Failing Just Fine: Assessing Careers of Venture Capital-backed Entrepreneurs Via a Non-Wage Measure*

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January 20, 2023

Abstract

This paper proposes a non-pecuniary measure of career achievement, *seniority*. Based on a database of over 130 million resumes, this metric exploits the variation in how long it takes to attain job titles. When non-monetary factors influence career choice, assessing career attainment via non-wage measures, such as seniority, has significant advantages. Accordingly, we use our seniority measure to study labor market outcomes of VC-backed entrepreneurs. Would-be founders experience accelerated career trajectories prior to founding, significantly outperforming graduates from same-tier colleges with similar first jobs. After exiting their start-ups, they obtain jobs about three years more senior than their peers who hold (i) same-tier college degrees, (ii) similar first jobs, and (iii) similar jobs immediately prior to founding their company. Even failed founders find jobs with higher seniority than those attained by their non-founder peers.

* We thank Christian Miller for his outstanding research assistance. We also thank seminar participants at Harvard Business School for helpful comments. Gompers has consulted to general partners and limited partners investing in venture capital. Gompers received research support from the Division of Research, Harvard Business School. The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Federal Reserve Bank of Philadelphia, the Federal Reserve Board, or the Federal Reserve System. Any errors or omissions are the responsibility of the authors. No statements here should be treated as legal or investment advice. All data used in this work are licensed through Harvard University.

1 Introduction

Economists generally use pecuniary measures when studying labor market outcomes. A prime example is the large literature on the returns to college education (Lovenheim and Smith, 2011), which conventionally estimates these returns through wages (Angrist and Krueger, 1992; Dale and Krueger, 2011). Pecuniary measures of career achievement appeal for two reasons. First, they are easily measurable, i.e., they are a convenient way for researchers to assess career advancement. Second, because money is a significant driver of human behavior, wages are one of the most important dimensions of career trajectory. However, using salary on its own to evaluate careers may have significant drawbacks, especially when comparing across industries and functional areas.

For example, comparing salaries of senior academics, government officials, or non-profit executives to earnings of junior tech or finance professionals would likely lead to erroneous conclusions about career achievement. When non-pecuniary factors influence career choice, researchers must look beyond wages to draw meaningful inferences. For this reason, many papers that assess career achievement along non-wage dimensions focus on single industries or individual companies (Li and Walder, 2001; Johnson and Walker, 2018). Nonetheless, the paucity of *general* non-wage measures has continued to limit analysis of career achievement across industries along non-wage dimensions.

To address these current limitations, we accordingly construct a new *general* non-wage measure of career achievement using a database of over 130 million resumes. This measure, which we call *seniority*, exploits the variation in the average time to attain a job title. We show that seniority characterizes career trajectories in an intuitive and robust manner and provides valuable insights in a variety of settings, such as the returns to tertiary education and (in particular) the returns to venture capital (VC)-backed entrepreneurship.

The seniority measure relies on resume data from Lightcast, which collects work history and education data from a large online professional networking company. The main data sample includes detailed information on graduation dates for post-secondary degrees, job titles, employers, employer's industry, and job start and end dates for more than 130 million individuals employed in the US. We use this universe of de-identified profiles to construct the seniority measure. A subset of these profiles includes more specific information on graduates from 44 prominent universities in the United States. Each profile in this subset contains the person's name, post-secondary education institution(s), degree(s), and respective graduation date(s), job titles, employers, employers' industry, and job start and end dates. Finally, we analyze a third set of identified profiles for the founders of VC-backed companies from the Dow Jones VentureSource data cataloguing the status and history of these founders' startups.

Seniority is calculated from the main data by examining all individuals who achieve a certain title in a given industry and firm size quintile as ranked by number of employees. We define a job title's seniority as the median time (in years) that it takes to first achieve that title after entering the labor force (i.e., from the year of undergraduate graduation). For example, the title "software engineer" in a top-quintile (i.e., largest size) firm within the IT industry is associated with a seniority of 5, which indicates that the median individual in our sample who at some point becomes a software engineer in a top-quintile IT firm first achieves that title five years after graduating college. Thus, software engineer is a relatively junior title. By contrast, "lead software engineer" within the same size quintile and industry has a seniority of 12. On the most senior end of the scale, "chief executive officer" in the same firm quintile and industry has a seniority of 21, and "director" has a seniority level of 22. Intuitively, our seniority measure quantifies an individual's position within the organization's hierarchy.

It is important to note that the seniority value of a job title is unrelated to an individual's tenure in the labor market.[1] An individual can get "stuck" at the same seniority level until the end of his or her career. This feature starkly contrasts with studies that use workers' tenure or "years on the job" as a measure of relative career progression within firms (Topel and Ward, 1992; Buchinsky et al., 2010; Buhai et al., 2014). Because our seniority measure reflects a job's hierarchical position, it helps quantify the relative economic significance of job changes. For example, we can say that an individual who spends one year in a job with a seniority of 3 and moves to a job with a seniority of 5 experiences a 2 unit gain in non-wage career progression. We can also compare this individual to one who moves from a job of seniority 3 to a job of seniority 4. Both switches are analogous to a promotion, but importantly, we can quantify and compare the changes. Changes in seniority thus have more economic meaning than an indicator that measures whether a person gets promoted. From this perspective, our seniority measure can also be used to capture the speed and magnitude of a person's career progression over time; exceptional workers will advance faster and achieve higher seniority levels earlier in their careers. Importantly, differences in seniority are meaningful even as individuals move between firms and even across industries.

To validate seniority, we present several empirical facts which confirm that the measure reasonably captures people's career trajectories. First, we directly compare our seniority measure with wage data from the Bureau of Labor Statistics (BLS). We show that seniority is positively

[1] Using "lead software engineer" as an example, an exceptional individual may achieve the lead software engineer title in five years after graduating from college, while another may take more than 12 years. The seniority value in both cases would be equal to how long it takes the median professional to achieve this title.

correlated with wages and that both measures increase over time. Careers tend to eventually reach a plateau—about 20 years after college graduation—both in terms of seniority and real wage. Reaching ever higher-seniority titles becomes a very rare event later in careers. For example, only 22% of people with 20 or more years of career information ever achieve job titles that have seniority level of 20. Much like wages, the distribution of seniority is right-skewed.

Next, we track seniority over time by educational attainment in two verification analyses. First, we show that graduates of elite undergraduate colleges rise in seniority faster and achieve higher terminal levels of seniority, on average, than graduates of second-tier or "Tier-2" colleges. In turn, graduates of Tier-2 colleges similarly outperform those who graduate from lower-ranked schools. Our second verification test examines the impact of receiving an MBA degree. We divide individuals in our sample into three groups: those that pursue an elite MBA (Harvard, Stanford, Wharton, Chicago, or Northwestern), those that pursue a non-elite MBA, and non-MBA holders. Prior to receiving an MBA, all three groups have comparable seniority. However, upon receiving an MBA degree, all MBA graduates receive a seniority boost relative to those who do not pursue an MBA, and the increase is substantially larger for elite MBA graduates. In addition, the difference in average seniority between these three groups increases over time. These patterns reassure us that our seniority measure reflects meaningful labor market information.

The second section of our paper uses seniority and (estimated) wage measures to examine career trajectories of VC-backed entrepreneurs before and after founding their companies. A detailed examination of the career patterns of VC-backed entrepreneurs can shed light on the returns to entrepreneurship, as conclusions from the existing literature on this topic remain somewhat ambiguous. Moskowitz and Vissing-Jorgensen (2002), Hamilton (2000), and Hall and Woodward (2010) find that the returns to entrepreneurship are, on average, quite low. Similarly, Bruce and Schuetze (2004) and Baptista et al. (2012) find that entrepreneurs suffer wage penalties when returning to salaried employment. Others, in contrast, find that entrepreneurs who hire others or incorporate businesses gain a (sometimes substantial) post-entrepreneurship wage premium, while self-employed individuals do not (Luzzi and Sasson (2016); Levine and Rubinstein (2017, 2022)).

This literature on returns to entrepreneurship has generally looked at Census or survey data that do not distinguish between different types of start-up activity. To our knowledge, ours is the first paper that examines the pre- and post-founding career trajectories of VC-backed entrepreneurs. Our focus on VC-backed entrepreneurs allows us to isolate the returns of high-potential entrepreneurship (i.e., entrepreneurship that raises tens or hundreds of millions of dollars) from the returns to small business ownership, in which the ability to scale up production and employment is substantially more constrained. Founders of VC-backed companies are typically highly educated, often attain advanced degrees, and have significant outside employment options prior to starting their companies. We are also able to analyze heterogeneity in entrepreneurial returns in the labor market for individuals formerly involved in successful, active, or failed start-up ventures. Most existing studies that examine labor market outcomes after entrepreneurship cannot observe whether entrepreneurs rejoin the labor force due to previous start-up failure, previous start-up success, or other reasons. Jenkins and McKelvie (2016) highlight the difficulty of identifying entrepreneurial failure and labor force reentry. By contrast, VC-backed companies have the clear goal of exiting via an IPO or a high-value acquisition, making firm success or failure easier to identify and study.

Simultaneous consideration of both seniority and wage trajectories for entrepreneurs post-founding thus resolves multiple difficulties faced in prior research. Each measure offers certain distinct advantages in evaluating these individuals' career trajectories. On the one hand, seniority measures that are differentiated within industries and by firm size offer a more accurate assessment of entrepreneurs' career trajectories than estimated wages, which publicly available data often fail to disaggregate beyond the industry level. Relatedly, firm-specific wages over the entire course of an individual's career are difficult to obtain even from restricted access sources such as the US Census and/or IRS. Additionally, seniority may more accurately characterize the changes in prestige that VC-backed founders experience in their post-founding careers than wages, especially since anecdotal evidence suggests that non-pecuniary motives often play a substantial role in shaping these founders' post-startup endeavors. On the other hand, examining the trajectory of wages in founders' post-founding careers offers a more established, familiar benchmark against which seniority trajectories can be qualitatively compared. Examination of wage trajectories also enables a closer consideration of how strictly pecuniary motives influence post-founding career choice.

To conduct these analyses, we merge data on the founders of VC-backed companies collected from Dow Jones VentureSource (Amornsiripanitch et al., 2021) to the entire database of 130 million Lightcast resumes. We are able to match 33,130 founders in VentureSource to their Lightcast profiles, 12,043 of whom list both a pre- and post-startup job and thus enter into our analysis.[2] We begin our empirical analysis by documenting stylized facts about career trajectories of VC-backed founders prior to the founding of their start-up. We compare founders to a cohort of individuals who (i) graduated from a similar tier college in the same year and (ii) took a first job with the same seniority in the same industry as the founder. We call this cohort the *labor market*

[2] We focus on entrepreneurs with post-startup employment to identify the labor market implications of startup outcome. Many founders in our sample are either still employed at their startup or have not listed post-founding roles.

entry cohort. We find that, on average, VC-backed founders are exceptional individuals. Their careers, as measured by both seniority and wages, progress faster and reach higher levels even before they found their companies relative to similar labor market entry peers.

Founders continue to outperform non-founders after they start their companies. We identify the effects of starting a VC-backed company on career outcomes by comparing founders to individuals who (i) graduated from a similar tier college within two years of the founder, (ii) had the same seniority in the year of the founder's first observed job, and (iii) had a job with the same seniority and in the same industry at the time of the founder's pre-founding job. We call this cohort the *pre-founding* cohort. Intuitively, this cohort is the subset of a founder's labor force entry cohort whose career trajectories mirrored the founder's up to entry into entrepreneurship. In regression analysis, we find that founders receive a roughly three-year increase in job seniority and 20% increase in real wages in their immediate post-founding job relative to their pre-founding cohort peers. Such an increase in job seniority is sizable given that (i) founders' average pre-founding jobs have a seniority of 15 and (ii) the average career in our sample plateaus at seniority of 12. Surprisingly, this labor market premium holds across all venture outcomes: failure, success, or departure from a still-active firm. Although failed founders receive somewhat smaller labor market returns than successful founders, the difference is not economically significant. Because we cannot fully address unobservable selection concerns, these results should be interpreted as suggestive correlations. Nonetheless, they indicate that potential labor market returns to VC-backed entrepreneurship are positive regardless of whether the founder succeeds or fails, suggesting that the labor market treats the receipt of venture funding as a positive signal of unobservable quality.

1.1 Contributions

Through the construction of the seniority measure as well as its application in empirical analysis, this paper extends and connects various existing literatures. First, this paper contributes to multiple areas within the labor economics literature (Ashenfelter and Card, 2010) by providing a new *general* measure of career progression that captures a job's non-wage dimension via an objective method. Our measure can compare career achievement across industries and functional areas in ways that wages cannot. Hence, our seniority measure is a significant improvement upon methods that previous studies have used to capture non-wage changes in a person's career.

One approach used in the prior literature is to exclusively consider one firm or one industry in which there is a well-defined career ladder. For example, Li and Walder (2001) study individuals who work for the Chinese government, while Johnson and Walker (2018) study US federal government employees. The main limitation of this approach is that the researcher is confined to only one industry or firm, potentially limiting the extent to which one can draw insights about general labor market phenomena. Our seniority measure does not have this limitation because, like wages, it is a general measure of career progression that can be used across industries.

A second approach relies on administrative data sets that readily classify jobs into levels where low-skilled (e.g., manual labor) jobs are generally ranked below high-skilled (e.g., managerial) jobs (Kunze, 2014; Kunze and Miller, 2014). The downside of this approach is that the classifications are often arbitrarily defined, coarse, and generally not economically interpretable (i.e., it is hard to grasp the significance of moving from a level-1 job to a level-2 job). For example, Baptista et al. (2012) use administrative Portuguese data to classify *all jobs* in the formal Portuguese economy into eight levels, over half of which are categorized as jobs of "skilled professionals." A related approach uses O*NET or survey data to classify jobs into low- and high-skill based on the set of skills associated with each job (Treiman, 1976; Speer, 2017). This approach also suffers from an arbitrary method of classification because researchers must determine how to map each job onto a skill distribution.

Finally, researchers have used promotions as a proxy for career progression (Javdani and McGee, 2019). While intuitively appealing, this promotion-based approach often lacks clear economic interpretability, as it cannot account for the heterogeneous quality of different promotions. Similarly, it can be difficult to quantify or even identify promotions when an individual switches between functional areas, firms, or industries.

Our seniority measure improves upon these earlier strategies by using a data-driven approach to classify job titles based on "years to first achievement." Seniority values have a straightforward economic interpretation, allowing us to compare jobs across different functional areas, firms, and industries. This advantage facilitates both a deeper understanding of individuals' career trajectories and a more robust evaluation of individuals' careers relative to their peers.

Our paper also contributes to the literature on VC-backed entrepreneurship, the literature on the returns to entrepreneurship, and the literature on labor market outcomes of former entrepreneurs. With some exceptions such as Manso (2016), the literature on the returns to entrepreneurship (Evans and Leighton, 1989; Hamilton, 2000; Moskowitz and Vissing-Jorgensen, 2002; Hall and Woodward, 2010) has largely found that pecuniary returns to entrepreneurship are on average low, which likely implies that individuals who choose to enter entrepreneurship must receive sizeable non-pecuniary benefits. We extend and reframe this debate by showing that regardless of venture outcome, VC-backed entrepreneurs on average receive a large, positive labor market return in the form of more senior post-founding jobs and wage increases. There are several potential explanations for this increase. First, venture capital funding may help ex-founders send a signal of superior ability to potential employers *after* they leave the companies they started. Second, founding a VC-backed company may increase human capital because of the learning that happens during the startup process. Similarly, human capital may be enhanced because a founder's network is expanded through the process or building their firm. The enhanced network brings value via contacts with potential employees and customers. More importantly, our findings suggest that the risk-return tradeoff that would-be entrepreneurs face may not be as grim as prior works (Moskowitz and Vissing-Jorgensen, 2002; Hall and Woodward, 2010) have suggested because VC-backed entrepreneurs seem to be taking on relatively low labor market risks.

Our results also contribute to the literature on labor market outcomes of ex-entrepreneurs and the self-employed. This literature has found a mix of negative, null, and positive effects of entrepreneurship on earnings. Using data from the Panel Study of Income Dynamics, Bruce and Schuetze (2004) find that self-employment is associated with a decrease in wages upon return to paid employment, though this effect is mostly explained by those forced into self-employment by job loss. Baptista et al. (2012) find largely similar results using Portuguese data. Botelho and Chang (2022) conduct an audit study and find that, as job applicants, entrepreneurs receive fewer callbacks, and that these negative effects are most severe for successful entrepreneurs.

