Venture Capital Cycles and the Startup Labor Market

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Abstract

I show that venture capital (VC) market shocks have real consequences for high-skill workers. Plausibly exogenous shocks to local VC increase local startup hiring but also increase startup labor turnover. Startup jobs created in hotter VC markets are shorter-lived, and workers in these jobs are more likely to leave the universe of venture-backed firms within two years. While job duration in hot markets falls across occupations, effects on career advancement differ by role: STEM workers who enter booming VC markets advance slower in seniority in the following two to five years, while workers in business and management occupations are less affected. I show that differences in technology-skill specificity across occupations can explain this heterogeneity.

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1 Introduction

Business startups are important drivers of job creation and economic growth (Haltiwanger, Jarmin, and Miranda, 2013; Adelino, Ma, and Robinson, 2017). These firms depend on both financial capital and the human capital of high-skill workers. It is well known that financing flows to startups are highly volatile, often with large variation across industries and regions (Gompers and Lerner, 2004). Inflows of funding may enable the mobility of high-skill talent, including scientists, engineers, and business professionals, into entrepreneurial opportunities. While variation in financial returns over the investment cycle has been well documented (e.g., Nanda and Rhodes-Kropf, 2013), less is known about the returns to *human capital* for employees at startups: what are the consequences of these movements for workers?

The answer is not obvious from theory alone. Innovative firms engage in heavy experimentation and experience high rates of failure. This is evident in the distribution of returns to financial capital in startups: most firms fail, with investors losing most of their money, but a select few deliver exceptionally high returns (Kerr, Nanda, and Rhodes-Kropf, 2014). However, unlike financiers who can diversify the risk of individual experiments, knowledge workers typically make human capital investments that are highly specific to a given firm or technology. This is especially likely at startups operating on the technological frontier, where workers contribute to the development and commercialization of emerging, often unproven technologies. As a result, these roles may entail significant career risk.

In contrast, both conventional wisdom and a body of evidence suggest that the distribution of returns to entrepreneurial workers may be positively skewed: payoffs are substantial if the startup succeeds, and the long-term career consequences of failure are minimal.[1] In particular, the skills and experiences gained from these roles may be valued in the broader labor market, or may be sufficiently transferable so that firm failure does not amount to a loss on one's human capital investments. In this case, the distribution of returns to human capital investments in startups could differ markedly from that of financial capital.

This paper provides new evidence on entrepreneurial worker outcomes using exogenous variation in venture capital (VC) funding, a key source of early-stage finance for innovative firms in the US.[2] I show that VC funding shocks have significant labor consequences. While

[1]This view aligns with both research on the returns to self-employment and anecdotal accounts: Manso (2016); Luzzi and Sasson (2016); Levine and Rubinstein (2016); Amornsiripanitch et al. (2023), as well as https://hbswk.hbs.edu/item/why-a-failed-startup-might-be-good-for-your-career-after-all; https://thehill.com/blogs/pundits-blog/technology/46081-the-acceptance-of-failure-as-a-spur-to-innovation/; https://www.cbsnews.com/news/facebooks-mark-zuckerberg-insights-for-entrepreneurs/.

[2]In recent decades, companies financed by VC have grown into some of the largest and most influential firms in the economy. Formerly VC-backed companies represented 52% of US IPOs between 2001 and 2023 (Ritter, 2024), and accounted for a staggering 92% of reported R&D expenditures and 93% of patent value

positive shocks to the supply of VC increase local startup employment and job creation, jobs created in "hot" VC markets are significantly shorter-lived, and the rate of job destruction increases. As startups founded in hotter VC markets are more likely to fail, workers in all roles experience higher turnover. However, the longer-term career consequences vary across occupations: STEM (science, technology, engineering, and mathematics) workers who join startups during VC booms experience slower subsequent career progression, while Business (business, finance, and management) workers are less affected. The findings indicate that the career risks of startups are not uniform across workers, but instead, vary with the specificity of workers' human capital investments.

Empirically investigating the implications of VC market shocks for startup workers comes with several data and identification challenges. First, studying these questions requires data on the employees of early-stage, privately-held companies, for which observing employment information is difficult. I address this challenge by constructing a novel dataset of VC-backed firms from Pitchbook matched to the online professional profiles of individuals who have reported working at these companies. These résumés provide rich information on employment and education histories, allowing me to observe the timing of each worker-firm match and track workers' career paths. My matched sample consists of 39 thousand US venture-backed startups linked to over 700 thousand college-educated workers from 2003 to 2018. Using these data, I assemble a panel dataset of VC financing flows and startup labor flows that varies across Metropolitan Statistical Areas (MSAs), industries, and over time. I refer to an MSA-industry pair as a "local market" throughout the paper.

A second empirical challenge is that VC flows may be endogenous: underlying demand shocks could drive changes in both VC investments and the startup labor market. To identify the causal impact of VC flows, I first employ a rich set of fixed effects to directly control for time-varying industry and location shocks. I then combine this with a Bartik-style instrumental variable (IV) approach that exploits differences across local markets in exposures to VC investor shocks. Specifically, I predict VC flows in a given MSA-industry-year using the weighted sum of each investor's nationwide investment activity–excluding activity in that local market–where the weight for each investor is its pre-shock market share.[3] The identifying variation of the IV relies on idiosyncratic differences in pre-shock investor allocations that remain after conditioning on key observables. The exclusion restriction (à la Goldsmith-Pinkham, Sorkin, and Swift (2020)) holds if these idiosyncratic differences relate to future changes in startup labor outcomes through realized VC flows but not through other

among publicly traded firms in 2020 (Gornall and Strebulaev, 2021).

[3] I also show robustness to excluding activity not just in that specific local market (MSA-industry pair), but also in any local market with that industry, MSA, or both.

channels. I provide supporting evidence for this assumption in the analysis. Combined with controls for industry and regional trends, this approach isolates variation in the supply of VC funding plausibly unrelated to local demand shocks.

Using the constructed panel of MSA-industry-year financing and startup labor flows, I first show that shocks to venture capital impact the allocation of high-skill workers, as plausibly exogenous inflows of VC create startup jobs in those markets. Specifically, a doubling of VC investments in a local market increases total startup employment by 39%. While positive shocks to local VC increase venture-backed employment, they also increase startup worker turnover: a doubling of local funding increases separations from startups by 44%. The estimates demonstrate that venture funding creates new startup jobs and also induces job destruction, highlighting the role of risk capital for knowledge worker churn.

After documenting the role of financing for startup job creation and employment, I turn to understanding the consequences for workers in these jobs using an individual-level specification. To address the concern that financing flows are not randomly assigned, I continue to employ the IV approach to isolate exogenous shocks to VC and recover their causal effect on workers. I also control for a host of granular worker characteristics, including differential time trends by occupation, highest educational degree obtained, and university ranking, in addition to a quadratic polynomial in labor market experience. These account not only for general differences between workers along these dimensions, but also for the possibility that workers with, e.g., different educational attainment may be exposed to different labor demand shocks.

I find that startup jobs created in hotter VC markets are shorter-lived. Specifically, a doubling of local VC at the time of hiring increases the likelihood of separating from the startup within two years by 3.5 percentage points, or 8.5% relative to the mean, and these effects are similar across occupations. One possibility is that shorter job durations are driven by mobility within the VC sector, i.e., workers moving from one startup to another. On the contrary, I find that workers who enter hotter VC markets are less likely to work in the VC-backed and formerly VC-backed universe (which includes tech giants such as Meta, Apple, Amazon, and Google) two years later. Specifically, a doubling of local VC at entry reduces the likelihood of working in the venture-backed universe in two years by 3.4 percentage points, or 5.5% relative to the mean.

I establish that these effects are unlikely to reflect differential worker selection in response to funding shocks. I first conduct a series of placebo tests using the worker control variables, which reveal that neither the treatment variable nor the IV systematically predicts differences in ex-ante worker characteristics. In addition to the covariates described above, I also control for each individual's turnover propensity as measured by their historical rate of job switching. I document that the estimates are highly stable and insensitive to the inclusion of these worker controls. I employ two additional tests when studying career advancement. First, I estimate a triple-difference specification that isolates differential effects across occupations. Second, I show that the effects are robust to the inclusion of *origin firm* fixed effects, absorbing productivity differences between workers joining startups from different firms. This imposes a strong restriction on the identifying variation to comparisons of workers leaving the same firm, e.g., Google or Microsoft, for startups.

While shorter job durations could reflect either improved outside options or increased job fragility, the evidence is most consistent with increased job fragility. In particular, I find that startups receiving their first round of funding in hot VC markets are more likely to fail, consistent with Nanda and Rhodes-Kropf (2013). Consistent with higher rates of firm failure, I show that the increase in separations is not explained by workers leaving the firm due to an acquisition or IPO. For further evidence, I turn next to an analysis of workers' subsequent career advancement.

It is not obvious how VC market shocks and the increase in churn that ensues ultimately affect longer-term career progress. Workers who join startups in hot VC markets could gain valuable, transferable skills that accelerate future advancement. Alternatively, increased turnover from failed ventures could lead to productivity losses, particularly if the human capital gained in these positions is highly specific. I proxy for the returns to human capital for workers who join startups using the worker's change in seniority over the next two to five years.[4] I construct seniority following the methodology of Amornsiripanitch et al. (2023), which takes into account not only one's job title, but also the industry and size of one's firm.

I show that the long-term career risks of startups are not borne uniformly across workers, but instead differ by role. In particular, employees in STEM occupations who join startups in hotter VC markets advance slower in seniority in the two to five years after joining. Specifically, a doubling of deal volume at worker entry slows the five-year seniority progression of STEM workers by 15% of the mean change in seniority. This implies a career setback of approximately nine months relative to the average five-year career path of a STEM worker.

In contrast, I find that the career progression of Business employees (those in business, financial, and management occupations) is significantly less affected. This heterogeneity is consistent with the hypothesis that the costs of job churn are higher for workers with more technology-specific skills than for workers with more general human capital. To test this hypothesis more directly, I turn to a measure of technology-skill specificity at the three-digit Standard Occupational Code (SOC) level constructed by Deming and Noray (2020) using

[4]Importantly for this analysis, I am able to track workers' career trajectories beyond their initial startup employment.

skill requirements from job posting data. I find that the effects of hot VC markets are more negative on the advancement of workers in occupations requiring more vintage-specific skills. Specifically, every standard deviation increase in the skill specificity measure raises the negative impact of doubling VC by 17% of the mean seniority progression.

Together, the results highlight the close linkage between financial market risks and labor market risks along the technological frontier. Capital supply plays an important role in the allocation of high-skill labor and startup job creation. As increases in available funding facilitate investments into riskier firms, workers acquire skills related to these firms and their underlying technologies. However, elevated rates of startup failure and increased turnover slow the career advancement of workers who acquire more specialized skills. These findings underscore how workers bear much of the risk inherent in creative destruction and the processes that drive aggregate productivity growth.

Related Literature. This paper contributes to an emerging literature on the labor market for startup employees. This includes studies on the types of workers who join startups (Ouimet and Zarutskie, 2014; Azoulay et al., 2020; Bernstein et al., 2022) and their implications for firm performance (Gupta, Qian, and Sun, 2024; Choi et al., Forthcoming), the preferences of startup workers (Kim, 2018; Bernstein et al., 2021; Bernstein, Townsend, and Xu, 2024), as well as how regulation and policy shocks affect startup hiring (Appel, Farre-Mensa, and Simintzi, 2019; Chen, Hshieh, and Zhang, 2021; Chen and Hshieh, 2024). I contribute by showing that variation in the supply of venture capital affects not only startup hiring but also the career returns to startup employment.

This paper also contributes to the literature on the determinants of entrepreneurial entry and new business formation (Klapper, Laeven, and Rajan, 2006; Babina, 2019; Bellon et al., 2021; Gottlieb, Townsend, and Xu, 2021; Herkenhoff, Phillips, and Cohen-Cole, 2021; Azoulay et al., 2022; Babina, Ouimet, and Zarutskie, 2022; Barrios, Hochberg, and Yi, 2022; Cespedes, Huang, and Parra, 2023; Denes, Lagaras, and Tsoutsoura, 2023; Babina and Howell, 2024; Gupta, 2025; Kwan et al., 2025). I add to this work by demonstrating the role of the supply of early-stage financing for worker mobility to startups, as well as by focusing on the broader labor force at startups, i.e., the non-founder employees, whose careers and human capital outcomes remain less understood.[5] In related work, Hombert and Matray (2023) document a long-term earnings discount of skilled workers who joined the ICT sector

[5]This also relates more broadly to the literature on the allocation of high-skill workers and implications for aggregate productivity growth (Murphy, Shleifer, and Vishny, 1991; Acemoglu et al., 2018; Bell et al., 2018; Hsieh et al., 2019; Bellon et al., 2021; Babina, Bernstein, and Mezzanotti, 2023; Akcigit and Goldschlag, 2023; Celik, 2023; Akcigit, Pearce, and Prato, 2024). This paper documents that shifts in the supply of funding affect the allocation of knowledge workers to entrepreneurial firms and across local markets.

during the late 1990s boom. This paper complements but differs from theirs in several key ways. First, I study the job creation and destruction dynamics of VC-backed startups and the human capital returns to employment at startups. Second, I exploit exogenous variation in VC activity across markets and over time in order to identify its effects on worker reallocation and job turnover. Third, I connect the documented job fragility to career progression risk, and show that this risk is greater for STEM workers and occupations requiring more technology-specific skills.

