Age and High-Growth Entrepreneurship*

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Abstract

Many observers, and many investors, believe that young people are especially likely to produce the most successful new firms. Integrating administrative data on firms, workers, and owners, we study startups systematically in the U.S. and find that successful entrepreneurs are middle-aged, not young. The mean age at founding for the 1-in-1,000 fastest growing new ventures is 45.0. The findings are similar when considering high-technology sectors, entrepreneurial hubs, and successful firm exits. Prior experience in the specific industry predicts much greater rates of entrepreneurial success. These findings strongly reject common hypotheses that emphasize youth as a key trait of successful entrepreneurs.

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"Young people are just smarter," Mark Zuckerberg, founder of Facebook

"The cutoff in investors' heads is 32…after 32, they start to be a little skeptical."
Paul Graham, venture capitalist and founder of Y Combinator[1]

I. Introduction

Entrepreneurship has long been heralded as a key driver of rising living standards (Smith 1776, Schumpeter 1942, Lucas 1978), but successful entrepreneurship is rare, with the vast majority of entrepreneurs failing to provide the major innovations or creative destruction that can drive economic growth (Glaeser 2009; Haltiwanger, Jarmin and Miranda 2013; Guzman and Stern 2017; Levin and Rubenstein 2015). In understanding entrepreneurship, and the rarity of substantial success, a key set of questions surrounds the traits of the entrepreneurs themselves. In this paper, we provide wide-ranging evidence about one trait often thought to play a central role: the founders' age.

The view that young people are especially capable of producing big ideas – whether in scientific research, invention, or entrepreneurship – is common and longstanding (see, e.g., Jones et al. 2014). Famous individual cases such as Bill Gates, Steve Jobs, and Mark Zuckerberg show that people in their early 20s can create eventually world-leading companies. Meanwhile, venture capital firms appear to emphasize youth as a key criteria in targeting their investments, which has led to charges of "ageism" in Silicon Valley.[2] At one extreme, Peter Thiel, the co-founder of PayPal, has created a prominent fellowship program that provides $100,000 grants to would-be entrepreneurs so long as they are below age 23 and drop out of school. Among the advantages of youth in technology and innovation, young people are sometimes argued to be cognitively sharper, less distracted by family or other responsibilities, and more capable of transformative ideas – this last in line with "Planck's Principle", whereby younger people may be less beholden

[1] Source: Nathaniel Rich, "Silicon Valley's Start-up Machine," *New York Times*, May 2, 2013.
[2] Vinod Khosla, the co-founder of Sun Microsystems and a prominent venture capitalist, has argued that "people under 35 are the people who make change happen," and "people over forty-five basically die in terms of new ideas." (source: Vivek Wadhwa, "The Case for Old Entrepreneurs," *Washington Post*, December 2, 2011). For public debate around venture capital activity and potential "ageism" see, for example "The Brutal Ageism of Tech" (Scheiber 2014). Contact emails: pazoulay@mit.edu; bjones@kellogg.northwestern.edu; jdkim@mit.edu; javier.miranda@census.gov.

to existing paradigms of thought and practice (Planck 1949; Dietrich and Srinivasan 2007, Weinberg 2006).

Despite these potential advantages, young entrepreneurs may also face substantial disadvantages. Older entrepreneurs might access greater human capital, social capital, or financial capital. Taking a human capital perspective, younger people may lack experience in running companies, including the effective management of operations, marketing/sales, finance, human resources, and culture, or lack sector-specific knowledge regarding customer needs, regulatory constraints, or strategic opportunities – forms of "market knowledge" that may be important to successful innovation (Kline and Rosenberg 1986). In deeper technological areas, young people may not have sufficient scientific knowledge to produce or manage effective R&D (e.g., Jones 2010).[3] Whether such issues impose important constraints in the entrepreneurial context is less clear, especially to the extent that young entrepreneurs can overcome personal limitations by assembling effective teams, accessing third-party financing, and tapping social networks.

The empirical literature on the characteristics of highly successful entrepreneurs is limited and mixed. Various studies suggest that mean age for starting companies of all kinds (i.e., including restaurants, dry cleaners, retail shops, etc.) is in the late 30s or 40s, but the data in these studies are dominated by small businesses without growth ambitions and do not focus on the relatively rare start-ups with the potential to drive innovation and economic growth. Other research suggests that growth-oriented firms and the people who start them have distinct characteristics (e.g., Guzman and Stern 2017, Levine and Rubinstein 2017). Meanwhile, studies of technology firms in the U.S. find contrasting results. Wadhwa et al. (2008) use a telephone survey of 502 technology and engineering firms with at least $1 million in sales and find that the mean founder age was 39. Ng and Stuart (2016) connect Angel List and CrunchBase data to individual LinkedIn profiles and find that the founding of tech ventures comes most commonly only 5 years after college graduation, which is in contrast to Wadhwa et al. (2008), who found a much larger 17-year delay on average after college graduation in their data. Frick (2014) studies

[3] Indeed, outside of entrepreneurship, studies have repeatedly shown that major scientific research contributions tend to come from people in their late 30s and 40s as opposed to their 20s (Zuckerman 1977; Stephan and Levin 1993; Jones 2010).

a sample of 35 VC-backed firms from the Wall Street Journal's Billion Dollar Startup Club list and finds a mean founder age of 31, echoing the popular view that the most successful and transformative new ventures come from young people.

Table 1 further characterizes popular perceptions by looking at founder ages for (a) annual winners of the TechCrunch awards, (b) lists of "Top Entrepreneurs" and "Entrepreneurs to Watch" from two leading magazines, and (c) the full sets of new ventures backed by two prominent venture capital firms. All three of these sources suggest that tech entrepreneurs—and, especially, successful tech entrepreneurs—are very young, with mean ages at 29 for the award winners, 31 from the media lists, and the mid-30s for the VC-backed founders. Overall, there is thus a conflict between views of the peak age for "successful entrepreneurs" and entrepreneurs more generally, and substantial conflict across datasets of successful entrepreneurs themselves. Notably, all the studies of successful entrepreneurs produce age information from selected samples, which might help explain the discrepancies in their findings.[4]

In this paper, we deploy U.S. administrative datasets to investigate the link between age and high-growth entrepreneurship in a systematic manner. By linking (a) newly available IRS K-1 data, which identifies the initial owners of pass-through firms, with (b) U.S. Census Bureau datasets regarding businesses, employees, and individuals throughout the economy as well as (c) USPTO patent databases and third-party venture-capital databases, we provide systematic new facts about founder age and entrepreneurship. Table A1 summarizes the data sets that were integrated to make this paper possible.

While we will include results for all new firms, our emphasis is on founders of "growth-oriented" firms that can have large economic impacts and are often associated with driving increasing standard of living (Schumpeter 1942, Glaeser 2009). To delineate growth-oriented start-ups, we use both *ex ante* and *ex post* measures. The ex-ante measures include being a participant in a high tech sector, owning a patent, or receiving VC backing. The ex-post

[4] The telephone surveys in Wadhwa et al. (2008) engaged a random sample of 1,800 firms, but the response rate was 28%, which may introduce bias. For Ng and Stuart (2016), individuals with both Angel List and Linkedin profiles may skew younger than the population of high-growth founders at large. The Frick (2014) study determines founder age for 71% of the firms in the target list, which the author acknowledges may create bias but, more generally, this sample focuses on VC-backed firms and thus inherits any age biases of VC investors, who are often thought to select on supporting (and thus giving high valuations to) start-ups founded by young people.

measures examine growth outcomes directly for each firm: our datasets allow us to develop and examine multiple measures of firm growth and success, including firm-level employment and sales growth, as well as exit by acquisition or initial public offering.

Our primary finding is that successful entrepreneurs are middle-aged, not young. Taking numerous measures to identify potentially high-growth firms as well as studying ex-post growth of each firm, we find no evidence to suggest that founders in their 20s are especially likely to succeed. Rather, all evidence points to founders being especially successful when starting businesses in middle age or beyond, while young founders appear disadvantaged. Across the 2.7 million founders in the U.S. between 2007-2014 who started companies that go on to hire at least one employee, the mean age for the entrepreneurs at founding is 41.9.[5] The mean founder age for the 1 in 1,000 highest growth new ventures is 45.0. The most successful entrepreneurs in high technology sectors are of similar ages. So too are the most successful founders in the entrepreneurial regions of the U.S. While the prevalence of the highest growth companies having middle-aged founders is due in part to the prevalence of entry by the middle-aged, we further find that the "batting average" for creating successful firms is rising dramatically with age. Conditional on starting a firm, a 50-year-old founder is 1.8 times more likely to achieve upper-tail growth than a 30-year-old founder. Founders in their early 20s have the lowest likelihood of successful exit or creating a 1 in 1,000 top growth firm.

The view that young people produce the highest-growth companies is in part a rejection of the role of experience: either because experience is not especially valuable or because it reduces the capacity for novel, transformative ideas. To test this underlying thesis, we further build employment histories for founders and examine whether the founder comes from outside or within the start-up's specific industry. Conditional on starting a firm, we find that prior employment in the specific sector predicts a vastly higher probability of an upper-tail growth outcome or successful exit, with success rates rising up to 125%. Moreover, the closer the industry match, the greater the success rate. This finding appears to reject a central presumption that motivates perceptions about young people's advantage.

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[5] We take all U.S. companies in the non-farm economy and exclude sole proprietors – see Section III.

The rest of the paper is organized as follows. Section II of this paper reviews relevant literature on age and age-related entrepreneurial traits that may explain the rate and quality of entrepreneurial ventures. Section III details the newly-integrated administrative datasets that make this study possible. Section IV presents our core results, showing that the most successful founders are middle-aged, not young. Section V provides additional discussion regarding industry experience, age variation within founding teams, entrepreneur outliers, and venture capital behavior. Section VI concludes.

II. Literature

Understanding what makes for a successful firm and identifying the traits associated with successful founders is the subject of intense interest. Entrepreneurs are often seen as key protagonists in the process of creative destruction that can advance modern market economies. Yet entrepreneurship is a risky business (Decker et al. 2014, Kerr et al. 2014), where many new firms exit quickly and only a small fraction of young firms exhibit very high growth (Haltiwanger et al. 2013, 2017). Consequently, both public and private investors struggle to identify new ventures that will succeed. Government polices often promote new firms they see as winners in an effort to create jobs and promote a stronger and more competitive economy, but not always with success (Lerner 2012; Howell 2017). Meanwhile, the return on the vast majority of private venture-capital investments is small or negative (e.g., Kerr et al. 2014). Private investors struggle to identify new ventures that are worth backing, and considerations of both the idea (the “horse”) and founder traits (the “jockey”) bear on their investment choices. In this regard the view that young people are especially capable of producing big ideas is common and longstanding (see, e.g., the review in Jones et al. 2014). Young people are arguably cognitively sharper, less distracted by family or other responsibilities, and more open to transformative ideas (e.g., Planck 1949; Dietrich and Srinivasan 2007; Weinberg 2006). However, many other forces may influence the life cycle of entrepreneurship. The opportunity for starting a business might increase with age because many entrepreneurial resources accumulate with age including human capital, financial capital, and social capital, all of which may promote both the decision to start a new firm and, conditional on entry, the success of the venture.

Research on entrepreneurship often emphasizes the role of accumulating resources over the life-cycle. Theories of entrepreneurship often take human-capital orientations (e.g., Lucas

1978; Kihlstrom and Laffont 1979) and regularly emphasize education and experience dimensions (e.g., Iyigun and Owen 1998; Lazear 2004, 2005; Amaral et al. 2011). Empirical studies have found that human capital, including the acquisition of relevant market and technical knowledge, can predict entrepreneurial success (e.g., Dunn and Holtz-Eakin 2000, Fairlie and Robb 2007, Gruber et al. 2008, Chatterji 2009, Lafontaine and Shaw 2014). For example, Lafontaine and Shaw (2014) find that an owner's prior experience at starting a business increases the longevity of the next business opened even after controlling for person fixed effects. Chatterji (2009) finds that ventures started by former employees of incumbent firms perform better than other new entrants, an advantage that appears related to industry-specific market knowledge.

In high technology areas, human capital that embodies deep technical knowledge may also be critical. Evidence from Jones (2010) and Jones and Weinberg (2011) indicates that scientific fields with deeper knowledge accumulation see inventive and scientific breakthroughs coming from people at greater ages and after longer educational periods. If technical innovations in deep areas of knowledge are necessary to a high tech venture, then young entrepreneurs might be at a disadvantage. This prediction is weakened if entrepreneurs can hire technical expertise (e.g., Elon Musk at SpaceX or Tesla), and more generally teamwork might allow individuals to overcome their own lack of technical or market knowledge (e.g., Jones 2009).

Age and experience may also be relevant when accessing financial capital. Models of entrepreneurship under liquidity constraints suggest younger individuals will have had less time to build up the capital needed to start a business or may face difficulties borrowing it (e.g., Evans and Jovanovic 1989; Stiglitz and Weiss 1981). In Evans and Jovanovic (1989) the entrepreneur's wealth limits the amounts of funds she can access. Empirical evidence for this mechanism continues to be debated (e.g., Holtz-Eakin et al. 1994a, 1994b; Hurst and Lusardi 2004; Nielsen 2012; Fort et al. 2013; Adelino et al. 2015).[6] At the same time, models such as Evans and

[6] Holtz-Eakin et al. (1994a, 1994b) find that receiving an inheritance increases the likelihood of entrepreneurship and the survival of existing businesses. Hurst and Lusardi (2004) however find no strong link between wealth and entry into self-employment. Andersen and Nielsen (2012) find that a windfall inheritance leads constrained entrepreneurs to enter but they also find them to be marginal entrepreneurs. These studies overall suggest financial constraints might only marginally prevent entrepreneurship but are based on worker-level data sets that identify entrepreneurs who are disproportionally sole proprietors. More recent studies using business data identifying employer businesses suggest financial constraints are particularly important for startups and young businesses (see Fort et al. 2014 and Adelino et al. 2015).