By contrast, using data from Norway, Luzzi and Sasson (2016) find that entrepreneurs enjoy a wage premium when they return to paid employment. They find no premium from leaving a poorly performing firm, but they find a positive premium for entrepreneurs leaving successful firms or firms in more innovative sectors. Relatedly, Sorenson et al. (2021) review the existing literature and conclude that entrepreneurs who start firms that employ others, as opposed to those who do not hire employees, enjoy a wage increase when returning to salaried employment (Braguinsky et al., 2012; Sorgner et al., 2017). We contribute to this line of work by showing that, when returning to the labor force, VC-backed entrepreneurs, regardless of venture outcome, receive increases in job title seniority and wages. This finding, in turn, also contributes to the literature on failure in entrepreneurship (Klimas et al., 2020).

The rest of the paper is organized as follows. Section 2 presents our data. In Section 3, we provide detail on the construction of our seniority and wage variables as well as the outcomes of our two verification tests summarizing seniority by educational attainment. Section 4 presents empirical results on VC-backed entrepreneurship and career trajectory. We conclude in Section 5.

2 Data

Our data come from two main sources, VentureSource and Lightcast. VentureSource, a commonly used database, provides information on venture capital investments. Lightcast collects resumes of a large number of individuals from a prominent professional networking site. We use the Lightcast data to construct our seniority measure. In our study of VC-backed founders, we combine VentureSource and Lightcast data. In these analyses, the comprehensive resume data from Lightcast supplement the VentureSource data by providing information on founders' education, prior work experience, and post-founding careers. Lightcast uses a proprietary algorithm to link VentureSource founders to individual profiles in Lightcast which include comprehensive education and work histories. We add to these matches with our own algorithm, summarized in Appendix A. Finally, we use data from the Bureau of Labor Statistics to examine individual wage trajectories in our analysis.

2.1 Lightcast

Lightcast collects data on resumes from a professional networking site. Lightcast's granular employment data include job title, start and end dates of employment, firm name, and

NAICS (North American Industry Classification System) code. Lightcast uses proprietary algorithms to streamline job titles and company names and to impute an Occupational Information Network (O*NET) code for each job.

Lightcast also maintains data on individuals' education. These data include start and end dates, institution names (for a subset of profiles), degree types, and areas of study. Education data help measure key elements of human capital, such as earning a STEM degree, receiving an MBA, and the rank of an undergraduate institution. For the subset of profiles with detailed, identified information on undergraduate institution name (see below for details), we categorize colleges into three mutually exclusive tiers: elite universities (i.e., Ivy League and similar institutions), Tier 2 institutions (i.e., elite liberal arts colleges and highly-ranked public universities), and non-top schools, which include all other US undergraduate institutions and all non-US institutions. Appendix Table 1 lists the elite and Tier 2 undergraduate institutions.

We first impute seniority for every title in an industry and size quintile using Lightcast's entire dataset of approximately 130 million profiles in the US. Overall, these data are largely de-identified, containing only graduation years, job titles, firm names, and job start and end dates, with no information on educational institution name, individual name, or O*NET code. We use the de-identified data to (i) separate firms into quintiles by the number of employees in each year and (ii) calculate seniority using a broad range of individuals.

Second, we collect more detailed individual, school, and job-level information for a 5.4 million profile subset of the 130 million profile dataset described above. This 5.4 million profile subset of the Lightcast data is comprised of three main components. First, we collect more detailed, identified data from Lightcast for graduates of 44 prominent undergraduate institutions in the US offering bachelor's degrees, listed in Appendix Table 2. The covered institutions in this subset of the Lightcast data include Ivy League schools, other elite universities (e.g., Stanford, Duke), and large public universities, (e.g., University of Florida, University of Michigan). Second, we supplement these data on university graduates with identified data on additional founders linked to the Lightcast profiles. For this second subset of data, we largely outsourced the collection and matching tasks to Lightcast so that confidential individual name information not provided in the 130 million profile dataset could be used to match as many VentureSource founders as possible. Finally, Lightcast also provides a third subset of identified profiles belonging to individuals who share a name with a founder in the VentureSource dataset. The VentureSource founders whom Lightcast fully matched with its algorithm, the VentureSource founders whom Lightcast matches only by name, and the graduates of the 44 covered institutions comprise 5.4 million profiles altogether. From these 5.4 million identified profiles, we add additional founders to the matched founders obtained via Lightcast's proprietary algorithm by using our own matching algorithm, described in greater detail in Appendix A.

This 5.4 million profile subset of data includes detailed information on individual and university names. Accordingly, we primarily use this identified subsample of resumes for our analysis on VC-backed entrepreneurs' careers. Specifically, as described above, we use the university name information to sort the 5.4 million individuals in the detailed/subsampled dataset into educational tiers. In turn, since assignment of educational tiers is only possible with institution name information, we draw from these 5.4 million profiles to construct the various peer cohorts described in Section 2.4 and used in Section 4.

The Lightcast data are granular and comprehensive, but self-reported. As a result, there are gaps[3] in some careers and some underreporting of education data. However, almost 80% of founders have no gaps at all, and only 2.6% of person-year observations are gaps. There are similarly few gaps in work history for non-founders in the 5.4 million profile dataset. While the incidence of gaps is small, if more successful individuals are more likely to report work history and thus appear in our sample, then our analysis likely yields a conservative estimate of the founders' labor market premium.

2.2 VentureSource

VentureSource contains detailed information on venture capital investors, investments, and key employees and board members of portfolio companies. Our data cover the near-universe of venture capital investments up to early 2019. For each portfolio company, VentureSource identifies the individuals involved with the portfolio company including founders, investors, board members, and early hires. VentureSource provides some employment history, but it is limited to a few roles prior to founding. Along with information on individuals, VentureSource provides portfolio firm-round-investor level information on investments, including identity of investors, type of round (e.g., Series A), and the amount of capital raised. Finally, VentureSource contains information on other portfolio firm characteristics, such as industry, location, and firm outcome.

We use the VentureSource data to classify VC-backed founders' startup firms according to three outcomes: failure, success, and private & active. We identify failed firms as those VentureSource records which go bankrupt or out of business, those acquired for less than total investment, and those that are listed as private but have not received funding in three years. We consider firms to be successful if they exited via an IPO or were acquired for a value greater than

[3] We consider a year to constitute a gap if there is no reported job or education in the year but it is within the span of a person's career.

total investment. Firms are labeled as private & active if they are listed by VentureSource as private and have received funding within the last three years. Although these firms will eventually either fail or exit successfully, the outcome is unknown at the time of observation. Many of the founders of these firms still work at their firm, but some leave their VC-backed firm before an exit or failure and are thus included in our analysis.

Along with firm outcome, we construct other variables for portfolio companies, including firm location, industry, and a dummy variable for receiving investment from a top (most experienced) VC firm. We define VC experience as the number of unique portfolio companies in which a VC firm has invested in the previous 10 years. VC firms in the 99th percentile of investing experience in a given year are considered top VCs. Portfolio companies are considered to have received investment from a top VC if they did so in any round. Although we only identify a small number of VCs as top VCs, they are particularly active investors and therefore 21% of portfolio companies in our data have an investment from a top VC.

As discussed in Section 2.1, Lightcast uses a proprietary algorithm to link profiles to the VentureSource data. To supplement the profiles matched by Lightcast, we construct a fuzzy matching algorithm to connect additional founders identified in VentureSource with resumes in the Lightcast data. Overall, 33,130 out of about 55,000 founders of US-based VC-backed firms are linked to resumes in the Lightcast data. Of these matched founders, 12,043 have a clearly identified pre- and post-founding job. These founders form the sample of founders evaluated in our entrepreneurial career analysis in Section 4. We summarize the merge results in more detail in Table 1 and Appendix Table 3 and show that there is limited selection bias on observable characteristics.

2.3 Bureau of Labor Statistics Data

We use the Bureau of Labor Statistics (BLS)-maintained Occupation Employment and Wage Statistics to estimate wages. The BLS reports median wage by Standard Occupational Classification (SOC) code from 1999-2020.[4] We adjust all dollar values for inflation, using 2020 as the base year. Administrative changes in data collection at the BLS may complicate estimation. Before 2003, the BLS used SIC rather than NAICS codes to classify industries. SOC classifications have changed over time, too, with different versions starting in 2000, 2010, and 2018. As the classifications have changed, the definitions of some codes have been adjusted, combined, or dropped. As a result, the BLS data do not cover every SOC-industry code for every year. We linearly impute any missing values. For example, if we know the SOC-industry median wage in 2011 and 2013 but are missing 2012 wages, we interpolate 2012 wages as the average of wages in 2011 and 2013. We then match the wage data to our Lightcast resume data by SOC code, 3-digit NAICS code, and year.[5] If a job is missing a NAICS code, we merge in the SOC-year national average instead.

There are a few drawbacks to using estimated wages. First, our estimation method produces coarse wage estimates that do not vary at the O*NET-industry level even though our seniority measures does. Second, the literature has found significant wage differences across firms (e.g., Akerman et al., 2013), but we cannot capture this variation. Finally, O*NET classifies most senior roles into a few categories. This reduces the variation in estimated wages which may exacerbate issues caused by unobserved inter-firm wage differences. However, we do not expect these

[4] There are no BLS-maintained data prior to 1999, so we impute wages for jobs earlier than 1999 as 1999 wages. This is a relatively small part of our total sample and affects few post-founding jobs.

[5] SOC and ONET codes are basically equivalent, though they are formatted slightly differently. Each digit in the SOC code identifies a level of specificity (e.g., 11-1123 and 11-1121 are both classified under the 11-1120 grouping, which is a subset of the 11-1100 grouping). If estimated wage is missing for the exact SOC code, we move to the next most granular SOC code until we get a match (e.g., from 11-1123 to 11-1120 or from 11-1120 to 11-1100).

drawbacks to change the main conclusions of the paper as we use wage data mainly to validate the seniority measure and support the main post-founding seniority results.

2.4 Cohort creation

As described above, our sample of founders differs significantly from our sample of non-founders. While underlying ability is unobservable, we can measure some elements of and proxies for human capital, such as undergraduate institution, the presence of graduate degrees, and work experience. We use these observable characteristics to identify non-founders in the 5.4 million profile subsample of the Lightcast data who are comparable to the founders found in VentureSource. We construct two benchmark cohorts for each founder, one based on the first observed job ("labor force entry cohort") and the other based on position immediately prior to founding ("pre-founding cohort"). The labor force entry cohort is designed to measure differences over a founder's vs. a non-founder's entire career. The pre-founding cohort helps isolate the seniority changes that occur after founding. Since we find that founders achieve more senior positions before founding, the pre-founding cohort is composed of similarly successful individuals to account for some of the unobserved ability that may drive founder performance.

We construct cohorts using criteria that best capture those individuals who are similarly situated to VC-backed founders at two points in time. For the labor force entry cohorts, we match to a founder all non-founders who graduated from an undergraduate institution in the same tier within two years of the founder. We also require non-founders to match on seniority and industry in their first observed job. Some founders do not report their earliest jobs, making matching on the true labor force entry job difficult. For these founders, we identify matching non-founders based on the seniority and industry of the founder's first observed job and specific college graduation year. Matching founders to individuals with a similar (and typically above average) early career trajectory is conservative and reduces the likelihood that we find a premium for the founders because the matched non-founders will also have progressed faster early in their careers than other individuals. Regardless of this potential issue, we find statistically and economically significant differences when comparing founders against their labor force entry cohort peers.

For the pre-founding cohort, we match founders to non-founder individuals who (i) graduated a college of the same tier within two years of the founder, (ii) hold a job of equal seniority at the time of the founder's first observed job, and (iii) hold a position with the same seniority in the same industry and year as the founder's pre-founding role. This restricts the initial labor force entry cohort (defined above) to non-founder individuals who follow a similar career path as the founder up until founding.

3 Seniority Measure

Our seniority metric reflects a job title's rank within an organization's hierarchy, adding a new dimension along which one can evaluate career attainment. For certain types of careers, non-pecuniary benefits (Hamilton, 2000) may make comparing achievement using wages difficult or misleading. Similarly, different functional areas within a firm may have different levels of compensation even for positions of similar level of achievement. Therefore, in these circumstances, seniority may more accurately capture a position's desirability than relative wages. In addition, seniority may more adequately compare the desirability of positions across industries where wages are systematically different. For example, the titles of "Assistant Professor" in higher education and "Vice President" in financial services may have relatively similar seniority values, even if average wages for these two titles are far apart. Below, we describe how we construct seniority and validate it with a series of tests.

3.1 Construction

Seniority is defined as the number of years it takes a median individual to reach a given title within an industry and given quintile of firm size. Using the full Lightcast data with 130 million profiles, we assign firm quintiles based on their employee headcount at the end of the year in which a title is achieved. Quintiles are assigned based on the full distribution of firm headcount within a given year across all industries. Given the inherently right-skewed nature of the firm size distribution (often modeled as lognormal or Pareto), we determine quintile cutoffs by headcount so that proportionate and equal shares of individual workers (as opposed to firms) are assigned to a given size quintile. In other words, we assign the largest firms responsible for the "first" 20% of total employment in a given year to the "first" quintile, the next largest firms responsible for the second 20% of total employment to the second quintile, and so on until all five firm size quintiles within a given year are populated. This methodology allows us to more accurately differentiate individuals' seniority than a quintile classification based on firms' ordinal headcount rank by ensuring that individual employees are not disproportionately represented in "top" size quintiles. Empirically, we observe differences in title-industry seniority across quintiles. In general, the same title at a larger firm has higher seniority, especially for high-level roles. However, there are exceptions. For example, the title "consultant" has its highest seniority in the smallest firm quintile, likely reflecting individuals who set up small firms or work as self-employed consultants, often in an industry in which they have extensive experience.

After we assign a quintile to each firm, we calculate seniority. First, we estimate an individual i's labor force entry date using i's college graduation date for all individuals $i \in I$ in the full Lightcast sample (with 130 million profiles). Given an entry date, for every title t in industry j in firm with size quintile k (henceforth denoted as tjk) obtained by individual i, we calculate the time it takes i to attain tjk as the difference between the date when tjk first appears in i's work history and i's labor force entry date. We denote this time as $T_{i,tjk}$. If tjk appears more than once in individual i's work history, we use the earliest occurrence. Finally, we examine all individuals in the Lightcast sample who have attained tjk (i.e., I_{tjk}) and use the median time it took them to first achieve tjk as an initial seniority value $\widetilde{S_{tjk}}$. In mathematical terms:

$$\widetilde{S_{tjk}} = Median_{i \in I_{tjk}}[T_{i,tjk}]$$

We choose to calculate seniority using the first year of a title-firm size-industry achievement even though individuals may hold multiple distinct jobs with the same title or hold a job for multiple years. Thus, higher levels of seniority indicate hierarchical *advancement* as opposed to *entrenchment*. Accordingly, for most individuals, their seniority plateaus at a maximum that total career length typically exceeds.

Finally, we adjust the initial seniority values $\widetilde{S_{tjk}}$ to account for the overrepresentation of younger individuals in our sample. The careers of young individuals typically keep progressing as time unfolds. Estimating seniority in the subsample of younger individuals, based on their truncated work histories, would inevitably bias down (especially for advanced roles) the seniority scores because it would fail to account for those young individuals yet to reach these senior positions.[6] To reduce the disproportionate influence of younger individuals who have achieved senior titles, we recalculate seniority for more senior titles. If the initial seniority $\widetilde{S_{tjk}}$ is between 0 and 6, we use the entire dataset to calculate seniority S_{tjk}, which in this setting equals $\widetilde{S_{tjk}}$. If

[6] For instance, we might expect that most 1980 college graduates who will achieve the CEO position have already done so. However, it is likely that most individuals in the 2010 cohort who will become CEOs have not already done so, while the cohort's current CEOs have reached the position in 12 years or less. Since careers are right-censored, we might obtain a much lower estimate of CEO seniority using only the 2010 cohort than we would using only the 1980 cohort (or using the 2010 cohort with hypothetical data from 2050).

$\widetilde{S_{tjk}}$ is between 7 and 12, we recalculate S_{tjk} using only data from individuals who graduated before 2010. Finally, if $\widetilde{S_{tjk}}$ is 13 or greater, we recalculate S_{tjk} using only pre-2000 graduates. For some jobs, we cannot link the raw firm name to a company ID or cannot estimate seniority using title-industry-firm size because the firm name and ID are missing in the raw Lightcast data. For these positions, we estimate seniority using just the title-industry combination. The method is analogous to the method described above, but we estimate $\widetilde{S_{tj}}$ instead of $\widetilde{S_{tjk}}$. The small number of jobs for which we use only title and industry do not vary markedly from those for which we can also calculate firm size. We describe our method of seniority construction, especially identification of graduation year and firm quintile assignment, in more detail in Appendix B.

3.2 Summary and Verification Tests

In this section, we present descriptive statistics and validate the utility of our novel seniority metric. Seniority reflects a comprehensive estimate of career attainment across different industries and functional areas. Our simple validation tests show that seniority is intuitive and highly informative. For example, more educated individuals reach higher levels of seniority, and high-level executive and oversight roles have the highest seniority. We also demonstrate how seniority can complement and differ from wages and how trends in seniority over one's career can differ in an intuitively expected manner for different groups of individuals.