This paper also contributes to studies on the real economic effects of venture capital (Kortum and Lerner, 2000; Samila and Sorenson, 2011; Bernstein, Giroud, and Townsend, 2016), and to the strands of the literature on the cyclicality of VC (Gompers and Lerner, 2000; Inderst and Müller, 2004; Gompers et al., 2008; Nanda and Rhodes-Kropf, 2013; Opp, 2019; Janeway, Nanda, and Rhodes-Kropf, 2021) and private equity (PE) investments (Kaplan and Stein, 1993; Kaplan and Schoar, 2005; Malenko and Malenko, 2015; Robinson and Sensoy, 2016; Haddad, Loualiche, and Plosser, 2017).[6,7] Young, R&D-intensive firms typically face volatile and uncertain returns, have limited collateral due to intangible assets, and exhaust their internal cash flow, leading to a reliance on external equity financing.[8] Brown, Fazzari, and Petersen (2009) show that shifts in the supply of equity finance can explain large fluctuations in R&D for young, high-tech companies. This paper contributes by examining an important but less understood consequence of supply shocks to equity finance: their effects on skilled labor supplying human capital to the technological frontier.

The rest of the paper proceeds as follows. Section 2 presents the theoretical framework. Section 3 describes the data and sample. Section 4 identifies the effect of VC flows on skilled labor flows. Sections 5 and 6 examine the effect of capital market conditions on startup worker outcomes. Section 7 concludes.

[6] See also studies that examine cyclicality in new equity issues (Ibbotson and Jaffe, 1975; Ritter, 1991; Lowry and Schwert, 2002; Benninga, Helmantel, and Sarig, 2005; Yung, Çolak, and Wang, 2008; Angeletos, Lorenzoni, and Pavan, 2022), or booms and busts in and the financing of innovative firms more broadly (e.g., DeMarzo, Kaniel, and Kremer, 2007; Johnson, 2007; Pastor and Veronesi, 2006, 2009; Kerr and Nanda, 2015; Haddad, Ho, and Loualiche, 2022).

[7] Agrawal and Tambe (2016) find evidence that employees at firms acquired in PE leveraged buyouts gain IT-complementary skills that benefit their careers. Note that the VC- and PE-backed labor markets differ substantially: VCs finance early-stage, high-growth, technology-intensive companies, in contrast to the large, established, and often retail- and services-oriented businesses targeted by PE. As a result, the human capital investments of workers in these roles are also markedly different and come with a unique set of risks.

[8] See also studies on the labor consequences of booms and busts in housing (Begley, Haslag, and Weagley, 2024; Charles, Hurst, and Notowidigdo, 2018) and credit (Blank and Maghzian, 2023) markets.

2 Theoretical Framework

2.1 Venture Capital and the Labor Market

To theoretically motivate the linkages between the supply of venture capital financing and skilled labor flows, I offer a general equilibrium model of VC financing, labor, and technical progress in Appendix A. The model demonstrates how exogenous shocks to the financial sector affect both funding prospects of entrepreneurs and job prospects of knowledge workers. I generate these linkages in a unified framework by introducing a frictional VC fundraising environment (Inderst and Müller, 2004; Wasmer and Weil, 2004; Silveira and Wright, 2016) to workhorse models of frictional labor markets (á la Pissarides, 2000) together with quality-improving innovations that drive economic growth (Aghion and Howitt, 1992; Grossman and Helpman, 1991; Mortensen, 2005; Aghion et al., 2016).

There are extensive literatures on both search and matching frictions and on endogenous growth. Different from previous studies, this work incorporates two-sided matching frictions in both financing and hiring alongside innovation-led growth. The model highlights the importance of the availability of finance for productivity growth, reinforcing the finding of King and Levine (1993), while simultaneously developing its consequences for equilibrium contracts and labor market conditions. Since this paper's primary focus is the empirical analysis of the implications for the startup labor market, the full model is presented in Appendix A and its main predictions are summarized below.

The economy in the model is populated by entrepreneurs, venture capitalists (VCs), and workers. Entrepreneurs have blueprints but lack the funds needed for hiring and production. VCs have capital and resources needed for implementation but no blueprints. Workers engage in the production of intermediate goods or contribute to research efforts. Like firms and workers, entrepreneurs and VCs face a search-and-matching problem à la Pissarides (2000) and bargain over the match surplus to determine the VC's compensation. The multi-sector production environment follows Grossman and Helpman (1991). I prove the existence of a unique, positive equilibrium in Appendix A.

Using the model, I study the equilibrium effects of an exogenous shock to the financial sector. I consider a shock that loosens the financial market while holding the other model primitives constant: a reduction in the VC's entry cost, which leads to an increase in the supply of VC in the economy. The key implication is that shifts in the supply of available funding have real economic consequences for the startup labor market and rate of innovation, as summarized in the following predictions:

Prediction 1. A positive shock to the supply of VC increases capital market competition (i.e., more "money chasing deals") and reduces the time it takes for entrepreneurs to find an available financier. The VC's equity stake falls and deal flow increases.

Prediction 2. A positive shock to the supply of VC increases labor market tightness and job creation as a result of increased new firm entry.

Prediction 3. A positive shock to the supply of VC increases the arrival rate of innovation.

Prediction 4. A positive shock to the supply of VC accelerates technical obsolescence, raising the turnover rate and lowering the expected duration of new jobs.

Proofs of the above predictions are located in Appendix A. The theoretical predictions highlight the role of risk capital in knowledge worker turnover. Increases in the supply of VC lead to "hot" funding markets and more job opportunities at venture-backed firms. While job creation increases in hotter VC markets, these jobs are shorter-lived as the rate of match destruction rises. At the same time, increased funding raises the arrival rate of innovation and consequently the economy's growth rate, highlighting a trade-off in the innovation economy between job fragility and technical progress.

2.2 Hypotheses for Startup Worker Career Progression

Positive shocks to the supply of capital could have differing implications for longer-term career outcomes. On the one hand, the model shows that when VC availability increases, both startup job creation and the arrival rate of innovation rise. Workers who join these firms could acquire valuable skills in frontier technologies that improve their job advancement opportunities. These skills may be transferable across firms or industries, enhancing future productivity even if the startup fails. In addition, the experiences gained in high-growth, innovative settings might be valued in the broader labor market, and could benefit workers when seeking subsequent employment.

On the other hand, the model's prediction of increased turnover suggests potential costs to workers that could slow productivity gains. Job displacement leads to earnings losses that persist beyond the period of unemployment (e.g., Jacobson, LaLonde, and Sullivan, 1993; Couch and Placzek, 2010), due in part to losses of accumulated firm-specific human capital (Becker, 1962; Lazear, 2009). This possibility is especially relevant at startups, where many workers contribute to rapidly evolving technologies and, in doing so, acquire vintage-specific skills (Chari and Hopenhayn, 1991; Violante, 2002; Kogan et al., 2021, 2022). Given the high probability that the firm's technology or product fails to take hold, it is likely that workers at startups could invest in specialized human capital with limited redeployability.

While not required for either hypothesis to hold, certain features of VC investing can amplify market-wide volatility. The model's prediction of increased capital market competition and smaller VC equity stakes aligns with anecdotal accounts of loosened investor discipline to compete for deals in hot markets (Lerner and Nanda, 2020). Due in part to the strong information asymmetries when investing in early-stage high-tech businesses, syndication and staged financing have emerged as common mechanisms in VC investing, generating a tendency to coordinate investments with other investors and potentially amplify booms (Janeway, Nanda, and Rhodes-Kropf, 2021).[9] If periods of capital abundance are followed by contractions in funding, workers may need to find new jobs not only at different firms but also in different technological domains, including those outside the venture-backed sector. This would lower the career returns to technology-specific human capital investments made at the startup, even if these investments were productive.

These hypotheses are not necessarily mutually exclusive, but instead highlight the potential for heterogeneous effects. Workers may gain valuable experience from joining startups during periods of abundant venture funding, when opportunities to engage with frontier technologies are high. At the same time, the accompanying career risks may be greater for workers who acquire more specialized skills as the rate of experimentation and job turnover increase. I now turn to investigating these questions empirically.

3 Data and Sample

Venture Capital Data. I obtain data on venture capital financing from Pitchbook (owned by Morningstar), which provides detailed information on companies, deals, funds, and investors in private capital markets. For this study's sample period of 2002 onwards in particular, Pitchbook has been shown to provide the most comprehensive coverage of VC financing deals relative to other datasets (Garfinkel et al., 2024). Pitchbook has been widely used in academic research, including in many publications in leading economics and finance journals (e.g., Ivashina and Lerner, 2019; Beraja, Yang, and Yuchtman, 2022; Ewens, Gorbenko, and Korteweg, 2022; Becker and Ivashina, 2023; Beraja et al., 2023; Gupta et al., 2023).

I use the company-level and financing round (deal)-level data to observe firm characteristics such as the location and industry of each startup, as well as the timing of each VC investment. In addition, the dataset provides information on the investors matched to each venture capital financing round, which I use in the construction of the instrumental vari-

[9] Additionally, other documented phenomena in securities markets may be relevant when investing in high-growth companies; these include systematic errors in expectations of future growth stemming from over-reaction (La Porta et al., 1997; Barberis, Shleifer, and Vishny, 1998), rationally high investment due to high uncertainty around novel technologies (Pastor and Veronesi, 2009; Johnson, 2007), and changes in prevailing narratives which alter aggregate beliefs (Goetzmann, Kim, and Shiller, 2022; Flynn and Sastry, 2024). These channels are not necessary to generate the implications discussed in this section, but may amplify overall labor market risks.

able. I first obtain the full sample of US-headquartered firms founded after 1995 that have received a completed round of venture capital financing and for which the date of the deal is available. I obtain exit dates for companies that have exited by merging the VC-backed companies with the dates of either a Merger/Acquisition or IPO. Figure C2 in the Appendix shows the geographic distribution of VC investments across Metropolitan Statistical Areas (MSAs). The figure shows that in addition to the concentration of investments in technology hubs like San Francisco, Boston, and New York City, firms in a broad range of geographic areas have received venture capital financing.

Employment Data. I obtain data on individual employment histories from Revelio Labs. These data are sourced from public profiles from online professional networks. A typical profile consists of a user's employment history, which includes the employer name, the start and end dates of employment, the worker's job title, and the geographic location of employment.

I first identify all users who have reported working at a VC-financed firm. I do this by linking the sample of firms from Pitchbook to user job histories using a combination of company profile identifiers, company names, locations, founding years, and years of the company's first VC financing. Of these workers, I keep college-educated workers who report information about where they attended university. Using a combination of the raw job titles and pre-classified roles, I map each position in the data to a standard occupational classification (SOC) code. Within the startup worker sample, I follow Jeffers (2023) in keeping "knowledge workers," that is, workers in occupations that typically require at least a Bachelor's degree according to the Bureau of Labor Statistics.[10] I then impose filters to remove positions that are not full-time employment positions. For example, I drop any instances in which users report internships, participation in professional development programs, or experience on boards of directors.

Next, I restrict the sample to employment at venture-backed startups by removing jobs starting at firms that are no longer venture-backed, i.e., firms that have undergone an exit (acquisition or IPO). Specifically, I keep employment positions up until the year prior to the company's exit, if applicable. For example, I consider employment at Meta Platforms through 2011, the year before its IPO in 2012. Some firms may remain privately-held even as they mature beyond the startup phase. Therefore, for any remaining companies, I also drop positions beginning 15 years after the company's founding year.

In the individual-level analysis, I study the outcomes of workers for several years after they join a venture-backed startup. In order to allow enough time to observe these outcomes, I consider startup jobs beginning in 2018 at the latest. The final sample consists of 38,491

[10]From: https://www.bls.gov/emp/tables/education-and-training-by-occupation.htm

venture-backed firms and 779,298 startup jobs beginning from 2003 to 2018. Appendix D.1 contains further details on the sample construction. Appendix D.2 contains further details on sample coverage and validates the representativeness of the matched sample.

Data Construction. After obtaining the matched sample of startup workers, I retrieve the full employment history of each user in my sample, including any positions before and after their startup experience. This allows me to study worker job mobility and reallocation into and out of startups. I then construct analysis datasets of two different structures. The first dataset aggregates startup employment at the MSA-by-industry-by-year level, which I then link to MSA-by-industry-by-year level VC financing flows. Pitchbook provides industry classifications of varying granularity. In the main text, I present results where the industry classification is the Pitchbook Industry Sector variable. This variable contains seven categories: Information Technology, Healthcare, Materials and Resources, Energy, Financial Services, Business to Consumer (B2C), and Business to Business (B2B). Appendix E presents the estimates at the more granular Industry Group level which consists of 41 industries. For example, this classification differentiates between semiconductors, software, and computer hardware within information technology. I show that the choice of the industry granularity does not impact the results.

The second dataset I construct is an individual-level dataset in which each observation is a job (defined as a worker-firm match). I measure job duration in months using the start and end date of the worker's tenure at a given firm. It is common for workers to report multiple positions over time at the same firm if their job title changes, typically in the case of a promotion. I make use of the job titles when measuring seniority, which I describe in detail below. Importantly, the measurement of job duration takes into account a worker's full tenure at the firm, regardless of title changes.