Jovanovic (1989) and Stiglitz and Weiss (1981) might be more relevant to mainstream firms accessing private debt markets.[7] Firms with high growth potential might instead rely on equity markets. Here too the evidence suggests the age of the entrepreneur might be important (Florin et al. 2003; Gompers et al. 2005, 2010).[8]

Acquiring the right set of skills or financial resources might not be all that facilitates successful entrepreneurship. Young entrepreneurs might be more optimistic or confident and might be willing to take more risk. Occupational choice models by Johnson (1978), Jovanovic (1979), and Miller (1984), imply that individuals will try riskier occupations such as entrepreneurship when they are younger. However, this choice does not necessarily make them successful entrepreneurs, and past studies indicate a complex relationship between optimism and performance.[9]

Ultimately, whether young entrepreneurs are more successful is an empirical question. Available empirical evidence suggests that the probability of engaging in general forms of entrepreneurship (i.e., including restaurants, dry cleaners, retail shops, etc.) follows an inverted U-shape in age, increasing up to the late 40s and decreasing thereafter.[10] There is however little evidence as to whether this relationship holds for successful entrepreneurs and whether the age distribution differs for high-tech or high-growth firms, or more generally firms with high growth

[7] In Stiglitz and Weiss (1981) solving the asymmetric information problem leads to credit rationing which might disproportionally affect young entrepreneurs who cannot establish a low risk profile. Over time banks acquire information reducing the perceived risk. Evidence of the importance of relationship banking is found in Berger and Udell (1995) and Petersen and Rajan (1994) and more recently in Jiangli et al. (2005) and Degryse and Ongena (2005) amongst other work.

[8] Florin et al. (2003) show market experience and social capital predict a venture's ability to accumulate financial capital during its growth stages and after its initial public offering. Gompers et al. (2005, 2010) show that entrepreneurial learning, networks, and previously demonstrated success appear important in the creation of venture-backed firms.

[9] Highly optimistic individuals tend to hold unrealistic expectations, discount negative information, and be overconfident. Given that entrepreneurs appear to be more optimistic than the general population, this tendency might lead to negative outcomes (Fraser and Greene 2006, Lowe and Ziedonis 2006, Hmieleski et al. 2009). For example, Fraser and Greene (2006) show that entrepreneurs are more optimistic than employees and both optimism and uncertainty diminish with experience. Lowe and Ziedonis (2006) show that entrepreneurs continue unsuccessful development efforts for longer periods of time than do established firms. Hmieleski et al. (2009) find a negative relationship between an entrepreneur’s optimism and business performance metrics (revenue and employment), with previous experience creating ventures moderating these effects.

[10] See Kautonen et al. (2014) for a review of this literature. For these general forms of entrepreneurship, further evidence suggests that the willingness to start a business decreases with age, while the opportunity to do so increases (Blanchflower et al. 2001; van Praag and van Ophem 1995). Levesque and Minniti (2006) describe a theoretical model to accommodate this observation.

potential, and the limited existing empirical evidence is contradictory. Overall, the inconsistent findings across these studies may not be surprising given the challenges of limited sample sizes, low response rates, and non-representative sampling frames used.

III. Data and Measurement

III.A Data Sets

Our study uses administrative data to identify the demographics of business founders in the U.S. and to track the performance of their businesses over time. Our primary datasets include administrative data from the U.S. Census Bureau's Longitudinal Business Database and Schedule K-1 business owners data, while also integrating numerous other datasets. We describe each dataset in turn. Detailed additional information about each data set is provided in the Appendix, with a summary displayed in Table A1.

Business characteristics

Our starting point for firm-level data is the U.S. Census Bureau's Longitudinal Business Database (LBD). Sourced from administrative income and payroll filings and enhanced with U.S. Census collections, the LBD provides basic information on all businesses in the U.S. with paid employees. It covers all industries in the private non-farm economy and all geographies except outlying U.S. territories. In addition, we exclude sole proprietorships to focus on companies with potential growth orientations.[11] The LBD starts in 1976 and currently runs through 2014. Data items include employment, payroll, industry, location, and legal form of organization for establishments and firms as long as they are payroll active (see Jarmin and Miranda 2002 for a description). Importantly, the longitudinal nature of the LBD allows us to identify business startups and shutdowns, acquisitions and divestitures as well as expansion and contractions.

Founder characteristics

[11] Our data further show that owners of sole proprietor businesses are older on average than owners of other legal forms of organization.

Business ownership data is available for partnerships and S-corporations directly from administrative Schedule K-1 forms. The K-1 is an administrative dataset identifying owners of "pass-through" businesses, which account for approximately 55% of all new businesses, or 73% of all new businesses that are not sole proprietorships. "Pass-through" businesses are those that pay no entity-level tax, so that income from these businesses is taxed as it flows through at the owner-level.[12] The IRS tracks income for these entities through Schedule K-1 income returns (Form 1065 for partnerships and Form 1120S for S-corporations), where "pass-through" entities are required to file one Schedule K-1 for each of its owners (partners or shareholders). The K-1 data detail the income, deductions, and credits that the entity is allocating to each owner.[13]

For the purposes of our study, a key database innovation is the ability to link the K-1 owner identifiers to business-level as well as individual-level characteristics in U.S. Census resources. In particular, the K-1 forms include both the employer identification number (EIN) of the business and the social security number (SSN) of the owner.[14] We use the EIN to link K-1 owners to the specific businesses in the LBD at founding, and we use the individual identification number to link the specific owners to demographic characteristics via the Census Numident file as well as to their earnings from W-2 records. K-1 data are available starting in 2007 and cover years through 2014.

Because K-1 data does not cover C-corporations, which account for approximately 20% of all new businesses, we examine the founders of C-corporations using two different datasets, W-2 records and the U.S. Census's Annual Survey of Entrepreneurs. The W-2 records provide earnings information for all employees of a business who receive remuneration for services performed, including noncash payments of $600 or more for the year. Businesses must file a Form W-2 for each employee, allowing us to identify all the employees of private-sector firms in the United States and their annual earnings, including by law owners who actively manage the

[12] See Goldschlag et al. (2017) and Cooper et al. (2015) for a detailed description of the data. Previously Bull, Fisher and Nelson (2009) used K-1 data to match S-corporations to their owners.
[13] "Pass-through" entities are required to allocate the full amount of their income to their owners.
[14] Personal Identifiable Information (PII) including names, addresses, and social security numbers are stripped from these records immediately upon arrival at the Census Bureau and replaced with a random Protected Identification Key (PIK). Researchers do not have access to the PII. All data holdings at the Census Bureau are stripped of their PII. All further matching across databases using individual identification numbers use the replacement PIK.

business.[15] Using the W-2 records we can thus examine founding teams under the assumption that managing business owners will pay themselves a salary. Separately, while the above data allows us to examine every C-corporation founded over our sample period, we can further examine C-corporation owners directly using the U.S. Census's Annual Survey of Entrepreneurs (ASE), which has been conducted annually since 2014 and samples approximately 290,000 businesses of any legal form that are operating in the survey year. The ASE provides age brackets for the owners and, by matching the ASE to the LBD and W-2 data, we can further determine a sample of C-corp founders defined as owner-workers, as with the K-1 data. The specific definitions of founders we use will be detailed below.

Additional datasets

We expand this data infrastructure further by linking in the Longitudinal Linked Patent-Business Database (see Graham et al. (forthcoming)). This database tracks patenting firms over time.[16] Information contained in granted patents between 2000 and 2011 was linked to firms in the LBD. We use this file as one approach to identify high tech industries, as well as to identify new firms that are specifically involved in patenting activity and owner-inventors. We additionally use internally available Census Bureau crosswalks linking the VentureXpert and the Private Capital Research Institute (PCRI) database to identify industries and firms where venture capitalists invest.[17] Lastly, when studying the employment histories of each founder (Section V), we will use the Longitudinal Employer-Household Dynamics (LEHD) data of the U.S. Census, which allows the construction of longer employment histories than the more recent database of W-2 records allows.

III.B Defining Startups, Founders, and Measures of Success

[15] The IRS requires manager owners to pay themselves a reasonable compensation for their services in the form of wages so as not to avoid paying employment taxes. See https://www.irs.gov/uac/Wage-Compensation-for-S-Corporation-Officers. The Internal Revenue Code establishes that any officer of a corporation is an employee of the corporation for federal employment tax purposes and they should not attempt to avoid paying employment taxes by having their officers treat their compensation as cash distributions, payments of personal expenses, and/or loans rather than as wages.

[16] This file was created under a joint effort between the U.S. Census Bureau and the U.S. Patent and Trademark Office (USPTO).

[17] The PCRI data are broader in scope than either Preqin, Cambridge Associates, or Thomson Reuters. For details, see http://www.privatecapitalresearchinstitute.org/index.php. The internal Census Bureau crosswalk to this data and the VentureXpert data are in beta testing and are currently not available for FSRDC use. We thank Josh Lerner for access to elements of the PCRI data crosswalk.

With the above databases we can analyze the demographics of business founders and track the performance of their firms over time. In this section we define several core measures for our study.

Identifying New Firms

We rely on the LBD to identify startup firms. The LBD tracks both establishments and firms over time through a series of establishment and firm identifiers. Merger and acquisition activity, reorganizations and data processing idiosyncrasies can result in new firm identifiers even when activity associated with that firm is not new. We do not want to treat these as startup firms. We follow Haltiwanger et al. (2013) and use the longitudinal establishment links in the LBD to define the age of the firm as the age of the oldest establishment present in the firm at time of first appearance of a new firm identifier. The firm then ages naturally in increments of one year following the birth year. In other words, startups are identified as de novo firms with no prior activity at any of its establishments (age zero firms in our data). This approach ensures our definition of entrepreneurial firms does not include spinoffs from existing firms or new firms that are the result of the reorganization or recombination of existing business.[18] It is important to recognize the LBD identifies the startup year of a firm as the year when the business first hires an employee; as such the LBD startup date might differ from the legal founding date of a business.[19] As a robustness check, we exclude businesses where the founding date as captured by the presence of a K-1 form differs from the LBD age by more than two years. All results are consistent with the main findings from the full sample.

Identifying Founders

Critical to our effort is the identification of founders. For S-corporations and partnerships, we use Form K-1 to define owners as individuals who own some portion of the firm at age zero in the LBD. We then use the W-2 data to define a founder as an owner who also works at the firm (as opposed to an investor who holds equity in the firm but does not work there). The

[18] We also drop age zero firms that have multiple establishments in their birth years. On average, their initial employment in year zero is unusually high relative to other new firms, suggesting that they are not de novo startups. Inspection of these startups suggest they are the result of multinational activity as well as newly created professional employer organizations.
[19] Employment in the LBD is a point in time measure. It describes all employees (part-time or full-time) receiving a wage by a business during the payroll period covering the week of March 12th.

identification of these "owner-workers" is, while traditionally very difficult in the U.S. data, straightforward in the linked administrative datasets we use.[20]

For C-corporations, we rely on two alternative approaches, as K-1 owner data is not available. For our primary analysis, we use the W-2 data to define the three highest paid workers in the first year of the firm's existence. This is the approach followed by Kerr and Kerr (2017), who argue that business owners are often among the top three initial earners in the firm.[21] Based on the S-corporation data, where ownership status can be determined with certainty, 90% of the owner-workers are in fact among the top three earners in the firm during the first year.[22] This "initial team" definition of founders can be applied to all firms. Secondarily, we will present results using the U.S. Census Annual Survey of Entrepreneurs (ASE), allowing us to look at a large subsample of C-corps for whom we can directly determine owners. By connecting these individuals to W-2 records, as with the K-1 data, we determine owner-workers in the year the firm is founded.[23] In general, we have analyzed all of our results separately for S-Corporations (K-1 entities), partnerships (K-1 entities), and C-Corporations (non K-1 entities). Because the results are similar for each type, the main results emphasize the age findings pooled across all U.S. startups. In Section IV, we will demonstrate robustness across different ways of defining founders and different legal forms.

Identifying High-Growth Startups

We are especially interested in examining growth-oriented startups. We take two approaches. The first approach considers technology-orientation, which can suggest the potential

[20] For about 20% of new S-corporations, none of the owners work at the firm, which we interpret as businesses where the equity holders are financing a new business and running it through hired management. These firms are not included in our analysis below; we will be considering these firms more closely in further work.
[21] Kerr and Kerr (2017) use LEHD data which currently excludes Massachusetts whereas we use more comprehensive W-2 earnings records. We have separately considered our analysis using LEHD records, including different definitions of founding team based on quarterly employment data, and find very similar results as in our W-2 sample.
[22] This approach is thus good at capturing owner-workers in the sense that few are missed. However, examining the S-Corporation data, the top three earners also typically include individuals who do not have ownership stakes in the firm. Thus this "initial team" definition of founders is best thought of as a related but distinct way of capturing the important individuals in the initial life of the firm, as opposed to an exact way of capturing owner-workers. We will consider distinctions between these approaches below.
[23] The Annual Survey of Entrepreneurs (ASE) is a representative survey of U.S. businesses with paid employees and receipts of $1,000 or more. The survey provides information on economic and demographic characteristics of businesses and business owners.

for high growth. The second approach considers the actual outcome for the firm, based on the 3, 5, or 7 year time window after founding.

Noting that there is no commonly accepted definition of "high tech" sectors or firms, we use three alternative definitions. First, following Hecker (2005), we define the high tech sector as the industries (4-digit NAICS) with the highest share of technology-oriented workers as defined by the Bureau of Labor Statistics.[24] Second, we make use of a comprehensive match between the Census LBD and the businesses covered by the PCRI and VentureXpert databases to determine whether a given firm receives venture capital, suggesting that the firm is seen as having substantial growth potential. Third, we leverage prior research that has comprehensively matched the USPTO patent database with the LBD (Graham et al. forthcoming) to determine whether a given firm has received a patent.