Table 1 summarizes the careers of all individuals in our dataset. Not all individuals will enter our analysis of the VC-backed founders; many are neither founders nor part of a matched cohort. Still, we document several relevant characteristics about the entire sample. The median earliest job in our sample is 2005, and 90% of our sample is still in the labor force as of 2021, implying that our sample is relatively young. The average individual has 4.39 jobs over an observed career of 17.60 years. Most individuals eventually attain senior positions, with a median (75^{th} percentile) career-high seniority of 12 (18).

Appendix Table 5 presents summaries of the fraction of individuals, stratified by career length, who reach a certain seniority. We see that very few individuals, even those with long careers, reach the highest levels of seniority. Only 31% of individuals with 30 years of observed career data reach a seniority of 20 or greater, and the median seniority reached for someone with an observed career length of 20 years is about 12.5.[7] Not everyone at a given level of seniority is promoted to the next level. This is consistent with the notion of a corporate pyramid; there are fewer spots at the top of a hierarchy, and it takes more years of experience to get there.

Figure 1 shows how the mean seniority of different individuals, grouped by the maximum seniority achieved over their careers, evolves over time. We see distinct groups of workers who differ not only in maximum seniority attained, but also in overall career trajectory. Some groups start and end their careers in low-seniority jobs. Other groups ascend to medium-seniority jobs 10-15 years into their careers and remain in similar positions. Finally, a small group of individuals gradually ascend throughout their careers toward high levels of seniority.

More influential and prestigious titles have higher seniority values. Table 2 Panel A reports the 30 most common titles and their seniority. The most junior of these titles are typically held by undergraduates or recent graduates (e.g., intern, research assistant, software engineer). The most senior titles are managerial roles, such as CEO, Principal, or President. As reported in Table 1, the maximum seniority obtained by the average individual is 11.82. This seniority level corresponds to titles like "Project Manager," or "Consultant." These are relatively high-ranking roles that are typically a level or two below the most senior managerial roles. These summary statistics imply

[7] High seniority jobs are very uncommon for individuals with shorter careers. Most of the individuals who reach senior jobs quickly are self-employed or are entrepreneurs who achieve high-seniority titles in small firms that they own.

that most individuals progress through an organizational hierarchy over time, but do not reach its highest levels.

Direct examination of job titles also suggests a strong correlation between seniority and one's position within an organization's hierarchy. Table 2 Panel B reports the most and least senior titles with at least 100 observations in the entire dataset. Advisory positions dominate the most senior titles, led by "Audit Committee Chair" with a seniority of 31. The most junior titles are typically junior service roles like "Customer Service Staff" or junior military roles like "Avionics Specialist" or "ROTC cadet."

Finally, we examine the relationship between seniority and education. Figure 3 shows the average seniority over time for graduates of elite colleges, Tier 2 colleges, and all other colleges.[8] The averages are roughly equal at graduation, but over time, graduates of elite colleges outperform those from Tier 2 colleges, who in turn outperform graduates from non-elite and non-Tier 2 colleges. Though discernible, the differences are small. Graduates of Elite undergraduate colleges achieve average seniority of approximately 15, a seniority about 1 year higher than Tier 2 graduates. In turn, Tier 2 college graduates achieve average seniority about 1 year higher than non-Elite or non-Tier 2 college graduates.

The divergence in seniority is clearer when we compare careers of those with and without an MBA in Figure 4. Over their careers, recipients of Elite MBAs reach, on average, a maximum seniority of 19, slightly greater than the 75th percentile of maximum seniority. Hence, it appears that receiving an Elite MBA is associated with a one quartile increase in seniority achieved, on average. Individuals with non-elite MBAs reach, on average, achieve a seniority of 16, while individuals without MBAs typically achieve an average seniority of 14. Furthermore, post-MBA

[8] Appendix Table 1 presents the classification of elite and Tier 2 colleges.

changes in career trajectory, as opposed to pre-MBA selection, appear to explain most of these seniority differences. Figure 5 looks at seniority centered around the year that someone receives their MBA and shows how an MBA increments seniority. All groups have similar early career trajectories; seniority for individuals who will earn MBAs are only slightly higher than those who do not pursue an MBA. At MBA graduation, however, those with an MBA see their seniority increase immediately relative to non-MBAs, and the gap between MBA and non-MBA seniority only increases over time. This post-MBA divergence is larger for Elite MBA recipients than for other MBA recipients. All of these simple summaries provide support for using seniority as a general measure of career attainment.

4 Career Trajectories of VC-Backed Entrepreneurs

In this section we apply our seniority variable to measure career progression and compare the results to industry-title wage estimates to evaluate the full career trajectories of VC-backed entrepreneurs. Given that both pecuniary and non-pecuniary benefits may motivate an individual's decision to both become an entrepreneur and choose a post-founding job, VC-backed entrepreneurship represents a suitable setting in which seniority can be used to complement wages in evaluating jobs. Since we observe VC-backed entrepreneurs' entire work histories in our merged VentureSource-Lightcast data, our analyses examine how their career trajectories are distinct from non-entrepreneurs (i) before they found their company, (ii) after they leave their start-up, and (iii) over their entire careers. By considering both pre- and post-founding outcomes, this section's analyses can simultaneously examine selection into and labor market returns to entrepreneurship.

The remainder of this section proceeds as follows. First, we compare VC-backed entrepreneurs to the overall Lightcast worker sample by collecting descriptive summary statistics on seniority, wages, and other characteristics within the subsample of founders matched into Lightcast. Second, we demonstrate that founders outperform similar non-founder (i.e., labor market entry) peers in terms of seniority and wage prior to founding their startups. Finally, we show that relative to non-founder peers in their pre-founding cohorts, founders experience an *additional* increase in seniority and wages in their immediate subsequent post-founding job. These additional post-founding premia prove robust across the performance/outcomes of founders' start-ups, though successful founders generally enjoy larger post-founding wage and seniority premia.

4.1 Overall Summary Statistics

We report descriptive career statistics for founders of VC-backed companies with both pre- and post-founding jobs in the Lightcast data in Table 3.[9] As Table 3 shows, the average observed career length for these founders is 25.54 years, with a median start year of 1996. The majority of founders in our dataset entered the labor force between 1990 and 2010, and 96% appear to still be in the labor force. The median founder reports 8 distinct jobs. Founders' overall career trajectories differ markedly from non-founders. Indeed, when compared to medians in the entire sample (shown in Table 1), we see that the median founder began his or her career about 9 years earlier than the median individual (1996 for founders vs. 2005 for general individuals), holds more jobs over his or her career (8 for founders vs. 4 for general individuals), and reaches substantially higher levels of maximum seniority (24 for founders vs. 12 for general individuals).[10] Some of these high-level differences reflect the Lightcast sample's overrepresentation of recent graduates who entered

[9] Many matched founders are either still working for the firm they started or do not report a post-founding job. Overall, we can identify a post-founding job for 75% of all founders and for almost 90% of founders whose firms have either exited or failed. Only 60% of founders who started still active firms list a post-founding role. Our descriptive statistics and regression analysis only consider founders with pre- and post-founding roles.
[10] Higher maximum seniority does not appear to be driven by high seniority in the founding role.

the labor force relatively recently and who, by definition, will have shorter careers. Accounting for this imbalance, however, does not eliminate the contrast between founders and non-founders.

The gap in seniority between founders and non-founders applies not only to maximum seniority, but also to average seniority at every year/stage within a career. Figure 6 compares the seniority of all founders and all non-founders over time from labor market entry and illustrates how the higher seniority achieved by founders persists across time. In this figure, we are not constraining non-founders to start their careers with the same seniority as we do in the regression analysis below. Founders begin their careers at a higher seniority level and progress up the seniority ladder much faster than non-founders in the early years of their career. The graph suggests that founders are exceptional employees before they begin their firms, yet it remains ambiguous whether this seniority gap continues to grow in the later, post-founding years of founders' careers. The following subsections detail how the startup experience affects careers of founders.

It thus appears that VC-backed founders outperform non-founders in the labor market at the start of their careers. Founders are also more highly educated than non-founders, with significant differences especially in STEM and graduate education. Appendix Table 8 lists the most common institutions for founders' undergraduate and MBA education. Elite universities, such as Stanford University and Harvard University, produce the most VC-backed founders in our data. Despite the overrepresentation of elite universities in founders' undergraduate educations, the 20 most common US-based undergraduate schools account for under 30% of VC-backed founders. The concentration of MBA programs is much greater. More than a third of our sample of founders who receive an MBA degree do so from Harvard, Stanford, or Wharton. Beyond institution name, we also examine founders' degree type and area of study. Descriptive statistics in Table 4 confirm the high-skilled nature of our founder sample suggested in Table 4. 16% of founders hold a bachelor's degree from an elite institution, defined as an Ivy League school, Duke University, MIT, Northwestern University, Stanford University, University of California, Berkeley, and University of Chicago. 23% of founders hold an MBA; slightly less than half of that group hold an Elite MBA (defined as an MBA from Harvard, Chicago Booth, Northwestern Kellogg, Stanford, or University of Pennsylvania-Wharton). Finally, most founders appear to have acquired significant technical expertise via education: 70% hold a STEM degree and 16% hold a PhD, of which over 80% are in a STEM field.

Finally, Table 5 reports the most common titles for founders in (i) their labor force entry job, (ii) their pre-founding job, and (iii) their post-founding job. Founders' labor force entry jobs are typically very junior. Common titles include "Software Developer," "Analyst," and "Research Associate." We define labor force entry jobs as the earliest reported job in a profile. In Table 5, we also require labor force entry jobs to have a seniority of at least 0 and less than 4.[11] While a cutoff of less than 4 is somewhat arbitrary, clear non-entry level titles, like "senior associate" enter the list of most common titles when we allow titles with a seniority of 4 or greater.[12] Tightening the cutoff to 2 or 3 yields a qualitatively similar list.

We likewise consider pre-founding jobs, which we define as the job held by a founder immediately prior to entrepreneurial entry, and post-founding jobs, which we define as the job held immediately after an entrepreneur leaves their start-up. Consistent with other summary tables

[11] We exclude jobs with negative seniority since these are typically held before full-time labor force entry. We believe there is some underreporting of early career jobs, especially by individuals with longer careers. To minimize potential error, we exclude relatively senior first jobs from our tabulation. This results in fewer labor force entry jobs. However, this should not bias our key analysis of changes around the founding role since we can still clearly identify the pre- and post-founding roles for these founders.

[12] We do not restrict titles to have a seniority of zero since many junior titles that appear to be at the bottom of hierarchies have positive seniority. For example, "software engineer" has a median seniority of 5 across all industries, and "analyst" has a median seniority of 2, indicating that some individuals switch into these junior roles several years into their careers.

and figures, the pre-founding titles listed in Table 5 suggest that founders rise through their respective organizations in the pre-founding stage of their careers. Within the table, the most common pre-founding titles appear to be managerial positions such as "Vice President," "Chief Executive Officer," and "Chief Technology Officer." Other pre-founding roles include advisory positions (e.g., "Director") or managerial roles below the C-suite (e.g., "Product Manager"). Finally, Table 5 suggests that founders continue to occupy high-seniority roles after leaving their VC-backed firms. After founding, CEO and other senior executive roles appear as the most common positions, while founders also take on more senior (but perhaps less taxing) advisory roles (e.g., "Director" or "Mentor"). Table 5 reflects the career progression of founders. Largely starting their careers in skilled technical roles, founders climb up organizational hierarchies before starting their own firms. After leaving their start-up firms, founders continue to advance.

4.2 Pre-Founding Career Trajectories

As the initial summary statistics suggest, founders are exceptional individuals: they attain higher levels of education, rise further up the hierarchy of jobs, and more quickly obtain high-seniority positions than non-founders. However, it remains unclear whether education or other characteristics can fully explain founders' superior labor market performance vis-à-vis non-founders, especially during founders' early pre-founding careers. In this subsection, we provide suggestive evidence that education and other observable characteristics cannot fully explain founders' exceptional career performance before the founding of their companies. Even relative to individuals with similar education and initial post-college jobs (i.e., their labor market entry cohort), future founders attain jobs with higher seniority and wages immediately before founding than their non-founder peers in a similar span of time.

First, to partially disentangle any explanatory impact education, industry characteristics, or time trends may have on founders' pre-founding careers, we match all founders in our data to a labor market entry cohort of non-founders. As detailed in Section 2.4, for each founder, we match every non-founder who (i) graduated within two years of the founder, (ii) received their undergraduate education at a school of the same tier, and (iii) achieved a job with the same seniority within the same industry as the founder at the time of the founder's first observed job. This matching procedure aims to capture the non-founders who appear most similar to a given founder at their time of labor market entry (or earliest available job). Comparing founders to their respective labor market entry cohorts should effectively control for the role of education and initial career starting point in explaining founders' apparently superior pre-founding career outcomes.

Table 6 summarizes founder seniority in pre-founding roles. The mean seniority of founders' pre-founding jobs is 14.77 years, with successful founders (i.e., founders who ultimately start a successful start-up) holding slightly more senior jobs (15.42) than failed founders (14.74) and founders who leave active start-up firms (14.52).

As Table 6 suggests, founders outperform their labor market entry peers before founding. To formalize this claim, we run fixed effects regressions to more rigorously quantify the extent to which founders attain more senior and higher paying pre-founding jobs. The regressions in Table 7 include labor market entry cohort fixed effects as well as a variety of demographic and additional educational controls. Control variables provide insight in terms of how seniority and wages vary with various demographic characteristics, and interaction terms illustrate how seniority premia might differ across different cohort characteristics.

Table 7 Panel A shows that all founders attain pre-founding positions with 2.0-2.9 more years of seniority than matched non-founders in all specifications. These results are robust to including a variety of controls for gender, career length, education, and founder interaction effects. Table 7 Panel B reports results for pre-founding log wages. Founders' pre-founding jobs have estimated wages that are 15-30% higher than matched non-founders' jobs. As in Panel A, we include controls for education and interactions between the founder variable and the controls. Again, we find that results are robust to including these controls. Together, Panels A and B demonstrate that founders outperform similar college graduates in their careers before founding. The higher achievement prior to founding is present for all founders independent of the startups' ultimate outcomes. Successful, failed, and departed (i.e., those who left an active firm) founders all attain pre-founding jobs with higher seniority and wages than peers in their cohorts.

The results in Table 7 also provide important support for seniority as a measure of career attainment. Many of the controls have signs and magnitudes that are meaningful for assessing career differences. First, we find gender differences in career attainment. Men appear to achieve higher career seniority and wages in their pre-founding positions. Second, measures of human capital appear positively correlated with career outcomes. Receiving a degree in STEM as well as receiving an MBA (especially an MBA from an Elite program) all lead to higher seniority and wages up to the pre-founding job. In contrast, we find that individuals with a Ph.D. have lower seniority and wages, potentially due to the amount of time necessary to earn a Ph.D. pushing off career attainment and potentially lower wages in academic positions. Finally, column 3 of both panels in Table 7 suggests that pre-founding seniority and wage premia are especially high for founders without an elite undergraduate or MBA degree. Such results may suggest that barriers to VC-backed entrepreneurship are especially high, on a relative basis, for non-elite educated individuals; founders without an elite education must more dramatically outperform their peers in order to enter VC-backed entrepreneurship than their counterparts with elite degrees.

Alternatively, these results may simply mechanically result from aggregate differences in the early career performances of cohort peers with elite vs. non-elite educational backgrounds.

4.3 Post-Founding Returns to Entrepreneurship

Founders accumulate seniority and wage premia relative to their labor market entry peers during their pre-founding careers, and these premia persist during their post-founding careers, as shown in Appendix Tables 6 and 7. However, the extent to which ability-based selection into entrepreneurship or tangible returns to entrepreneurship explain the post-founding premia remains unclear. Accordingly, we match founders to a new set of similar peers (i.e., their pre-founding cohort) and obtain suggestive evidence that both ability-based selection and returns to entrepreneurship might explain the additional post-founding premia that all types of founders appear to enjoy.

First, we directly compare the seniority and wages of founders' pre-founding and post-founding jobs. In Table 8, we report the distribution of seniority in pre- and post-founding jobs, the difference in seniority between the pre- and post-founding jobs, and time spent in the startup job. Founders of successful firms experience larger seniority gains (3.48) than founders of failed firms (2.47) or founders who departed active firms (1.79). We also see that there is a difference in the length of time spent at their startups. Successful founders, on average, spend 5.78 years at the company they started, founders of failed startups spend 4.62 years on average, and founders who depart active (still private) firms spend the shortest time at their companies, 3.51 years.