I now summarize the construction of the seniority variable (further details are located in Appendix D.3). I follow the methodology of Amornsiripanitch et al. (2023), whose measure takes into account not only one's job title, but also the characteristics of one's firm. Specifically, let $T_{i,j,k,q}$ denote the number of years it takes individual i to reach job title j at a firm in industry k and size quintile q. Firm size varies over time and is measured using the firm's employee headcount at year end. Firm size quintiles are then calculated over the distribution of firm size in each year. Seniority is given by:

$$\text{Seniority}_{j,k,q} = \text{Median}(T_{i,j,k,q}) \tag{1}$$

That is, seniority is calculated as the median number of years it takes workers to reach a given job title of firms in a given industry and size quintile. Importantly, I calculate this measure over the full sample of firms, not just over the sample of startup jobs. Appendix Table D7 presents examples of the most common titles in my sample and their corresponding seniority values for the largest and smallest firm size quintiles. In general, more senior titles at larger firms receive higher seniority values than the same titles at smaller firms.

Table 1: Startup Worker Descriptive Statistics

	N	Mean	p25	p50	p75	Std. Dev.
All Workers						
Years of Experience	779,298	8.61	3.00	7.00	12.00	7.51
Seniority	746,474	7.95	5.00	7.00	11.00	4.24
Job Duration in Months	779,298	41.21	14.00	30.00	57.00	35.95
Elite School (Binary Variable)	779,298	0.11	0.00	0.00	0.00	0.31
Highest Degree: Bachelor (Binary Variable)	779,298	0.58	0.00	1.00	1.00	0.49
Highest Degree: Masters Level (Binary Variable)	779,298	0.31	0.00	0.00	1.00	0.46
Highest Degree: Doctoral Level (Binary Variable)	779,298	0.08	0.00	0.00	0.00	0.27
STEM Workers						
Years of Experience	327,405	8.31	3.00	7.00	12.00	7.24
Seniority	315,263	7.32	4.00	7.00	10.00	3.85
Job Duration in Months	327,405	41.92	15.00	31.00	58.00	35.97
Elite School (Binary Variable)	327,405	0.12	0.00	0.00	0.00	0.33
Highest Degree: Bachelor (Binary Variable)	327,405	0.54	0.00	1.00	1.00	0.50
Highest Degree: Masters Level (Binary Variable)	327,405	0.33	0.00	0.00	1.00	0.47
Highest Degree: Doctoral Level (Binary Variable)	327,405	0.10	0.00	0.00	0.00	0.31
Business & Management Workers						
Years of Experience	372,926	9.18	3.00	7.00	13.00	7.78
Seniority	359,798	8.72	5.00	8.00	12.00	4.45
Job Duration in Months	372,926	40.84	14.00	29.00	56.00	35.79
Elite School (Binary Variable)	372,926	0.10	0.00	0.00	0.00	0.30
Highest Degree: Bachelor (Binary Variable)	372,926	0.63	0.00	1.00	1.00	0.48
Highest Degree: Masters Level (Binary Variable)	372,926	0.30	0.00	0.00	1.00	0.46
Highest Degree: Doctoral Level (Binary Variable)	372,926	0.04	0.00	0.00	0.00	0.20
Other Workers						
Years of Experience	78,967	7.17	2.00	5.00	10.00	6.99
Seniority	71,413	6.85	4.00	6.00	9.00	4.03
Job Duration in Months	78,967	40.05	13.00	28.00	56.00	36.51
Elite School (Binary Variable)	78,967	0.08	0.00	0.00	0.00	0.28
Highest Degree: Bachelor (Binary Variable)	78,967	0.54	0.00	1.00	1.00	0.50
Highest Degree: Masters Level (Binary Variable)	78,967	0.25	0.00	0.00	0.00	0.43
Highest Degree: Doctoral Level (Binary Variable)	78,967	0.18	0.00	0.00	0.00	0.38

Note. This table provides descriptive statistics for the sample of startup jobs.

Descriptive Statistics. The final sample consists of 779,298 jobs at 38,491 VC-backed startups, where a job is defined as a worker-firm match. Table 1 presents descriptive statistics of the sample of jobs from 2003 to 2018 for all workers, as well as for subgroups of workers by role: STEM (42%), Business and Management (48%), and Other (10%). Throughout, I follow the Bureau of Labor Statistics in defining STEM roles as computer and mathematical, architecture and engineering, life and physical science occupations, as well as sales engineers.[11] Business and Management workers are defined as workers in business and financial operations occupations, sales occupations (excluding sales engineers), and management occupations. Workers that are not classified as either STEM or Business fall under "Other." These include workers in legal occupations, healthcare practitioners, and media and communications workers.

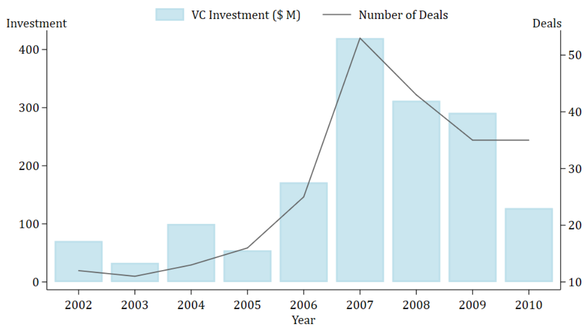
The median number of years of labor market experience at the time of job start is seven years. Early-stage, high-growth startups are risky; over half of the jobs in my sample end within three years. 10% of workers attended an elite university, defined following Amornsiripanitch et al. (2023) as Ivy League plus UC Berkeley, UChicago, Duke, MIT, Northwestern, and Stanford. The highest educational degree attained is a Bachelor's degree for 58% of workers, a Master's level degree for 31% of workers, and a doctoral level degree for 8% of workers. Doctoral level degrees include both research doctorates (i.e., PhD) and professional doctorates such as JD and MD. Attainment of doctoral-level degrees is highest for workers in the Other category at 18%, as this group includes legal and medical professionals.

Figure 1 presents examples of VC investment flows and startup labor flows using the matched dataset. The figure shows several examples from different locations and industries: consumer products and services (B2C) investments in the Boston metropolitan area, energy investments in the San Jose metropolitan area, and financial services investments in the Chicago metropolitan area. Each pair of panels illustrates a specific episode for that MSA-industry pair, highlighting a boom in VC funding before the financial crisis, the clean energy VC boom of 2006 to 2011, and the boom in financial technology VC investments around 2015, respectively. The labor figures show the year-over-year change in startup employment, the rate of hires (startup hires divided by total startup employment), and the rate of separations (separations from startups divided by total startup employment). In these examples, each local market experiences temporal variation in VC investments and contemporaneous changes in venture-backed startup employment. Peaks in funding coincide with peaks in labor entry. The figures also reveal an interesting pattern about labor turnover: the rate of separations from startups rises soon after the peak: in 2008 in Panel (b), in 2011 and 2012 in Panel (d), and in 2016 in Panel (f).

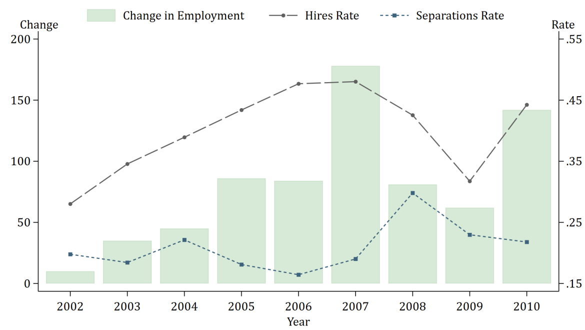
While these graphs provide anecdotal evidence of the strong co-movement between VC

[11] See https://www.bls.gov/emp/tables/stem-employment.htm

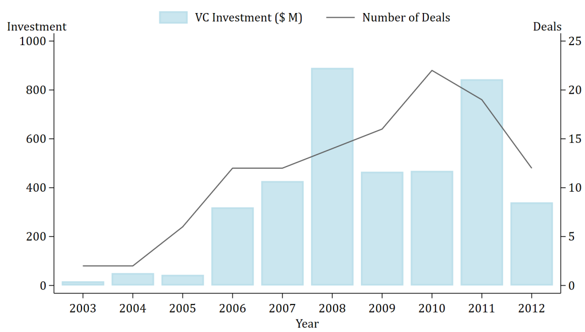
Figure 1: VC and Startup Labor Flows: Examples from Matched Data



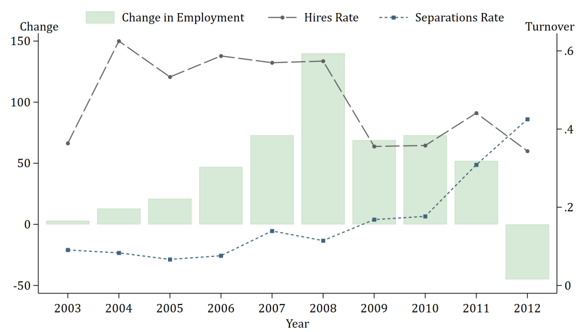
(a) VC Flows: Boston - B2C (Consumer)



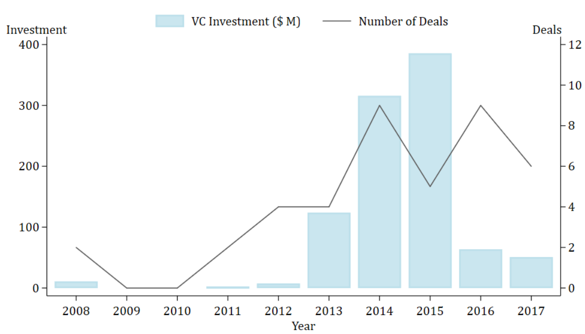
(b) Startup Labor Flows: Boston - B2C (Consumer)



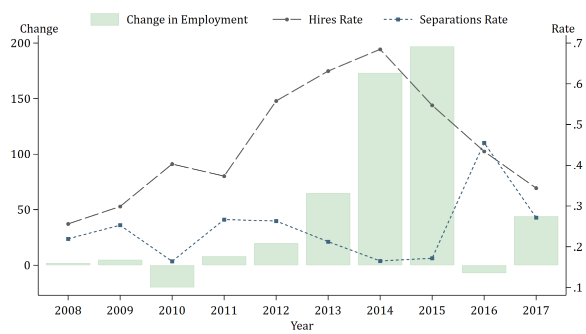
(c) VC Flows: San Jose - Energy



(d) Startup Labor Flows: San Jose - Energy



(e) VC Flows: Chicago - Financial Services



(f) Startup Labor Flows: Chicago - Financial Services

Note. This figure shows examples of venture capital financing flows (left) and startup labor flows (right) at the MSA-industry-year level. Each pair of panels covers a different episode specific to that MSA-industry.

investment volume and startup labor flows, I now turn to a systematic analysis of the relationship across all markets and years in the sample. I investigate whether VC plays a causal role in skilled worker flows and quantify these effects.

4 VC Markets and Skilled Worker Flows

4.1 Empirical Design

I exploit variation in VC financing and employment across regions, industries, and time to understand the impact of VC on knowledge worker flows. I refer to an MSA-industry pair, e.g., Energy investments in Austin, Texas, as a "local market." Consider the following model at the local market-by-year level:

$$\mathbb{E}[y_{s,t} \big| \text{Ln VC Deals}_{s,t-1}, D_{s,t}, \varepsilon_{s,t}] = \exp(\beta \times \text{Ln VC Deals}_{s,t-1} + D'_{s,t}\alpha + \varepsilon_{s,t}) \qquad (2)$$

where $y_{s,t}$ is a nonnegative dependent variable such as startup hiring in market s and year t, and Ln VC $\text{Deals}_{s,t-1}$ represents the natural log of VC investment volume in market s and year $t-1$. I consider lagged VC flows to avoid concerns of reverse causality. $D_{s,t}$ is a vector of control variables which contains, at a minimum, market fixed effects and year fixed effects, and $\varepsilon_{s,t}$ contains unobserved variables.

Because the dependent variable is nonnegative and contains zeroes, I specify the conditional expectation of $y_{s,t}$ in exponential form and estimate the model using Poisson pseudo-maximum likelihood (PPML). This approach is recommended for nonnegative dependent variables that would typically motivate a log transformation but contain zeroes (Silva and Tenreyro, 2006; Chen and Roth, 2023). Importantly, PPML does not require the dependent variable to follow a Poisson distribution, and yields consistent estimates as long as the conditional mean is correctly specified (see Wooldridge, 2010).

The coefficient of interest is β, the elasticity of, e.g., startup hiring with respect to VC investment. It has an elasticity interpretation because the conditional mean is specified in exponential form and the explanatory variable is in logarithmic form. Right-skewness in VC deal volume, the key explanatory variable, motivates a log transformation. Throughout the paper, I add one before taking the natural log of VC to retain observations with zero VC activity. I also explore an alternative specification in which I take the natural log while conditioning on observations with non-zero VC.[12] Appendix D.4 shows that the choice of transformation for the treatment variable is inconsequential for the results.

[12]In the first approach, if x tends to be large, the estimated coefficient on $\ln(x+1)$ can be interpreted as an elasticity as usual. The second approach is a standard subsample analysis.

However, the estimate of β may be biased due to unobservable shocks in $\varepsilon_{s,t}$ that relate to both VC investment volume and startup labor flows in a market. The direction of the bias is not completely obvious. On the one hand, an unobservable investment opportunity that attracts VC financing and increases job creation would generate upward biased estimates of β. On the other hand, omitted factors that increase startup job creation but may be a substitute for venture funding, such as targeted industrial policy, would downward bias the estimate of β.