While the above measures attempt to delineate firms with substantial *potential* for growth, by virtue of the LBD we are also able to quantify growth outcomes for each firm directly. Our primary outcome measures include (a) employment growth, and (b) sales growth, while we also consider (c) exit by acquisition and (d) initial public offerings. In the main text, we will emphasize employment growth, denoting a high-growth new venture as one that achieved a given threshold of employment 5 years after founding. We examine employment thresholds based on the Top 10, 5, 1, or 0.1 percentile. Analyses using sales growth are provided in the Appendix and show extremely similar results.[25] Startups can grow and expand to become large multi-establishment corporations spanning multiple types of activities and locations. For these startups we calculate total firm employment by aggregating the establishment level records for

[24] The list of Hecker (2005) includes 46 four-digit NAICS industries. An industry is considered high tech if the share of technology-oriented workers is at least twice the overall average of 4.9%. Defined by the Bureau of Labor Statistics, technology-oriented occupations are generally roles that require knowledge of science, engineering, mathematics, and/or technology typically acquired through specialized higher education.

[25] Details regarding the construction of the sales dataset (also known as the Revenue Enhanced LBD or RE-LBD) can be found in Haltiwanger, Jarmin, Kulik, and Miranda (2016). We examine total revenue growth in a similar manner to employment growth, relying on the revenue-enhanced LBD (RE-LBD) and examining whether a new venture achieves an upper tail level of sales within a given number of years after founding.

each firm-year observation. From these firm-level measures it is straightforward to compute measures of employment growth by looking at the change in total employment over time.[26]

Startups can also become the target of acquisitions by existing firms. For example, the owner(s) of a successful venture might decide it is in their best interest to sell their idea and the assets embodied in their firm. In this case the original firm will cease to exist as such after the acquisition.[27] Some startups will simply fail and shutdown. We separately identify acquisitions of startups by existing firms as well as shutdowns and classify these events as distinct types of firm outcomes.[28] Lastly, we use the Compustat-Business Register bridge to identify firms that enter public equity markets through an IPO. Our measure of "successful exit" below is an indicator for acquisition or IPO ever occurring within the scope of our databases.

IV. Results

We now turn to the analysis of founder age in the universe of U.S. startups delineated above. Table 2 presents the results. Focusing on the first row, which shows the U.S. as a whole, and the first column, which considers all new ventures, we see that the mean age at founding is 41.9. This finding is broadly consistent with other population surveys of general types of new firms. Of course, while the word "startup" may conjure the image of technology entrepreneurs hard at work in their proverbial Silicon Valley garage, the great bulk of the new ventures that constitute our universe do not match this archetype. Though our data do not include sole proprietor businesses, it is still the case that most U.S. firms do not have the ambition and/or the business model to grow and scale their business (Hurst and Pugsley, 2011).[29]

To focus on growth-oriented entrepreneurs within our universe of U.S. startups, we will take several approaches. Our first set of approaches examines the nature of the startup at founding, based on technology-related criteria. Our second set of approaches examines the

[26] Our analysis includes startups that transition from single-unit to multi-unit firms. We track these transitions by following the establishment-level activity over time.
[27] In the LBD these firms will cease to exist as such and their establishments will take on the acquiring firms' identifiers.
[28] In order to distinguish successful acquisitions (i.e., those that generate positive returns for investors) from fire sale acquisitions, we drop observations in which the total employment after the acquisitions is lower than the initial employment.
[29] While excluded from the analysis, our data show that the average age of new sole proprietors in 2010 was 44.8, significantly older than the rest of the population.

growth performance of the startups themselves. Given the scale of the administrative data, we can further look at intersections of these criteria to focus on narrow subgroups of firms that both grow quickly and are in high-technology areas.

IV.A Ex-Ante Growth-Orientation

The results for different measures of growth-orientation are found in columns (2)-(4) of Table 2. They show the mean founder age according to the different high-technology criteria. We see that focusing on "high-tech" does not substantively affect mean founder age compared to the overall U.S. sample. Depending on the definition, mean founder age now ranges from 41.9 to 44.6, with founders in high-tech sectors (43.2) and founder of patenting firms (44.6) appearing somewhat older on average than founders in the U.S. overall.

To the extent that mean founder age across broad groupings of technology firms may hide important differences across sectors, where very young founders may occasionally be the norm, we further examine the oldest and youngest technology sectors by founder age. Table 3 presents these results, grouping technology firms at the NAICS 4-digit level. We see that the computing-oriented ventures as well as wireless telecom ventures appear to have the youngest founders. Yet even here the mean founder ages range from 38.5 to 40.8– approximately a decade older than the entrepreneurs often emphasized in media accounts (see, e.g. Table 1), which often focus on computing-oriented new ventures. Meanwhile, the oldest five technology sectors by founder age involve manufacturing as well as oil and gas ventures. These sectors see mean founder ages from 47.3 to 51.4. Thus there are some substantial differences across sectors in the mean age of founders. Yet there is no sector, including in computing, where the mean founder ages are below 38, and only 3 of the 315 NAICS-4 digit sectors show a mean founder age below 40.

We can further partition the data geographically and consider California, Massachusetts, and New York separately given that these three states account for a significant portion of high-growth startup activity in the U.S. (Chen et al. 2010 with respect to VC-backed startups). In addition, we use more granular geographic variation by identifying regions with the most entrepreneurial activity at the zip code level. Using the Entrepreneurial Quality Index developed by Guzman and Stern (2017), we define entrepreneurial hubs as the 50 zip codes with the highest entrepreneurial quality.[30] We also look specifically at Silicon Valley, considering all new ventures in the zip codes of Santa Clara and San Mateo counties.

The results appear in Table 2. Taking the overall population of new ventures (column 1), we see little variation with geography. Even when looking at the zip codes with the most growth-oriented new ventures, the mean founder age is 40.8, or approximately 1 year younger than the U.S. population average. One interpretation of this result may be that, even in entrepreneurial regions, most new firms are not in technology or growth-oriented sectors. However, reading across columns and rows in the table, we can further examine the intersection of geography with technology or growth-orientation. Remarkably, we see only modest differences in age. Mean founder ages rarely dip much below age 40, let alone ages 35, 30, or 25. The only category where the mean ages appear (modestly) below age 40 is when the firm has VC-backing. The youngest category is VC-backed firms in New York, where the mean founder age was 38.7. More generally, across the various narrow cuts in Table 2, the mean age ranges from 38.7 to 45.3. Put another way, even when reducing the set of 2.7 million founders to the 1,900 associated with firms that are both in entrepreneurial hubs and receive VC backing, the mean age at founding is 39.5. Meanwhile, founders in high-tech employment sectors tend to be slightly older than the U.S.-wide average, and founders of patenting firms are the oldest of all, with an average age of 44.3 in Silicon Valley and 43.8 in the entrepreneurial hubs.

IV.B Ex-Post High-Performance Firms

It may still be that younger founders produce the highest performance new firms. Our second approach to looking at founder age thus considers firm-level outcomes, including growth itself. The capacity to examine actual outcomes draws on the strengths of the LBD, which provides employees and sales for each firm, as well as indicating exit by acquisition and, via the Compustat Bridge, initial public offerings. A potential limitation in the intersection of our

[30] Since the Entrepreneurial Quality Index is an average score of all startups in a given region, we exclude zip codes with fewer than 20 entrepreneurial firms.

databases is that we have a limited time-period in which we can examine firm performance. Here we will focus on outcomes five years after the hiring of the first employee.[31]

To delineate "successful" entrepreneurs within the population of new ventures, we focus on the upper tail of the new venture's employment growth. Specifically, we examine upper tail growth performance for firms alternatively in the Top 10%, Top 5%, Top 1%, and Top 0.1% of growth. We complement these employment-based growth measures with a metric that tracks whether these ventures ever exited by acquisition or IPO within our sample period.

Table 4 presents mean founder age for new ventures that prove to be in the Top 5% of employment growth. The structure of Table 4 repeats the structure of Table 2, allowing easy comparison with the results for the whole sample. The Top 5% subsample allows sufficient observation counts to break down founder age by geography, technology-intensiveness, and their interactions.[32] Examining the first column, we see that the Top 5% firms appears to have similarly-aged founders, with mean ages in the U.S. as a whole rising from 41.9 (Table 2) to 42.1 (Table 4). Reading down the rows and across the columns, we see that mean founder age can be slightly higher or slightly lower than for the full population, but the overall founder age tendencies for these 1 in 20 top growth firms remains similar to the broader population. While sample sizes become very small, we now see that the 400 founders of high-growth firms with VC-backing in entrepreneurial zip codes show the youngest mean age, at 39.6. This is the only case where the mean age drops below 40.

While a Top 5% growth outcome indicates a quite successful new venture, it may still be that the extreme upper tail growth successes come from relatively young people. Table 5 thus examines founder age across a range of upper-tail performance definitions, up to the Top 0.1% (the 1 in 1,000 upper tail firms). Table 5A displays the results for startups overall and across geographic areas; Table 5B further considers different typologies of technology firms. Across these tables, it appears that more successful startups have, if anything, slightly older founders on average. For example, the 1,700 founders of the fastest growing new ventures (1 in 1,000) in our

[31] Using 3-year windows and 7-year windows shows broadly similar results.
[32] Results are similar when looking at firms in the Top 5% of sales growth instead. We focus here on the Top 5%, rather than the Top 1% or Top 0.1% because this still leaves enough firms to further decompose the sample along both technology orientation and geographic location.

universe of U.S. firms had an average age of 45.0 (compared to 43.7 for the top 1% and 42.1 for the top 5%). Looking across geographies (Table 5A) shows that moving towards extreme-upper tail growth outliers is associated with older founders, not younger founders, especially for the top 1 in 1,000 firms. Firms that exit by acquisition or IPO also tend to have older founders. The age at founding for these successful exits is 46.7 across the U.S. sample, and is systematically higher within each region. Looking at technology-intensiveness measures (Table 5B) we also see older founders as we move toward upper-tail performance, especially for the top 1 in 100 or top 1 in 1,000 firms. This evidence is at odds with the conventional wisdom that successful founders skew younger.

IV.C Founder Age Distributions

One limitation of the foregoing discussion is that it only analyzes mean founder age. While the mean age provides a standard summary statistic, and one that we can compare across technology-intensity, regions, and outcome measures, investigating the entire age distribution may reveal particular bands of age where founder activity is especially intense or founders are especially successful.

Figure 1 presents the full founder age distribution. We present the age distribution for the founders of all U.S. firms (blue line) and the age distribution for founders of Top 1% firms by employee growth after five years (red line).[33] Studying all founders, we see that age distribution is single peaked, with a relatively flat plateau at ages 37-43. Studying founders of high-growth firms, we see clearly that the founder age distribution shifts systematically to the right. Thus, the highest-growth new firms not only appear to come from those in middle-age, but also tend to come at even older ages than the background age distribution for founders would imply. Below their late 30s, the frequency of successful founders is well below the frequency of these founders in the population. Starting in the late 30s, and especially by the mid-to-late 40s, the frequency of successful founders is substantially greater than the frequency of these founders in the population. We dig deeper into this result using regressions below.

[33] Appendix Figures A1 and A2 present analyses using upper tail sales growth instead of employment growth and show similar results.

Figure 2 explores the founder age distribution further, comparing it against the underlying workforce age distribution. Figure 2A presents the age distribution of the workforce in 2010 based on the population of earners from W-2 records. The workforce age distribution declines slightly from age 20 to age 56 and then falls sharply thereafter. Figure 2B then considers a normalized founding rate, showing the percentage of founders per worker of each given age. Compared to Figure 1, the effect of normalizing by workforce size is to make a sharper slope at younger ages and a flatter slope at older ages. Thus, very young founders now appear even less common (because young workers appear a bit more often in the workforce) and founders in late middle age and beyond appear more common (because the workforce at these more advanced ages is smaller). The peak rate for founding companies now appears at age 38. Finally, Figure 2C looks at the founding rate of high-tech new ventures as defined by the average STEM composition of the industry of activity (Hecker 2005) featured in Tables 2, 4, and 5B. We see that the shape is similar to Figure 2B, although the peak is slightly flatter and the decline with age is less steep.

IV.D The Likelihood of Success

Our previous results have demonstrated that growth-oriented start-up founders in the US economy tend to be middle-aged, not young. Thus, when asking where most high-growth or technology-intensive firms in the U.S. come from, the answer is "middle aged people." However, an equally important question is to ask how the probability of entrepreneurial success changes with founder age, conditional on starting a new firm. This statistic may be more informative for an individual considering founding a company or for investors deciding where to place their bets. For example, if two founders (of two distinct firms) come to pitch their idea to a venture capitalist, and all the venture capitalist knows is these founders' ages, which founder would be more likely to produce an upper-tail growth outcome?

To examine the relationship between the likelihood of success and age, we run linear probability models where an indicator for "success" is regressed on a full set of founder age fixed effects (age 20 and below is the omitted category). We graph each age coefficient and the associated 95% confidence interval in Figure 3.[34] Our success indicators are (a) exit by acquisition or IPO and (b) employment in the top 0.1%, both measured here at 5 years from founding.

Figure 3A considers successful exits, which occurs for roughly 4,000 (or 0.15%) of the founders in our universe. We see that the relationship between age and successful exit is monotonically increasing up until about age 60 and declining slightly thereafter. A founder at age 50 is approximately twice as likely to experience a successful exit compared to a founder at age 30. Figure 3B replicates this analysis using Top 0.1% employment growth as the metric of success. Here again, the relationship between success and age is increasing, though the individual age coefficients are estimated less precisely. The rate of increase with age is similar as with exits: a founder at age 50 is approximately twice as likely of achieving upper-tail employment growth compared to a founder at age 30.