In addition, post-founding increases in seniority differ across a variety of firm and founder characteristics. Table 9 reports post-founding seniority increases within founder subgroups (i.e., successful, failed, and departed) by firm and founder characteristics. We find that founders with a STEM background or from Elite undergraduate colleges generally have larger increases in seniority pre- to post-founding. Similarly, founders in California or Massachusetts or who received venture capital backing from a top venture capital firm experience larger increases in seniority. Finally, we find that time period also matters. Founders who began a startup right before the great recession (2006-2008) experience smaller increases in seniority relative to other founders while those who started their companies during the Dot-com bubble generally experience higher increases in seniority. These patterns hold across all the subgroups of founders.

As an alternative to our seniority measure, we also present descriptive statistics for changes in wages after founding experience in Table 8. Results are similar to seniority changes, as all types of founders on average attain post-founding increases in estimated wages. Likewise, successful founders enjoy a larger increase ($17,805) than failed ($12,249) or departed founders ($6,124). As with seniority, there is considerable variation in post-founding wage differences by firm and founder characteristics.

Complementing Table 9's analyses on seniority, Table 10 tabulates how wages change across different subgroups of founders. Again, there are differences within founder outcome subgroups. For example, holding an elite undergraduate degree is associated with a larger wage increase for founders of successful firms than for other groups, and holding a STEM degree is associated with a larger wage increase for failed founders. As with seniority, founders attain higher pre-founding wages and earn more in post-founding employment than non-founders.

To look at how these various patterns interact, we also present regression analyses which evaluate how entrepreneurial experience might result in post-founding wage and seniority gains. Just as we show that founders have accelerated career achievement compared to other wage workers with a similar background before founding in Section 4.2, we examine how founders' seniority and wages change relative to workers with similar pre-founding career trajectories in the labor market after leaving their VC-backed firm. In other words, relative to those whose careers looked virtually identical prior to founding their company, does the startup experience boosts their seniority and wages?

For each founder we construct a "pre-founding" peer cohort, defined as the set of non-founder individuals who (i) graduated within two years of the given founder, (ii) attended a school in the same tier as the founder, (iii) held a job with the same seniority in the same year as the founder's first observed job, and (iv) held a job with the same seniority in the same industry as the founder's pre-founding job at the same time as the founder. Comparison with the pre-founding cohort enables us to better isolate the potential labor market returns to entrepreneurship. Specifically, whereas ability-based selection could account for most or all of the post-founding gap in wages and seniority between founders and their labor market entry peers, tangible returns to entrepreneurship could more plausibly explain a substantial portion of any wage and seniority premia that founders might enjoy over individuals whose career trajectories mirrored those of founders in the period before they choose to start their companies. Nonetheless, we admit that unobservable selection into entrepreneurship could still explain a portion of our results, even when we focus on this pre-founding peer group.

Figure 7 compares the seniority of founders to non-founders in their pre-founding cohorts of similar peers who have a job with the same seniority at the beginning of their career as well as a job of the same seniority in the position immediately prior to founding their company.[13] We adjust time so that for each cohort, the earliest year is at time 0 on the x-axis and the latest year is at the maximum time value on the x-axis. Although the career length differs for each cohort, this

[13] This restriction allows us to compare founders to non-founders who enjoyed similarly exceptional pre-founding careers. Given founders' rapid ascent up the seniority ladder in their pre-founding careers, we would expect that the post-founding seniority gap between founders and the average non-founder would be even larger than the founder-peer gap displayed in Figure 7.

construction ensures that cohorts do not "drop out" as time goes on; our adjustment of time means each cohort is plotted at each point. Figure 7 omits the founding period (although we graph a point for the founder's seniority in their startup), showing instead a discontinuity in seniority between the pre- and post-founding periods. This method highlights the change from pre- to post-founding, consistent with our approach in the rest of our analysis. By construction, the founder and non-founder career trajectory looks virtually identical prior to founding their startup, rising to a seniority of 14 in their job immediately prior to founding. Founder seniority initially increases more quickly than that of matched non-founders ahead of founding, but non-founders catch up by the pre-founding year. Founders' seniority typically jumps substantially during their time at their startup; founders achieve an average seniority of 18 in their (founding) role within their startup. In the post-startup period, however, we see substantial differences between founders and non-founders. While founders' seniority tends to fall slightly (to 17.5) in their immediate post-startup role, it is still substantially higher than the average seniority of their pre-founding matched cohort (14.5) at the analogous point in time. After their reentry into the labor force, founder seniority gradually increases, reaching an average of 20 by the end of their careers. By contrast, the seniority of the matched non-founders plateaus around 15.

We examine the cross-sectional relationship of these seniority changes between the pre- and post-founding period in Table 11. We compare founders in their post-founding roles relative to their pre-founding cohort. Panel A presents results on how entrepreneurial experience relates to post-founding seniority level. Founders acquire post-founding jobs with 2.7 to 4.2 more seniority than their matched pre-founding cohort, despite having identical seniority pre-founding. Analogously, Panel B reports results on the post-founding wage level using the pre-founding cohorts. Even compared to pre-founding cohorts with the same seniority, we find that founders have 14-24% higher wages on average. We find that the increment to seniority is larger for successful founders than it is for those founders that fail or leave active firms, although relative to the pre-founding cohort, failed and departed founders still gain substantial seniority. Successful founders also have higher wage increases (relative to pre-founding cohorts) than do failed or departed founders. These results are robust to controlling for gender, career length, education, and founder-interaction terms.

Once again, the cross-sectional variation with control variables provides support for the use of seniority as a career attainment metric. We find that men have higher increases in seniority and wages in their post-founding or post-founding equivalent jobs, although post-founding seniority premia do not appear to differ in a significant manner across gender. We find that some proxies for human capital such as MBAs and Elite MBAs have a positive effect on the increment to seniority and wages. STEM education is associated with larger wage increases but insignificant seniority changes. Interestingly, we find that having a Ph.D. is positively related to increments to seniority after founding, but wage increases for those with Ph.D. are somewhat smaller. As we saw in our verification tests, the type of education that one receives appears to affect not only the initial level of career attainment, but its trajectory over time as well. Finally, analogously to Table 7, we find that post-founding seniority premia generally appear larger for founders without an elite undergraduate or MBA degree. Such results may suggest that the signaling value associated with VC-backed entrepreneurship is non-negligible, especially if one believes that elite degrees often serve as reasonably sufficient or distinguishing signals of ability for many high seniority jobs.

Our final set of analyses examines the founder-specific characteristics that might influence post-founding wage and seniority premia. Table 12 analyzes post-founding outcomes using only the founder sample. We include controls for firm characteristics applicable only to the founder sample, as well as interaction terms with the failed founder indicator variable. Columns (1)-(4) of Table 12 report results on how founder and firm characteristics might influence post-founding seniority levels. Failed founders achieve less senior roles by between 1.4 and 1.7 years than successful founders, the reference group. However, while statistically significant, this difference is small relative to the post-founding seniority premium we estimated relative to non-founders. Founders with longer pre-founding careers, more senior pre-founding jobs, or MBAs have significantly higher post-founding seniority. Analogously, columns (5)-(8) of Table 12 present regression results on post-founding wage. Both failed and departed founders, on average, receive lower wages post-founding, as do founders with PhDs. However, founders with MBAs receive a wage premium relative to other founders as do founders with higher wage pre-founding roles and longer total careers. Results are similar when we analyze the change from pre- to post-founding seniority and wages.

5 Conclusion

In this paper, we propose a non-pecuniary measure of career achievement, *seniority*. We construct this measure based on a detailed database of over 130 million resumes. This measure exploits the variation in median time to attain different job titles in different industries for firms of different size. By evaluating the time required to reach a certain job title, seniority captures a person's standing in a general employment hierarchy. These standings facilitate inference about career progression across industries or functional roles—even when stark differences in wages render these sectors or areas of business not directly comparable. As such, the seniority measure offers an important new measure for evaluating labor market outcomes, complementing the traditionally used pecuniary measures, such as wages.

Seniority captures meaningful variation across people's career trajectories. First, the most common job titles follow a clear pattern. Typical entry-level roles (e.g., "analyst") are more junior, while executive and advisory roles are the most senior. Second, career trajectories by educational attainment follow paths we would expect. Graduates of more prestigious colleges and especially individuals with MBAs outperform other individuals in terms how quickly their seniority rises and the maximum seniority they achieve over their careers. For most individuals, seniority plateaus around 15 to 20 years into their careers. Relatively few individuals progress to the highest levels of their organization; most reach middle levels of seniority and remain there.

We use seniority to study employment outcomes of venture capital-backed entrepreneurs and compare how our seniority measure compares to career trajectories measured by wages. We contribute to the literature that has explored self-employment and labor market returns to entrepreneurship, both through our seniority measure and our focus on high-potential firms, as opposed to small business or self-employment typically studied in the literature.

Using both seniority and wages to measure career progression, we find that founders display accelerated career achievement prior to founding, significantly outperforming contemporaneous graduates of same-tier colleges with similar first jobs. Compared to individuals graduating from similar colleges and starting with similar jobs (in terms of industry and seniority), founders have already achieved positions that are 2-3 years more senior with wages are more than 25% higher prior to starting their company. We also show that men, individuals with MBAs, and (especially) individuals with Elite MBAs achieve higher seniority and wages.

Post-entrepreneurship, founders keep advancing. After exiting their start-ups, they obtain jobs 2-4 years more senior and wages that are 14-24% higher than peers with similar pre-founding career trajectories, i.e., those that graduated from a similar institution, entered the labor force with a job of similar seniority in the same industry, and had a position with the same seniority in the same industry as the founder immediately prior to their startup. Importantly, while a startup's success offers a larger seniority (and wage) increase for its founder, even failed founders land positions with higher seniority (and wages) than those attained by their peers in the meantime. Although we cannot fully eliminate selection concerns, these results suggest that venture capital-backed entrepreneurs receive significant benefits when returning to the labor market—even if their venture did not lead to an IPO or a high-value acquisition. Thus, risk to future earnings does not appear to be present for venture capital-backed founders. Understanding the lack of downside career risk to founding a venture-backed company is important given that more than 75% of such startups ultimately fail.

We view seniority as an important new metric by which researchers can assess career achievement. While standard analysis of wages will always be important, we believe that in many contexts, seniority will have greater utility in assessment of achievement across industries and functional areas. While our examination of career outcomes for venture capital-backed entrepreneurs is just one application, we believe the seniority measure will shine a new light on labor market outcomes in a broad range of settings.

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Figure 1: Mean Seniority, Grouped by Maximum Seniority Achieved

This figure plots the mean seniority over time, grouped by maximum seniority achieved. Individuals are assigned to a group based on the maximum seniority they reach over the course of their entire careers. The seniority for each group-year point is the average seniority of individuals in the group at the relevant year after graduation.

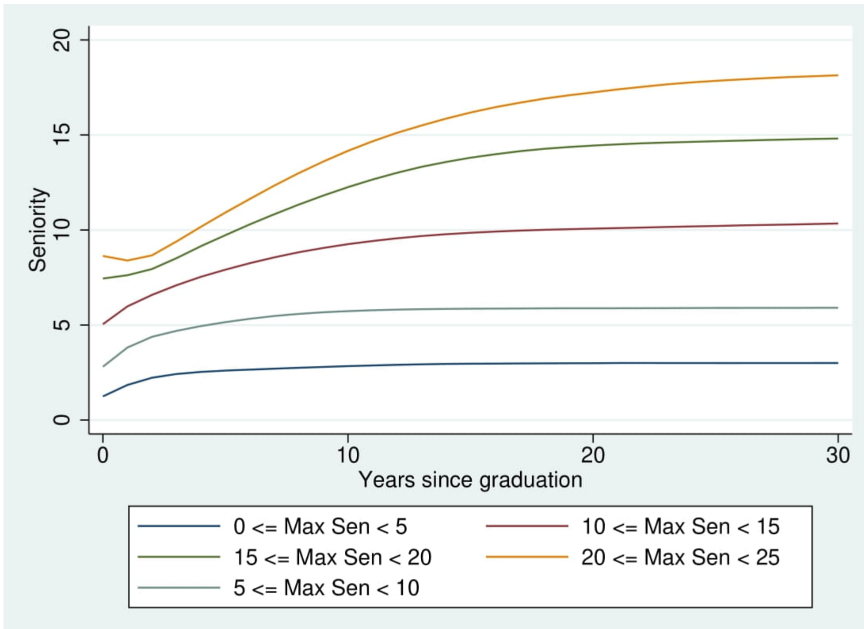

Figure 2: Seniority at Selected Percentiles over Time

This figure presents seniority percentiles for the Lightcast dataset with detailed resumes (>5,000,000 resumes). Percentiles are calculated for each year using the resumes of all individuals who have career information for the relevant year after graduation.

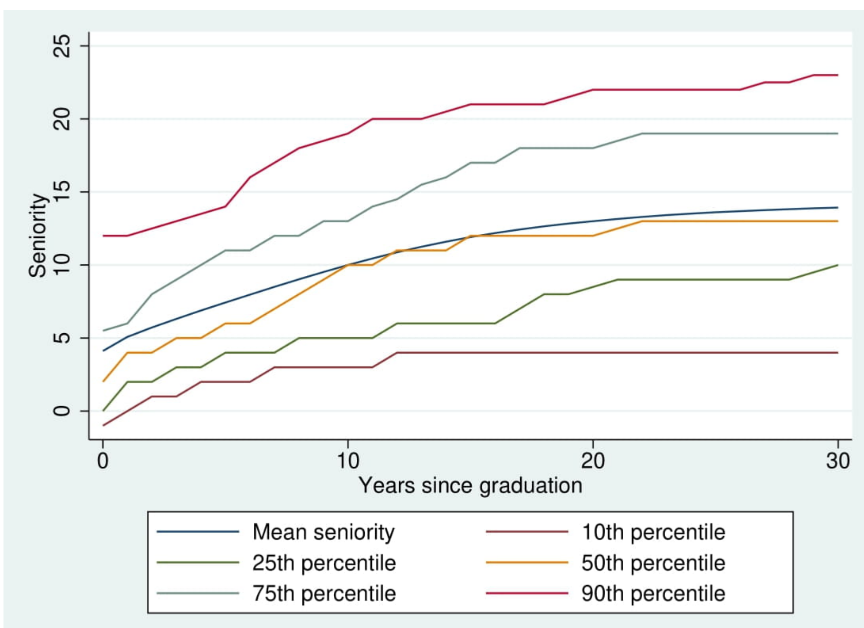

Figure 3: Seniority Achievement by Undergraduate Education

This figure displays seniority over time by tier of undergraduate institution. The seniority for each group-year point is the average seniority of individuals in the group at the relevant year after graduation. See Appendix Tables 1 and 2 for the classification of schools into Elite and Tier 2 categories.

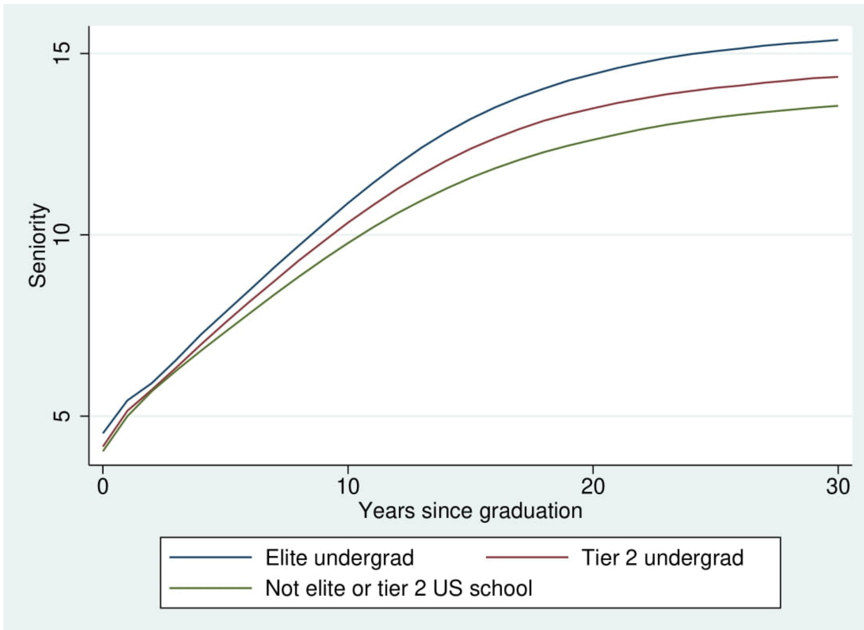

Figure 4: Seniority Achievement by MBA Status

This figure displays seniority over time by MBA education. The seniority for each group-year point is the average seniority of individuals in the group at the relevant year after graduation. Elite MBAs schools are Harvard, Kellogg, Stanford, Booth, and Wharton.

