 1000* measures the percent of workers who gain employment with a firm listed in the Russell 1000 Index; third, *High-wage Industry* measures the percent of workers who gain employment within a high-wage industry; and *Graduate School* measures the percent of workers who enter a graduate program (MS, MBA, JD, or PhD) following college graduation. *Unemployment at Graduation* measures the national unemployment rate. *Cohort FE* is a fixed effect for all students graduating in the same major in a three-year span. A student can belong to only one cohort. *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 between the corresponding subsamples. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level. We cluster standard errors at the state-year level.

Panel A: All workers

	Prestigious Firms		Russell 1000		High-Wage Industry		Graduate School	
Unemployment at Graduation	−0.410***	−0.460***	−0.370***	−0.433***	−0.234**	−0.255**	1.078***	1.094***
	(−6.02)	(−7.46)	(−3.38)	(−4.67)	(−2.32)	(−2.52)	(9.99)	(11.37)
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	641,144	641,144	641,144	641,144	641,144	641,144	641,144	641,144
R^2	0.065	0.15	0.035	0.14	0.05	0.17	0.044	0.16

(*Continued*)

Table III
Continued

Panel B: Workers from top-20 schools versus non–top-20 universities

	Prestigious Firms			Russell 1000		
	Top 20	Non-Top 20	diff	Top 20	Non-Top 20	diff
Unemployment at Graduation	−1.269***	−0.242***	−1.026***	−0.762***	−0.345***	−0.417**
	(−9.75)	(−4.85)	(−7.23)	(−4.95)	(−3.71)	(−2.51)
	High-Wage Industry			Graduate School		
	Top 20	Non-Top 20	diff	Top 20	Non-Top 20	diff
Unemployment at Graduation	−0.932***	−0.072	−0.859***	1.180***	1.071***	0.109
	(−4.71)	(−0.80)	(−4.01)	(5.59)	(10.70)	(0.48)
University × Gender × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
N	124,919	516,225	641,144	124,919	516,225	641,144

Table IV

Do Labor Shocks Impact the Rate of Entrepreneurship?

This table reports the impact of a change in the unemployment rate on the likelihood that individuals become entrepreneurs. Panel A analyzes all workers in our sample. Panel B separately analyzes workers graduating from a top-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 one to three years after graduation. *Unemployment at Graduation* measures the national unemployment rate. *Cohort FE* is a fixed effect for all students graduating in the same major and in a three-year span. A student can belong to only one cohort. *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 between the corresponding subsamples. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes 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	
Unemployment at Graduation	0.195***	0.198***	0.188***	0.207***	0.147***	0.170***
	(4.95)	(5.34)	(4.99)	(6.08)	(3.94)	(4.95)
Cohort FE	Yes	No	Yes	No	Yes	No
Gender FE	Yes	No	Yes	No	Yes	No
University FE	Yes	No	Yes	No	Yes	No
University × Gender × Cohort FE	No	Yes	No	Yes	No	Yes
N	641,144	641,144	641,144	641,144	641,144	641,144
R^2	0.016	0.14	0.017	0.14	0.017	0.14

Panel B: Workers from top-10, top-20, and other universities

	1-Y Post College			1-Y Post College		
	Top 10	Non–top 10	diff	Top 20	Non–top 20	Diff
Unemployment at Graduation	0.570***	0.170***	0.400**	0.334***	0.161***	0.173*
	(3.04)	(5.00)	(2.08)	(3.37)	(5.08)	(1.69)
University × Gender × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
N	41,881	599,263	641,144	124,919	516,225	641,144
R^2	0.051	0.16	0.14	0.041	0.18	0.14

One potential concern is that unemployment shocks affect the timing of firm creation. In particular, we may be concerned that poor labor market opportunities 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 IV, a 1 percentage point increase in the unemployment rate increases the cumulative entrepreneurship rate by 0.21 percentage points within two years and by 0.17 percentage points within three years. We therefore document that unemployment shocks lead to a permanent increase in the rate of entrepreneurship as the nontreated group fails to catch up with the treated group.

B.2. Nonlinear Specification

Given that the likelihood of firm creation within three years of graduation is only 3.3% according to Table I, 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 poor fit for this application. To mitigate this concern, we reestimate our results using a probit regression model to verify that the results are robust to the modeling choice in the baseline estimation. Table IA.III of the Internet Appendix reports the results. We confirm that an increase in the unemployment rate increases the rate of entrepreneurship within the year following graduation; in addition, this effect continues to hold through the three years after graduation. The results suggest that our prior estimates under the linear probability model do not depend on the particular empirical specification.