I address this identification challenge using the combination of two approaches. First, in addition to MSA-industry fixed effects to control for any time-invariant heterogeneity across local markets, I control for demand shocks by introducing industry-by-year fixed effects, absorbing any unobservable confounding channels that can be explained by industry-level shocks, such as technological advancements or changes in industrial policy. I also introduce state-by-year fixed effects to control for confounding variation related to broader regional shocks, or finer MSA-by-year fixed effects to control for changes in local economic conditions.

Next, I turn to an instrumental variable (IV) approach to isolate shifts in the supply of VC available to different local markets. With the IV, a two-step control function method can be used to obtain a consistent estimate of β in a Poisson regression with endogenous regressors and fixed effects (Wooldridge, 2010). I provide further details on this approach in Appendix B.1.

Constructing an IV for Local VC Flows. A growing body of research documents factors unrelated to fundamentals that influence the supply of venture funding. These include, for example, regulatory changes, shifts in limited partner (LP) allocations stemming from unrelated asset classes or macroeconomic conditions, contagion effects within VC portfolios, and the recent increase in non-traditional investor capital (Gompers and Lerner, 2003; Kortum and Lerner, 2000; Ewens and Farre-Mensa, 2020; Townsend, 2015; Chernenko, Lerner, and Zeng, 2020; Brown et al., 2021).[13] This section describes an IV approach that exploits cross-market differences in exposures to common investor-level shocks.

Why would shocks to investors affect the total supply of VC in a local market? VC investors actively monitor and advise their portfolio companies (Lerner, 1995; Hellmann and Puri, 2000, 2002; Bernstein, Giroud, and Townsend, 2016). The strong information frictions present when investing in early-stage innovative companies, together with the accumulation of private information by investors, can lead to "lock-in" between VCs and their portfolio companies (Admati and Pfleiderer, 1994; Townsend, 2015). As a result, it is not costless for

[13]See Lerner and Nanda (2020) and Janeway, Nanda, and Rhodes-Kropf (2021) for more detailed discussions of these factors as well as how features of the venture model may amplify fundamental shocks.

startups to substitute the funding or one investor for another, or for investors to enter new markets. Hence, capital supply shocks to VCs invested in certain local markets are likely to affect the overall supply of funding in those markets.

These features motivate a shift-share-style approach (Bartik, 1991; Blanchard and Katz, 1992). Let $I_{s,j,t}$ denote the VC investments of investor j in market (MSA-industry pair) s, year t, and $w_{s,j,t}$ denote the market share of investor j in market s, year t. Define

$$\text{Predicted VC}_{s,t} = \sum_j \left(w_{s,j,t_0} \sum_{s' \neq s} I_{s',j,t} \right) \tag{3}$$

That is, VC flows in a given MSA-industry-year are predicted by interacting each investor j's national investment activity (i.e., across all markets) in year t, excluding any activity in market s, with j's market share of s in $t_0 \leq t$. Since VC fund life typically ranges from five to ten years, I let t_0 take the values of 2001, 2007, and 2013. This application of the shift-share approach is most similar in nature to Greenstone, Mas, and Nguyen (2020), who interact pre-existing bank market shares with national changes in bank lending to study the consequences of credit supply shocks. Throughout the paper, I use the natural log of predicted VC as the instrument. The IV satisfies the relevance condition; across specifications, the smallest first-stage F-statistic is 32.

For intuition, consider the example of Softbank, which received a \$45 billion investment from the Saudi Public Investment Fund in 2017 before closing its \$93 billion Vision Fund in May 2017. According to the Pitchbook data, Softbank's total number of US VC investments grew 74% from 2016 to 2018. Meanwhile, the VC firm New Enterprise Associates grew US investments by 15% from 2016 to 2018. The intuition of the IV approach is that local markets with a higher exposure to Softbank relative to New Enterprise Associates in 2013 would have experienced a larger increase in available capital over this period.

The identifying assumption for the instrument is that the pre-period investor market shares are exogenous conditional on observables (Goldsmith-Pinkham, Sorkin, and Swift, 2020).[14] That is, $\mathbb{E}[\varepsilon_{s,t} w_{s,j,t_0} | D_{s,t}] = 0$, where $D_{s,t}$ is a vector of control variables. In other words, the differential effect of a higher initial exposure to one VC (compared to another) only affects changes in the outcome through the endogenous variable of VC investments.[15,16]

[14] Borusyak, Hull, and Jaravel (2021) show consistency of the Bartik IV estimator under many exogenous and independent shocks. Adao, Kolesar, and Morales (2019) derive inference methods under general conditions.

[15] Note that given the inclusion of local market (MSA-industry) fixed effects, the assumption only requires that the initial shares are exogenous to future *changes* in the outcome (as opposed to levels).

[16] This identifying assumption is analogous to the parallel trends assumption in difference-in-differences designs that treated and control units would evolve on similar trends in the absence of treatment.

Since the exposures are not randomly assigned, threats to exogeneity would be confounding factors related to the shares and also related to future changes in startup hiring through means other than realized VC flows.

I now discuss how the components of $D_{s,t}$ isolate plausibly exogenous variation in the investor shares. Importantly, industry-by-year fixed effects ensure that identification comes from within-industry comparisons. This alleviates concerns about confounding industry-level shocks, including the possibility that differential exposures could reflect differences in investment mandates. Similarly, state-by-year fixed effects or finer controls for MSA-by-year fixed effects address the concern that shares could be co-determined with local economic conditions. The individual-level design described in Section 5 further conditions on characteristics of the labor force by additionally accounting for differential time trends by occupation, educational attainment, and university ranking. Consequently, the identification exploits residual variation in the pre-shock exposures purged of industry, location, occupation, and education specific trends. The identifying assumption, then, is that *idiosyncratic differences* in pre-shock investor allocations do not predict future changes in startup worker outcomes through channels other than *realized VC investments*, the endogenous variable.

While the exclusion restriction is not directly testable, several pieces of evidence support its validity. Appendix C.3 shows that funding flows predicted by the shift-share have little correlation with the observable characteristics of workers in those markets. This suggests that the pre-shock exposures are not systematically related to the composition of local labor markets. Appendix E.1 shows the results are similar under three variants of the leave-out groups for investors' national VC activity, including leaving out investments in any market of the same region *or* industry. Appendix E.4 verifies that the estimates are similar when conducting the analyses at the more granular industry level and controlling for these granular industry shocks. This specification relies on variation in the shares within specific technology groups, e.g., Semiconductors, Healthcare Technology Systems, or Computer Hardware. The stability of the estimates across designs provides further support for the IV's validity.

4.2 Effects on Startup Labor Flows

I now turn to estimating the effect of VC flows on job creation and destruction at the local market level. Given that the dependent variables are nonnegative and in some MSA-industry-years take the value zero, I estimate Poisson pseudo maximum likelihood (PPML) regressions. I consider three outcomes of interest: (i) hires, defined as hires by VC-backed startups in a given MSA-industry-year, (ii) separations, defined as worker exits from VC-backed startups in a given MSA-industry-year, and (iii) total startup employment, defined as workers at VC-backed startups in the MSA-industry at year end.

Table 2 presents results. Since the conditional mean is modeled in exponential form and the right-hand side variable considers the natural log of VC investments, the estimates recover elasticities of labor flows with respect to VC flows. Panel A presents the estimates of the PPML regression and Panel B presents the IV PPML regression estimates. Each column contains industry-by-year fixed effects, absorbing any confounding channels that can be explained by industry shocks. Columns (2), (4), and (6) additionally include state-by-year fixed effects, controlling for any changes in statewide economic conditions. Panel B uses the control function estimator obtained from a two-step estimation procedure as described in Wooldridge (2010). Additional details on this approach are located in Appendix B.1. Standard errors are clustered by MSA-industry and are obtained via bootstrap.

Table 2: The Effect of Increased Capital on Startup Labor Flows

	Startup Employment		Startup Hires		Startup Separations	
	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML
Panel A. PPML Estimates						
Ln VC Deals $(t-1)$	0.327***	0.273***	0.309***	0.268***	0.367***	0.308***
	(0.043)	(0.035)	(0.047)	(0.041)	(0.046)	(0.038)
Panel B. IV PPML Estimates						
Ln VC Deals $(t-1)$	0.518***	0.440***	0.437***	0.364***	0.627***	0.521***
	(0.147)	(0.132)	(0.150)	(0.136)	(0.150)	(0.140)
FE: MSA × Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: State × Year		Yes		Yes		Yes
First Stage F-Stat	249.72	228.00	249.72	228.00	249.72	228.00
Mean	61.07	61.07	26.63	26.63	13.91	13.91
Observations	47,253	47,253	47,253	47,253	47,253	47,253

Note. This table shows the effect of increased capital on startup job creation, destruction, and net employment. The sample includes college-educated workers at US VC-backed startups. Each observation is an MSA-industry-year. The dependent variable in columns (1) and (2) is total employment of VC-backed startups as of year end. The dependent variable in columns (3) and (4) is the number of startup hires. The dependent variable in columns (5) and (6) the number of worker separations from startups. Ln VC Deals $(t-1)$ is the natural log of VC deals in the MSA-industry in the year prior. Panel A presents the PPML estimates while Panel B presents IV PPML estimates using the shift-share instrumental variable. The IV PPML estimates are obtained from a two-step control function approach, described in Appendix B.1. Standard errors reported in parentheses are clustered by MSA-industry, and are obtained by bootstrap in Panel B. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

Throughout, I consider the effect of a doubling in local VC, which is given by $[\exp(\hat{\beta}\ln(2))-1]\times 100\%$.[17] Panel B, column (4) shows that a doubling of local VC increases startup hiring

[17] Since I consider a large percent increase, I do not use the usual small change approximation for a 1% increase.

by 31%, and column (6) shows that a doubling of local VC increases worker separations from startups by 44%. An increase in worker reallocation to startups may directly imply that separations from other firms increase. However, this estimate shows that lagged deal volume predicts an increase in startup separations as well, suggesting that the startup jobs themselves are shorter-lived. Note that the larger elasticity for separations does not imply that net startup employment falls, as the sample mean of hires is almost twice as large as that of separations. Indeed, Column (2) shows that a doubling of local VC increases aggregate VC-backed startup employment by 39%.[18]

While the IV estimates are larger than the PPML estimates in magnitude, the PPML estimates fall within the 95% confidence intervals for the IV PPML point estimates – except in the case of separations. The larger IV estimate for separations is consistent with the prediction of the theoretical framework that non-fundamental supply shocks to VC increase the rate of job destruction. For startup employment and hires, the larger IV magnitudes are consistent with two potential explanations.[19] The first is that the non-instrumented estimates are downward biased. This could be the case if there are omitted factors that may correlate negatively with VC flows but also increase local startup employment. One potential example is targeted industrial policy that could potentially crowd out private investment. The second explanation is treatment effect heterogeneity. In other words, the IV estimate recovers the average treatment effect for local markets whose VC flows are more sensitive to general supply shocks of existing investors. These may be markets where ex-ante financial constraints or information frictions are high, and consequently, firm investment and job creation are more sensitive to changes in funding availability.

These results are highly robust. Appendix Table E8 presents the estimates with three different variants of the leave-out group of the shift-share IV, including leaving out investor activity in any market of the same region or industry. Appendix Table E9 shows the results continue to hold after dropping Silicon Valley, indicating that the effects are not driven by this specific region. Appendix Table E10 shows the estimates are robust to the specification with fully saturated fixed effects, which includes the set of MSA-by-Industry, Industry-by-Year, and MSA-by-Year fixed effects. The magnitudes of the IV estimates are highly robust, but the standard errors are slightly larger due to the reduced degrees of freedom. Appendix Table E11 shows the stability of the estimates when conducting the analysis at the MSA-

[18]Note that these regressions aim to recover the role of VC flows for job creation and job destruction at startups, as opposed to aggregate employment effects. Samila and Sorenson (2011) estimate the effect of VC on total MSA-level employment over the period of 1993 to 2002. Because Table 2 estimates percent increases in startup employment rather than percent increases in aggregate employment across all firms, the elasticities are larger than those of Samila and Sorenson (2011).

[19]Samila and Sorenson (2011) estimate an IV estimate around five times larger than OLS on log employment.

industry group (granular industry) level.

Overall, positive shocks to local VC increase skilled worker flows into startups in these markets. However, high investment volume also leads to an increase in worker separations the following year. The IV estimates show that the effect on separations is more pronounced when deal volume can be explained by investor supply shocks as opposed to market-specific demand. The finding on startup separations suggests that, consistent with the theoretical prediction in Section 2, jobs created amid positive capital supply shocks may be shorter-lived. I directly explore this using job-level data in the next section. Thus far, the findings underscore a tension implied by the theory between labor turnover and longer-term productivity, as jobs created amid increases in risk capital may be less stable but also help propel technological progress.

5 VC Markets and Startup Worker Outcomes

The previous section documents that VC shocks play a causal role in the allocation of skilled labor to high-growth startups. I now turn to the key question of the consequences of these shocks for worker outcomes.