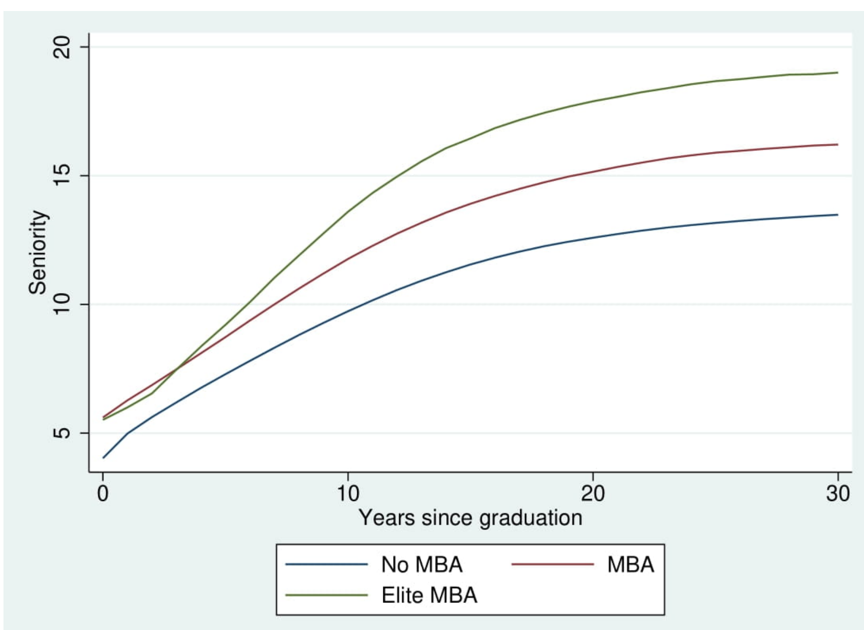

Figure 5: Seniority Achievement by MBA Status, Centered at MBA Graduation

This figure displays seniority over time by MBA education, centered at the date of MBA graduation. The seniority for each group-year point is the average seniority of individuals in the group at the relevant year after graduation. Elite MBAs schools are Harvard, Kellogg, Stanford, Booth, and Wharton. Time is normalized so that for MBA recipients, 0 is the year of MBA graduation. For individuals without MBAs, time is standardized so that 0 is 7 years after college graduation, the median time for MBA graduation.

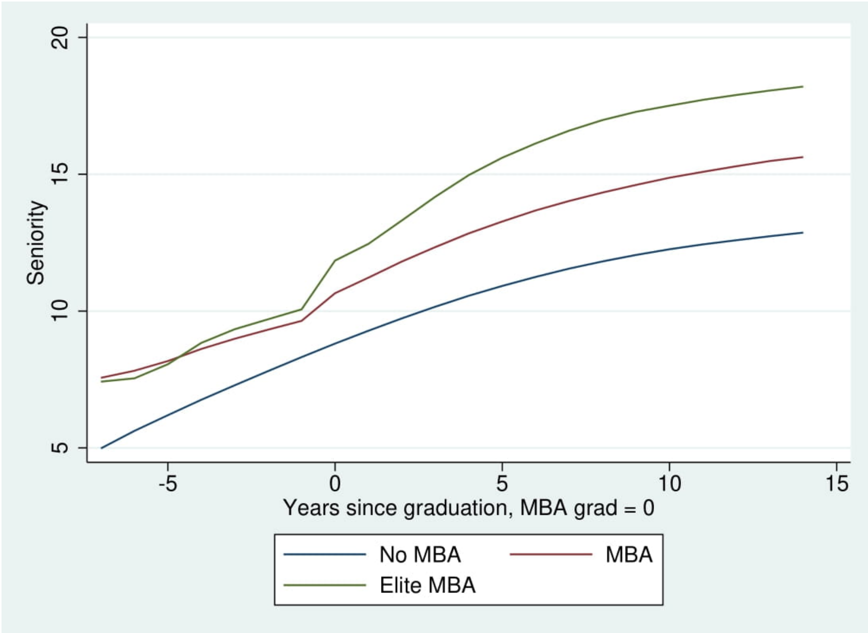

Figure 6: Founder and Non-Founder Seniority

This figure presents founder and non-founder seniority over time. The seniority for each group-year point is the average seniority of individuals in the group at the relevant year after graduation. All founders and non-founders in the detailed resume sample are included.

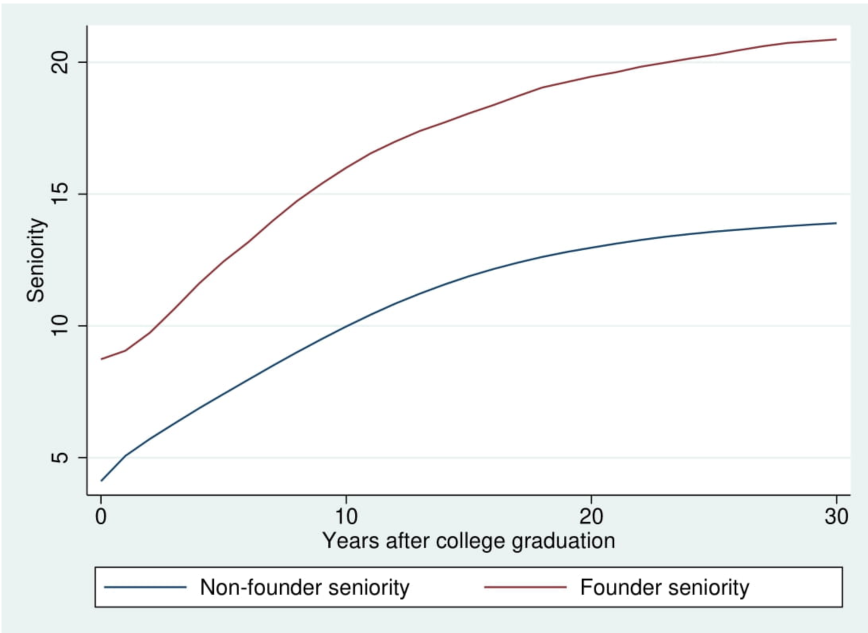

Figure 7: Founder and Matched Non-Founder Seniority

This figure presents founder and non-founder seniority over time. Only founders and non-founders matched to a pre-founding cohort are included. The non-founder curve is the unweighted average of each non-founder cohort average. The founder curve is the average of founder seniority. Time is normalized so that all cohorts have pre- and post-founding periods of the same length. The founding period is omitted. Founder seniority during the founding period is represented by the labeled point.

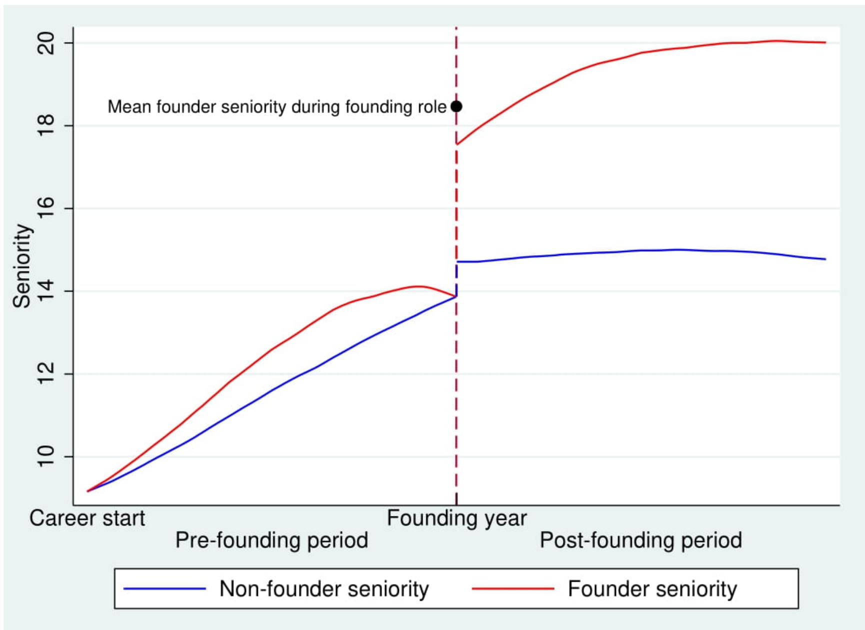

Table 1: Summary statistics of the Lightcast data

The table presents summary statistics for all individuals in the Lightcast sample. Seniority, defined precisely in the data section, captures the number of years it takes, on average, to obtain a given job title in a given industry. Wage is the median wage of the ONET code for a job. The career end year is considered undetermined and is left missing if the individual has a job continuing through 2021 or lists a job ending in 2021. Highest seniority/wage achieved is an individual's maximum seniority/wage over the course of their career.

	Count	Min	Max	Mean	S. Dev.	25th Pct.	Median	75th Pct.
Career start	4,570,084	1950	2020	2003	10.82	1996	2005	2011
Career end	554,761	1950	2020	2014	5.72	2012	2015	2017
Job listed in 2021	5,465,579	0	1	0.90	0.30	1	1	1
Total jobs	5,465,579	1	93	4.39	3.39	1	4	6
Total years in data	4,569,172	0	71	17.60	10.83	10	15	24
Seniority								
Seniority in first reported job	3,785,266	-4.00	40.00	5.83	5.98	1.00	4.00	10.00
Highest seniority achieved	5,173,499	-4.00	40.00	11.82	7.27	5.00	12.00	18.00
Wage								
Wage in first reported job	2,982,703	10,224	244,801	77,047	41,273	45,756	69,341	98,641
Highest wage achieved	3,898,738	11,013	244,801	117,073	47,085	81,575	110,534	148,895

Table 2: Job titles and their seniority

The table lists the most common job titles in the Lightcast sample (Panel A) and the most senior and the most junior job titles (Panel B). Seniority, defined precisely in the data section, captures the number of years it takes, on average, to obtain a given job title in a given industry. Reported is the median seniority across industries. Titles with fewer than 100 observations are excluded from the Panel B.

Panel A: Most common job titles

Rank	Title	Median seniority	Rank	Title	Median seniority
1	Intern	0	11	Founder	13
2	Owner	12	12	Partner	16
3	President	18	13	Manager	5
4	Research Assistant	1	14	Account Executive	5
5	Project Manager	11	15	Sales Associate	-1
6	Associate	6	16	Director	13
7	Chief Executive Officer	18	17	Attorney	9
8	Software Engineer	5	18	Principal	19
9	Consultant	11	19	Account Manager	6
10	Vice President	16	20	Teacher	4

Panel B: Most senior and most junior job titles

Title	Median seniority	Title	Median seniority
Audit Committee Chair	31	Customer Service Staff	-3
Member of Scientific Advisory Board	31	Bag Room Attendant	-3
Professor Emeritus	30	ROTC Cadet	-3
Audit Committee Member	30	Carhop	-3
Member of the Board of Advisors	29	Lifeguard Assistant Manager	-3
Executive Chairman	29	Model Associate	-3
Member of Strategic Advisory Board	29	Courtesy Clerk and Cashier	-3
Executive in Residence	29	Avionics Specialist	-3

Pastoral Intern	29	Bag Room Employee	-3
Strategic Advisor	28	Youth Advisory Board Member	-3

Table 3: Employment summary statistics for founders

The table presents summary statistics for founders in the analysis sample. These are VentureSource-Lightcast matched founders who have at least one pre-founding job and at least one post-founding job listed in the Lightcast resume data. Seniority, defined precisely in the data section, captures the number of years it takes, on average, to obtain a given job title in a given industry. Wage is the median wage of the ONET code for a job. The career end year is considered undetermined and is left missing if the individual has a job continuing through 2021 or lists a job ending in 2021. Highest seniority/wage achieved is an individual's maximum seniority/wage over the course of their career.

	Count	Min	Max	Mean	S. Dev.	25th Pct.	Median	75th Pct.
Career summary								
Career start	12,043	1950	2016	1995	9.26	1989	1996	2002
Career end	497	2003	2020	2017	3.05	2015	2017	2019
Ongoing job in 2021	12,043	0	1	0.96	0.20	1	1	1
Total jobs	12,043	3	48	9.03	4.14	6.00	8.00	11.00
Years in data	12,043	3	71	25.54	9.25	18.00	25.00	32.00
Seniority								
Pre-founding seniority	12,043	-3.50	35.00	14.76	7.24	10.00	15.00	21.00
Post-founding seniority	12,043	-3.00	39.00	17.16	6.92	13.00	18.00	23.00
Seniority in first reported job	10,915	-4.00	35.00	9.10	6.73	4.00	8.00	13.00
Highest seniority achieved	12,043	2.00	39.00	23.40	4.07	21.00	24.00	26.00
Wages								
Wage in first reported job	7,916	18,354	244,801	103,391	40,695	76,771	99,092	126,956
Highest wage achieved	9,245	25,864	244,801	186,519	26,160	177,178	194,028	197,249

Table 4: Education Summary Statistics

This table presents the proportion of founders that fall into each education category. Elite undergraduate institutions are defined as Ivy League schools, Stanford, MIT, Northwestern, UC-Berkeley, and Duke. STEM degrees are defined as degrees in the Lightcast data that contain keywords for STEM fields of study. Lightcast data identify master's and PhD degrees as well as bachelor's degrees graduation dates. Elite MBA programs are defined as Harvard, Northwestern, UChicago, Stanford, and Wharton.

	Non-founders	All Founders	Failed Founders	Successful Founders	Founders Who Left Active Firms
Elite undergraduate degree	0.13	0.16	0.16	0.19	0.14
Master's degree reported (non-MBA)	0.21	0.26	0.26	0.26	0.25
MBA reported	0.09	0.23	0.23	0.25	0.22
Elite MBA	0.01	0.10	0.10	0.12	0.09
PhD reported	0.06	0.16	0.14	0.21	0.17
STEM degree (any kind)	0.56	0.70	0.70	0.76	0.69
Master's STEM degree	0.09	0.20	0.21	0.22	0.19
PhD STEM degree	0.03	0.13	0.11	0.17	0.13
Bachelor's graduation: pre-1980	0.06	0.07	0.08	0.11	0.03
Bachelor's graduation: 1980-1989	0.13	0.21	0.24	0.30	0.11
Bachelor's graduation: 1990-1999	0.16	0.23	0.23	0.23	0.22
Bachelor's graduation: 2000-2009	0.24	0.21	0.18	0.10	0.31
Bachelor's graduation: 2010-2014	0.17	0.05	0.03	0.01	0.10
Bachelor's graduation: 2015-later	0.23	0.24	0.24	0.24	0.23

Table 5: Most common titles of founders in labor force entry, pre-founding, and post-founding jobs

The table reports the most common titles held by founders at labor-force entry and in their pre- and post-founding jobs. Shown in the table are the number of founders with each title, as a count and as a percentage of all founders.

Rank	Labor force entry title	Count (%)	Pre-founding title	Count	Post-founding title	Count (%)
1	Intern	436 (5.8%)	Vice President	1,092 (9.8%)	Chief Executive Officer	1,412 (12.7%)
2	Research Assistant	369 (4.9%)	Chief Executive Officer	840 (7.6%)	Vice President	925 (8.3%)
3	Analyst	250 (3.3%)	Chief Technology Officer	294 (2.6%)	Director	528 (4.8%)
4	Software Engineer	247 (3.3%)	Director	271 (2.4%)	Chief Technology Officer	411 (3.7%)
5	Software Engineering Intern	129 (1.7%)	President	203 (1.8%)	Advisor	312 (2.8%)
6	Software Developer	123 (1.6%)	Consultant	140 (1.3%)	President	220 (2.0%)
7	Summer Intern	115 (1.5%)	Software Engineer	137 (1.2%)	Chairman	141 (1.3%)
8	Associate	113 (1.5%)	Principal	118 (1.1%)	Partner	122 (1.1%)
9	Investment Banking Analyst	104 (1.4%)	Managing Director	96 (0.9%)	Principal	118 (1.1%)
10	Engineer	90 (1.2%)	Chairman	95 (0.9%)	Managing Director	114 (1.0%)
11	Programmer	90 (1.2%)	Advisor	93 (0.8%)	Entrepreneur-in-Residence	109 (1.0%)
12	Researcher	85 (1.1%)	Chief Operations Officer	91 (0.8%)	Consultant	104 (0.9%)
13	Research Intern	85 (1.1%)	Partner	90 (0.8%)	Advisory Board Member	104 (0.9%)
14	Research Associate	74 (1.0%)	Product Manager	87 (0.8%)	Chief Operations Officer	99 (0.9%)
15	Design Engineer	68 (0.9%)	Associate	80 (0.7%)	Member-at-Large	95 (0.9%)
16	Engineering Intern	62 (0.8%)	Owner	80 (0.7%)	Mentor	89 (0.8%)
17	Business Analyst	61 (0.8%)	Director of Business Development	74 (0.7%)	Managing Partner	84 (0.8%)
18	Financial Analyst	59 (0.8%)	Executive Vice President	71 (0.6%)	Director of Engineering	80 (0.7%)
19	Web Developer	56 (0.7%)	Professor	68 (0.6%)	Software Engineer	78 (0.7%)
20	Associate Consultant	56 (0.7%)	Director of Engineering	66 (0.6%)	Owner	67 (0.6%)
1–20		2,672 (35.8%)		4,086 (36.8%)		5,212 (46.9%)

Table 6: Seniority in the Pre-founding Job Summary Statistics

The table reports founder seniority in the pre-founding job. The pre-founding job is the job held immediately before the entrepreneurial firm. This table includes only founders who have both a pre- and post-founding job identified in their work history.