B.3. Subsample Analysis

In Table IA.IV of the Internet Appendix, we evaluate whether the results are driven by the 2008 Great Recession or the 2001 Tech Bubble. We split the sample into two subperiods: workers graduating between 1998 and 2005 and workers graduating between 2006 and 2012. We find evidence of increased entrepreneurship regardless of the time period, although the effect is slightly strong in the later subperiod. We also examine whether the results are driven by a small sample of the workers in our data. In separate regressions, we exclude workers graduating in California, and workers employed in the technology industry. Across specifications, we estimate that a 1 percentage point increase in the unemployment rate increases the four-year entrepreneurship rate by 0.17 percentage points. Our results therefore do not appear to depend on any specific industry or geography.

A separate concern is that the students entering entrepreneurship were not necessarily intending to enter the workforce following graduation, but rather would have entered graduate school had they graduated during a period of low unemployment. While this narrative offers an alternative counterfactual to our hypothesis, we provide two arguments against it. First, Panel A of Table III documents 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, in Table IA.IV of the Internet Appendix we exclude all workers who entered a graduate program within four years following college graduation and confirm that a negative labor shock increases the entrepreneurship rate by 0.25 percentage points.

B.4. State, Regional, and Industry Employment Shocks

We focus on national unemployment shocks as graduates are able to move across state lines to find work, potentially mitigating the effect of more local employment shocks. Motivated by prior evidence that the majority of undergraduate students are in-state residents (Wozniak (2018)) and employed in-state following graduation (Foote (2019)), we examine whether our results hold when defining employment shocks at the state or regional level.[26] We present our findings in Table IA.V of the Internet Appendix. We estimate that a 1 percentage point increase in the state-level unemployment rate leads to a 0.17 percentage point increase in entrepreneurship within one year of graduation. Similarly, we estimate a 0.19 percentage point increase in entrepreneurship when we estimate the unemployment rate at the regional level as defined by the Census.

In our main analyses, we examine unemployment shocks aggregated across all industries. However, some sectors may be more relevant measures of labor market opportunities for recent college graduates. Accordingly, we collect data on employment within each two-digit NAICS industry classification and evaluate the effects of industry-specific shocks on entrepreneurship in Table IA.VI of the Internet Appendix. Although we find that decreases in labor market opportunities increase entrepreneurship across all 12 sectors, the effects are most pronounced in response to declines in (i) education and health care and (ii) finance.

C. Employment Shocks and Startup Characteristics

C.1. Successful Entrepreneurship

One concern with the results above is that employment shocks may only influence the creation of small and unsuccessful firms. Assuming that the economic value of firm creation depends on the likelihood of survival and growth, we should instead evaluate whether economic conditions impact the rate of successful firm creation. To this end, we tighten the definition of an entrepreneur based on reaching various thresholds of entrepreneurial success. In Panel A of Table V we require that, as of 2019, sample firms continue to (i) be in business, (ii) employ at least 10 workers, (iii) employ at least 20 workers, or (iv) employ at least 50 workers. In Panel B, we require that, as of 2019, the sample firms (i) developed at least one patent, (ii) received VC funding, (iii) were acquired, or (iv) successfully completed an IPO.

The point estimates reported in Table V have several implications. First, together with the results in Table IV, the estimates show that 33% of the firms started due to heightened unemployment risk remain in business today. Moreover, among the firms created due to weak labor markets, 7% employ at least

[26] For instance, based on the Census Post-Secondary Employment Outcomes Database, which includes information on graduates from the flagship state universities of University of Michigan, University of Wisconsin, University of Colorado, and University of Texas, 80% of graduates from the University of Texas are employed in-state within one year of graduation. This rate is 66% for the University of Colorado, 55% for the University of Wisconsin (55%) and 41% for the University of Michigan. In addition, these last two percentages increase 15% each when we consider employment across other states in the East North Central Census Division (i.e., Illinois, Indiana, Michigan, Ohio, and Wisconsin).

Table V

Do Labor Shocks Impact the Rate of Successful Entrepreneurship?