In interpreting these results one possibility is that older founders tend to enter industries where acquisitions or large-scale employment is more common. Thus industry effects may confound the relationship between success and age. Figure 3C therefore adds to the regression specification a full set of fixed effects for each NAICS-4 industry code. We see that the steepness of the relationship with age is somewhat attenuated, but otherwise looks similar, increasing substantially until entrepreneurs reach the age of 60 at the time of founding.

Overall, we see that younger founders appear strongly *disadvantaged* in their tendency to produce the highest-growth companies. That said, there is a hint of some interesting age thresholds and plateaus in the data. Below age 25, founders appear to do badly (or rather, do well extremely rarely), but there is a sharp increase in performance at age 25. Between ages 25 and 35, performance seems fairly flat, or even possibly decreasingly slightly. However, starting after age 35 we see a jump in success probabilities, now outpacing the 25-year-olds. Another large surge in performance comes at age 46 and is sustained toward age 60.

Lastly, and given the interest in very young entrepreneurs, Figure 4 considers a broader range of outcome measures, comparing founders below age 30 with those above. We see that

[34] The regression calculates robust standard errors, clustered at the new venture level, to account for potentially correlated errors across the founder ages within a given firm.

"failed" ventures, defined as those businesses that cease operations or no longer have employees, exhibit a somewhat higher failure rate for under-30 founders. Similarly, the likelihood of high-growth ventures is slightly lower for under-30 founders, when examining Top 10% or Top 5% firms. As we move to Top 1% growth, Top 0.1% growth, or successful exit as the outcome, the success rate of under-30 founders is increasingly outpaced by older founders.

IV.E Results by Founder Definition and Legal Form

We can further consider the results by legal type and across distinct definitions of the founder team. Figure 5A shows the age distributions for K-1 firms and C-corporations separately using an "owner worker" definition, where for the C-corporations we use the ASE sample to isolate owners who work at the firm at founding. We present the overall age distribution as well as the age distributions for the firms with upper tail growth outcomes.[35] Commensurate with our earlier findings, we see that the age distribution peaks in middle age for high growth firms and shifts to yet older ages for the firms with the best growth outcomes. Figure 5B shows the age distributions for K-1 firms and C-corporations separately using an "initial team" definition, studying the three highest paid workers in the firm in the year of founding. Here we see broadly similar findings, although the rightward shift in age with success is even more pronounced, and especially for the very highest growth firms. Overall, the findings are robust to all these cuts at the data: regardless of legal form or founding team definition, we see that the highest-growth firms are started by individuals in middle age and beyond.

V. Discussion

U.S. Census data reveal that the fastest growing new firms, including those in technology sectors or in entrepreneurial hubs, are founded by middle-aged and older entrepreneurs. This finding appears substantially different from what some prior studies using selected samples suggested, and remarkably at odds with public perception. At the same time, the findings are

[35] The ASE survey provides data in age brackets, as indicated in the figure. In Figure 5A we also consider growth outcomes up to the top 1 in 100, rather than the top 1 in 1,000, due to the smaller size of the ASE sample compared to the administrative data as a whole. To assist visual comparison, we present the K-1data in Figure 5A in the same age brackets and growth categories as for the ASE. Appendix Figures A3 and A4 present analyses using upper tail sales growth instead of employment growth and show similar results.

consistent with numerous theories that emphasize the accumulation of entrepreneurial resources over the entrepreneur's life cycle. Amidst the many forces outlined in Section II, the steep gains seen in entrepreneurial success rates with age are consistent with large net increases in entrepreneurial capabilities as the life cycle proceeds. In this section, we further explore these findings. First, we consider the role of industry experience. Second, we examine age variation within founding teams. Third, we focus on extreme cases of entrepreneurial success that do feature very young founders. Finally, we discuss the behavior of VC investors in light of our results.

V.A Industry Experience

Young people are often thought to have a creative advantage in producing transformative ideas. One version of this reasoning, in line with Planck's principle (Planck 1949; Dietrich and Srinivasan 2007, Weinberg 2006), is that experience within a paradigm of thought can foreclose transformative thinking, so that lack of experience can become a specific, creative virtue. We can examine an important dimension of this perspective by looking at whether work experience within an industry is positively or negatively predictive of entrepreneurial success in that industry.

To proceed, we use the LEHD employment records to link all 2.5 million founders to their prior employment histories, which collectively encompass 20 million former jobs.[36] We can then consider, for every founder, whether the individual has prior work experience in the sector of the start-up. We can measure both (a) how close, and (b) how long the individual's experience is in the relevant industrial sector and then examine whether industry experience is predictive of entrepreneurial success. To study "how close", we group founders according to experience at the same 2-digit, 4-digit, and 6-digit NAICS industry code of the start-up.[37] To study "how long", we group founders according to whether they have never worked in the sector, have worked for one or two years in the sector, or have worked for at least three years in the sector.

[36] The LEHD allows for a longer prior work history than W-2 records. In practice, the LEHD prior work sample goes back in time to at least the early 2000s, with some state level records going back to 1990. Because the LEHD does not include Massachusetts, we miss some prior employment as well as some founders.
[37] In the 2012 NAICS, there are 24 2-digit NAICS industries, 312 4-digit NAICS industries, and 1,065 6-digit industries.

Table 6 presents the key results. The columns define various success measures by growth threshold (the top 10, 5, 1, and 0.1 percent) and by successful exit. The rows then group founders by their industry experience. Each cell presents the percentage of founders of the given type that achieve the given growth outcome. Panel A considers work experience in the same 2-digit industry as the start-up. Panels B and C repeat these analyses for experience at the 4-digit and 6-digit levels.

Consider NAICS2 first. Reading down the rows in Panel A, we see clearly that experience in the 2-digit industry predicts higher rates of entrepreneurial success. Moreover, conditional on having some prior experience in the 2-digit industry, having longer experience (three or more years) shows higher success rates than having shorter experience (one or two years). Reading right across the columns in Panel A, longer experience is strongly predictive of success for all growth thresholds, as well as for successful exit. For the 1 in 1,000 highest-growth firms, founders with three or more years of experience in the 2-digit industry see upper tail success at twice the rate as founders with no experience in the 2-digit industry.

Now consider increasingly close industrial experience. Comparing across Panels A-C, we see that success rates rise as the founder's work experience becomes increasingly closely matched to the start-up sector. Increasing success rates with increasingly close experience are seen at all growth thresholds. For achieving a 1 in 1,000 highest-growth firm, having no experience in the 2-digit level industry leads to a success rate of 0.11%, while having at least three years of experience in the start-up's industry shows success rates that rise from 0.22% (NAICS2 experience) to 0.24% (NAICS4 experience) to 0.26% (NAICS6 experience). [38,39]

Overall, these findings indicate that founders with both closer and longer experience in the industry of the start-up see substantially greater success rates. These findings reject the idea that coming from outside a sector predicts outsized entrepreneurial success, and thus work against theories of entrepreneurial creativity that emphasize an outsider advantage in producing

[38] Note that, for the Top 0.1% case, the baseline rate for founders is above 0.1%. This is because the 0.1% is defined at the firm level (according to firm performance) and here we are looking at rates at the founder level, where the most successful firms tend towards somewhat larger founding teams.

[39] One might also wonder if the age effect reflects in part prior entrepreneurial experience (so-called "serial entrepreneurship") as well as experience in a specific sector. Because our ability to track founding experience prior to 2007 is limited, we leave this important question to future research.

transformative ideas—a primary rationale underlying the broader belief that young people will produce the highest growth firms. More precisely, there might still be some creative advantage in being such an outsider, but, if so, this advantage is being overwhelmed by other forces positively linking founder experience with success among the highest growth firms. The findings are instead consistent with views stressing the importance of market knowledge (Kline and Rosenberg 1986) in innovation, which can include both industry-specific human capital and social capital.[40]

V.B Unpacking Age within Founding Teams

Our results have looked at the age distribution of founders across the population of new firms in the United States. A related line of inquiry regards the age distribution of founders within a given firm. To the extent that different members of a founding team play different roles, it is theoretically possible that the youngest members play outsized roles. To be conservative in assessing the role of youth in high-growth firms, we may then be additionally interested in the age of the very youngest founders of these firms. Furthermore, successful firms might feature founding teams with heterogeneous ages, possibly leveraging advantages of both youth and experience within a founding team.

Table 7 explores within team age heterogeneity. We consider two definitions of founders. In Panel A we consider the "owner-worker" definition, using all K-1 firms. In Panel B, we consider the "initial team" definition focusing on the top three earners in the first year of the firm and using all K-1 firms and all C-corporations. The table entries present the minimum and maximum ages in the founding team, averaging across firms of a given type, as indicated by the column heading.

Using the "owner-worker" definition (Panel A), we see that the youngest founder for each startup averages age 42.7. Looking at growth-oriented firms, the age of the youngest founder tends to rise for patenting and high-tech employment firms, although it drops to 39.8 for

[40] These industry experience results can be further confirmed in regressions that control for founder age. Thus both the proximity and length of industry experience are not simply proxying for advancing age. At the same time, age fixed effects in these regressions remain jointly significant for predicting upper-tail success. Thus industry experience is not the only factor underlying the age advantage established in the main results. This suggest that general forms of experience, social, and/or financial capital remains as potentially important pieces to understanding the age relationship and provide avenues for further research.

VC-backed firms. Looking at ex-post success, the top 1 in 1,000 highest-growth firms show a mean age of the youngest founder of 42.3. Meanwhile, the oldest founder for each firm averages 44.6 in the broad sample, rising to a range of 45.8-47.8 among the growth-oriented firms. Overall, and compared to the background population of K-1 firms, we see that the age of the youngest founder does not show a systematic pattern with growth-orientation but the age of the oldest founder rises systematically with growth orientation.

Using the "initial team" definition (Panel B), we find broadly similar results but with wider age gaps among the initial top three earners in the firms' first year of operation. Now the youngest individual averages 35.1 in the broad sample and typically increases with ex-ante growth-orientation or ex-post growth success, with average minimum age ranging from 35.0-39.1. The oldest individual now averages 46.0 for the broad sample, and again tends to rise with growth-orientation, with the age ranging from 45.7-51.4.

Interestingly, age heterogeneity tends to go up with the ex-post most successful firms. This tendency is largely due to the rising maximum age. The top 1 in 1,000 highest-growth firms are populated with the largest maximum founder ages in Panel A (owner-worker definition) or Panel B (initial team definition). At the same time, the minimum founder ages for these 1 in 1,000 firms tend to be more middle-of-the-pack in both Panel A and Panel B compared to other firms. These findings are consistent with advantages of (relative) youth coupled with experience, although still the youngest founders are typically middle-aged.[41]

Overall, we continue to see little evidence, even looking at the very youngest founder, that highly-successful firms are populated by especially young founders. The fact that the youngest founder of each firm is middle-aged, even among the highest-growth firms, indicates that successful firms are not a marriage between very young and substantially older founders.

[41] Much has been written in the business press about the optimal timing for young start-ups to hire seasoned executives as a form of "adult supervision," with the examples of Google's Eric Schmidt and Facebook's Sheryl Sandberg prominent in many observers' minds. However, although such experienced managers are often offered sizeable equity packages to entice them into joining, they appear to rarely join as soon as the first year of a firm's existence. Thus our age findings do not speak to the implications of professional management being engaged later in the firm's existence. That said, the finding that highest-growth firms show the highest maximum ages among the founders is consistent with the idea that seasoned individuals may bring advantages.

Rather middle age remains the rule, while the age of the oldest founder tends to shift to still older ages for the most successful firms compared to ordinary firms.

V.C Entrepreneur Outliers

Although we have looked at the Top 0.1% of firms and the rare outcome of successful acquisition or IPO, a skeptic may still wonder if even more extreme upper-tail outliers are the province of the very young. More precisely, several cases of extreme entrepreneurial success in the software and IT sectors have prominently featured very young founders (e.g., Steve Jobs, Bill Gates, and Mark Zuckerberg). One response to this observation is to balance the ledger by noting that there are also cases of extraordinary successes featuring older founders. For example, Herbert Boyer was age 40 when, based on his genetic engineering breakthroughs, he founded Genentech (which would eventually be acquired for $47 billion), and David Duffield was 64 when he founded Workday (which currently has a market cap of $28 billion).

At the same time, a subtler but perhaps more important response may lie among the greatest young founders themselves. Namely, the claim that young people are especially good at starting companies is a *within person* claim. That is, a given individual is thought to be "better" when s/he is young (e.g., when s/he may have greater energy, deductive abilities, originality, etc.). If so, then we would expect great young entrepreneurs to become "worse" when they age. At a cursory level, this seems doubtful. Elon Musk's Tesla and SpaceX seem no less visionary or successful than his earlier ventures, Zip2 and X.com. Steve Jobs and Apple computer appeared to find their blockbuster innovation with the iPhone, which came decades after the Apple II. Jeff Bezos and Amazon have moved far beyond selling books online. These examples suggest that these prominent founders themselves may not have peaked when very young.

To examine this idea quantitatively, Figure 6 presents the forward 5-year stock price multiple as a function of founder age for each of Microsoft, Apple, Amazon, and Google.[42] This analysis allows us to examine whether the additional growth in market valuation tends to decline as these individuals age. We see no such tendency. In fact, the five-year multiples tend to rise

[42] The stock price multiple is the ratio of the January 1st closing stock price five years in the future to the January 1st closing stock price in the current year. The stock price series are post IPO (by their nature) and account for dividends and splits. While Facebook would be a natural addition to this quartet of major information technology firms, the stock price series is too short as yet to allow such analysis.

toward middle age. The peak for each founder comes at age 48 (Steve Jobs), age 39 (Bill Gates), age 45 (Jeff Bezos), and age 36 (Sergei Brin and Larry Page).[43]

From this perspective, one may reconcile the existence of great young entrepreneurs with the advantages of middle age by noting that extremely talented people are also extremely talented when they are young. That is, there are individual fixed effects that allow some people to succeed at very young ages, even when people (including these young successes) get better with age. Thus there is no fundamental tension between the existence of great young entrepreneurs and a general tendency for founders to reach their peak entrepreneurial potential in middle age.