	Count	Mean	SD	25th Percentile	Median	75th Percentile
All founders	11,962	14.77	7.23	10.00	15.00	21.00
Seniority by outcome:						
Founders of successful firms	1,638	15.42	6.89	11.00	16.00	21.00
Founders of failed firms	6,876	14.74	7.04	10.00	15.00	20.50
Founders who departed active firms	3,448	14.52	7.74	9.00	14.00	21.00
Seniority by firm start year:						
Firm start: 1990-1994	68	13.63	6.15	9.00	13.00	19.00
Firm start: 1995-1999	1,571	14.69	6.64	10.00	15.00	20.00
Firm start: 2000-2004	1,885	15.32	6.63	11.00	17.00	21.00
Firm start: 2005-2009	1,925	15.74	6.91	11.00	17.00	21.00
Firm start: 2010-2014	3,601	14.27	7.49	9.00	14.00	20.50
Firm start: 2015-2019	2,908	14.47	7.73	9.00	14.00	21.00

Table 7: Pre-founding Seniority and Wage — Labor Force Entry Cohort

This table presents OLS regression results where pre-founding seniority (Panel A) and log wage (Panel B) are regressed onto founder status and characteristics. Departed founder refers to founders who left active and private firms. Active firms are defined as firms without an exit and less than 10 years old and received funding within the last 3 years. The sample includes founders and his or her labor force non-founder cohort. Standard errors are in parentheses and are clustered at the cohort level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Pre-founding seniority			*Panel B: Pre-founding wage*		
	(1)	(2)	(3)	(1)	(2)	(3)
Successful Founder	2.161***	2.221***	2.470***	0.145***	0.151***	0.268***
	(0.201)	(0.201)	(0.358)	(0.0135)	(0.0135)	(0.0253)
Failed Founder	2.042***	2.100***	2.259***	0.157***	0.162***	0.269***
	(0.0970)	(0.0970)	(0.286)	(0.00697)	(0.00697)	(0.0218)
Departed Founder	2.643***	2.696***	2.888***	0.156***	0.162***	0.269***
	(0.140)	(0.140)	(0.292)	(0.0119)	(0.0119)	(0.0232)
Cohort Year		-0.141***	-0.142***		-0.0123***	-0.0122***
		(0.00409)	(0.00415)		(0.000453)	(0.000450)
Male			0.541***			0.0958***
			(0.0125)			(0.000858)
Founder × Male			0.200			-0.0696***
			(0.264)			(0.0203)
STEM			0.0292***			0.0624***
			(0.00897)			(0.00117)
Founder × STEM			-0.0239			-0.0404***
			(0.176)			(0.0137)
Founder			-1.034***			-0.0760***
× Elite Undergrad			(0.207)			(0.0153)
MBA			1.368***			0.0801***
			(0.0211)			(0.00111)
Founder × MBA			-0.837***			-0.0648***
			(0.232)			(0.0160)
Elite MBA			1.251***			0.0860***
			(0.0421)			(0.00225)
Founder × Elite MBA			-1.264***			-0.0871***
			(0.355)			(0.0236)
Has a PhD			-0.187***			-0.0816***
			(0.0508)			(0.00493)
Founder × PhD			-0.862***			-0.0573***
			(0.224)			(0.0176)
Cohort FE	Y	Y	Y	Y	Y	Y
Observations	2,991,876	2,991,876	2,774,607	2,855,874	2,855,874	2,650,636
Adjusted R-squared	0.323	0.323	0.332	0.212	0.213	0.235

Table 8: Seniority and Wage Before and After Founding Experience

This table characterizes how seniority changes after founding experience at a VC-backed start up. Panel A reports means for changes in seniority from the pre-founding to post-founding job. Panel B reports means for changes in wages from the pre-founding to post-founding job. *Difference (Post-Pre)* is the difference between a founder's seniority or wage in their immediate post-founding job and their seniority or wage in their immediate pre-founding job. Time working at start up job is the number of years that a founder spends working as the founder of a VC-backed firm before leaving for a post-founding job. The definitions of failed, successful, and active firms follow definitions used throughout the paper. Means for failed and departed founders are compared to means for successful founders using two-sample T-tests. *, **, and *** indicate significant differences from the T-tests at the 10%, 5%, and 1% levels, respectively.

	Panel A: Seniority			*Panel B: Wage*		
	Successful	Failed	Departed	Successful	Failed	Departed
Value in pre-founding job	15.42	14.74***	14.52***	125,768	124,343	127,959***
Value in post-founding job	18.90	17.2***	16.31***	143,573	136,592***	121,835**
Difference (Post-Pre)	3.48	2.47***	1.79***	17,805	12,249***	6,124***
Time working at start up job	5.78	4.62***	3.51***	5.93	4.75***	3.82***
Observations	1,638	6,876	3,448	1,110	4,569	1,530

Table 9: Observable Characteristics and Seniority Differences

Table 9 summarizes how various founder and firm characteristics may account for variation in post-founding seniority differences (post-founding minus pre-founding seniority) within different subgroups of VC-backed founders. A firm is classified as successful if it exited via IPO or was acquired for more than total investment. A firm is classified as failed if it was acquired for less than total investment, went out of business, or has not received VC funding in the 3 most recent years in our sample. Lastly, a firm is classified as still active if it is neither successful nor failed and has received VC funding within the 3 most recent years in our sample.

All observable characteristics/variables by which founders within each group are sorted are binary indicators. Education variables (MBA, STEM, and elite undergraduate education) come from the Lightcast resume data. Firm-level come from the VentureSource data, and they indicate whether a firm was founded (i) at the start of the great recession (Great Recession Start), (ii) at the start of the Dot-com bubble (Dot-com start), (iii) in California or Massachusetts (Firm in CA or MA), and/or (iv) in the IT industry (Firm in IT). Finally, "Top VC" indicates whether a portfolio firm received funding from a top VC, defined as a VC firm in the top percentile of number of investments made over the prior 10 years.

The mean difference is mean of founders for whom the indicator variable is equal to 1 minus the mean of founders for whom the indicator variable is equal to 0. We compare means with two-sample T-tests. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Successful founders		Failed founders		Departed founders	
Indicator variable:	Yes	No	Yes	No	Yes	No
MBA	3.536	3.440	2.657	2.489	1.626	1.920
STEM	3.833	2.301***	2.598	2.365	2.081	1.358**
Elite undergraduate education	4.309	3.264*	2.902	2.455	2.241	1.790
Great recession start	2.149	3.733***	2.293	2.494	1.477	1.799
Dot-com start	4.063	3.308	2.708	2.395	1.750	1.791
Firm in CA or MA	3.646	3.213	2.527	2.398	1.882	1.707
Firm in IT	3.551	3.424	2.532	2.418	2.139	1.655
Top VC	3.834	3.278	2.547	2.453	2.175	1.689

Table 10: Observable Characteristics and Wage Differences

Table 14 summarizes how various founder and firm characteristics may account for variation in post-founding wage differences (post-founding minus pre-founding wages) within different subgroups of VC-backed founders. A firm is classified as successful if it exited via IPO or was acquired for more than total investment. A firm is classified as failed if it was acquired for less than total investment, went out of business, or has not received VC funding in the 3 most recent years in our sample. Lastly, a firm is classified as still active if it is neither successful nor failed and has received VC funding within the 3 most recent years in our sample.

All observable characteristics/variables by which founders within each group are sorted are binary indicators. Education variables (MBA, STEM, and elite undergraduate education) come from the Lightcast resume data. Firm-level come from the VentureSource data, and they indicate whether a firm was founded (i) at the start of the great recession (Great Recession Start), (ii) at the start of the Dot-com bubble (Dot-com start), (iii) in California or Massachusetts (Firm in CA or MA), and/or (iv) in the IT industry (Firm in IT). Finally, "Top VC" indicates whether a portfolio firm received funding from a top VC, defined as a VC firm in the top percentile of number of investments made over the prior 10 years.

The mean difference is mean of founders for whom the indicator variable is equal to 1 minus the mean of founders for whom the indicator variable is equal to 0. We compare means with two-sample T-tests. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Successful founders		Failed founders		Departed founders	
Indicator variable:	Yes	No	Yes	No	Yes	No
MBA	17,103	18,227	10,667	13,006	3,373	6,906
STEM	17,361	20,277	13,162	10,502	6,375	5,253
Elite undergraduate education	22,665	16,791	10,944	12,735	-1,256	7,497*
Great recession start	15,603	18,192	12,516	12,206	15,900	5,759
Dot-com start	22,566	16,267	17,687	10,285***	27,656	5,867
Firm in CA or MA	18,147	17,198	11,849	12,709	7,625	4,696
Firm in IT	18,203	17,426	13,493	11,259	11,637	3,836**
Top VC	20,480	16,390	12,355	12,197	7,840	5,543

Table 11: Post-founding Seniority and Wage — Pre-founding Cohort

This table presents OLS regression results where post-founding seniority (Panel A) and log wage (Panel B) are regressed onto founder status and characteristics. Departed founder refers to founders who left active and private firms. Active firms are defined as firms without an exit and less than 10 years old and received funding within the last 3 years. The sample includes founders and his or her pre-founding non-founder cohort. Standard errors are in parentheses and are clustered at the cohort level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Post-founding Seniority			*Panel B: Post-founding Wage*		
	(1)	(2)	(3)	(1)	(2)	(3)
Successful Founder	3.924***	3.989***	4.230***	0.219***	0.223***	0.244***
	(0.294)	(0.295)	(0.506)	(0.0185)	(0.0185)	(0.0382)
Failed Founder	2.902***	2.955***	3.154***	0.186***	0.190***	0.201***
	(0.135)	(0.135)	(0.412)	(0.00957)	(0.00957)	(0.0336)
Departed Founder	2.690***	2.735***	2.745***	0.137***	0.140***	0.140***
	(0.199)	(0.199)	(0.423)	(0.0185)	(0.0185)	(0.0363)
Years After Graduation		0.134***	0.132***		0.0115***	0.0111***
		(0.0116)	(0.0117)		(0.00117)	(0.00118)
Male			0.475***			0.0866***
			(0.0298)			(0.00215)
Founder × Male			-0.203			0.00705
			(0.387)			(0.0314)
STEM			0.0196			0.0589***
			(0.0251)			(0.00285)
Founder × STEM			0.284			-0.0400**
			(0.254)			(0.0198)
Founder			-0.830***			-0.0807***
× Elite Undergrad			(0.311)			(0.0224)
MBA			1.144***			0.0737***
			(0.0502)			(0.00307)
Founder × MBA			-1.491***			-0.0740***
			(0.319)			(0.0243)
Elite MBA			1.135***			0.0806***
			(0.104)			(0.00659)
Founder × Elite MBA			0.497			-0.0312
			(0.491)			(0.0356)
Has a PhD			0.246*			-0.0352**
			(0.136)			(0.0137)
Founder × PhD			0.0553			0.0818***
			(0.324)			(0.0259)
Cohort FE	Y	Y	Y	Y	Y	Y
Observations	312,207	311,971	289,333	271,071	270,841	251,645
Adjusted R-squared	0.391	0.392	0.399	0.235	0.237	0.255

Table 12: Post-founding Seniority and Wage — Founder Sample

This table presents OLS regressions relating post-founding seniority (Columns 1–4) and post-founding log wages (Columns 5–8) to founder status and characteristics. Departed founder refers to founders who left active and private firms. Active firms are defined as firms without an exit and less than 10 years old and received funding within the last 3 years. Standard errors are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Post-founding Seniority				*Post-founding Wage*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Failed Founder	-1.695***	-1.715***	-1.597***	-1.374***	-0.0675***	-0.0627***	-0.0577***	-0.0452**
	(0.189)	(0.219)	(0.221)	(0.292)	(0.0139)	(0.0162)	(0.0164)	(0.0227)
Departed Founder	-2.592***	-2.615***	-2.462***	-2.457***	-0.170***	-0.164***	-0.159***	-0.158***
	(0.206)	(0.238)	(0.239)	(0.241)	(0.0163)	(0.0190)	(0.0191)	(0.0193)
Pre-founding Seniority		0.163***	0.157***	0.156***				
		(0.0106)	(0.0107)	(0.0107)				
Pre-founding Log Wage						0.00288***	0.00310***	0.00311***
						(0.000733)	(0.000749)	(0.000750)
Years After Graduation		0.0791***	0.0799***	0.0799***		0.00288***	0.00310***	0.00311***
		(0.00951)	(0.00966)	(0.00967)		(0.000733)	(0.000749)	(0.000750)
STEM Degree			0.240	0.241			0.0170	0.0168
			(0.166)	(0.166)			(0.0133)	(0.0133)
Elite Undergrad			0.0339	0.0184			-0.0264*	-0.0365
			(0.190)	(0.293)			(0.0147)	(0.0242)
MBA			0.758***	1.090***			0.0117	0.0656**
			(0.211)	(0.322)			(0.0162)	(0.0270)
Elite MBA			1.045***	0.834*			0.0168	-0.0411
			(0.297)	(0.456)			(0.0230)	(0.0383)
PhD			0.122	0.128			-0.0241	-0.0232
			(0.206)	(0.206)			(0.0168)	(0.0168)
Firm in CA			0.258*	0.561**			0.0137	0.0172
			(0.149)	(0.228)			(0.0117)	(0.0193)
Top VC			0.231	-0.0163			0.0300**	0.0330
			(0.177)	(0.258)			(0.0138)	(0.0214)
Failed × MBA				-0.572				-0.0833**
				(0.423)				(0.0335)
Failed × Elite MBA				0.369				0.0903*
				(0.601)				(0.0479)
Failed				0.0228				0.0154
× Elite Undergrad				(0.385)				(0.0305)
Failed × Firm in CA				-0.530*				-0.00514
				(0.300)				(0.0242)
Failed × Top VC				0.460				-0.00514
				(0.353)				(0.0280)
Observations	11,962	8,751	8,729	8,729	7,946	5,773	5,761	5,761
Adjusted R-squared	0.013	0.063	0.071	0.071	0.015	0.029	0.031	0.032

Appendix Table 1: Elite and Tier-2 universities

This table presents the elite and Tier-2 classification of colleges. Bold font represents institutions included in the core sample of 44 colleges.

Elite universities	Tier 2 universities
Brown University	Amherst College
Columbia University	**Boston University**
Cornell University	**Georgetown University**
Dartmouth College	**Johns Hopkins University**
Duke University	Macalester College
Harvard University	New York University
Massachusetts Institute of Technology	**Northeastern University**
Northwestern University	Pomona College
Princeton University	**Rice University**
Stanford University	**Tufts University**
University of California, Berkeley	University of California - San Diego
University of Chicago	**University of Michigan**
University of Pennsylvania	**University of North Carolina at Chapel Hill**
Yale University	**University of Southern California**
	University of Virginia
	Vanderbilt University
	Wesleyan University
	Williams College

Appendix Table 2: List of colleges in the core Lightcast dataset

This table presents an alphabetical list of colleges whose graduates in the Lightcast database make up the core of our dataset. As described in the text, we supplement this dataset with a list of individuals who match by name to the founders.

1	Boston University	23	Stanford University
2	Brigham and Young University	24	Syracuse University
3	Brown University	25	Texas A&M University
4	Colgate University	26	Tufts University
5	Colorado University	27	U. of Arizona
6	Columbia University	28	U. of California (Berkeley)
7	Cornell University	29	U. of California (Davis)
8	Dartmouth College	30	U. of California (Los Angeles)
9	Duke University	31	U. of Florida
10	Georgetown University	32	U. of Illinois (Urbana-Champaign)
11	Georgia Institute of Technology	33	U. of Maryland (College Park)
12	Harvard University	34	U. of Michigan
13	Indiana University	35	U. of Minnesota (Twin Cities)
14	Johns Hopkins University	36	U. of North Carolina (Chapel Hill)
15	Lehigh University	37	U. of Pennsylvania
16	Michigan State University	38	U. of Southern California
17	Northeastern University	39	U. of Texas
18	Ohio State University	40	U. of Virginia
19	Penn State University	41	U. of Washington
20	Purdue University	42	U. of Wisconsin
21	Rice University	43	US Naval Academy
22	Southern Methodist University	44	Yale University

Appendix Table 3: Founders matched from VentureSource to Lightcast

The table reports the number and percentage of founders matched from VentureSource to the Lightcast resume data. Founders are considered to enter the VentureSource database when their first start-up receives its first funding.