5.1 Individual-Level Empirical Strategy

I begin by describing the empirical strategy for the analysis at the individual level, which aims to identify the effect of capital supply shocks on shorter-term job outcomes and longer-term career outcomes. The specification takes the following form, where each observation is an individual i starting a job at a VC-backed startup in local market s in year t:

$$y_{i,t+k} = \beta \times \text{Ln VC Deals}_{s,t-1} + \gamma_s + x'_{i,t}\delta + \theta_{s,t} + \epsilon_{i,t}. \tag{4}$$

Here, $y_{i,t+k}$ is a worker-level dependent variable, such as seniority k years after joining the startup. As before, β is the coefficient on lagged VC investments in market s and is the estimand of interest. An identification concern is that omitted factors that may be correlated with both VC flows and employee career outcomes may lead to biased estimates of β. For example, suppose markets that experience increased funding are markets with a larger supply of highly productive workers. These workers are likely to advance faster along the job ladder, leading to an upward biased estimate of β. I now describe how I address this concern. First, at a minimum, the specification includes MSA-industry fixed effects γ_s to absorb baseline differences of workers across local markets, as well as year fixed effects to account for general differences in job characteristics over time.

Next, I continue to employ the shift-share IV described in Section 4 as an instrument for the treatment variable of interest Ln VC Deals$_{s,t-1}$. This allows me to isolate exogenous shifts in the availability of venture funding across markets. Intuitively, one can think of the job-level design as comparing changes in average worker outcomes around a capital supply shock in a market to contemporaneous changes in the outcomes of workers in unaffected markets. When using the shift-share 2SLS estimator, these differences in capital supply are driven by idiosyncratic differences in pre-shock investor exposures. In addition, the specification further restricts the identifying variation to within-industry or within-MSA comparisons through the introduction of industry-by-year or MSA-by-year fixed effects, contained in $\theta_{s,t}$. This controls for unobservable confounds that can be explained by time-varying industry or local economic conditions.

Moreover, the individual-level design allows me to further restrict the identifying variation to comparisons of observably similar workers at the same point in time. I start by controlling for observable cross-worker differences in a vector of covariates $x_{i,t}$, which contains a quadratic polynomial in labor market experience, occupation-by-year fixed effects, as well as highest educational degree-by-year fixed effects. In addition, a unique benefit provided by the résumé data is the ability to observe the school attended by each worker. I additionally introduce $1\{\text{elite university}\}$-by-year fixed effects in $x_{i,t}$, where I follow Amornsiripanitch et al. (2023) in defining elite university as Ivy League schools plus UC Berkeley, UChicago, Duke, MIT, Northwestern, and Stanford. These controls account not just for general differences along these dimensions but also for the possibility that workers of different occupations or educational attainment face different time-varying labor demand shocks.

Workers might also differ in their innate propensities to switch jobs. To the extent that this is not already accounted for by differences in educational attainment, occupation, and years of experience, I directly address this by additionally controlling for each worker's *historical turnover rate*, measured as the number of jobs the worker has held in the past scaled by the number of months in the labor force at the time of joining the startup.

Finally, when studying long-term career outcomes, I show that the effects are robust to the inclusion of *origin firm* fixed effects, absorbing average differences in productivity between workers joining startups from different firms. This specification further restricts the identifying variation to comparisons of workers leaving the same firm, e.g., Google or Microsoft, for startups.

Covariate Balance. After establishing the empirical design, I test for observable relationships between the worker covariates and VC flows in Appendix Tables C2 and C3. In these tests, I estimate Equation (4) with each worker characteristic as a dependent variable, but without controlling for any other worker characteristics other than occupation. Table C2 investigates the relationships between worker characteristics and realized VC flows, while Table C3 investigates the relationships with predicted VC flows (used as the instrument). The estimates reveal a lack of clear relationships between either realized or predicted VC flows and observable characteristics of workers in those markets. In particular, Table C3 shows that the variation isolated by the shift-share instrument does not relate to university ranking, educational attainment, or pre-startup seniority in a statistically and economically significant way. This provides further support for the validity of the IV (Goldsmith-Pinkham, Sorkin, and Swift, 2020). There does appear to be a negative relationship between years of experience and the IV for Business workers. I control for a quadratic polynomial in labor market experience in all specifications.

Consistent with the covariate balance shown above, I find that controlling for additional worker characteristics does not impact the estimates. Appendix Figure C3 displays the coefficient estimate from Equation (4) when progressively saturating the specification with controls for worker experience, education, and turnover history. The stability of the estimate when conditioning on observables provides additional support for the identifying assumption (e.g., Oster, 2019).

5.2 Effects on Job Duration and Reallocation

I first turn to studying the effects of capital market conditions on job duration and worker reallocation. Table 3 reports the estimates of Equation (4). Panel A estimates the impact of increased VC at the time of hiring on the likelihood that a worker leaves the startup within 24 months. The OLS estimates are reported in columns (1) through (3) while the corresponding 2SLS estimates are reported in columns (4) through (6). Standard errors are clustered by MSA-industry-year to account for serial correlation among jobs started in the same local labor market.

The 2SLS estimates show that a doubling of local VC at the time of hiring increases the likelihood that the worker separates from the startup within two years by 3.9 percentage points.[20] The mean separation rate within two years is 0.41. Thus, this corresponds to a 9.5% effect relative to the mean. The magnitudes of these estimates match the estimated elasticities when I directly use the natural log of job duration in months as the dependent variable, as shown in Appendix Table F13. In additional robustness tests, Appendix Table F14 shows the results are highly robust to controlling for each worker's turnover rate prior to joining the startup, and Appendix Table F15 shows the results hold when controlling for more granular industry shocks.

[20]From $\hat{\beta}\ln(2)$ where $\hat{\beta}$ is obtained from column (4).

Table 3: The Effect of Increased Capital at Time of Hiring on Job Duration and Reallocation

Panel A.	Dependent Variable: Leave Startup within Two Years					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Ln VC Deals ($t-1$)	0.018***	0.018***	0.015***	0.056***	0.059***	0.051**
	(0.002)	(0.002)	(0.003)	(0.016)	(0.023)	(0.022)
Dependent Var. Mean	0.41	0.41	0.41	0.41	0.41	0.41
Panel B.	Dependent Variable: Work in VC-Backed Universe ($t+2$)					
Ln VC Deals ($t-1$)	-0.005**	-0.006**	-0.011***	-0.049***	-0.049**	-0.042*
	(0.003)	(0.003)	(0.003)	(0.016)	(0.023)	(0.022)
Dependent Var. Mean	0.62	0.62	0.62	0.62	0.62	0.62
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: MSA × Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Occupation × Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry × Year		Yes			Yes	
FE: MSA × Year			Yes			Yes
First Stage F-Stat				131.31	69.85	90.30
Observations	779,298	779,298	779,298	779,298	779,298	779,298

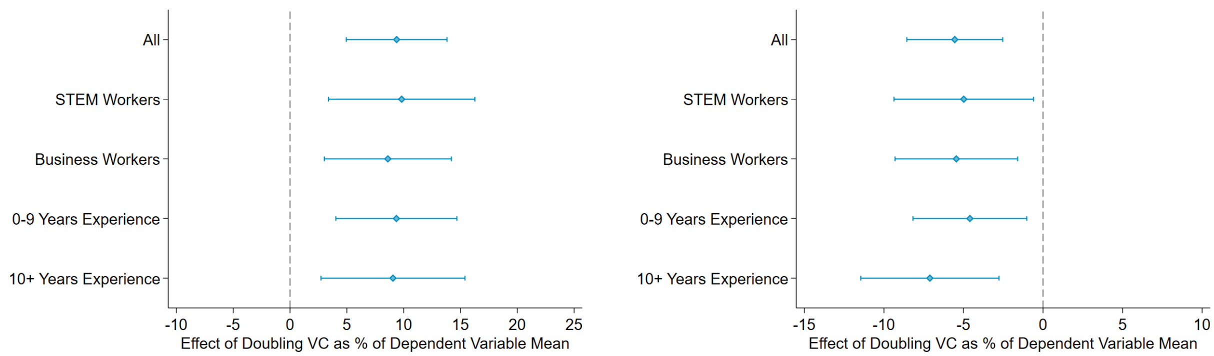
Note. This table shows the effect of increased capital at the time of hiring on the likelihood that (i) the worker separates from the firm and (ii) the worker remains in the universe of venture-backed firms. Each observation is an individual starting a job in year t at a VC-backed startup in local market (MSA-industry pair) s. In Panel A, the dependent variable is an indicator equal to one if the worker leaves the startup within 24 months and zero otherwise. In Panel B, the dependent variable is an indicator equal to one if the worker is employed in the VC-backed universe at the end of calendar year $t+2$ and zero otherwise. Ln VC Deals is the natural log of VC deals in local market s in year $t-1$. Individual Controls include a quadratic polynomial in labor market experience at job start, highest degree-by-year fixed effects, and elite university-by-year fixed effects. OLS estimates are shown in columns (1) through (3) and 2SLS estimates are shown in columns (4) through (6). Standard errors are clustered by MSA-industry-year and are reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

A natural question is whether workers are leaving their startups to join different startups, or perhaps to join formerly VC-backed companies such as the Big Tech firms. I examine this in Table 3 Panel B, where the dependent variable is an indicator equal to one if the worker is still employed in the universe of venture-backed and formerly venture-backed firms at the end of calendar year $t+2$ (where year t is the year they join the startup), and zero otherwise. Column (4) shows that a doubling of local deal volume at the time of joining reduces the likelihood of working in the VC-backed universe two years later by 3.4 percentage points (computed from $-0.049 \times \ln(2)$). This corresponds to a 5.5% effect relative to the mean retention rate of 0.62.

Figure 2 shows that these effects are not concentrated among particular subgroups. I compare workers in different occupations (STEM versus Business) as well as workers of different experience levels (0-9 years of experience or greater than 10 years of experience).

All estimates are scaled to show the effect of doubling VC as a percentage of the dependent variable mean. The figure shows that the job duration and reallocation effects are similar across groups.[21]

Figure 2: Worker Separation and Reallocation Effects by Subgroup



(a) Leave Firm $(t+2)$ (b) Work in VC-Backed Universe $(t+2)$

Note. This figure shows the effect of increased capital at the time of hiring on the likelihood of worker separation from the startup and VC-backed universe by subgroup: STEM workers, Business workers, workers with 0 to 9 years of experience, and workers with at least 10 years of experience. The figure plots the effect of doubling VC as a percentage of the dependent variable mean, calculated as $\hat{\beta}\ln(2)/\text{Mean} \times 100\%$ where $\hat{\beta}$ is estimated from Equation (4) by 2SLS. In Panel (a), the dependent variable is an indicator equal to one if the worker leaves the startup within 24 months and zero otherwise. In Panel (b), the dependent variable is an indicator equal to one if the worker is employed in the VC-backed universe at the end of calendar year $t+2$ (where year t is the year the worker joins the startup) and zero otherwise. Additional details on the regression model can be found in Table 3. Standard errors are clustered by MSA-industry-year and 90% confidence intervals are shown.

It is also worth noting that the 2SLS estimates are larger than the OLS estimates. This suggests that when high VC deployments are driven by exogenous increases in capital rather than market-specific fundamental shocks, jobs are increasingly shorter-lived and workers are more likely to leave the VC-backed universe.[22]

Turnover Mechanism. Shorter-lived jobs in hot financing markets could be explained by either an increase in job fragility or an improvement in one's outside option. The evidence

[21] The effect on high-experience workers leaving the VC-backed universe appears somewhat larger, but is not statistically different from the others.

[22] This is also consistent with a treatment effect heterogeneity interpretation as the IV estimator recovers a local average treatment effect (Imbens and Angrist, 1994). Markets more sensitive to the instrument are those for which early investor exposures are relevant and funding correlates more strongly with national VC flows. These may be markets that face tighter financial constraints or where information frictions are more severe ex-ante. Jobs created in response to supply shocks in these markets are likely to be more fragile as firm investment is sensitive to funding availability.

I find is most consistent with job fragility. First, I document that startups receiving their first funding round in hotter VC markets are more likely to fail, consistent with the findings of Nanda and Rhodes-Kropf (2013). Appendix C.2 presents this analysis.

Consistent with the finding of increased firm failures, I show that the increase in separations is not driven by the firm becoming acquired or going public. Appendix Table F12 presents the job duration analysis but additionally drops any positions starting within the three years prior to an acquisition or IPO, if applicable. For the remaining workers, any separations from the firm within two years must have occurred long before the firm's change in ownership. The stability of the estimates shows that firm acquisitions or IPOs do not explain the finding of shorter-lived jobs. This is especially indicative of job fragility in the startup setting, where workers typically earn submarket salaries but hold equity claims that pay off if the firm achieves a successful exit (Hall and Woodward, 2010).

In summary, evidence from startup outcomes, workers' subsequent employers, and the timing of the worker separations indicate that job fragility increases in hot VC markets. I turn next to an analysis of workers' subsequent job ladder advancement.

6 VC Markets and Startup Worker Career Progression

6.1 Measuring Career Progression

I now turn to studying the career progression of startup workers. Workers who join startups in capital-abundant markets could gain valuable skills and experience that, if transferable, could lead to productivity gains and career advancement, regardless of whether they remain at the firm. Alternatively, increased job fragility from more failure-prone startups could slow career advancement, especially if the human capital gained in the position is highly firm- or technology-specific.