This table reports the impact of a change in the unemployment rate on the likelihood that individuals create successful firms. In the first row, we measure firm success 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 of 2019 employing at least 10 workers, the fifth and sixth columns measure success as of 2019 employing at least 20 workers, and the seventh and eighth columns measure success as of 2019 employing at least 50 workers. In the second row, we assess firm success based on patent creation, access to capital through VC 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; in the third and fourth columns, we measure success based on access to VC funding; 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 IPO. *Unemployment at Graduation* measures the national unemployment rate. *Cohort FE* is a fixed effect for all students graduating in the same major and in a three-year span. A student can belong to only one cohort. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for each gender. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level. We cluster standard errors at the state-year level.

	Survived		> 10 Emp		> 20 Emp		> 50 Emp	
Unemployment at Graduation	0.058***	0.065***	0.021**	0.024***	0.014**	0.016***	0.011**	0.014***
	(4.63)	(5.54)	(2.53)	(3.19)	(2.06)	(2.85)	(2.27)	(3.36)
	Patents > 0		VC Funding > 0		Acquired		IPO	
Unemployment at Graduation	0.018***	0.022***	0.041***	0.044***	0.016***	0.015***	0.001	0.001
	(2.88)	(3.87)	(4.37)	(4.96)	(2.85)	(3.69)	(0.69)	(1.19)
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	641,144	641,144	641,144	641,144	641,144	641,144	641,144	641,144

50 employees today, 11% hold at least one patent, 21% receive VC funding, 8% are acquired by other firms, and 1% eventually enter an IPO. In sum, labor opportunities influence the likelihood of significant and productive firms, highlighting the potential for real effects on the economy.

C.2. Industrial Composition

In Panel A of Table VI, we evaluate the impact of labor market declines on entrepreneurship across eight separate industry classifications. We find that an increase in the unemployment rate increases the level of entrepreneurship across seven of the eight industry classifications, with the one exception being the Trade and Transportation sector. The majority of firms founded due to labor market declines are in the Finance and Professional, Business, and Technical Services sectors: Comparing the size of the coefficients across industries, we estimate that a full 69% of firms are founded in this sector.

What explains the high rate of firm creation in the Finance, Professional, and Technical Services sector? One possible explanation is the skillsets of the graduates in our data set uniquely qualify these workers for entrepreneurship in these industries. To test this hypothesis, we estimate the effects of labor market distress on entrepreneurship separately by undergraduate major. As shown in Panel B, we find that increased unemployment leads to a greater rate of entrepreneurship across all nine major classifications. However, employment shocks disproportionately increase the rate of entrepreneurship among graduates with majors in (i) Computer Science, (ii) Engineering, and (iii) Social Science including Economics. Assuming that the skills developed in these majors are valuable to enter the Finance and Professional, Business, and Technical Services sector, these results help explain the industry composition of new firms in the economy.

An alternative explanation is that labor market declines open up new opportunities in the Finance and Professional, Business, and Technical Services sector, leading to more firms in these industries. To test this hypothesis, we estimate how the national unemployment rate affects the composition of employment across industries, defining industries at the two-digit NAICS code. We presents the results in Table IA.VII of the Internet Appendix. Across all 12 industry classifications, we find that increases in the unemployment rate are associated with a higher share of employment in (i) Education and Health Services and (ii) Government. In contrast, we find limited effects on the Finance, Professional, Business, and Technical Service sector. Therefore, our results do not suggest that forced entrepreneurs select into these sectors due to unique demand opportunities during recessions.

D. Employment Shocks and Entrepreneurial Quality

D.1. Measures of Entrepreneurial Quality

We next turn to our primary hypothesis: Employment shocks increase the relative quality of entrepreneurial firms. Testing this hypothesis depends on

Table VI

Which Entrepreneurs Are Missing in Strong Labor Markets?

This table reports the impact of a change in the unemployment rate on the industry of new firms and skills of the entrepreneurs. Panel A includes the sample of all workers and the dependent variable is a binary variable measuring whether the worker founded a firm in a given industry within one year of graduation. Panel B splits workers across nine academic majors, and the dependent variable is a binary variable measuring whether the worker founded a firm within one year of graduation. *Unemployment at Graduation* measures the national unemployment rate. *Cohort FE* is a fixed effect for all students graduating in the same major in a three-year span. A student can belong to only one cohort. *University FE* is a fixed effect for each undergraduate institution. *Gender FE* is a fixed effect for each gender. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level. We cluster standard errors at the state-year level.