Year	Founders		Percentage matched	Year	Founders		Percentage matched
	Total	Matched			Total	Matched	
1980	1	0	0%	2000	4,306	2,039	47%
1981	2	0	0%	2001	1,579	779	49%
1982	7	1	14%	2002	860	429	50%
1983	5	0	0%	2003	889	484	54%
1984	12	1	8%	2004	983	539	55%
1985	16	3	19%	2005	1,184	643	54%
1986	17	1	6%	2006	1,389	818	59%
1987	38	2	5%	2007	1,696	984	58%
1988	29	6	21%	2008	1,725	1,013	59%
1989	37	7	19%	2009	1,322	800	61%
1990	51	21	41%	2010	1,701	1,068	63%
1991	70	23	33%	2011	2,451	1,593	65%
1992	126	37	29%	2012	2,998	1,994	67%
1993	161	61	38%	2013	3,174	2,096	66%
1994	265	101	38%	2014	3,111	2,033	65%
1995	529	210	40%	2015	2,719	1,761	65%
1996	1,094	462	42%	2016	5,785	4,143	72%
1997	1,232	541	44%	2017	5,017	3,657	73%
1998	1,613	757	47%	2018	3,011	2,216	74%
1999	3,355	1,641	49%	2019	256	166	65%
Total for 1980–2019					54,816	33,130	60%

Appendix Table 4: Selection bias checks

This table compares the matched and unmatched founder subsamples in VentureSource across start-up (Panel A) and VC/founder (Panel B) characteristics to evaluate the extent of selection bias in our VentureSource -Lightcast merge. All variables come from VentureSource or hand-collected data. VentureSource provides portfolio firm industry, start and end dates, headquarters location, firm outcome, and characteristics of VC investors. Demographic data on gender and ethnicity are hand-collected. Matched founders are founders whom we link to a resume in the Lightcast data. Unmatched and matched founders are all listed as founders of US-based VC-backed firms. The p-value is from a two-sample t-test of differences in means between the matched and unmatched groups.

Panel A: Firm Characteristics	Total count	Founders not in analysis sample	Founders in analysis sample	Difference	Mean (not in sample)	Mean (in sample)	P-value
				Industry			
Business/Financial Services	54,530	42,534	11,996	0.013	0.213	0.226	0.003
Consumer Goods	54,530	42,534	11,996	-0.008	0.035	0.027	0.000
Consumer Services	54,530	42,534	11,996	0.012	0.174	0.186	0.003
Energy and Utilities	54,530	42,534	11,996	0.000	0.013	0.012	0.778
Healthcare	54,530	42,534	11,996	-0.031	0.164	0.133	0.000
Industrial Goods/Materials	54,530	42,534	11,996	-0.004	0.022	0.018	0.016
Information Technology	54,530	42,534	11,996	0.019	0.379	0.397	0.000
				Time period and location of firm start			
Firm start year	54,564	42,564	12,000	-0.116	2008.805	2008.688	0.128
Start just before Great Recession (2006-08)	54,564	42,564	12,000	-0.003	0.169	0.166	0.440
Start in dot-com era (1999-2001)	54,564	42,564	12,000	0.025	0.082	0.106	0.000
Firm start: pre-1990	54,564	42,564	12,000	-0.004	0.004	0.000	0.000
Firm start: 1990-1994	54,564	42,564	12,000	-0.008	0.014	0.006	0.000
Firm start: 1995-1999	54,564	42,564	12,000	-0.015	0.146	0.131	0.000
Firm start: 2000-2004	54,564	42,564	12,000	0.001	0.156	0.157	0.720
Firm start: 2005-2009	54,564	42,564	12,000	0.036	0.125	0.161	0.000
Firm start: 2010-2014	54,564	42,564	12,000	0.072	0.230	0.301	0.000
Firm start: 2015-2019	54,564	42,564	12,000	-0.082	0.326	0.244	0.000
Firm in CA	54,564	42,564	12,000	0.021	0.420	0.441	0.000
Firm in CA or MA	54,564	42,564	12,000	0.028	0.506	0.534	0.000
				Firm outcome			
IPO	54,564	42,564	12,000	-0.010	0.049	0.040	0.000
Successful Acquisition	54,564	42,564	12,000	0.046	0.137	0.184	0.000
Unsuccessful Acquisition	54,564	42,564	12,000	0.046	0.131	0.177	0.000
Firm bankrupt	54,564	42,564	12,000	0.000	0.001	0.001	0.701
Firm out of business	54,564	42,564	12,000	-0.003	0.099	0.096	0.322
Firm assets acquired	54,564	42,564	12,000	0.003	0.013	0.016	0.019
Firm private (unexited and not failed)	54,564	42,564	12,000	-0.096	0.385	0.289	0.000

Panel B: VC and Founder Characteristics

	Total count	Founders not in analysis sample	Founders in analysis sample	Difference	Mean (not in sample)	Mean (in sample)	P-value
Log of oldest VC firm age	54,393	42,426	11,967	0.035	3.053	3.088	0.000
Total rounds	54,564	42,564	12,000	0.111	3.327	3.438	0.000
Time as a private firm	54,542	42,543	11,999	-0.805	6.744	5.939	0.000
Total investment (inflation adjusted) in millions	54,026	42,156	11,870	-4.532	38.028	33.496	0.022
Log total investment (inflation adjusted)	54,026	42,156	11,870	0.109	14.681	14.790	0.033
				Demographics			
Female	53,588	41,636	11,952	-0.005	0.103	0.098	0.081
White	53,422	41,470	11,952	-0.010	0.659	0.649	0.050
East Asian	53,422	41,470	11,952	-0.013	0.087	0.074	0.000
Indian	53,422	41,470	11,952	0.011	0.098	0.109	0.001
Jewish	53,422	41,470	11,952	-0.003	0.166	0.163	0.468
Hispanic	53,422	41,470	11,952	-0.011	0.064	0.053	0.000
African	53,422	41,470	11,952	0.000	0.004	0.004	0.849
Middle Eastern	39,475	29,935	9,540	0.000	0.001	0.002	0.251
				Education			
College info in VentureSource	54,850	42,841	12,009	-0.292	0.356	0.064	0.000
Top school in VentureSource (Ivies+)	54,850	42,841	12,009	-0.037	0.050	0.013	0.000

Appendix Table 5: Seniority Achievement Matrix

This table shows the percentage of individuals who reach at least a given seniority (horizontal axis) tabulated by career length in years (vertical axis) as listed in the Lightcast resume data. Seniority, defined precisely in the data section, captures the number of years it takes, on average, to obtain a given job title in a given industry.

Career length \ Seniority	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	100	66	42	21	16	12	9	9	8	8	6	5	4	3	2	2	2	2	1	1
2	100	73	51	29	22	16	12	12	11	10	9	7	6	4	3	3	2	2	2	1
3	100	83	65	44	32	24	18	17	16	14	12	10	8	6	4	4	3	3	2	2
4	100	89	74	56	43	32	24	23	22	20	17	13	10	7	6	5	4	4	3	3
5	100	92	80	64	51	39	30	29	27	24	21	16	12	9	7	6	5	4	4	3
6	100	93	84	70	58	46	35	34	32	29	25	20	15	11	8	7	6	5	5	4
7	100	94	87	75	63	51	40	39	37	33	28	22	17	12	10	8	7	6	5	5
8	100	96	89	78	68	57	46	44	42	38	32	26	20	14	11	9	8	7	6	5
9	100	96	91	82	72	61	50	48	46	41	35	28	22	16	13	11	10	9	7	6
10	100	97	92	84	75	66	54	53	50	45	39	32	24	18	15	13	11	10	9	7
11	100	98	93	86	78	69	59	57	54	49	42	35	27	20	16	14	13	12	10	9
12	100	98	94	88	81	73	63	61	58	53	46	38	30	23	19	17	15	14	12	10
13	100	98	95	89	82	75	66	64	61	56	49	41	32	25	21	19	17	16	13	11
14	100	98	95	90	84	77	68	67	64	59	52	44	35	28	23	21	19	17	15	13
15	100	99	96	91	85	79	71	69	67	61	55	47	38	30	26	23	21	19	17	14
16	100	99	96	91	86	80	73	72	69	64	58	50	41	33	29	26	24	22	19	16
17	100	99	97	92	87	82	75	74	71	66	60	52	43	35	31	28	26	24	21	18
18	100	99	97	92	88	82	76	75	72	68	61	54	45	37	32	30	28	25	22	19
19	100	99	97	92	88	83	77	76	74	70	64	56	47	39	35	32	30	27	24	20
20	100	99	96	92	88	83	77	76	74	70	65	58	49	41	36	34	31	29	25	22
21	100	99	97	92	89	84	79	78	76	72	66	59	51	43	38	36	33	30	27	23
22	100	99	97	92	88	84	79	78	76	72	67	60	51	44	40	37	35	32	28	24
23	100	99	97	92	89	85	79	79	77	73	68	62	53	46	41	38	36	33	29	25
24	100	99	97	92	89	84	80	79	77	74	69	62	54	47	42	40	37	34	30	26
25	100	99	97	92	89	85	80	79	78	75	70	63	55	48	44	42	39	36	32	27
26	100	99	97	92	89	85	80	79	78	75	70	64	55	48	44	42	39	36	32	27
27	100	99	97	92	89	85	81	80	78	76	71	65	57	50	45	43	40	37	33	29
28	100	99	96	91	88	84	80	79	78	75	70	64	57	50	46	43	40	37	33	28
29	100	99	97	92	89	85	80	80	78	76	71	65	57	51	47	44	42	38	34	30
30	100	99	97	92	89	85	81	80	79	76	72	66	58	52	48	46	43	39	35	31

Appendix Table 6: Post-founding Seniority and Wage — Labor Force Entry Cohort

This table presents OLS regression results where post-founding seniority (Panel A) and log wage (Panel B) are regressed onto founder status and characteristics. Departed founder refers to founders who left active and private firms. Active firms are defined as firms without an exit and less than 10 years old and received funding within the last 3 years. The sample includes founders and his or her labor force non-founder cohort. Standard errors are in parentheses and are clustered at the cohort level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Post-founding Seniority			*Panel B: Post-founding Wage*		
	(1)	(2)	(3)	(1)	(2)	(3)
Successful Founder	5.027***	3.608***	3.632***	0.245***	0.149***	0.124***
	(0.227)	(0.258)	(0.461)	(0.0148)	(0.0172)	(0.0362)
Failed Founder	3.788***	2.473***	2.530***	0.207***	0.108***	0.0837***
	(0.111)	(0.122)	(0.377)	(0.00792)	(0.00909)	(0.0324)
Departed Founder	3.812***	2.091***	2.036***	0.145***	0.0446***	0.0120
	(0.163)	(0.176)	(0.386)	(0.0153)	(0.0172)	(0.0353)
Pre-founding Seniority		0.687***	0.679***			
		(0.00359)	(0.00361)			
Pre-founding Wage					0.658***	0.649***
					(0.00408)	(0.00415)
Years after Graduation		0.0247***	0.0203***		0.000542**	0.000360
		(0.00343)	(0.00341)		(0.000231)	(0.000232)
Male			0.307***			0.0352***
			(0.00889)			(0.000699)
Founder × Male			-0.298			0.0394
			(0.350)			(0.0310)
STEM			0.0797***			0.0189***
			(0.00722)			(0.000709)
Founder × STEM			0.380*			-0.0116
			(0.226)			(0.0188)
Founder			-0.287			-0.0581***
× Elite Undergrad			(0.268)			(0.0204)
MBA			0.981***			0.0430***
			(0.0173)			(0.000931)
Founder × MBA			-1.176***			-0.0688***
			(0.270)			(0.0220)
Elite MBA			0.889***			0.0239***
			(0.0330)			(0.00202)
Founder × Elite MBA			0.403			0.0213
			(0.417)			(0.0330)
Has a PhD			0.677***			0.0177***
			(0.0410)			(0.00365)
Founder × PhD			0.0402			0.0592***
			(0.279)			(0.0229)
Cohort FE	Y	Y	Y	Y	Y	Y
Observations	2,828,898	2,584,452	2,395,770	2,772,331	2,529,292	2,346,708
Adjusted R-squared	0.213	0.517	0.523	0.144	0.501	0.505

Appendix Table 7: Seniority and Wage Differences — Labor Force Entry Cohort

This table presents OLS regression results for seniority and wage differences between pre- and post-founding jobs. Seniority difference (Panel A) and log wage difference (Panel B) are regressed onto founder status and characteristics. Departed founder refers to founders who left active and private firms. Active firms are defined as firms without an exit and less than 10 years old and received funding within the last 3 years. The sample includes founders and his or her labor force non-founder cohort. Standard errors are in parentheses and are clustered at the cohort level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Seniority Difference			*Panel B: Wage Difference*		
	(1)	(2)	(3)	(1)	(2)	(3)
Successful Founder	2.941***	2.934***	2.847***	0.101***	0.0994***	0.0339
	(0.293)	(0.293)	(0.523)	(0.0143)	(0.0199)	(0.0410)
Failed Founder	1.848***	1.841***	1.819***	0.0543***	0.0528***	-0.00859
	(0.136)	(0.136)	(0.425)	(0.00669)	(0.0103)	(0.0365)
Departed Founder	1.279***	1.273***	1.125***	-0.00886	-0.0104	-0.0792**
	(0.197)	(0.197)	(0.433)	(0.0108)	(0.0194)	(0.0398)
Years after Graduation		-0.0170***	-0.0224***		-0.00344***	-0.00370***
		(0.00337)	(0.00338)		(0.000224)	(0.000227)
Male			0.126***			0.00116*
			(0.00794)			(0.000658)
Founder × Male			-0.348			0.0641*
			(0.392)			(0.0352)
STEM			0.0647***			-0.00340***
			(0.00726)			(0.000692)
Founder × STEM			0.386			-0.000647
			(0.254)			(0.0214)
Founder × Elite Undergrad			0.0602			-0.0317
			(0.304)			(0.0235)
MBA			0.524***			0.0152***
			(0.0164)			(0.000882)
Founder × MBA			-0.888***			-0.0480*
			(0.307)			(0.0248)
Elite MBA			0.460***			-0.00633***
			(0.0363)			(0.00221)
Founder × Elite MBA			0.828*			0.0572
			(0.477)			(0.0381)
Has a PhD			0.712***			0.0427***
			(0.0429)			(0.00402)
Founder × PhD			0.331			0.0831***
			(0.315)			(0.0264)
Cohort FE	Y	Y	Y	Y	Y	Y
Observations	2,584,452	2,584,452	2,395,770	2,529,292	2,529,292	2,346,708
Adjusted R-squared	0.074	0.074	0.077	0.035	0.035	0.036

Appendix Table 8: Most common undergraduate and business schools of founders

The table reports the most common undergraduate and business schools of founders in the analysis sample, which covers those VentureSource-Lightcast matched founders who have at least one pre-founding job and at least one post-founding job listed in the Lightcast resume data. Shown in the table are the number of founders with an undergraduate or an MBA degree from each school, as a count and as a percentage of all founders with that degree.