I measure career progression using worker seniority, constructed following the methodology of Amornsiripanitch et al. (2023). Appendix D.3 contains details on the construction of this measure in my sample. One challenge that arises with using job titles is that organizational hierarchies may differ across firms. This measure addresses this challenge by accounting for differences in the meanings of titles that may be systematic to different industries or firm sizes, which are two key dimensions along which hierarchical structures may vary. For example, the title "Vice President" typically denotes a different level of seniority at financial services firms than it does at technology corporations. I obtain a seniority value for each job title–industry–firm size quintile combination by calculating, over the full sample of employment, the median number of years it takes individuals to reach that title at firms of a given industry and size. Appendix Table D7 shows that in general, more senior job titles at larger firms receive higher seniority scores than the same titles at smaller firms.

Another possibility is that different firms (even of the same size and industry) could use different nomenclatures. For example, one firm might use "Senior Software Engineer" while another firm might use "Software Engineer III" to denote the same level position. This challenge is addressed by the way seniority is constructed: scores are calculated for each possible job title with a sufficient number of observations over the full sample of employment. Over a large distribution, job titles that denote similar levels should ultimately receive similar seniority scores.

Finally, this measure is economically meaningful. Using a dataset of US job postings, Marinescu and Wolthoff (2020) find that job titles explain more than 90% of the variance in posted firm wages. Even after conditioning on six-digit SOC codes, jobs with more senior or managerial titles tend to offer higher wages. Their findings, together with the validation tests in Amornsiripanitch et al. (2023), indicate a strong correlation between seniority (as measured by job titles) and earnings.

In this analysis, I consider each worker's first entry into a startup in calendar year t. I then measure seniority as of the worker's latest employment position in calendar year $t+2$. I estimate Equation (4) with seniority in $t+2$ as the dependent variable while controlling for initial seniority in year t on the right-hand side. To understand the timing of these changes, I additionally estimate the model for each time period from $t+1$ to $t+5$, where seniority is measured from the last employment position observed in each year.

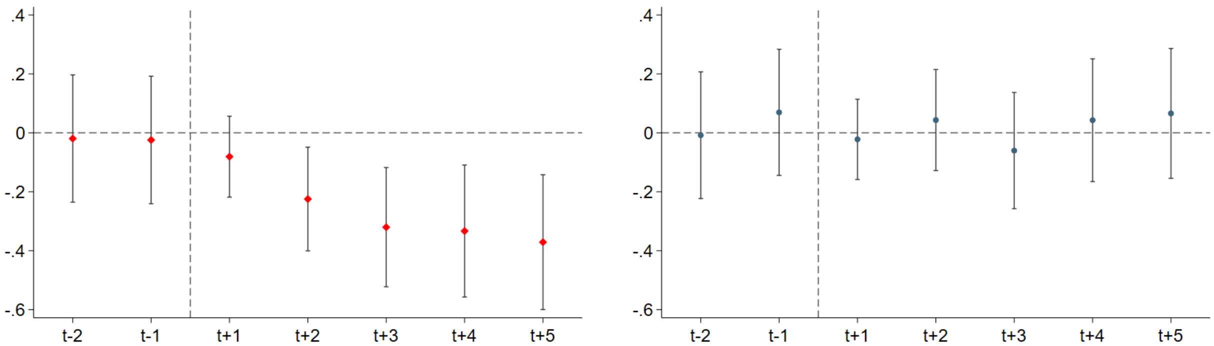
6.2 Effects on Seniority

Figure 3 plots the 2SLS coefficient estimates of β in Equation (4) estimated separately for STEM and Business workers. Panel (a) shows that for STEM workers, the effect of hotter VC markets on seniority progression is not distinguishable from zero one year later, but becomes negative two years following the entry year. Note that the negative coefficient estimates do not necessarily indicate declines in seniority; rather, they imply that STEM workers who enter hotter VC markets advance slower in seniority relative to their counterparts who entered less hot markets.

One concern could be that STEM workers who enter hotter VC markets are on a downward seniority trajectory even prior to joining the startup. I check for this by plotting dynamics. In addition to estimating effects one to five years after the worker's first startup experience, I also consider seniority in years $t-1$ and $t-2$. The pre-startup estimates are close to zero and not statistically distinguishable from zero, ruling out the concern that the workers are on different career trajectories prior to joining.

Turning to magnitudes, the coefficient estimate for year $t+2$ is -0.28, meaning that a

Figure 3: The Effect of Increased Capital at Worker Entry on Seniority Advancement



(a) STEM Workers

(b) Business Workers

Note. This figure shows the effect of increased capital at the time of hiring on subsequent career progression. Each observation is an individual beginning their first job at a VC-backed startup in year t and local market (MSA-industry pair) s. Equation (4) is estimated where the dependent variable is seniority in year $t+k$ for $k \in \{-2, 5\}$. The figure plots the 2SLS estimate of the coefficient on Ln VC Deals$_{s,t-1}$, the natural log of VC deals in local market s in year $t-1$. Panel (a) shows the estimates for workers in STEM occupations, and Panel (b) shows the estimates for workers in business, financial, and management occupations. Additional details on the regression model can be found in Table 4. Standard errors are clustered by MSA-industry-year and 90% confidence intervals are shown.

doubling of local VC lowers two-year seniority progress by $\hat{\beta}\ln(2) = 0.19$ units. The effect persists and grows over time, reaching -0.26 seniority units in year $t+5$. The average five-year seniority change for STEM workers is 1.7. Therefore, a doubling of deal volume at entry hinders seniority progress for STEM workers by 15% of the average change. Put differently, STEM workers who join hot VC markets are set back approximately 15% $\times$ 5 years = 9 months relative to the average career path over the next five years.

In contrast, Panel (b) of Figure 3 shows that the seniority advancement of Business workers is less affected by the initial funding environment, as none of the estimates is statistically distinguishable from zero.

Table 4 Panel A quantifies the difference in the effect for STEM workers versus non-STEM workers and tests whether this difference is statistically significant. I regress seniority in year $t+2$ on the variable Ln VC Deals$_{s,t-1}$ and its interaction with the STEM worker indicator. (The main effect for the STEM indicator is absorbed by the occupation fixed effects). Columns (1) through (4) report the OLS estimates, where each column controls for a different set of industry- and location-by-year fixed effects, while Columns (5) through (8) report the analogous 2SLS estimates. Due to the interaction term, there are two endogenous variables and two instrumental variables in the 2SLS regressions, where the instruments are the IV for Ln VC Deals$_{s,t-1}$ and the interaction between the IV and the STEM indicator. To separately identify the effects, the market (MSA-industry) fixed effects in Panel A are further interacted with the STEM indicator, controlling for baseline differences between STEM and non-STEM workers within each local market.[23]

Table 4: The Effect of Increased Capital at Worker Entry on Seniority Advancement

	Dependent Variable: Seniority $(t+2)$							
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) 2SLS	(6) 2SLS	(7) 2SLS	(8) 2SLS
Panel A.								
Ln VC Deals $(t-1)$	0.031**	0.035**	0.035**	0.019	0.044	0.004	0.019	0.169
	(0.016)	(0.016)	(0.017)	(0.018)	(0.097)	(0.127)	(0.190)	(0.126)
Ln VC Deals $(t-1)$	-0.060**	-0.062***	-0.064***	-0.063***	-0.326**	-0.340**	-0.311**	-0.272*
$\times$ *STEM Worker*	(0.024)	(0.024)	(0.024)	(0.024)	(0.151)	(0.153)	(0.152)	(0.152)
Panel B.								
Ln VC Deals $(t-1)$	0.006	0.009	0.007	-0.007	-0.060	-0.098	-0.062	0.093
	(0.012)	(0.013)	(0.013)	(0.015)	(0.078)	(0.120)	(0.203)	(0.111)
Ln VC Deals $(t-1)$	-0.024**	-0.023**	-0.025**	-0.028**	-0.176**	-0.172**	-0.171**	-0.169**
$\times$ *Skill Specificity*	(0.011)	(0.011)	(0.011)	(0.011)	(0.075)	(0.075)	(0.075)	(0.077)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: MSA $\times$ Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Occupation $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry $\times$ Year		Yes	Yes			Yes	Yes	
FE: State $\times$ Year			Yes				Yes	
FE: MSA $\times$ Year				Yes				Yes
First Stage F-Stat					129.49	67.39	32.35	89.73
Observations	627,312	627,312	627,312	627,312	627,312	627,312	627,312	627,312

Note. This table shows the effect of increased capital at the time of hiring on subsequent career progression. Each observation is an individual beginning their first job at a VC-backed startup in year t and local market (MSA-industry pair) s. The dependent variable is the worker's seniority at the end of calendar year $t+2$. Ln VC Deals$_{s,t-1}$ is the natural log of VC deals in local market s in year $t-1$. Panel A includes an interaction term between this variable and an indicator for whether a worker is a STEM worker. Panel B includes an interaction term between Ln VC Deals and the rate of skill change measure from Deming and Noray (2020). Individual Controls include initial seniority in year t, a quadratic polynomial in labor market experience at job start, highest degree-by-year fixed effects, and elite university-by-year fixed effects. OLS estimates are shown in columns (1) through (4) and 2SLS estimates are shown in columns (5) through (8). Standard errors are clustered by MSA-industry-year and reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

In all specifications, the effect of increased capital on seniority progression is more negative for STEM workers than for other workers, and the difference is statistically significant. While the OLS estimates also imply a negative total effect for STEM workers, the 2SLS esti-

[23] The results are unchanged if I interact with occupation and allow for separate intercepts for each occupation within a local market.

mates are more negative than OLS.[24] This is consistent with the previous results: when high VC deployments are driven by increases in supply rather than market-specific fundamental shocks, jobs are shorter-lived and subsequent seniority advancement is slower.

Potential Alternative Explanations. I now discuss several potential alternative explanations and explain why these are unlikely to account for the result. I first further establish that differential selection into hot VC markets does not explain the observed effects. First, recall that the research design compares observably similar individuals by including granular worker-level controls for education and past experience. Second, placebo tests with worker characteristics as the dependent variable (Table C3) show that VC market shocks do not systematically predict differences in the average characteristics of either STEM or Business workers.

Next, I conduct a series of tests that address the possibility of selection on unobservables. Table 4 presents a triple-difference specification that examines whether the effect of funding conditions differs across occupations. By comparing the relative change in outcomes for STEM versus Business workers, this estimate differences out any potential component of selection into hot VC markets that is common to both groups. Within this triple-difference framework, I then evaluate several tests that increasingly restrict the identifying variation. Appendix Table G16 shows the effect is stable when controlling for worker's past turnover history. Appendix Table G17 shows the effect is stable when controlling for more granular industry-specific shocks. Finally, Appendix Table G18 shows that the effects are similar when controlling for origin firm fixed effects, restricting to comparisons of workers who share the same prior employer prior to the startup, e.g., software engineers from Google or Microsoft.

Another potential question is whether differences in the properties of the seniority distribution between STEM and non-STEM workers could explain the result. For example, if the job ladder for STEM workers has more variation than the job ladder for Business workers, this could generate more observable differences across STEM workers. However, Table 1, which reports summary statistics separately for both groups, shows that the standard deviation of seniority for Business workers is similar and in fact slightly larger than that of STEM workers. Overall, the seniority distributions of STEM and Business workers are similar.

A different question about the relationship between seniority and earnings is whether cash-constrained firms might offer higher titles as a substitute for pay. However, I find that startups financed in hot markets are less likely to be successful on average. Therefore, if true, this possibility would work against the estimated effect, in that workers who join startups in hotter VC markets would receive higher titles on average.

[24] That said, the OLS estimates fall within the 95% confidence intervals of the 2SLS estimates.

Therefore, it is unlikely that any of these alternative explanations could drive the result. Taken together with the turnover effects shown in the previous section and the increased rate of firm closures, the triple-difference by occupation instead appears to be consistent with varying costs of job churn across workers. In particular, reduced job stability may lead to larger productivity losses for workers with higher human capital specificity. I turn directly to an occupation-level measure of vintage-specific skill to probe this hypothesis further.

Occupation-Level Skill Specificity. To more directly test the hypothesis of skill specificity, I turn to an occupation-level measure of technology-skill specificity that varies at the three-digit SOC level. I obtain the rate of skill change score from Deming and Noray (2020) constructed using skill requirements from job posting data. The score can be interpreted as a measure of the extent to which skills are vintage-specific. The occupation-specific measure allows for variation within STEM or Business classified occupations. For instance, statisticians and data scientists are considered STEM workers, as are engineers and life scientists. However, workers in the former group may accumulate more transferable human capital across technological fields than the latter. To more easily interpret magnitudes, I standardize the skill specificity measure to have mean zero and standard deviation one.

Panel B of Table 4 regresses seniority on Ln VC Deals$_{s,t-1}$ and its interaction with the skill specificity measure. (The main effect for the skill specificity measure is absorbed by the occupation fixed effects). In columns (5) through (8), the instrumental variables are the shift-share IV and its interaction with the specificity score. To separately identify the effects across occupations, the market fixed effects in Panel B are further interacted with occupation, absorbing baseline differences across occupations within each local market.

Across all specifications, the effects of hot VC markets are more negative on the advancement of workers in occupations requiring more technology-specific skills. The table shows that for a worker at the mean level of skill specificity, the effect of the initial funding environment is not distinguishable from zero. However, column (6) shows that every standard deviation increase in skill specificity increases the negative impact of a doubling in VC on two-year seniority progress by $0.17 \times \ln(2) = 0.12$ seniority units. This amounts to 17% of the overall average two-year change of 0.7. Translated to career-time units, this implies that every standard deviation increase in skill specificity above the mean predicts an additional four-month career setback. Panel B of Appendix Tables G16, G17, and G18 show that the results continue to hold after controlling for each worker's historical turnover rate, granular industry shocks, and origin firm fixed effects, respectively. Overall, the results show that the slowed career advancement is concentrated among employees with more technology-specific skills, highlighting how the career risks of startup employment are borne by workers with more specialized human capital.