Panel A: 1-digit NAICS industry classifications of new firms

	Construct	Manufact	Trade & Transport	Finance & Bus Services	Education & Healthcare	Leisure	Other Services
Unemployment	0.003	0.020**	−0.003	0.113***	0.021***	0.016***	0.003
	(1.01)	(2.17)	(−0.64)	(3.21)	(3.15)	(2.87)	(0.94)
Uni × Gender × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	641,144	641,144	641,144	641,144	641,144	641,144	641,144
R^2	0.095	0.09	0.14	0.13	0.14	0.16	0.14

Panel B: Academic major of entrepreneurs

	College Major								
	Comm & Edu	Bio & Health	Humanities	Social & Econ	Arts	Computer Science	Business	Engineering	Sciences
Unemployment at Graduation	0.249**	0.099	0.058	0.229**	0.207	0.285*	0.079*	0.306***	0.093
	(2.58)	(0.95)	(0.57)	(2.55)	(1.06)	(1.85)	(1.80)	(4.22)	(0.96)
Univ. × Gender × Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	47,415	37,098	49,951	104,314	25,112	68,185	132,158	95,527	39,472
R^2	0.18	0.19	0.13	0.1	0.22	0.11	0.1	0.073	0.15

directly observing the success of entrepreneurial endeavors. Similar to Table V, we measure quality across several measures: (i) continues to be in business as of 2019, (ii) employs at least x workers as of 2019, (iii) developed a patent prior to 2020, (iv) received VC financing prior to 2020, (v) was acquired prior to 2020, or (vi) completed an IPO prior to 2020. We define each measure as a binary variable. We then compare same gender entrepreneurs who graduated from the same university and major but in the two consecutive years. Specifically, we estimate the regression model introduced in equation (10).

We present the results in Table VII. As we limit this analysis to entrepreneurs who found firms within five years of graduation, our sample drops to 12,059 total observations. 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 better equip individuals to become entrepreneurs. In such a case, university fixed effects would absorb important variation as they would not allow us to learn whether negative labor shocks push fewer 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 *forced* and *voluntary* entrepreneurs.

We find little evidence that employment shocks decrease the quality of entrepreneurship. In particular, we show that a 1 percentage point increase in unemployment leads to a 1.5 percentage point increase in the likelihood of survival, a 1.3 percentage point increase in the likelihood of receiving VC funding, a 0.7 percentage point increase in the likelihood of patent creation, and a 0.5 percentage point increase in the likelihood of an acquisition. In addition, we find no relationship between the unemployment rate and employment or an IPO. Taken together, the evidence suggests that labor market declines may increase the quality of entrepreneurship and provides no support of a decrease in quality.

D.2. Entering within Two Years of Graduation

In Table VII 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 address this concern, in Table VIII we rerun the analysis above by considering only firms started within two years following graduation, which reduces the sample to 6,335 observations. Within this subsample of workers, we continue to find that an increase in the unemployment rate increases the likelihood of survival, VC funding, and eventual acquisition; however, we no longer document any effect on patent creation. The other measures are not statistically different from zero.

Table VII
Do Labor Shocks Impact Entry of Low-Quality Firms Founded within Five years?

This table reports the impact of a change in the unemployment rate on the proportion of new firms that reach success. 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 firm achieved success. In first row, the first and second columns define success based on survival, the third and fourth columns measure success as employing at least 10 workers of 2019, the fifth and sixth columns consider 20 workers, and the seventh and eighth columns consider 50 workers. In the second row, in the first and second columns we measure success as receiving VC funding, in the third and fourth columns we measure success at creating at least one patent, in the fifth and sixth columns we measure success as being acquired by an established firm, and in the seventh and eighth columns we measure success as the likelihood of successfully completing an IPO. *Unemployment at Graduation* measures the national unemployment rate. *Cohort FE* is a fixed effect for all students graduating in the same major in a three-year span. A student can belong to only one cohort. *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. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level. We cluster standard errors at the state-year level.