V.D Venture Capitalist Behavior

We also see that venture capitalists tend to bet on relatively young founders. Given that younger founders have substantially lower batting averages (e.g., see Figure 3), the founder age tendency in VC investments may be surprising. VCs may thus be seen as making bad bets, which may be consistent with empirical findings elsewhere suggesting that VCs have earned low returns (Kaplan and Lerner 2010). However, it may also be the case that young founders are more in need of early-stage external finance, thus leading to this relationship. More subtly, and noting that VCs are seeking high returns, which is not identical to high growth, it may be that younger founders tend to sell their equity at lower prices, and thus VCs are making optimal return decisions. Teasing apart why VCs bet young is an interesting area for further work. We can say now however that venture capital, a major source of early-stage financing that can help drive creative destruction and economy-wide growth, does not currently appear allocated to the firms with the highest growth potential.

VI. Conclusion

Researchers, policymakers, investors, and entrepreneurs themselves all strive to understand entrepreneurial traits that predict the creation of successful new firms. This paper has focused on founder age, which is often thought to be a key predictor of entrepreneurial success. We find that age indeed predicts success, and sharply, but in the opposite way that many

[43] Page, who remains as CEO of Alphabet (Google), is only 44 today.

observers and investors propose. The highest success rates in entrepreneurship come from founders in middle age and beyond.

These findings are consistent with theories in which key entrepreneurial resources (such as human capital, financial capital, and social capital) accumulate with age. Mechanisms by which young people are proposed to have advantages (such as energy or originality) may still be operating, but if so they appear to be overwhelmed by other forces. Popular perceptions that celebrate youth as a key characteristic for creating high-growth firms appear largely misplaced. To the extent that venture capital targets younger founders, early-stage finance appears biased against the founders with the highest likelihood of successful exits or top 1 in 1,000 growth outcomes.

Future work can explore how variation in specific founder traits predict entrepreneurial entry and success, further informing underlying theories for the life cycle of entrepreneurs and provide additional capacity to predict entrepreneurial success. More broadly, new administrative datasets linking founder traits and business outcomes promise to further reveal core facts about the high-growth new ventures that can drive economic growth and the advance of socioeconomic prosperity.

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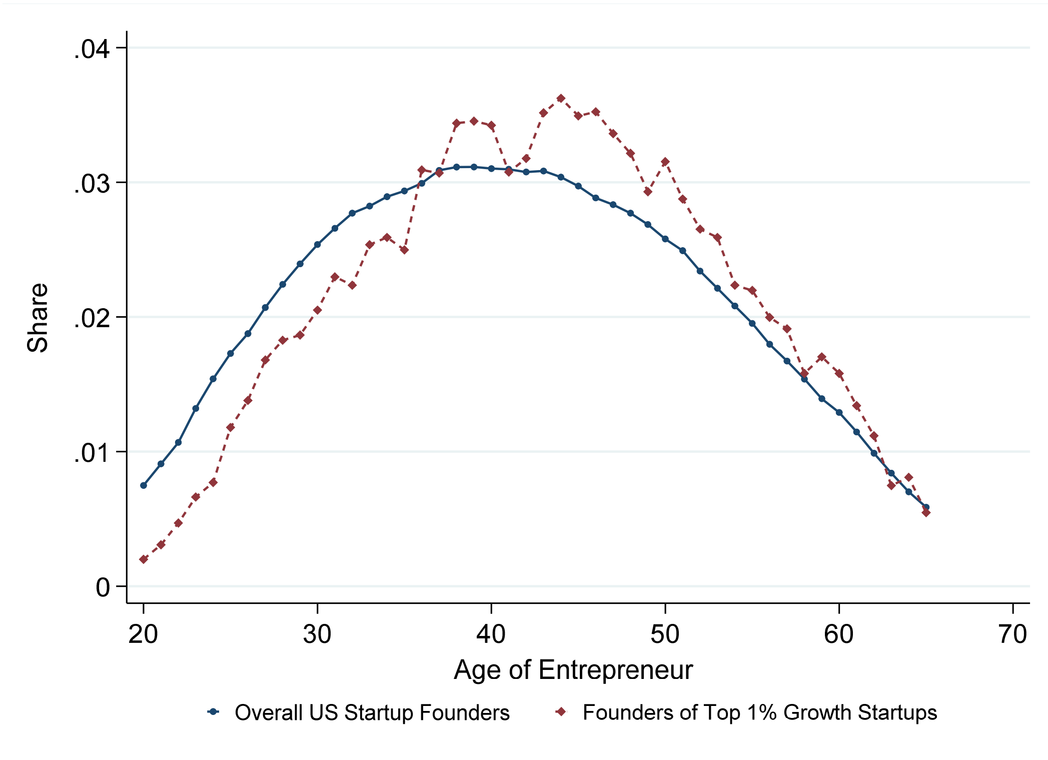
Figure 1: Founder Age Distribution:
All Startups and High Performance Startups



Source: Authors calculations based on W-2 earnings records, form K-1 and Longitudinal Business Database.
Notes: This set of kernel density plots shows the age distribution of startup founders (at year of founding) in the US. Each bin represents an age cohort. Ages between 20 and 65 are incorporated in the plots. The blue (left) plot incorporates all founders of new C-corporations, S-corporations, and Partnerships with employees founded between 2007 and 2014 as identified in the Longitudinal Business Database (LBD). The red (right) plot represents founders of the top 1% growth firms founded over the 2007-2009 period. Top 1% employment growth threshold value is calculated for each yearly cohort based on the raw employment figures from the LBD in the five years after the birth of the firm.

Figure 2: Founder Rates by Age

Fig. 2A: Size of Workforce by Age

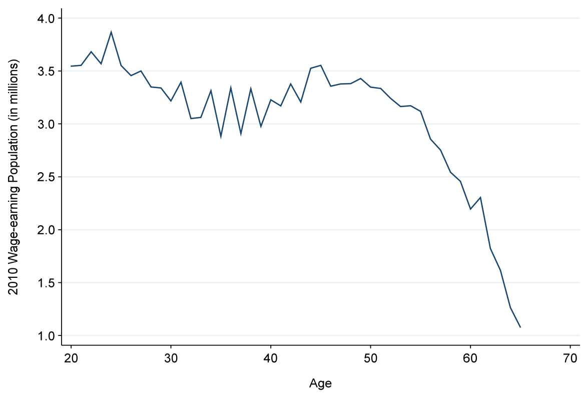


Fig. 2B: Founders per Worker, by Age

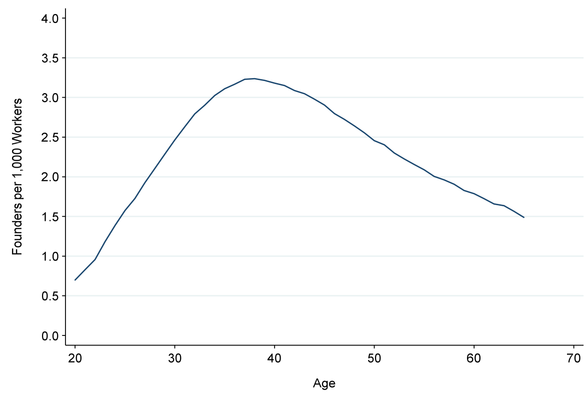
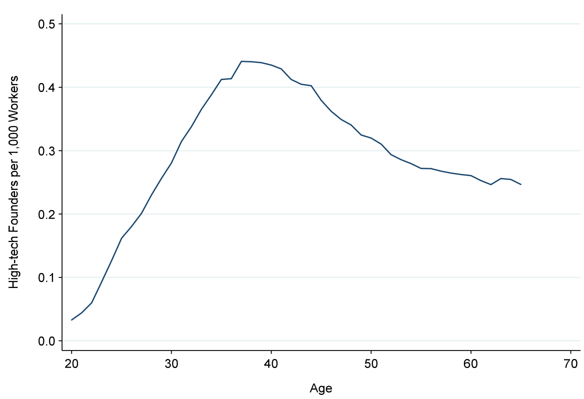


Fig. 2C: Tech Founders per Worker, by Age



Source: Authors calculations based on W-2 earnings records, form K-1, and Longitudinal Business Database between 2007 and 2014.
Notes: These figures show the number of wage earners, founders, and high-tech founders in the US. Each bin represents an age cohort. Ages between 20 and 65 are incorporated in the plots. Figure 2A uses the 2010 W-2 file. Figures 2B and 2C use data over 2007-2014.

Figure 3: Likelihood of Extreme Success, Conditional on Starting a Firm

Fig. 3A: Probability of Successful Exit (IPO or acquisition), by Age

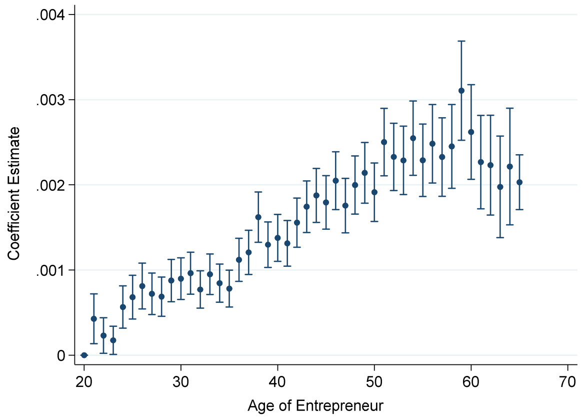


Fig. 3B: Probability of Top 0.1% Employment at 5 Years, by Age

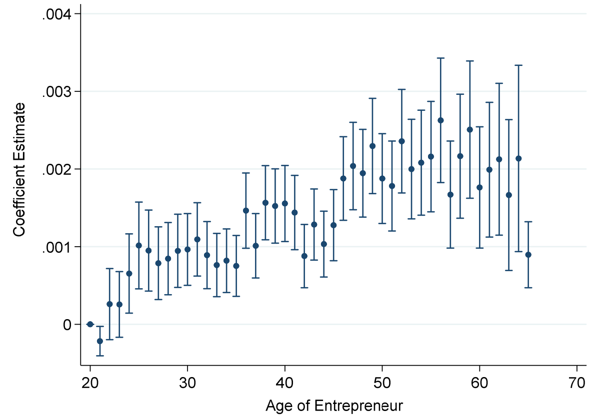
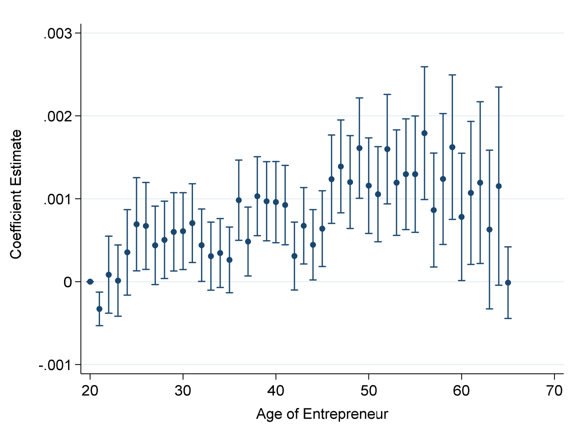


Fig. 3C: Probability of Top 0.1% Employment at 5 Years, Conditional on Industry, by Age



Source: Authors calculations based on W-2 earnings records, form K-1, Longitudinal Business Database and Compustat for firms founded over the 2007-2009 period.
Notes: OLS regression coefficients from estimating the likelihood of extreme firm success on a series of age indicators are shown. Ages 19 and below are grouped as 19 while ages 66 and above at grouped as 66. IPO data are sourced from Compustat. Acquisitions are based on firm ownership changes in the Longitudinal Business Database (LBD). Top 0.1% employment outcome is calculated based on five-year employment growth in the LBD.