7 Conclusion

The availability of entrepreneurial finance is important for innovation and consequently, for economic growth. Financing innovation involves a high degree of risk and uncertainty (Kerr and Nanda, 2015). While the venture model has evolved to shoulder this uncertainty (e.g., through staged financing), employees who accumulate firm- and technology-specific human capital remain exposed to the risk of experimentation.

Using a novel dataset of VC financing linked to employment histories of 700 thousand startup workers, this paper's results highlight the interim costs of increased risk capital to skilled labor. As positive supply shocks to venture capital increase investments in experimental and risky firms, many workers acquire skills tied to these firms and their technologies. Reduced job stability leads to losses of investments in specific human capital, slowing the subsequent job ladder advancement of those with more specialized skills. These findings highlight the relationship between long-run aggregate productivity gains and the short-run costs incurred by startup workers, and demonstrate how capital markets contribute to these effects.

These findings suggest several avenues for future research, particularly on the social and private returns to knowledge worker mobility. For workers, the choice of which labor market opportunity to pursue is a high-stakes career decision. However, it may be difficult for individuals to predict future changes in the availability of VC funding, and it also conceivable that joining markets in which capital is abundant may be perceived as less risky ex-ante. Understanding these perceptions may be a fruitful avenue for future research. In addition, further understanding the social implications of these forms of job mobility, which involve the redeployment of human capital investments, is a promising area for exploration.

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A Theory Appendix: An Equilibrium Model of VC, Labor, and Innovation

A.1 Venture Capitalists, Entrepreneurs, and the Labor Market

Preferences. The model is set in continuous time. A continuum of infinitely-lived individuals maximize utility given by:

$$U_t = \int_0^\infty \ln C_{t+s} e^{-\rho s} ds \tag{A.1}$$

where $\rho > 0$ is the rate of time preference and $\ln C_t$ is the instantaneous utility of consumption. Nominal consumption expenditures at time t are $E_t = P_t C_t$, where P_t is the price of the consumption good. Optimal consumption expenditure must satisfy $\dot{E}_t / E_t = r_t - \rho$ for interest rate r_t. Following Grossman and Helpman (1991) and Mortensen (2005), the numeraire is chosen so that $\dot{E}/E = 0$, implying that $r_t = \rho$.

Fundraising. The economy in the model is populated by entrepreneurs, venture capitalists (VCs), and workers. Entrepreneurs have blueprints but lack the funds needed for hiring and production. VCs have capital and resources needed for implementation but no blueprints. Workers engage in the production of intermediate goods or contribute to research efforts. Entrepreneurs must fundraise from VCs in order to finance hiring. However, like firms and workers in the labor market, entrepreneurs and VCs face a search-and-matching problem. I follow Wasmer and Weil (2004) in incorporating these frictions in a tractable manner by adopting the technology of Pissarides (2000) in the financial sector.

The flow of matches between VCs and entrepreneurs is produced by a matching technology $s(e_t, k_t)$ where e_t denotes the measure of entrepreneurs seeking funding and k_t denotes the measure of VCs seeking an entrepreneur. The matching function s is assumed to be increasing in both arguments, concave, and satisfy constant returns to scale. Following Inderst and Müller (2004), I refer to the quantity $\phi_t = k_t/e_t$ as a measure of *capital market competition*. The Poisson rates of arrival for entrepreneurs and VCs can be expressed in terms of ϕ: the instantaneous probability that a VC finds an entrepreneur seeking funding is $s(e_t, k_t)/k_t = s(1/\phi_t, 1) \equiv p(\phi_t)$, and the instantaneous probability that a searching entrepreneur finds an available VC is $s(e_t, k_t)/e_t = s(1, \phi_t) = \phi_t p(\phi_t)$. Once the entrepreneur and VC match with each other, both parties negotiate a contract specifying a flow payment τ from the entrepreneur to the VC.

Hiring. VC-financed firms post vacancies to hire production labor. The flow of matches is produced by an analogous matching technology $m(u_t, v_t)$ where the inputs u_t and v_t denote unemployed workers and vacancies at time t, respectively. The Poisson arrival rates of a match for a vacant job and for an unemployed worker can be expressed as functions of *labor market tightness* $\theta_t = v_t/u_t$, the ratio of vacancies to unemployed workers. That is, the instantaneous probability that a firm finds an available worker is $m(u_t, v_t)/v_t = m(\theta_t^{-1}, 1) \equiv q(\theta_t)$ and the instantaneous probability that an unemployed worker finds a firm is $m(u_t, v_t)/u_t = m(1, \theta_t) = \theta_t q(\theta_t)$. The tighter the labor market, the less probable it is for an entering firm to find an available worker ($q'(\theta) \leq 0$), and the more probable it is for an unemployed worker to find a job opening.

Production and Destruction. Upon acquiring production labor, the firm moves on to the production stage and earns profit π_t. Production workers earn wage w_t while employed but face the risk of unemployment as new entrants displace current producers. I follow Aghion et al. (2016) and assume that employed workers appropriate a fraction β of firm profits, $w_t = \beta\pi_t$. Once the firm is fully operating, the firm-worker match is destroyed with Poisson arrival rate δ_t. When destruction occurs, the worker enters the unemployment pool and searches for a new job opportunity. I assume for simplicity that destruction of the match also leads to both firm and VC exit.

Asset Value Equations. In summary, the four stages of a firm are: (1) search for a financier, (2) search for production labor, (3) production, and (4) destruction. In the equilibrium considered below, the asset values of leading firms are the same across industries. I therefore consider a representative industry. Let V_i^0, V_i^1, and J_i denote the present discounted value of expected profits of the firm ($i = e$) or financier ($i = k$) while searching for each other, searching for production labor, and during production, respectively. The value equations of the firm over these stages are:

$$rV_e^0 = \phi p(\phi)(V_e^1 - V_e^0) \tag{A.2}$$

$$rV_e^1 = q(\theta)(J_e - V_e^1) \tag{A.3}$$

$$rJ_e = \pi - \tau - \delta J_e \tag{A.4}$$

while those of the venture capitalist are:

$$rV_k^0 = p(\phi)(V_k^1 - V_k^0) \tag{A.5}$$

$$rV_k^1 = -c + q(\theta)(J_k - V_k^1) \tag{A.6}$$

$$rJ_k = \tau - \delta J_k \tag{A.7}$$

where c is the instantaneous cost of posting a vacancy which is financed by the VC, τ is the flow payment from the entrepreneur to the VC, and π is the firm profit.

The VC and entrepreneur negotiate a binding contract upon matching. The VC's stake is determined by generalized Nash bargaining, in which both parties split the surplus of the venture:

$$\max_{\tau} S_k^{\eta} S_e^{1-\eta} \tag{A.8}$$

where $\eta \in (0, 1)$ is the VC's bargaining weight, and where $S_k = V_k^1 - V_k^0$ and $S_e = V_e^1 - V_e^0$ are the surpluses of the match to the VC and entrepreneur, respectively.

Production and Technical Progress. The multi-sector production environment follows Grossman and Helpman (1991). Final output Y_t is produced using a continuum of intermediate goods. The logarithmic production technology for the final good is

$$\ln Y_t = \int_0^1 \ln(z_t(\omega))d\omega \tag{A.9}$$

where $z(\omega)$ denotes the quantity of input $\omega \in [0,1]$ demanded. Let $p_t(\omega)$ denote the price of variety ω. The production function generates unit elastic demand with respect to each input. Factor demands are given by $z_t(\omega) = P_t Y_t / p_t(\omega)$. With the numeraire chosen so that nominal expenditures remain constant, one can choose $P_t Y_t = 1$, so that $z_t(\omega) = 1/p_t(\omega)$. The intermediate inputs that make up the final output are produced monopolistically and are subject to technical innovation in the form of quality ladders. That is, each innovation moves a product's technology one step up a ladder with levels $\Lambda^{j_t(\omega)}$ where $\Lambda > 1$ and $j_t(\omega)$ is the number of innovations made in input ω up to date t. The production technology for the leading firm in industry ω at ladder position $j_t(\omega)$ is

$$y_t(\omega) = A_t(\omega) n_t(\omega) = \Lambda^{j_t(\omega)} n_t(\omega), \tag{A.10}$$

where productivity in industry ω is $A_t(\omega)$ and labor demanded is given by $n_t(\omega)$. With wage w_t, the monopolist's unit cost is thus $w_t / A_t(\omega)$. The producer of product ω earns a profit flow of $\pi_t(\omega) = p_t(\omega) y_t(\omega) - w_t n_t(\omega)$. Competition among firms in a single industry à la Bertrand leads each incumbent firm to set the price equal to a gross markup Λ over unit cost, that is, to the marginal cost of the most efficient rival firm:

$$p_t(\omega) = \frac{\Lambda w_t}{A_t(\omega)}. \tag{A.11}$$

Thus, the profit of the leading producer is $\pi_t(\omega) = (\Lambda - 1) w_t(\omega) n_t(\omega)$.

The R&D technology in each industry is as follows. In industry ω, $x_t(\omega)$ units of R&D labor input results in the arrival rate of research success $\delta_t(\omega)$ according to

$$\delta_t(\omega) = x_t(\omega) h \tag{A.12}$$

where h is a constant that represents research efficiency.

Aggregate Productivity Growth. In a steady state growth path, real final output grows at a constant rate. Let $A_t = \exp(\int_0^1 \ln A_t(\omega) d\omega)$ denote the aggregate productivity index. We have

$$\begin{aligned} \ln Y_t &= \int_0^1 \ln(A_t(\omega) n_t(\omega)) d\omega \\ &= \ln(\Lambda) \int_0^1 j_t(\omega) d\omega + \int_0^1 \ln n_t(\omega) d\omega \end{aligned}$$

The assumption that the Poisson arrival rate of innovation is δ for all products implies

$$\ln Y_t = \delta t \ln(\Lambda) + \int_0^1 \ln n(\omega) d\omega$$

Let $g = \dot{Y}/Y$ denote the steady state growth rate of real final output, also the growth rate of real consumption. The equality above implies that g is equal to the growth rate of aggregate productivity, and that

$$g = \delta \ln \Lambda. \tag{A.13}$$

A.2 Solving the Model

I am interested in a steady state growth path where real aggregate quantities grow at a constant rate g, the measures (e, k, u, v, n) are stationary, and input production quantities $z(\omega)$ and innovation frequencies $\delta(\omega)$ are invariant across industries.

Profits, Wages, and the Labor Market Identity. Firms take the wage rate as given. From the unit elastic demand function, monopolist price setting, and linear production function, production labor demand is

$$n_t(\omega) = n_t = \frac{1}{\Lambda w_t} \tag{A.14}$$

Equilibrium profits and wages are given by

$$\pi_t(\omega) = 1 - \frac{1}{\Lambda} \quad \text{and} \quad w_t = \beta\left(1 - \frac{1}{\Lambda}\right). \tag{A.15}$$

As the expressions indicate, equilibrium profits and wages are invariant across industries. They are also stationary since the price of the consumption good falls at the rate of productivity growth due to the choice of the numeraire. I omit t subscripts for convenience going forward.

The total labor force is allocated to the production of intermediates, research, and unemployment u:

$$\int_0^1 n(\omega) d\omega + \int_0^1 x(\omega) d\omega + u = 1 \tag{A.16}$$

In a steady state equilibrium, the flow rate into vacancies, which is the rate of creative destruction, equals the flow rate out of vacancies, which entails the production of new matches (see Mortensen, 2005). That is,

$$\delta = m(u, v) = \theta q(\theta) u. \tag{A.17}$$

Together, the steady state matching condition (A.17), labor market clearing condition (A.16), production worker demand (A.14), and (A.12) require that the following holds in equilibrium:

$$\delta = \left(1 - \frac{1}{\beta(\Lambda - 1)}\right) \frac{\theta q(\theta) h}{h + \theta q(\theta)} \tag{A.18}$$

which I will henceforth refer to as the labor market identity.

Equilibrium Valuations with Financial and Labor Market Frictions. I assume that each industry is small with diversifiable idiosyncratic uncertainty so that firms and investors are concerned about expected profits. Equation (A.4) gives us the asset value of a representative producing firm:

$$J_e = \frac{\pi - \tau}{\rho + \delta} \text{ and } J_k = \frac{\tau}{\rho + \delta} \tag{A.19}$$

In effect, (A.19) is the present value of expected profits, discounted at a rate adjusted for endogenous obsolescence. The expression embeds the business-stealing effect in each product line, in that potential capital losses from new entry lower the market value of the leading producer (Aghion and Howitt, 1992; King and Levine, 1993).