	Survival		10+ Employees		20+ Employees		50+ Employees	
Unemployment at Graduation	1.487**	1.378*	−0.208	0.134	−0.174	0.042	−0.143	−0.024
	(2.14)	(1.76)	(−0.50)	(0.21)	(−0.50)	(0.09)	(−0.58)	(−0.07)
	Venture Capital > 0		Patent > 0		Acquired		IPO	
Unemployment at Graduation	1.314***	1.420**	0.713**	0.752**	0.452	0.458	−0.002	0.062
	(2.60)	(2.22)	(2.14)	(2.05)	(1.47)	(1.55)	(−0.03)	(0.60)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	No	No	No	No	No	No	No	No
University FE	No	No	No	No	No	No	No	No
Univ. × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes
N	12,059	12,059	12,059	12,059	12,059	12,059	12,059	12,059

Table VIII

Do Labor Shocks Impact Entry of Low-Quality Firms Founded within Two years?

This table reports the impact of a change in the unemployment rate on the proportion of new firms that reach success. 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 firm achieved success. In first row, the first and second columns define success based on survival, the third and fourth columns measure success as employing at least 10 workers of 2019, the fifth and sixth columns consider 20 workers, and the seventh and eighth columns consider 50 workers. In the second row, in the first and second columns we measure success as receiving VC funding, in the third and fourth columns we measure success at creating at least one patent, in the fifth and sixth columns we measure success as being acquired by an established firm, and in the seventh and eighth columns we measure success as the likelihood of successfully completing an IPO. *Unemployment at Graduation* measures the national unemployment rate. *Cohort FE* is a fixed effect for all students graduating in the same major in a three-year span. A student can belong to only one cohort. *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. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level. We cluster standard errors at the state-year level.

	Survival		10+ Employees		20+ Employees		50+ Employees	
Unemployment at Graduation	2.002**	2.319**	0.092	1.137	0.013	0.604	0.032	0.315
	(2.53)	(2.36)	(0.17)	(1.22)	(0.03)	(1.08)	(0.10)	(0.61)
	Venture Capital > 0		Patent > 0		Acquired		IPO	
Unemployment at Graduation	1.796***	1.732*	0.480	−0.274	0.948**	1.021*	0.034	0.176
	(2.95)	(1.94)	(1.17)	(−0.37)	(2.11)	(1.77)	(0.37)	(0.96)
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Cohort FE	Yes	No	Yes	No	Yes	No	Yes	No
Gender FE	No	No	No	No	No	No	No	No
University FE	No	No	No	No	No	No	No	No
Univ. × Gender × Cohort FE	No	Yes	No	Yes	No	Yes	No	Yes
N	6,335	6,335	6,335	6,335	6,335	6,335	6,335	6,335

D.3. Quality across the Firm Lifecycle

Overall, the results highlight limited differences in entrepreneurial quality between entrepreneurs graduating in weak and tight labor markets. A potential downside of the analysis 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, but, these firms may also grow more quickly and eventually reach the employment size of their competitors. In this section we compare firm quality across points in time. Specifically, we use our regression model (10) to estimate the relationship between the national unemployment rate and firm outcomes for each year since establishment. As before, we compare firms within the same industry and year of establishment. We also continue to interact university fixed effects with cohort fixed effects.

Figure 1 plots both the estimated coefficient along with the 95% confidence intervals. In Panel A we estimate the percent of firms that develop a patent in year t, where $t = 1, .., 10$. We find that graduating during a poor labor market leads to higher rates of patent creation with the results statistically significant at the 5% level for all 10 years following establishment. In Panel B we estimate the cumulative percent of firms that received VC funding by year t, and find that entrepreneurs graduating during a period of high unemployment are more likely to receive VC funding from the second to the tenth year following establishment. Thus, across the lifecycle of the firm, we continue to find that labor market opportunities lead to an increase in average entrepreneurial quality.[27]

D.4. Entrepreneurs without Graduate Degrees (MS, JD, MBA and PhD)

In Panel A of Table III, we confirmed that students facing a tough labor market are more likely to apply for and enter graduate programs. If these programs increase human capital and improve the entrepreneurial ability of the student, then firms founded by workers graduating during a period of high unemployment may 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. We address this concern in Table IA.VIII of the Internet Appendix, by excluding all workers holding a graduate degree (i.e., Masters, MBA, JD, and PhD); we then include all firms founded within five years of 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, receive VC funding, or be acquired. We find no other evidence that the labor market impacts alternative measures of success.

[27] 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.