Figure 4: Entrepreneurial Outcomes for Founders Above and Below Age 30

Fig. 4A: Firm Death, High Growth

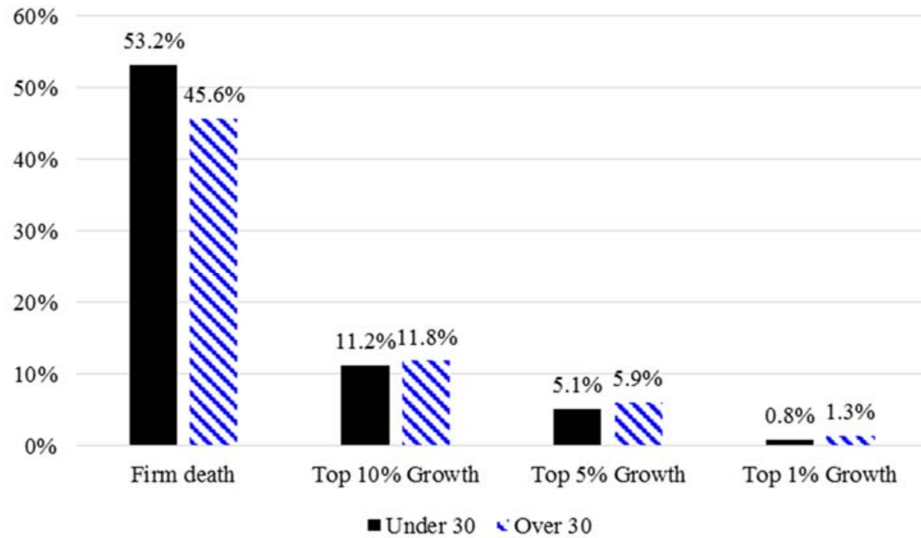
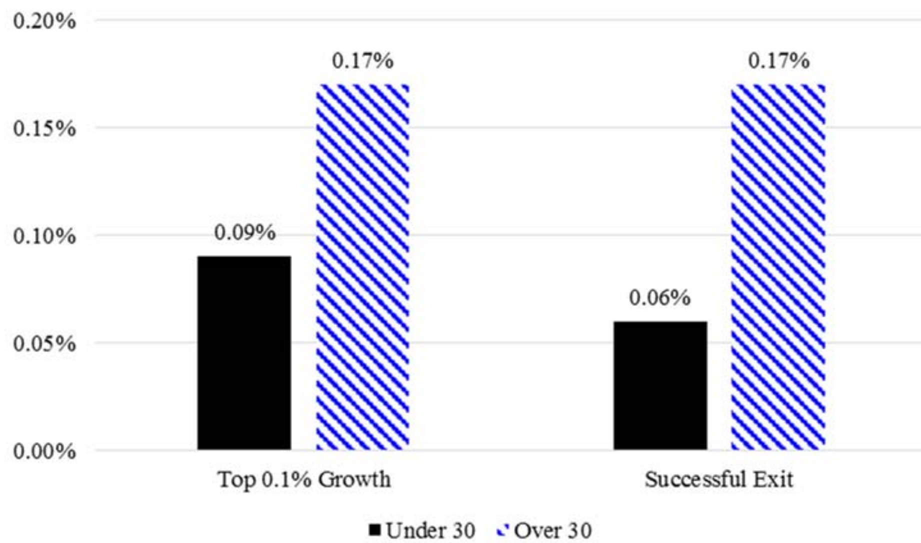


Fig. 4B: Extremely High Growth or Successful Exit



Source: Authors calculations based on Longitudinal Business Database and Compustat firms founded over the 2007-2009 period.

Notes: To track firm dynamics over a five year window for each cohort, all startup firms born between 2007-2009 in the Longitudinal Business Database (LBD) are included in the sample. For each yearly cohort of new firms, top growth thresholds are calculated based on five-year employment growth in the Longitudinal Business Database (LBD). Successful exits include Initial Public Offering based on Compustat data and acquisitions based on firm ownership changes in the LBD.

Figure 5: Results by Founder Definition and Legal Form

Fig. 5A: Owner-Worker, C-Corporation and K-1 Firms

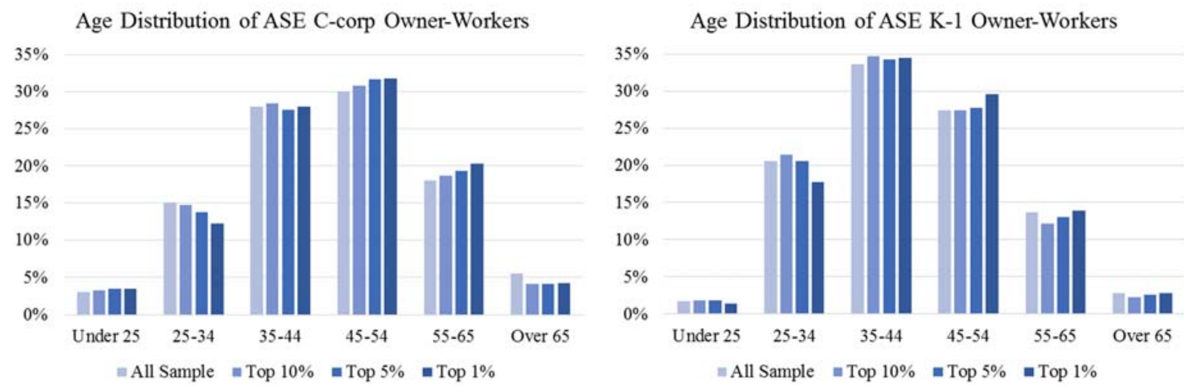
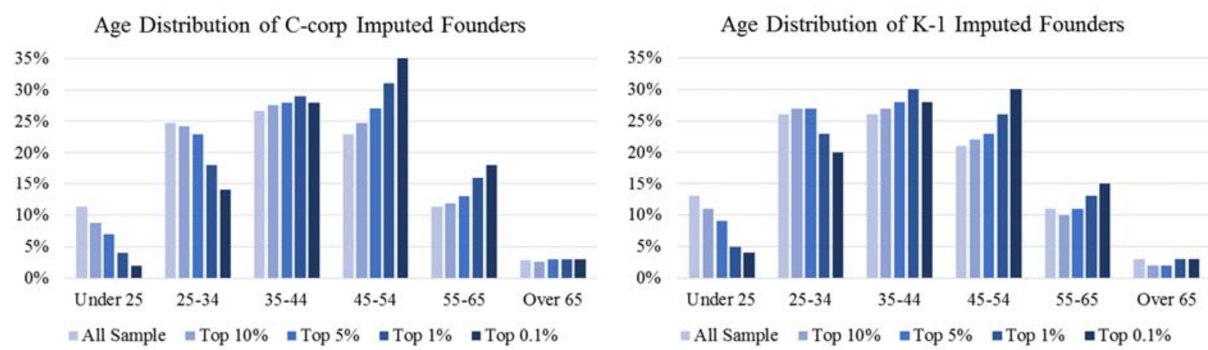


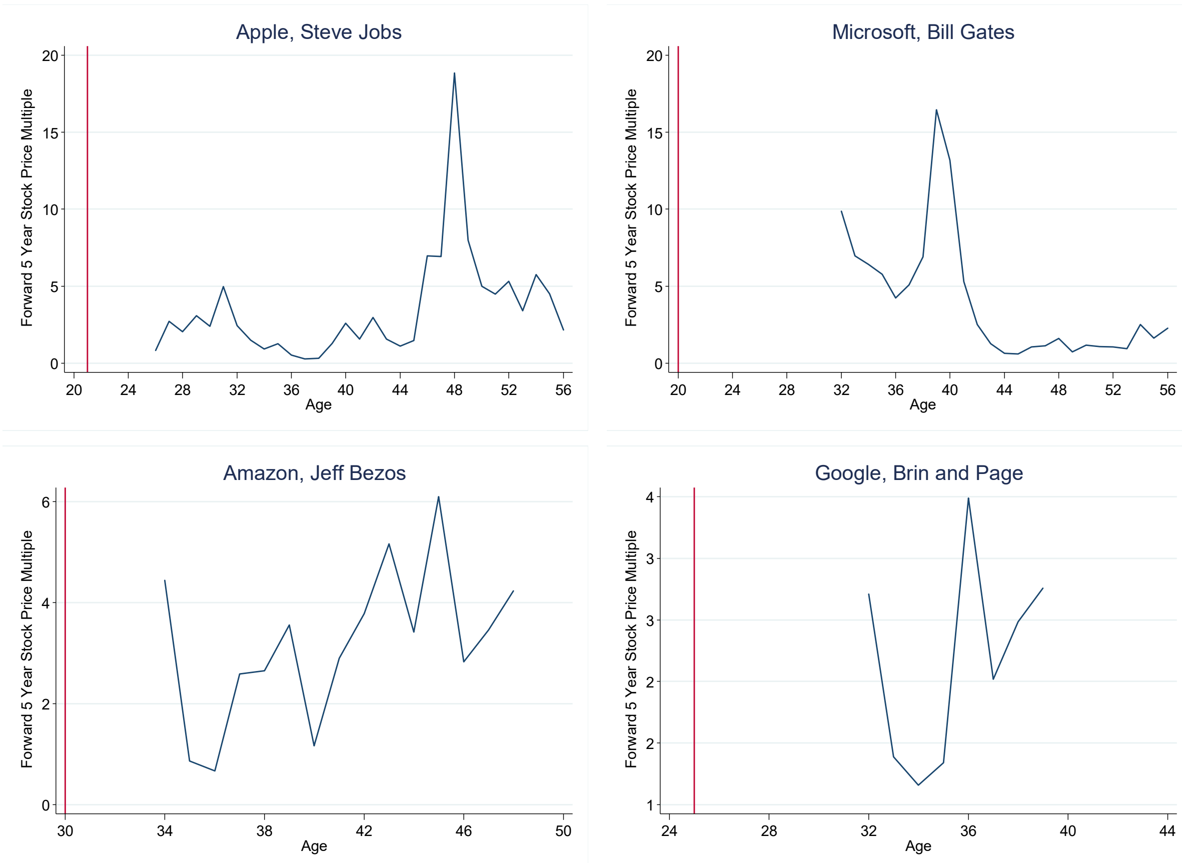
Fig. 5B: Initial Top 3 Earners, C-Corporation and K-1 Firms



Source: Authors calculations based on Longitudinal Business Database and Annual Survey of Entrepreneurs.

Notes: Startup firms born between 2007 and 2012 in the Annual Survey of Entrepreneurs (ASE) are included for the left panel of Figure 5A. Growth outcomes are calculated over a three-year window for each cohort and the top 1%, 5% and 10% is identified from the distribution. The rest of the figures include all new C-corporations, S-corporations, and Partnerships in the Longitudinal Business Database (LBD) born between 2007 and 2011. Growth outcomes are calculated over a three-year window for each cohort and the top 0.1%, 1%, 5% and 10% is identified from the distribution. The left panel of Figure 5A is based on founders of C-corporation firms in the Annual Survey of Entrepreneurs. The right panel of Figure 5A is based on founders of S-corporations and partnerships in the K-1 database. Figure 5B is based on imputed founders (first-year joiners who are among top three earners) using W-2 wage-records.

Figure 6: Forward Stock Multiples as the Founder Ages:
Apple, Microsoft, Amazon, and Google



Source: Authors calculations based on public data.
Notes: The vertical red line indicates the founders' age in the year of the firm's founding. The x-axis then presents the age of the indicated founder as time passes. The forward stock-price series begins in the year of the initial public offering for each firm. For Google, Brin and Page were born in the same year (1973). Historical share prices are sourced from Bloomberg.

Table 1: Founder Age – Perceptions from Media & Two Prominent VCs

	TechCrunch Awards	Inc. and Entrepreneur Magazines	Sequoia	Matrix Partners
Mean	31.0	29.1	33.9	36.5
Median	30	27	33	36
(St. Dev.)	(7.1)	(7.0)	(8.7)	(8.6)
Observations	232	51	415	246
Period	2008-2016	2015	1969-2014	1948-2014
Sectoral Focus (top 5)	Education, Software, Social Media, Consumer Electronics, e-Commerce	Technology, Retail, Media, Consumer Goods, Food Delivery	Semiconductors, Networks, Task Mgmt. Apps, Website Compilers, Cloud	Networks, Applications, Commerce, Platform/ Infrastructure, Semiconductors/ Materials

Notes: TechCrunch gives annual awards to the "most compelling startups, internet and technology innovations of the year". Inc. magazine and Entrepreneur magazine provided "Entrepreneurs to Watch" lists in 2015. The founder ages for new ventures backs by the two venture capital firms (Sequoia Capital and Matrix Partners) were obtained by the authors through researching all the companies listed on their respective websites.

Table 2: Founder Age – Averages across U.S. and by Technology Definition

	All Startups	High Tech Employment	VC-Backed Firms	Patenting Firms
US (entire)	41.9	43.2	41.9	44.6
	(12)	(11.5)	(10.6)	(11.3)
	2,658,000	334,000	11,000	10,000
California	41.7	42.1	39.6	43.9
	(12)	(11.3)	(10)	(11)
	374,000	61,700	4,000	3,000
Massachusetts	41.7	43.2	42.3	45.3
	(11.8)	(11.2)	(9.8)	(10.6)
	52,000	8,100	900	400
New York	41.4	41.8	38.7	42.7
	(11.6)	(11.6)	(10.1)	(11.4)
	276,000	22,600	800	600
Silicon Valley	41.6	41.5	40.2	44.3
	(11.4)	(10.3)	(9.7)	(9.8)
	32,000	11,700	1,700	900
Entrepreneurial hubs	40.8	40.5	39.5	43.8
	(11.3)	(10.6)	(9.8)	(10.2)
	23,000	9,300	1,900	700

Notes: Mean founder age is shown in the first row, standard deviation in parentheses, and observation count in the third row. Data incorporates all C-corporations, S-corporations, and Partnerships founded over 2007-2014. Based on the Longitudinal Business Database (LBD), only new firms from each year are included. High tech sectors in column 2 are defined at 4-digit NAICS level (see text). Column 3 represents firms that ever receive venture capital, which is sourced from Private Capital Research Institute. Column 4 represents firms that are ever granted a patent, which is derived from the Longitudinal Linked Patent-Business Database. Silicon Valley is defined as zip codes in Santa Clara and San Mateo counties. Entrepreneurial hubs are defined as zip codes with the highest entrepreneurial quality as defined by Guzman and Stern (2017). Counts are rounded to comply with disclosure rules.

Table 3: Founder Age — Oldest and Youngest Technology Sectors

Panel A: Technology Sectors, Youngest 5

NAICS Code	Sector	N	Mean
5172	Wireless Telecommunications Carriers (except Satellite)	1,500	38.5
5182	Data Processing, Hosting, and Related Services	6,100	39.7
5112	Software Publishers	3,600	39.8
5415	Computer Systems Design and Related Services	100,000	40.1
8112	Electronic and Precision Equipment Repair and Maintenance	4,900	40.8

Panel B: Technology Sectors, Oldest 5

NAICS Code	Sector	N	Mean
4862	Pipeline Transportation of Natural Gas	50	51.4
3251	Basic Chemical Manufacturing	700	47.9
3255	Paint, Coating, and Adhesive Manufacturing	400	47.5
2111	Oil and Gas Extraction	3,100	47.5
3336	Engine, Turbine, and Power Transmission Equipment Manufacturing	400	47.3

Notes: Sector is shown in the first column, observation counts of founders in the second column, and mean founder age in the third column. Sectors are defined at the 4-digit NAICS level. Only new firms are included. Counts are rounded to comply with disclosure rules. Sample is all new businesses in the U.S. from 2007-2014 based in the Longitudinal Business Database (LBD).