Rank	Undergraduate institution	Count (%)	MBA institution	Count (%)
1	University of California-Berkeley	309 (3.0%)	Harvard Business School	573 (15.7%)
2	Stanford University	295 (2.9%)	Stanford Graduate School of Business	493 (13.5%)
3	Harvard University	233 (2.3%)	The Wharton School of the University of Pennsylvania	309 (8.5%)
4	Massachusetts Institute of Technology	188 (1.8%)	Northwestern University, Kellogg School of Management	157 (4.3%)
5	Cornell University	178 (1.7%)	MIT Sloan School of Management	157 (4.3%)
6	University of Michigan	172 (1.7%)	University of Chicago, Booth School of Business	123 (3.4%)
7	University of Pennsylvania	157 (1.5%)	UC Berkeley, Haas School of Business	104 (2.9%)
8	The University of Texas at Austin	153 (1.5%)	Columbia Business School	92 (2.5%)
9	University of Illinois at Urbana-Champaign	133 (1.3%)	UCLA Anderson School of Management	74 (2.0%)
10	University of California, Los Angeles	125 (1.2%)	New York University Stern School of Business	64 (1.8%)
11	Princeton University	121 (1.2%)	McCombs School of Business, University of Texas-Austin	58 (1.6%)
12	Yale University	108 (1.1%)	University of Michigan, Ross School of Business	44 (1.2%)
13	Carnegie Mellon University	107 (1.0%)	Carnegie Mellon University	36 (1.0%)
14	Brigham Young University	103 (1.0%)	Tuck School of Business	36 (1.0%)
15	Dartmouth College	103 (1.0%)	Duke University, Fuqua School of Business	35 (1.0%)
16	Duke University	99 (1.0%)	Cornell University, Samuel Curtis Johnson Graduate School of Management	34 (0.9%)
17	Pennsylvania State University	98 (1.0%)	Santa Clara University	34 (0.9%)
18	Columbia University	97 (0.9%)	Pepperdine University	27 (0.7%)
19	University of Washington	92 (0.9%)	Babson College	26 (0.7%)
20	The Wharton School of the University of Pennsylvania	88 (0.9%)	Boston University	24 (0.7%)
1–20		2,959 (28.8%)		2,500 (68.6%)

Appendix A: Matching between Lightcast and VentureSource

A.1 Matching between Lightcast and VentureSource

In this appendix, we outline our procedure for merging the VentureSource dataset with the Lightcast dataset. We use this process to supplement the founders Lightcast merges using their proprietary algorithm. We identify potential matches between the datasets as individuals who match on the first three letters of their first names, their last names, and data on (i) their undergraduate institution, (ii) their MBA institution, or (iii) their employment at the VC-backed firm. Founders for whom we find a unique match in the Lightcast data are linked to that profile. Non-unique matches are discarded. Combined with Lightcast's initial proprietary merge, about 30,000 out of about 55,000 founders of US-based VC-backed firms are matched to resumes in the Lightcast data. Of these matched founders, roughly 12,000 have clearly identified founding, pre-, and post-founding jobs and are included in our analysis of post-entrepreneurship labor market premium.[14]

We report the results of this merge in Table 1. Starting in 1990, when VentureSource data become reasonably comprehensive (Amornsiripanitch et al., 2019), we match at least 30% of founders a year. There is an upward trend in the percentage of matched founders, with rates in the 2000's and 2010's between 50% and 60%. Some of the unmatched founders might not exist in our Lightcast sample of mainly graduates of 44 US colleges, some founders might not provide enough information in their resume to produce a reliable match, and some founders might not maintain a profile on the professional networking site from which Lightcast collects data.

Overall, about half of the matched founders report a pre- and post-founding job and enter into our analysis. This fraction is about 60% for founders whose firms have exited or failed and about 30% for founders of still active firms, as many remain employed at the VC-backed firm.

We check for possible selection bias into the sample of founders that we ultimately analyze. Overall, founders in the analysis sample have very similar observable characteristics to those not in the analysis sample. Appendix Table 3 reports sample means and t-tests comparing the two groups of founders. Differences in firm industry, firm location, total investment received, total recorded rounds of investment, founder demographics, and VC quality are not economically

[14] Few founders exclude their VC-backed firm from their resume. Most founders who were dropped at this stage do not report pre- or post-founding work history or were, at the time of the data pull, still employed in their VC-backed firm.

significant. Although the most important characteristics for selection are similar between groups, there are some significant differences.

We do observe significant differences in firm start years; founders in the analysis sample are much more likely to have started firms between 2000 and 2014 and much less likely to start firms between 2015 and 2019. This partly reflects the matching process as Lightcast's database seems to skew towards younger individuals. The time difference is also partly mechanical; firms started after 2014 are more likely to be active and have founders still working for them and thus with no post-founding job.

Rates of IPOs and business failure are similar between the analysis sample and our universe of founders, but there are also small differences in firm outcome. Analyzed founders are much more likely to start firms that were acquired, either successfully or unsuccessfully, and are much less likely to be associated with private and active firms, in large part because many of those founders are still working at the VC-backed firm.

A2. Merge steps:

Below, we describe the steps for the Lightcast-VentureSource merge. Both the Lightcast and VentureSource datasets contain information on individuals' undergraduate and graduate institutions, graduation years, and firm names and firm start years. There are four steps in the merge, in which we match founders based on different education or professional criteria. Data availability in the VentureSource dataset often determines into which merge or merges an individual enters. Despite the differences in data availability in the VentureSource dataset, there does not seem to be much selection on observable characteristics between matched and unmatched founders, as described above. In Step 2, we use the individual's birth year from the Infutor database in the merge. We use the same procedure as described in Amornsiripanitch et al. (2021) to match founders between VentureSource and Infutor.

Step 1 – Founders with undergraduate education and graduation year available in VentureSource

Step 1A: We first subset the VentureSource dataset to individuals with non-missing institution name and graduation year.

Step 1B: We identify potential matches between the VentureSource and Lightcast datasets. We consider an individual in the Lightcast data to be a potential match for a founder in VentureSource if they share the same first three letters of the first name, the last name, and the undergraduate institution. We also require that their listed graduation years be fewer than 4 years apart.

Step 1C: We impose the following criteria, in the order listed, to the potential matches and extract unique matches that fit each criterion. We consider a match to be unique if filtering by one of the listed criteria yields a one-to-one match between Lightcast and VentureSource. The criteria are:

1. The first three letters of the first name, the last name, and the undergraduate institution.
2. The full first name, the last name, and the undergraduate institution.
3. The full first name, the last name, the undergraduate institution, and the unique smallest difference in graduation years across potential matches. A potential match is considered to have the unique smallest difference if (i) it has the smallest absolute difference in graduation years between VentureSource and Lightcast and (ii) no other potential match has an equally small difference.

Step 1D: We combine the matches from Step 1C and keep all one-to-one matches.

Step 2 – Founders with undergraduate education but no graduation year available in VentureSource

Step 2A: We begin by removing individuals in the Lightcast dataset who were merged in Step 1 to avoid creating non-unique matches. We assume that a match uses graduation year as a criterion will be more reliable than one that does not use graduation year.

Step 2B: We identify potential matches between the VentureSource and Lightcast datasets. We consider an individual in the Lightcast data to be a potential match for a founder in VentureSource if they share the same first three letters of the first name, the last name, and the undergraduate institution.

Step 2C: We estimate the birth year of a potential match as the reported Lightcast college graduation year minus 22. We then calculate the estimated age at founding as the firm start year in VentureSource minus the estimated birth year. We drop potential matches where the estimated age at founding is less than 20 or greater than 60 or the estimated age is missing.

Step 2D: We merge in the Infutor birth year for VentureSource individuals matched in the VentureSource -Infutor merge, described in Amornsiripanitch et al. (2021). This step merges in an alternate birth year variable for a subset of founders. Since the Infutor data use social security numbers to determine birth year, we consider the birth year from Infutor to be reliable. For the subset of founders with a birth year from the Infutor dataset, we discard potential matches where the difference in birth years between Lightcast and Infutor is greater than 5 years.

Step 2D: We impose the following criteria, in the order listed, to the potential matches and extract unique matches that fit each criterion. We consider a match to be unique if filtering by one of the listed criteria yields a one-to-one match between Lightcast and VentureSource. The criteria are:

1. The first three letters of the first name, the last name, and the undergraduate institution.
2. The full first name, the last name, and the undergraduate institution.

Step 2E: We combine the matches from Step 2D and keep all one-to-one matches.

Step 3 – Founders with business school education data available in VentureSource

We next merge on name and business school information. We use business school data as opposed to other graduate school data because the VentureSource data on business school education cover far more founders than non-business school post-secondary education. This may result in an overrepresentation of MBA graduates in our matched founder sample, but as described above, this does not lead to significant selection on observable characteristics. Step 3 follows a method similar to Steps 1 and 2.

Step 3A: We begin by removing individuals in the Lightcast dataset who were merged in Step 1 and Step 2.

Step 3B: We identify potential matches between the VentureSource and Lightcast datasets. We consider a person in the Lightcast data to be a potential match for a founder in VentureSource if they share the same first three letters of the first name, the last name, and the business school.

Step 3C: We impose the following criteria, in the order listed, to the potential matches and extract unique matches that fit each criterion. We consider a match to be unique if filtering by one of the listed criteria yields a one-to-one match between Lightcast and VentureSource. The criteria are:

1. The first three letters of the first name, the last name, and the business school.
2. The full first name, the last name, and the business school.
3. The full first name, the last name, the business school, and the unique smallest difference in graduation years across potential matches.

Step 3D: We combine the matches from Step 3C and keep all one-to-one matches.

Step 4 – VC-backed firm name and start date

In the last of the four merge steps, we match on individual name and the name of the VC-backed firm identified in the VentureSource dataset. We use firm name, job title, and firm start years to identify founders in the Lightcast data. While many of the VC-backed firms grow quickly and employ many individuals, almost all start with few employees. By matching on firm name, firm start year, and founder job title, we are able to accurately identify founders of these firms.

Step 4A: We identify potential matches between the VentureSource and Lightcast datasets. We consider a person in the Lightcast data to be a potential match for a founder in VentureSource if they match on the first three letters of the first name, last name, and have a job at a firm that matches with the first 7 letters of the VC-backed firm name.

Step 4B: We require the job start year in Lightcast to be 2 or fewer years greater than the firm start year in VentureSource. We allow the reported job start in Lightcast to begin before the firm start year in VentureSource as some founders report starting their founding job before incorporating the firm or raising capital from outside investors, milestones at which VentureSource begins tracking the firm.

Step 4C: We impose the following criteria, in the order listed, to the potential matches and extract unique matches that fit each criterion. We consider a match to be unique if filtering by one of the listed criteria yields a one-to-one match between Lightcast and VentureSource. The criteria are:

1. The first three letters of the first name, the last name, and the full firm name.
2. The full first name, the last name, and the full firm name.
3. The full first name, the last name, the full firm name, and job title.

Step 4D: We combine the matches from Step 4C and keep all one-to-one matches.

Step 5 – Combining all matches

After completing the four merge steps, we combine the matches. We drop any non-unique matches that might result from founders matching to more than one individual in the Lightcast dataset or a single individual in the Lightcast dataset matching to multiple founders in VentureSource. To this final set of unique matches, we add a set of founders that Lightcast matched using its entire database. We cannot replicate this merge as we do not have access to the full Lightcast database. Though we use selected fields of the full database to construct seniority, these data are deidentified, so we cannot match individuals into the full dataset. In total, about 30,000 founders in VentureSource are matched to a profile in Lightcast.

Appendix B: Seniority construction

In this appendix, we explain our method for constructing seniority in more detail. As described in Section 3.1, we calculate seniority using the universe of de-identified resumes provided by Lightcast and apply the seniority values to the more detailed sample of resumes. We take the following steps to compute seniority: (i) separate firms into quintiles by employee headcount, (ii) identify individuals' graduation/labor force entry dates, and (iii) calculate values of seniority.

B.1 Assigning firms to quintiles

We use the Lightcast data to assign a quintile rank to each firm in each year using employee headcount at the end of a given year. To minimize disproportionate assignment of employees to large size quintile firms, we base our quintiles on total shares of aggregate employment instead of firms' ordinal size ranking by employee headcount. That is, the largest firms responsible for the "first" 20% of total employment, as opposed to the top 20% of firms by employee headcount, would be assigned to the top size quintile. To determine size cutoffs for each quintile, we use headcount at one point, rather than the total number of unique employees over a year, to minimize mismeasurement due to employee turnover and obtain an accurate estimate of the number of workers at any given time.

Our assignment algorithm proceeds as follows. First, we order firms within a year from smallest to largest by headcount and compute a running sum (over headcounts) of total employees in the year. Next, we use the maximum running sum of each headcount to determine cutoffs for inclusion in each quintile. Intuitively, the maximum running sum of each headcount represents the total employee headcount of firms at or below the specified size. Therefore, dividing this sum by total employment allows us to back out the total employment share of firms at or below the sum's specified headcount. These headcount specific employment shares largely pin down which employee headcount sizes represent "cutoffs" for each of the size quintiles. However, throughout this cutoff assignment process, we ensure that all firms with the same number of employees are assigned the same quintile. This criterion introduces certain nuances and requires a flexible approach to quintile assignment.

To illustrate, using typical quintile cuts of 20%, 40%, 60%, and 80% of the running sum might separate firms with the same headcount into different quintiles. For example, suppose firms with headcounts of 25 account for 6% of all employees and that firms with headcounts of less than

25 account for 36% of all employees. In this case, firms with 25 employees would account for the segment of the distribution of employees from 36-42%, straddling the 40% cutoff that would typically be used to separate firms into Quintiles 2 and 3. Strictly separating firms by the running count would randomly assign some 25-employee firms to Quintile 2 and some to Quintile 3. Instead of this method, we identify cutoffs in the distribution such that all firms with the same headcounts are assigned to the same quintile and the cutoff chosen for each quintile is as close as possible to 20%, 40%, 60%, or 80%.

Accounting for these complexities in the data, we generally proceed by assigning all firms whose headcount has a corresponding running sum below 20% of total employment to the smallest size quintile, all firms whose headcount has a corresponding running sum between 20% and 40% to the second smallest size quintile, and so on until all 5 size quintiles are filled. More specifically, given our smallest-to-largest ordering, we identify the cutoff for the smallest size quintile as the headcount with a running sum closest (in absolute value) to 20%. All firms with that headcount or a smaller headcount are assigned to the smallest quintile. The cutoff for the second-smallest quintile is determined as the headcount with a running sum closest to 40%. All firms with a headcount above the cutoff for inclusion in the smallest quintile and at or below the cutoff for the second-smallest quintile are included in the second-smallest quintile. We repeat this process to fill all 5 size quintiles.

We describe our process mathematically below:

Let E be the total number of employees in a year. Let the number of employees in Firm *i* be F_i. The number of employees within a given headcount *j* is $H_j = \Sigma F_i$, for all $F_i = j$. The number of employees in headcount *j* is simply the sum of employees at all firms with *j* employees. We define the running sum for a given headcount *j*, R_j, as the number of employees who work at a firm with *j* or fewer employees: $Rj = \sum_{i=1}^{j} H_i$. We define the cutoff for Quintile *q* as: $C_q = j$ where *j* satisfies $Min\{\left|R_j - \left(E * \frac{q}{5}\right)\right|\}$. The cutoff C_q for Quintile *q* is the headcount which has the running sum closest (in terms of absolute value) to the total number of employees multiplied by *q*/5, which corresponds to 20%, 40%, 60%, or 80% of the total number of employees in a year. Firms with headcount C_q are included in Quintile *q*. Theoretically, it is possible for one headcount to be the closest headcount to two of the 20%, 40%, 60%, and 80% fractions of all employees, but this does not occur in the data.

B.2 Identifying graduation years

We next use the Lightcast education data to identify individuals' graduation years. We consider labor force entry to occur at the completion of an associate or bachelor's degree. While the professional networking site we use is weighted heavily towards professionals with post-secondary education and advanced degrees, some individuals have not pursued or completed an undergraduate degree. These individuals are not assigned a graduation year and thus will be dropped from our seniority calculations. They likely follow different career paths than the rest of the mainly college-educated sample, so we expect minimal overlap in the jobs (and titles) they hold. Further, since the vast majority of our analysis sample is college-educated, dropping non-college-educated individuals here does not impact our analysis.

For individuals whose undergraduate education we observe, we consider as their graduation year the first year in which they (i) have at least three years of total education at the associate, bachelor's, or master's levels and no education the following year or (ii) reach four total years of education at the associate, bachelor's, or master's levels, even if their education continues. Our second set of criteria is intended to capture individuals who enroll in a master's or doctorate program directly after obtaining a bachelor's degree. They will exit their advanced program with more human capital than individuals who enter the labor force immediately after finishing an associate or bachelor's degree. We consider this human capital accumulation process part of their careers. Similarly, when we calculate career length, we count all years after graduation towards career length, even if the individual leaves the workforce to return to education.

B.3 Calculating seniority

With firm size and graduation year calculated, we are ready to calculate seniority. We keep the earliest instance of a title-industry-firm quintile combination for each person. As discussed in Section 3.1, we are interested in the time it takes to reach a particular title for the first time, not the average career length of individuals holding the title. Before calculating seniority, separate compound titles where an individual holds two or more roles at the same time. In this step, we treat each part of the compound title as a separate title for the purposes of calculating seniority. We take the average seniority of each role to determine the seniority of jobs with compound titles.

We compute seniority as the median time to reach a title, identifying unique titles using one of the following combinations:

1) Title-industry-firm size
2) Title-firm size

3) Title-industry
4) Title

We first attempt to compute seniority as the median time to reach a specific title-industry-firm size combination. We assign this value to a title if (i) all variables in the title-industry-firm size combination are non-missing, (ii) there are at least 10 observations, and (iii) the standard deviation of time to reach the title-industry-firm size combination is less than or equal to 10. We include criteria (ii) and (iii) to ensure that the seniority value we assign to a given combination captures meaningful information. If one of the criteria is not satisfied, we move sequentially down the list and calculate seniority as the first combination that satisfies the above criteria.

As described in Section 3.1, we recalculate seniority if the initial seniority is greater than or equal to 7. If initial seniority is greater than or equal to 7 but less than 13, we recalculate seniority using only individuals who graduated after 2011. If initial seniority is greater than 13, we recalculate seniority using only individuals who graduated after 2000. In both cases, we follow the same process as above using a subset of the universe of resumes.