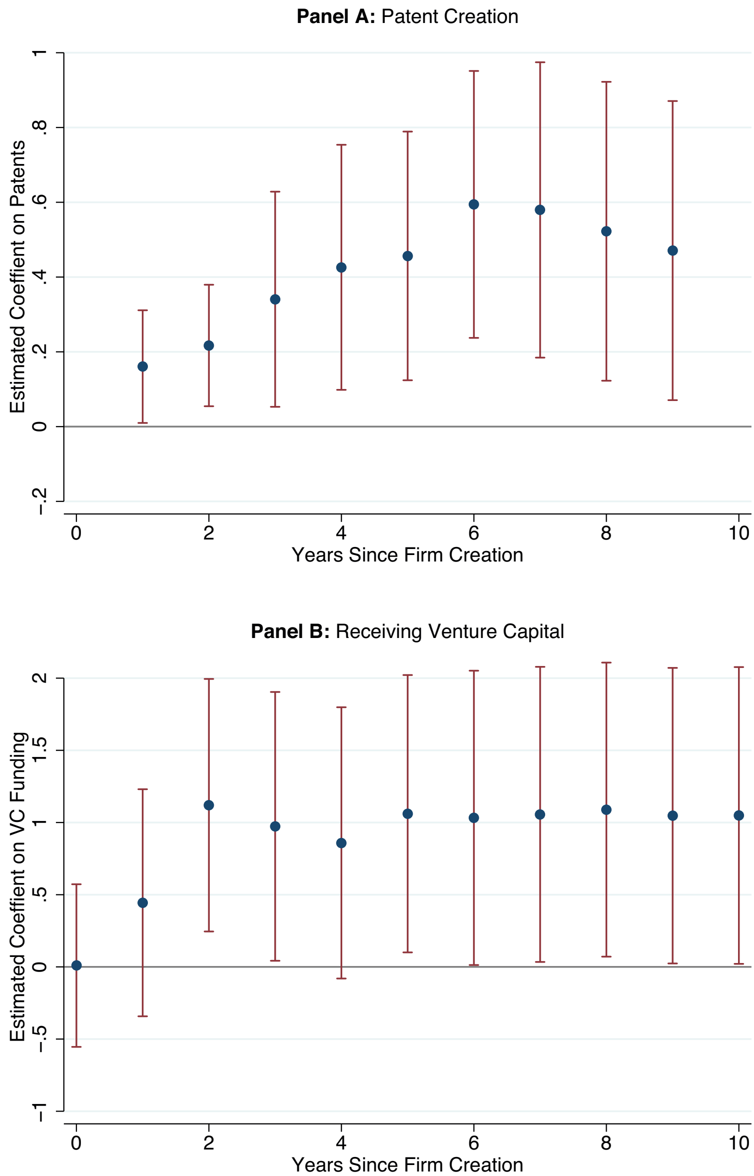

Figure 1. Patent creation and venture capital of new firms. In Panel A (Panel B), we plot the estimated regression coefficients of labor market opportunities on the likelihood of a new firm developing a patent (receiving venture capital). We estimate this relationship separately for each year x following firm establishment:

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

Unemployment measures the national unemployment rate. *Cohort FE* is a fixed effect for all students graduating in the same major in a nonoverlapping three-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 provide the 95% confidence intervals. (Color figure can be viewed at wileyonlinelibrary.com)

D.5. Entrepreneurs Graduating before and after 2005

A separate concern with our empirical framework is that graduating in a poor labor market will encourage potential entrepreneurs to start a new firm more quickly; these workers will then have more time to expand the business and reach significant milestones. Alternatively, it may be the case that the majority of variation in labor market opportunities occurs in the later half of the sample during the Great Recession. Given these concerns, we split the sample into two subperiods based on year of graduation: (i) 1998 to 2005 and (ii) 2006 to 2012. We present the results in Tables IA.IX and IA.X of the Internet Appendix. Across both sample periods, the evidence suggests that labor market distress increases the average quality of entrepreneurship in the economy.