Table 4: Founder Age — Top 5% Firms by Employment at 5 Years

	All Startups	High Tech Sectors	VC-Backed Firms	Patenting Firms
US (entire)	42.1	42.3	42.5	44.6
	(11.5)	(10.5)	(10.1)	(9.9)
	62,000	7,800	2,000	1,300
California	41.6	41.4	40.3	43.6
	(11.7)	(10.3)	(9.9)	(9.9)
	9,700	1,500	700	400
Massachusetts	41.5	42.2	41.3	43.5
	(10.7)	(10)	(9.1)	(8.6)
	1,400	400	200	80
New York	41.8	41.2	40.3	42.6
	(11.5)	(10.4)	(9.6)	(10.5)
	4,300	400	80	60
Silicon Valley	41.4	42.0	40.6	43.2
	(10.7)	(9.3)	(9.2)	(9)
	1,200	500	300	200
Entrepreneurial hubs	40.6	41.3	39.6	42.3
	(10.5)	(10.2)	(9.6)	(9.4)
	1,000	500	400	200

Notes: Notes: Mean founder age is shown in the first row, standard deviation in parentheses, and observation count in the third row. Data incorporates all C-corporations, S-corporations, and Partnerships founded over 2007-2009 in the Longitudinal Business Database (LBD). Only new firms from each year are included. Employment growth is measured using a 5-year window. Sectors are defined at the 4-digit NAICS level. Column 3 represents firms that ever receive venture capital, which is sourced from Private Capital Research Institute. Column 4 represents firms that are ever granted a patent, which is derived from the Longitudinal Linked Patent-Business Database. Silicon Valley is defined as zip codes in Santa Clara and San Mateo counties. Entrepreneurial hubs are defined as zip codes with the highest entrepreneurial quality as defined by Guzman and Stern (2017).

Table 5: Founder Age and Success — Upper Tail Growth or Acquisition

Panel A: Comparisons across Region and in Entrepreneurial Centers

	All Startups	Top 10%	Top 5%	Top 1%	Top 0.1%	Successfully Exited Startups
US (entire)	41.8	41.6	42.1	43.7	45.0	46.7
	(11.9)	(11.5)	(11.5)	(11.1)	(10.7)	(10.6)
	1,079,000	126,000	62,000	13,000	1,700	4,000
California	41.4	41.4	41.6	42.3	43.5	46.6
	(12.1)	(11.7)	(11.7)	(11.3)	(10.1)	(10.3)
	154,000	20,000	9,700	1,900	200	400
Massachusetts	41.7	41.5	41.5	42.8	43.2	47.7
	(11.6)	(10.9)	(10.7)	(10.3)	(10.6)	(9.5)
	20,000	2,700	1,400	300	60	100
New York	41.5	41.4	41.8	42.5	44.2	46.2
	(11.4)	(11.5)	(11.5)	(11.2)	(10.5)	(11.5)
	104,000	9,400	4,300	800	110	300
Silicon Valley	41.7	41.8	41.4	41.9	44.3	47.2
	(11.4)	(10.9)	(10.7)	(10)	(9.8)	(8.1)
	12,000	2,100	1,200	300	40	60
Entrepreneurial hubs	41.2	40.9	40.6	40.9	42.6	46.7
	(11.3)	(10.7)	(10.5)	(9.7)	(10.1)	(9.7)
	8,400	1,600	1,000	300	50	80

Notes: Mean founder age is shown in the first row, standard deviation in parentheses, and observation count in the third row. See notes to Table 2 for row definitions. Data incorporates all C-corporations, S-corporations, and Partnerships founded over 2007-2009 in the Longitudinal Business Database (LBD). Columns restrict sample to different employment growth thresholds, as indicated, based on employment five years after founding. To examine five years after founding, the sample period is restricted to 2007-2009. The success thresholds, in 2007 for example, are as follows: Top 10% is 9 employees; Top 5% is 16 employees; Top 1% is 56 employees; Top 0.1% is 904 employees. The final column considers exit by IPO (sourced from Compustat) or acquisition (derived from the LBD based on firm ownership changes).

Panel B: Technology Firms

	All Startups	Top 10%	Top 5%	Top 1%	Top 0.1%	Successfully Exited Startups
US (entire)	41.8	41.6	42.1	43.7	45.0	46.7
	(11.9)	(11.5)	(11.5)	(11.1)	(10.7)	(10.6)
	1,079,000	126,000	62,000	13,000	1,700	4,000
Tech Employment	43.2	42.1	42.3	43.6	45.9	48.4
	(11.3)	(10.5)	(10.5)	(10)	(9.6)	(9.8)
	132,000	13,000	7,800	2,200	400	1,100
VC-Backed Firms	42.4	42.3	42.5	43.3	43.4	47.9
	(10.3)	(10.1)	(10.1)	(10)	(10.1)	(9.5)
	6,600	2,500	2,000	800	140	180
Patenting Firms	44.4	44.4	44.6	45.0	46.2	49.3
	(11.1)	(10.4)	(9.9)	(9.2)	(9.7)	(10.1)
	7,000	1,900	1,300	500	90	200

Notes: Mean founder age is shown in the first row, standard deviation in parentheses, and observation count in the third row. Data incorporates all C-corporations, S-corporations, and Partnerships founded over 2007-2009 in the Longitudinal Business Database (LBD), for which we can observe 5 years of performance data after founding. Only new firms from each year are included. Employment growth is measured using the 5-year window. Tech Employment consists of NAICS-4 sectors with high shares of STEM-trained workers.

Table 6: Industry-Specific Experience and Growth Outcomes

Panel A: Founders with Work Experience in Startup's 2-Digit Industry Classification

	Top 10%	Top 5%	Top 1%	Top 0.1%	Successful Exit
NAICS-2 Experience					
Never	8.6%	4.1%	0.9%	0.11%	0.13%
1-2 years	10.1%	4.8%	1.0%	0.11%	0.10%
>= 3 years	15.0%	7.7%	1.7%	0.22%	0.20%

Panel B: Founders with Work Experience in Startup's 4-Digit Industry Classification

	Top 10%	Top 5%	Top 1%	Top 0.1%	Successful Exit
NAICS-4 Experience					
Never	9.1%	4.5%	1.0%	0.12%	0.14%
1-2 years	11.6%	5.6%	1.1%	0.14%	0.12%
>= 3 years	16.8%	8.5%	1.7%	0.24%	0.20%

Panel C: Founders with Work Experience in Startup's 6-Digit Industry Classification

	Top 10%	Top 5%	Top 1%	Top 0.1%	Successful Exit
NAICS-6 Experience					
Never	9.4%	4.6%	1.0%	0.12%	0.13%
1-2 years	12.6%	6.0%	1.2%	0.15%	0.13%
>= 3 years	17.7%	9.0%	1.8%	0.26%	0.21%

Notes: Data incorporates all C-corporations, S-corporations, and Partnerships founded over 2007-2009 in the Longitudinal Business Database (LBD), for which we can observe 5 years of performance data after founding. Growth outcome is determined by employment growth, using the 5-year window after founding.

Table 7: Minimum and Maximum Ages within Founder Teams

Panel A: Owner-Worker Definition of Founders (K-1)

	All Startups	High-Tech Startups	VC-backed Startups	Patenting Startups	Top 1%	Top 0.1%	Successful Exit
Within Startup							
Min Founder Age	42.7	44.0	39.8	43.6	40.9	42.3	43.3
Max Founder Age	44.6	45.5	47.8	46.9	45.6	47.8	47.1

Panel B: Initial Team Definition (K-1 and C-Corporations)

	All Startups	High-Tech Startups	VC-backed Startups	Patenting Startups	Top 1%	Top 0.1%	Successful Exit
Within Startup							
Min Founder Age	35.1	39.1	36.5	37.8	35.0	37.4	38.5
Max Founder Age	46.0	45.7	47.3	48.4	50.1	51.4	51.4

Notes: Panel A incorporates all S-corporations and Partnerships founded over the 2007-2014 period in the Longitudinal Business Database (LBD), except for the Top 1% and Top 0.1% columns, which include those firms founded over the 2007-2009 period for which we can observe 5 years of employment data after founding. Panel B incorporates all S-corporations, Partnerships, and C-corporations founded over the 2007-2014 period, except for the Top 1% and Top 0.1% columns, which include those firms founded over the 2007-2009 period for which we can observe 5 years of performance data after founding.

Appendix I: Data Sets

This appendix provides additional details regarding the datasets used in this paper. Table A-1 provides a summary of the datasets and their key variables. Many data sets are available to researchers through Census approved projects and accessible through Federal Statistical Research Data Centers (FSRDC), as further indicated in the table. The Schedule K-1 and Form W-2 datasets are currently accessible only by U.S. Census employees who have been granted access through approved internal projects.

The Longitudinal Business Database (LBD)

The LBD is an establishment-level longitudinal database tracking all establishments and firms in the US with at least one employee. Starting in 1976 and updated annually, the LBD currently covers years through 2015. The LBD is sourced from administrative income and payroll filings and enhanced with Census collections, including the Economic Census and the Company Organization Survey.

Key variables in the LBD include payroll, employment, industry, location (including state and county), and legal form of organization. Establishment and firm identifiers allow us to aggregate establishment-level information to the firm to identify firm-level employment and payroll. The ability to track establishments over time makes it possible to identify de novo firms (startups) distinctly from firms that emerge from corporate restructuring or M&A activity. Startups are defined as single-unit firms during the year in which the firm first appears in the LBD with at least 1 employee. In order to identify M&A activity using the LBD, we manually track changes in firm ownership. More specifically, we flag a firm ownership change when all of the existing establishments in a firm simultaneously receive a new firm identifier in the following year. In order to ascertain that the firm ownership changes are the result M&A rather than corporate expansions, we impose the following conditions: (1) the owning firm is an incumbent firm that exists in the LBD prior to the ownership change; (2) the original EIN and names of the establishments prior to the acquisitions differ from those of the new owner's prior to the acquisition. For additional information regarding the LBD, see Jarmin and Miranda (2002).

Schedule K-1 (Form 1065/1120)

Schedule K-1 is a tax form used to report business income or loss for owners of S-corporations and partnerships. Partnerships and S-corporations are pass-through entities, meaning that their profits are not taxed at the entity level but rather as they flow through to the owners. The

Schedule K-1 reports the amount of income passed through to each party. Partnerships and S-corporations file a separate K-1 form for each of their owners and are required to account for 100% of profits. The availability of both employer identification numbers (EIN) and person identification numbers (SSN) allow us to identify all the owners of pass-through entities. The data start in 2007 and currently cover years through 2015. These data are confidential and currently can only be accessed through an internal U.S. Census project.

Key variables in Schedule K-1 include the income, deduction, and ownership share of partners and shareholders as well as the name, location, and employer identifier of the company. Unlike S-corporations, partnerships can be owned by other legal entities including partnerships and corporations. These tiered entities can make it hard to identify the ultimate owners of these enterprises when there are circular references. For more information see Goldschlag et al. (2017) and Cooper et al. (2015).

Form W-2

Form W-2 is a tax form used to report the income paid to employees in remuneration for services rendered to an employer. Employers must file a W-2 for each of their employees for services performed during the year. The availability of both employer identification numbers (EIN) and person identification numbers (SSN) allow us to identify all the salaried workers associated with employer businesses in the US. The data start in 2005 and currently cover years through 2016. Key variables in Form W-2 include the income, social security taxes, and Medicare taxes as well as individual and employer identifiers. For more information about the W2 see (https://www.irs.gov/forms-pubs/about-form-w2).

Longitudinal Employer-Household Dynamics- Employment History File (LEHD-EHF)

The LEHD-EHF is one of the core infrastructure files of the LEHD program. The EHF is sourced from quarterly unemployment insurance earnings records collected by labor market information systems across the country for unemployment insurance purposes. The EHF provides a time series of all jobs held by individuals each quarter in each state. Key variables in the EHF include employer and individual identifiers, employment quarter and year, quarterly earnings, and industry of activity. The unit of analysis is the job or an employer-employee combination. A crosswalk between the state employer identifier (SEIN) and the federal employer identifier (EIN) is available. For additional information see the LEHD infrastructure file documentation (https://lehd.ces.census.gov/doc/technical_paper/tp-2006-01.pdf).

The Annual Survey of Entrepreneurs (ASE)

The ASE is a survey of approximately 290,000 firms in the non-farm private sector. The survey is a representative sample of firms in the US with employees. Starting in 2014, the ASE was conducted on an annual basis up to 2016. The ASE will be replaced with the Annual Business Survey starting in 2017. The ASE collects information on up to 4 owners of US businesses including age, gender, race, ethnicity and veteran status. Additional information includes the business owners' education, experience, and ownership role. The ASE is the source of core demographic statistics of US business owners and includes information such as number of firms, sales and receipts, annual payroll, and employment by gender, ethnicity, race, and veteran status. The survey includes modules to collect information on specific business activities. In 2014 the ASE collected additional information on R&D and innovation and the 2015 survey asked questions about management practices. For additional information see Foster and Norman (2017).

The Census Numerical Identification System File (Numident)

The Census Numident is sourced from the Social Security Administration (SSA) applications for Social Security Numbers (Form SS-5). This is the SSA's master list of social security numbers (SSN) and includes all individuals in the US that have been issued a social security number. The Numident file is updated annually with years currently through 2016. Key variables include a protected identification key (PIK, which replaces the individual's SSN so as to protect their identity), date of birth, country of origin, gender, race and ethnicity. Starting in 1980 the SSA changed its collection of race and ethnicity so these data became non-mandatory items. The Census enhances these files with demographics data from its own data holdings including the decennial census and the American Community Survey to improve its quality.