E. Why Employment Shocks Increase Entrepreneurial Quality

E.1. Employment Shocks and Entrepreneurship by Undergraduate Institution

Contrary to conventional wisdom, we find that workers starting firms due to limited labor market opportunities perform no worse—and often perform better—than voluntary entrepreneurs. Based on our extension of the standard Lucas (1978) model, these patterns can arise when workers with the greatest entrepreneurial potential are disproportionately exposed to economic downturns. To confirm this argument, we next evaluate whether the workers with the greatest ex ante entrepreneurial potential are disproportionately likely to enter entrepreneurship when graduating into a poor labor market. As we demonstrated in Table II above, (i) graduates of the top 20 institutions are better entrepreneurs than other graduates in the sample and (ii) graduates of the top 10 institutions are substantially better entrepreneurs than graduates of the next 10 institutions. Accordingly, we distinguish graduates based on the ranking of their undergraduate institution.

In Panel B of Table IV, we split the sample between graduates of top-10, top-20, and all other institutions. We focus on entrepreneurship within one year of graduation, though the results are similar under alternate time intervals. We estimate that a 1 percentage point increase in the unemployment rate leads to a 0.57 (0.35) percentage point increase in the rate of entrepreneurship among workers graduating from a top-10 (top-20) institution. For comparison, we estimate a 0.17 (0.16) percentage point increase among workers graduating from institutions outside the top-10 (top-20). These findings are striking since graduates of the highest ranked institutions are more likely to reach entrepreneurial success according to Table II.

These results indicate that even within the 20 most selective undergraduate institutions, labor market shocks disproportionately increase entrepreneurship among the 10 highest ranked institutions. Assuming that ranking is indicative of ex ante entrepreneurial ability, we should continue to find that decreased employment opportunities do not decrease the average quality of firms even within this subsample of workers. We verify this conjecture in Table IA.XII of the Internet Appendix. We consider the set of entrepreneurs (i) graduating from a top-20 institution and (ii) starting a firm within five years of graduation.[28] Across all specifications, we find that graduating in a poor labor market is associated with a greater rate of survival, VC, and patent creation. We find no statistically significant effects for other measures.

E.2. Employment Shocks and Underemployment by Undergraduate Institution

For our model to sufficiently explain why entrepreneurial quality can rise during periods of labor market distress, labor market shocks must be disproportionately costly for graduates with the greatest entrepreneurial potential. We now confirm this assumption. In Panel B of Table III we estimate the impact of employment opportunities on the underemployment rate of workers graduating from top-20 institutions. We estimate that a 1 percentage point increase in the unemployment rate decreases the rate of employment with top finance, consulting, or technology firms by 1.3 percentage points; in comparison, we estimate a 0.24 percentage points decline for all other workers, with the difference statistically significant at the 1% level. Based on this measure, we find evidence that graduates of highly ranked undergraduate institutions are particularly exposed to labor market shocks.[29]

For additional evidence, we also extend our analysis to alternative measures of underemployment outside finance, technology, and consulting. We estimate a 0.76 percentage point decrease in the likelihood of joining a Russell 1000 employer (compared to a 0.35 percentage point decline for all other workers) and a 0.93 percentage point decrease in employment within a high-wage industry (compared to a 0.072 percentage point decrease for other workers). In both cases the differences in coefficients are statistically different, providing additional evidence that employment shocks are more costly for graduates of high-ranked undergraduate institutions. Finally, in Table IA.XI of the Internet Appendix we estimate the effect of labor market shocks on underemployment within graduates of top-10 institutions. We find that a 1% increase in the unemployment rate is associated with a 1.4% decrease in the likelihood of joining a top finance, consulting, or tech firm. This is sightly larger than the estimate across all top-20 graduates (1.3%).

[28] The results are similar if we do not place a restriction on the time until firm creation.

[29] An alternative explanation of these findings is that students outside highly ranked institutions rarely have access to these employment outcomes regardless of the labor market dynamics upon graduation. However, we confirm that even among students outside the top-20 institutions, 7% of workers in our sample join a top finance, consulting, or technology firm, 25% join a firm listed in the Russell 1000, and 40% enter a high-wage industry.

F. Alternatives

F.1. Alternative Data Sources

The evidence above provides a simple explanation of our findings: Workers with the greatest entrepreneurial ability are disproportionately exposed to a shock to labor market opportunities. A potential concern with this explanation is that differences in exposure may not hold in more representative data sets. To alleviate this concern, we first note that prior research finds that workers at the top of the income distribution are the most exposed to recessions and that these effects are largely driven by the cyclicality of the financial services industry (Parker and Vissing-Jorgensen (2010), Guvenen, Ozkan, and Song (2014)). For example, Guvenen et al. (2017) estimate the correlation between growth in earnings and growth in GDP across earnings percentile bins, and find a GDP-beta of 2 for male workers in the top 1 percentile of wage earnings and over 3.5 for male workers in the top 0.1 percentile. For comparison, they find that workers at the 75^{th} percentile of earnings have a beta below one.

Next, we confirm that these relationships continue to hold for recent graduates of highly selective institutions included in our data. Specifically, we analyze publicly available data on GDP-betas across age cohorts from Guvenen et al. (2017) and focus on the financial sector given the prevalence of students from highly selective institutions that enter the financial sector following graduation (Goldin and Katz (2008)). We then plot the GDP-betas separately for four age groups—26 to 35, 36 to 45, 46 to 55, and 56 to 65—in Figure IA.6 of the Internet Appendix. Focusing on the youngest cohort, we find that the GDP-beta remains relatively flat across the income distribution until reaching the top of the distribution. Thus, we continue to find evidence that higher earners are disproportionately exposed to economic declines, even among younger cohorts.

We also retest our first hypothesis using data from the U.S. Census Bureau Current Population Survey. We focus our analysis on all college-educated workers graduating from 1995 to 2015, and estimate the effect of the unemployment rate at graduation on the likelihood of entering entrepreneurship within three years of graduation. According to Table IA.XIII of the Internet Appendix, we find that a 1 percentage point increase in the national unemployment rate at graduation increases the entrepreneurship rate by 0.1 to 0.11 percentage points. These coefficients are similar to our estimates among graduates from non–top-20 undergraduate institutions using LinkedIn data. As these estimates are far smaller than the effects for top-20 and top-10 graduates, the results continue to confirm that labor market distress disproportionately leads to entrepreneurship among workers with the greatest income potential.

F.2. Alternative Theories

A separate concern is that alternate theories of entrepreneurship better explain our results. However, we believe that our findings are largely incompatible with models in which agents are equally exposed to technology shocks.

Consider three types of theoretical models where selection into entrepreneurship is driven by (i) ability, (ii) risk tolerance, or (iii) wealth. We first return to the canonical model of Lucas (1978) to understand the role of ability. Under this framework, shocks to technology ultimately have no impact on the level of entrepreneurship: While a positive technology shock makes entrepreneurship more desirable, it also leads to higher wages in equilibrium. These effects exactly offset one another such that the level of entrepreneurship in the economy remains constant. Alternatively, we could analyze models in which agents select into entrepreneurship based on risk tolerance (Kihlstrom and Laffont (1979)) or wealth (Rampini (2004)). However, these models generally find that a positive technology shock increases, rather than decreases, the level of entrepreneurship. This increase is due to the fact that technology shocks can decrease exposure to entrepreneurial risk, leading to less wealthy (or less risk tolerant) entrepreneurs. Given labor market declines appear to increase the level of entrepreneurship in the economy, our findings conflict with the implications of these standard models.

V. Conclusion

Conventional wisdom suggests that workers with the greatest ability select into entrepreneurship prior to any labor shocks. According to this argument, any firms created due to local employment shocks will be a stop-gap measure until the founder can rejoin the workforce. *Forced entrepreneurs* would then disproportionally lead to the creation of low-quality firm. However, in contrast to these arguments, we find that businesses formed by entrepreneurs entering weak labor markets perform as well as, and often better than, those that enter during strong labor markets. Upon further examination of the data, we find that (i) entrepreneurial success is driven by the top of the income distribution and (ii) these same workers are disproportionately impacted by labor shocks. These results suggest that labor shocks can increase entrepreneurial quality. Our results therefore provide the best evidence to date that even the best entrepreneurs are not destined to select into entrepreneurship, and thus many wage workers today have high entrepreneurial potential.

More broadly, this paper highlights the current data limitations researchers face when studying firm creation. Current data sets lack detailed information on both founder characteristics (such as occupation and education) and attributes of small firms (employment size, revenue, financial access). By relying on newly hand-collected data from LinkedIn, we construct a unique data set covering over 640,000 college graduates across the United States. This paper illustrates the value of these data for research purposes, especially to understand dynamics and preferences of workers entering entrepreneurship.

Initial submission: November 9, 2016; Accepted: March 22, 2021
Editors: Stefan Nagel, Philip Bond, Amit Seru, and Wei Xiong

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.