The Patent Longitudinal Business Database Crosswalk (LPBD)

The LPBD is a crosswalk file linking individual firms to specific patents in the US Patent and Trademark Office patent grants database. Starting in 2000 the LPBD links all inventors and firms identified in patent grant documents to firms in the LBD. The LPBD uses a triangulation strategy where the best possible match is identified by comparing matches to two alternative data sources: inventors are matched to the LEHD jobs file for workers, and patent assignees are matched to the Business Register file for firms. The file starts in 2000 and is updated annually. The LPBD currently cover years through 2015. Key variables in the LPBD include firm id, patent id, application year, assignee country, assignee state, and assignee type. The LPBD is able to match in excess of 75% of all patent-assignee combinations in the USPTO and 91% of patents with US firm assignees. For additional information see Graham et al. (forthcoming).

The Private Capital Research Institute-LBD Bridge (PCRI)

The Private Capital Research Institute (PCRI) is a database of private capital data assembled by PCRI directly from several dozen private capital firms as well as from four major data vendors and private capital associations, including the Emerging Markets Private Equity Association (EMPEA), NYPPEX FUNDSIQ ("NYPPEX") Thomson Reuters, and Unquote. PCRI were matched to the Business Register using name and address linking techniques. Key variables in the PCRI database include a company id, business name, street address, zip code, state, country, day of investment, and investment category. The PCRI bridge provides a link between the LBD and the PCRI database. Match rates of US headquartered firms to the LBD are in excess of 90%. For additional information about the matching methodology see Brown and Tello-Trillo (2017). External researchers wishing to use the linked PCRI and LBD data and both internal and external Census researchers wishing to use additional PCRI variables need to submit a proposal to Leslie Jeng, Director of Research at PCRI (leslie.jeng@gmail.com). The proposal guidelines can be found at http://www.privatecapitalresearchinstitute.org/images/news/call_f_proposals.pdf.

VentureXpert

VentureXpert is a commercial database for information covering venture capital and private equity investments. The data are linked to the LBD using name and address matching techniques. Key variables include firm name and address, funding type, funding round, amounts, date of funding, and names of the VC firms. Years covered include 1980-2005.

Compustat Bridge & Compustat

The Compustat Bridge provides a link between the COMPUSTAT data and the LBD. Compustat provides financial, statistical and market information for publicly traded companies.

Appendix II: Additional Analyses using Sales Data

In this section we present additional analyses of the growth results, repeating key findings from the paper but using the firm's sales rather than employment to delineate the highest growth firms.

- Figures A1-A2 correspond to Figure 1 in the text. The background population of firms and founder ages are the same as in Figure 1. However, for the high-growth new ventures, we now consider founder age for the Top 1% of firms by sales, measured three years after founding (Figure 1A) or five years after founding (Figure A2).
- Figures A3-A4 correspond to Figure 5 in the text. We present the age distribution for various high-growth thresholds, now using sales growth through three years rather than employment growth. Figure A3 presents C-corporations (corresponding to Figure 5B, left panel), and Figure A4 presents K-1 firms (corresponding to Figure 5B, right panel).

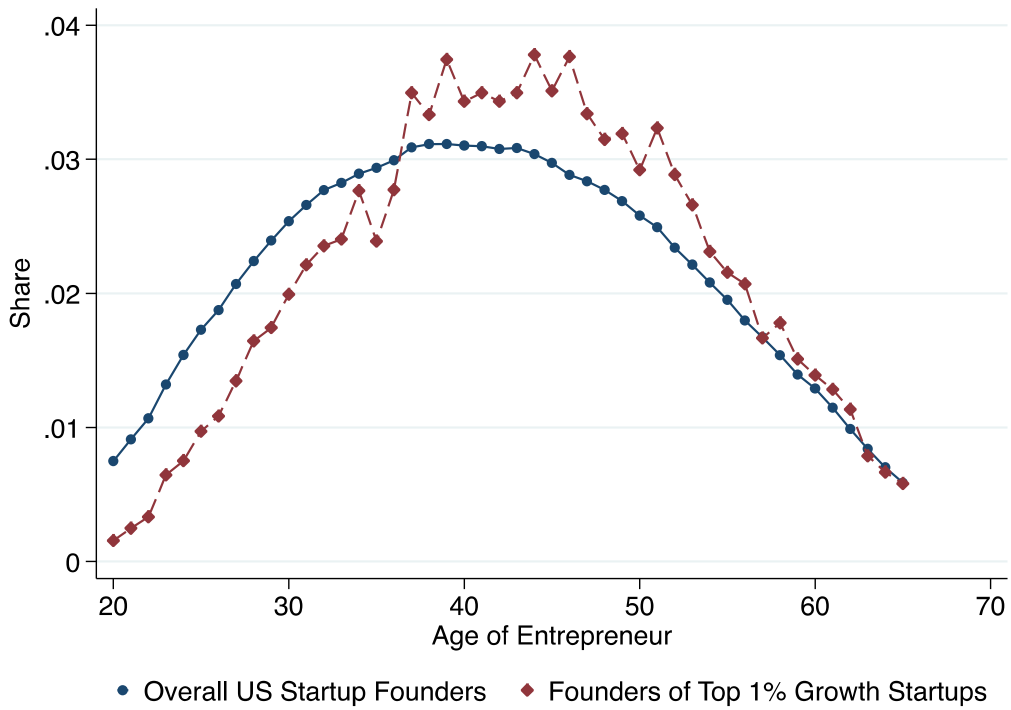
Overall, these figures show that defining the highest-performance startups using sales growth yields very similar findings as using employment growth.

Table A1: Summary of Data Sets

Dataset	Units and coverage	Relevant Variables	Period and Frequency	Access
Longitudinal Business Database (LBD)	• Establishments and firms • All private non-farm employers in the US and outlying territories	Firm identifier, establishment identifier, payroll, employment, industry, location, legal form of organization	Annual, 1976-2015	FSRDC/Census approved projects
Schedule K-1 (Form 1065/1120)	• Owners • All pass through entities (partnerships and S-corporations)	Individual identifier, firm identifier, business income, deductions, share of profit/loss	Annual, 2007-2016	Census Bureau employees on approved projects and a need to know
Form W-2	• Employees • All workers in the US for whom employers made payments	Individual identifier, employer identifier, wage income, social security, or Medicare wages.	Annual, 2005-2016	Census Bureau employees on approved projects and a need to know
Longitudinal Employer-Household Dynamics-Employment History File (LEHD-EHF)	• Salaried workers by employer • All salaried workers subject to unemployment insurance	Individual identifier, employer identifier, earnings (quarterly and annualized), industry	Quarterly, 20XX-2015 (Initial year varies by state)	FSRDC/Census approved projects
Annual Survey of Entrepreneurs (ASE)	• Businesses • Sample of 290,000 non-farm businesses with paid employees and receipts of $1,000 or more	Firm identifier, information for up to 4 owners including age, gender, race, ethnicity, education, experience and type of ownership	Annual, starting in 2014-2016 to be replaced by the Annual Business Survey in 2017	FSRDC/Census approved projects
Census Numident	• Individuals • All individuals with a US social security number	Individual identifier, date of birth, gender, race, ethnicity, country of origin	Updated annually	FSRDC/Census approved projects
Longitudinal Patent Business Database (LPDB)	• Patent-firm links • All patents in the USPTO grants database matched to the LBD	Firm identifier, Patent identifier, year	Annual, 2000-2014	FSRDC/Census approved projects

Private Capital Research Institute-LBD Bridge (PCRI)	• Firms • Private capital deals including buy outs, VC, growth equity, secondary purchases.	Firm identifier, Category of private capital	1990-2015	FSRDC/Census approved projects prior approval of PCRI
VentureXpert	• Firms • VC deals	Firm identifier, Venture capital funding	1980-2005	Data provided by researcher through a license agreement
Compustat-Bridge	• Publicly traded firms	Firm identifier, financial and market data	1976-2013	FSRDC/Census approved projects prior approval of PCRI

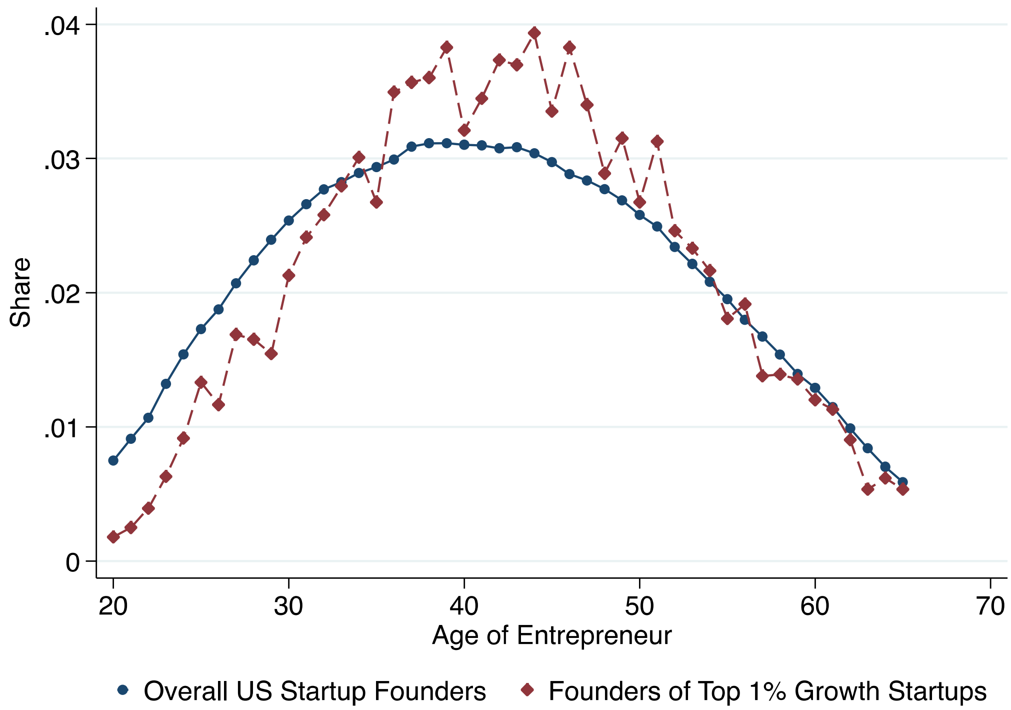
Figure A1: Founder Age Distribution:
All Startups and High Performance Startups by Sales (3 Years after Founding)



Source: Authors calculations based on W-2 earnings records, form K-1 and Revenue-Enhanced Longitudinal Business Database.

Notes: This set of kernel density plots shows the age distribution of startup founders (at year of founding) in the US. Each bin represents an age cohort. Ages between 20 and 65 are incorporated in the plots. The blue (left) plot incorporates all founders of new C-corporations, S-corporations, and Partnerships with employees founded between 2007 and 2014 as identified in the Longitudinal Business Database (LBD). The red (right) plot represents founders of the top 1% growth firms founded over the 2007-2010 period, given that revenues data are available up to 2013. Top 1% employment growth threshold value is calculated for each yearly cohort based on the real revenue figures from the LBD in the three years after the birth of the firm.

Figure A2: Founder Age Distribution:
All Startups and High Performance Startups by Sales (5 Years after Founding)



Source: Authors calculations based on W-2 earnings records, form K-1 and Revenue-Enhanced Longitudinal Business Database.

Notes: This set of kernel density plots shows the age distribution of startup founders (at year of founding) in the US. Each bin represents an age cohort. Ages between 20 and 65 are incorporated in the plots. The blue (left) plot incorporates all founders of new C-corporations, S-corporations, and Partnerships with employees founded between 2007 and 2014 as identified in the Longitudinal Business Database (LBD). The red (right) plot represents founders of the top 1% growth firms founded over the 2007-2008 period, given that revenues data are available up to 2013. Top 1% employment growth threshold value is calculated for each yearly cohort based on the real revenue figures from the LBD in the five years after the birth of the firm.

Figure A3: High Performance Startups by Sales (C-Corporations)

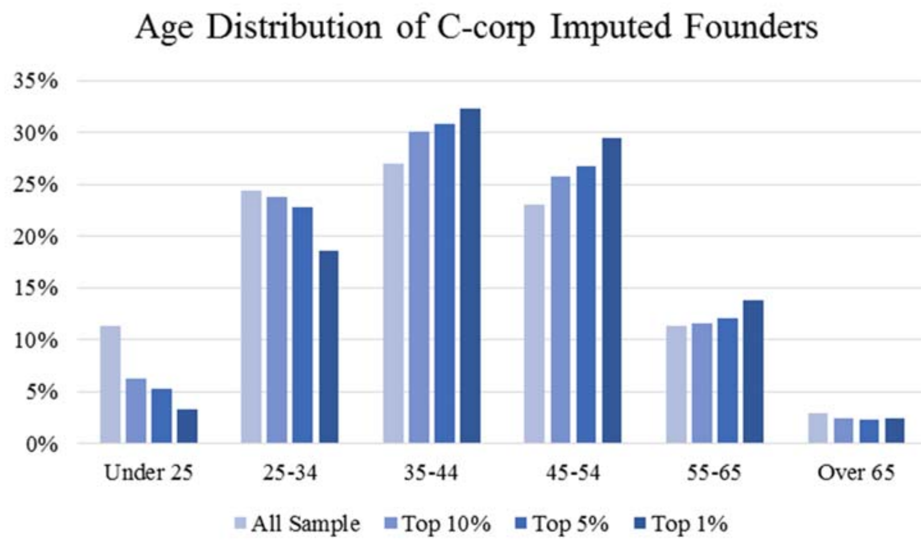


Figure A4: High Performance Startups by Sales (K-1 Firms)