Solving for V_e^1 and V_k^1 in equations (A.3) and (A.6), then substituting in the equations of (A.19) gives:

$$V_e^1 = \frac{q(\theta)}{\rho + q(\theta)} \frac{\pi - \tau}{\rho + \delta} \tag{A.20}$$

and

$$V_k^1 = \frac{-c}{\rho + q(\theta)} + \frac{q(\theta)}{\rho + q(\theta)} \frac{\tau}{\rho + \delta} \tag{A.21}$$

The valuation of a new entrant firm in (A.20) has an intuitive interpretation as the present discounted value of net profits accounting for frictional labor market matching (Petrosky-Nadeau and Wasmer, 2017). The discount rate ρ is strictly positive. The stream of profits earned by a new entrant are further discounted by $q(\theta)/(\rho + q(\theta)) < 1$ given the delay from having to match with an available worker, which occurs at rate $q(\theta)$. Since the expected duration of the firm's search for labor is $1/q(\theta)$, the expected cost of the vacancy posting is $c/q(\theta)$. Thus, on the VC side in (A.21), both the expected recruiting cost and payment are discounted by $q(\theta)/(\rho + q(\theta))$.

I now solve for the equilibrium VC stake, derived from the generalized Nash bargaining solution.

LEMMA 1. *In equilibrium, the VC's stake is given by*

$$\tau = \frac{\eta(\rho + p(\phi))\pi + (1-\eta)(\rho + \phi p(\phi))(\rho+\delta)c/q(\theta)}{\eta(\rho + p(\phi)) + (1-\eta)(\rho + \phi p(\phi))} \tag{A.22}$$

PROOF. See Appendix A.4.

As shown in Appendix A.4, τ can be expressed as a weighted average of the expected firm profit and the expected capitalized value of the VC's investment (the recruiting cost). τ is decreasing in $q(\theta)$, i.e., increasing in θ. Intuitively, the tighter are labor markets, the longer the duration of the firm's search for an available worker, and consequently, the larger the cost borne by the financier.

Entry and Equilibrium Capital Market Competition. VCs must pay a fixed entry cost equal to c_k before entering the market, while entrepreneurs must similarly pay c_e before entering. In terms of the assumption that entrepreneurs have no wealth of their own, c_e can be thought of as nonpecuniary, e.g., a sweat cost of breaking into entrepreneurship. Free entry drives the value of the outside option down to the entry cost, that is, $V_k^0 = c_k$ and $V_e^0 = c_e$. From (A.27) below, this means:

$$c_e = \frac{\phi p(\phi)}{\rho + \phi p(\phi)} \frac{q(\theta)}{\rho + q(\theta)} \frac{\pi - \tau}{\rho + \delta} \tag{A.23}$$

and

$$c_k = \frac{p(\phi)}{\rho + p(\phi)} \left[\frac{-c}{\rho + q(\theta)} + \frac{q(\theta)}{\rho + q(\theta)} \frac{\tau}{\rho + \delta} \right] \tag{A.24}$$

Combining both entry conditions with the Nash bargained payment of (A.22) yields the equilibrium level of capital market competition:

$$\phi = \frac{\eta}{1-\eta} \frac{c_e}{c_k} \tag{A.25}$$

Steady-State Equilibrium. An equilibrium steady-state growth path is a vector $(\tau, \phi, \delta, \theta, u, g)$ that satisfies (A.22), equilibrium capital market competition (A.25), the entry condition (A.20), the job matching condition (A.17), labor market clearing (A.16), the rate of aggregate productivity growth (A.13) where (w, π, n) satisfy (A.14) and both equalities of (A.15).

PROPOSITION 1. *A unique positive equilibrium exists if and only if*

$$\frac{\phi p(\phi)(1-\gamma)}{\rho + \phi p(\phi)} \pi > \rho c_e \quad \text{and} \quad \beta > \frac{1}{\Lambda - 1}$$

where ϕ is given by (A.25) and γ by (A.28) below.

PROOF. See Appendix A.5.

The first condition ensures that the entrepreneur's share of profits, accounting for the delay from having to match with a financier, exceeds the return that could be earned by saving the entry cost at interest rate ρ. As shown in Appendix A.5, this inequality evaluated at the equilibrium ϕ necessarily implies that the analogous participation constraint holds for the VC. The second condition relates the share of profits appropriated by workers to the innovation step size. The inequality ensures that there are enough workers to meet the production firms' demand for labor.

A.3 Model Implications

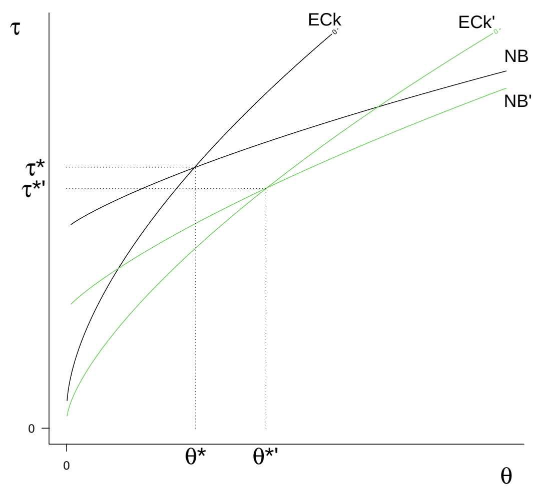
I now turn to studying the equilibrium effects of an exogenous shock to the financial sector. Specifically, I consider a shock that loosens the financial market while holding the other model primitives constant: a reduction in the VC's entry cost c_k. A fall in c_k induces more VC entry, increasing the supply of available VC funding. As (A.25) makes clear, capital market competition increases as more VCs search for entrepreneurs in need of funding. The matching technology implies that the increase in ϕ lowers the time it takes for entrepreneurs to find a financier and increases deal production.

Panel (a) of Figure A1 plots the solution to the Nash bargaining problem (NB) together with the VC's entry condition (ECk), evaluated at (A.25) and where δ satisfies (A.18). The equilibrium values of τ and θ lie at the intersection of the two curves. Both curves are upward sloping in (τ, θ) space; a tighter labor market raises the expected recruiting cost for the VC-backed firm, so τ must also be higher to maintain the entry condition. In the NB curve, τ must be higher if θ is higher given the solution to the Nash bargaining problem (A.22). Having already evaluated at the equilibrium value of ϕ, the entrepreneur's entry condition makes the system overidentified, but would pass through the same intersection point. From (A.24), the reduction in the VC's cost of entry c_k means that, for any θ, the VC's compensation τ must fall to maintain equilibrium. The ECk curve shifts down. From (A.22), a decrease in c_k lowers the VC's outside option, meaning that the Nash bargained τ must fall for any value of θ. The NB curve also shifts down. The downward shifts in both curves result in a lower equity stake. These results are summarized in the following proposition:

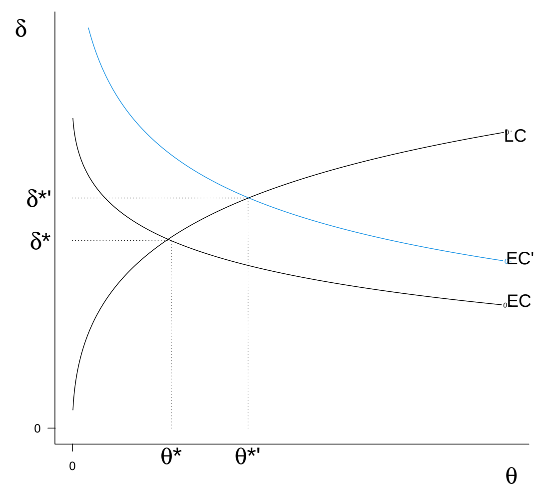
PROPOSITION 2. *VC entry cost, deal flow, and equilibrium contracts.* A decrease in VC entry cost c_k increases match production, increases capital market competition, reduces the duration of an entrepreneur's search for VC funding, and reduces the size of the VC's equity stake τ.

A high level of capital market competition implies that "money chases deals." In terms of empirical implications, the proposition predicts that following a positive shock to the supply of VC, deal flow increases, entrepreneurs raise funding rounds faster, and investor equity stakes fall. These patterns are consistent with empirical evidence that shifts in the relative supply of VC affect equilibrium valuations (Gompers and Lerner, 2000).

Figure A1: Illustration of Model Equilibrium



(a) VC Equity Stake & Labor Market Tightness



(b) Job Turnover & Labor Market Tightness

Note. Panel (a) illustrates the equilibrium solutions for the VC's equity stake τ and labor market tightness θ where ϕ is given by (A.25) and δ satisfies (A.18). The equilibrium lies at the intersection of the steeper curve, which is the VC's entry condition, and the flatter curve, which is the Nash bargaining solution. A fall in the VC's entry cost c_k lowers the VC's outside option and shifts both curves down, as indicated by the green curves, resulting in a smaller equity stake and increased labor market tightness. Panel (b) illustrates the model's equilibrium solution with positive creative destruction. The turnover rate δ is plotted as a function of labor market tightness θ. The equilibrium lies at the intersection of the downward sloping entry curve (EC curve) and the upward sloping labor market identity (LC curve). A fall in the VC's entry cost c_k shifts the EC curve up, resulting in increased job turnover.

Figure A1 also demonstrates that an increase in financier entry increases labor market tightness. As the VC entry cost falls, the increase in capital market competition makes it easier for entrepreneurs to obtain funding. Increased firm entry increases the amount of available jobs at startups. A tighter labor market increases the probability that an unemployed worker finds a job opening. However, the following result shows that the rate of job destruction also increases, increasing the probability that workers at producing firms become unemployed.

At the equilibrium levels of ϕ and τ, the two entry conditions (A.23) and (A.24) define equivalent functions in (δ, θ) space. I refer to this function as the entry condition. Panel (b) of Figure A1 plots the entry condition (EC curve) and labor market equilibrium condition of Equation (A.18) (LC curve) in (δ, θ) space. Provided that the conditions of Proposition 1 hold, the EC curve is downward sloping and the LC curve is upward sloping in the positive quadrant. The equilibrium lies at the intersection of the two curves. From the entry condition, following a fall in the VC's entry cost c_k, for any given θ, the arrival rate of destruction δ must increase to maintain the balance between the cost of entry and the expected benefit of entry. Therefore, a reduction in c_k shifts the EC curve up. Meanwhile, the LC curve is unaffected since the VC's entry cost has no direct effect on any of the terms of (A.18). Hence, the net result is an unambiguous increase in job turnover. Job turnover δ increases in response to a positive shock to the supply of VC, lowering the expected duration of worker-firm matches.

PROPOSITION 3. *Hot VC markets, creative destruction, and labor markets.* A decrease in the VC entry cost c_k increases venture-backed labor market tightness θ and job turnover rate δ, decreasing the expected duration of jobs.
PROOF. See Appendix A.6.

Though Panel (b) of Figure A1 makes the result clear, I also provide an analytical proof in Appendix A. The effect on labor market tightness overcomes the effect on the job destruction rate, leading to a decrease in unemployment.[25]

The result highlights the role of risk capital in knowledge worker turnover. Exogenous shocks to the supply of VC lead to "hot" funding markets and more job opportunities at venture-backed firms. However, jobs created in hotter VC markets are shorter-lived as an increase in the rate of technical obsolescence raises the probability of displacement. This shock increases the arrival rate of innovation and consequently the economy's growth rate, highlighting the trade-off in the innovation economy between job fragility and technical progress.

A.4 Proof of Lemma 1

The equilibrium payment to the VC is the solution to the maximization problem in (A.8), taking the outside options V_k^0 and V_e^0 as given. From (A.8), τ must satisfy the first order

[25] It is straightforward to verify that the upward sloping iso-unemployment curve defined by (A.17) is steeper than (A.18) at the equilibrium point. The shift along the LC curve leads to a new equilibrium that lies to the right of the iso-unemployment curve, indicating a fall in unemployment.

condition

$$\eta(V_e^1 - V_e^0) = (1-\eta)(V_k^1 - V_k^0) \tag{A.26}$$

which implies the VC obtains a fraction η of the total surplus that a venture creates. From (A.2) and (A.5), the entrepreneur and VC value functions satisfy

$$V_e^0 = \frac{\phi p(\phi) V_e^1}{r + \phi p(\phi)} \text{ and } V_k^0 = \frac{p(\phi) V_k^1}{r + p(\phi)}. \tag{A.27}$$

in a steady state. Solving for τ using (A.26), (A.20), (A.21), and (A.27) yields the result.

Note that the equilibrium payment can be expressed as a weighted average of the expected firm profits and capitalized recruiting cost, that is, as

$$\tau = \gamma\pi + (1-\gamma)(\rho+\delta)\frac{c}{q(\theta)}$$

where

$$\gamma = \frac{\eta(\rho + p(\phi))}{\eta(\rho + p(\phi)) + (1-\eta)(\rho + \phi p(\phi))} \tag{A.28}$$

is the weight on firm profits. ■

A.5 Proof of Proposition 1

The solution to the Nash bargaining problem τ is a function of δ, θ, and ϕ, where ϕ is pinned down by (A.25). Equation (A.18) combines the job matching condition and the labor market clearing condition, removing one equation and one endogenous variable, u:

$$\delta = \left(1 - \frac{1}{\beta(\Lambda - 1)}\right)\frac{\theta q(\theta) h}{h + \theta q(\theta)}$$

The destruction rate δ and labor market tightness θ remain to be determined. Since $\theta q(\theta)$ is increasing in θ, the above equation defines an increasing relationship between δ and θ if and only if the total labor force is larger than the demand for production labor under the profit sharing rule, i.e., $\beta(\Lambda - 1) > 1$. Moreover, the curve passes through the origin.

With ϕ and τ satisfying (A.25) and (A.22), respectively, the two entry conditions (A.23) and (A.24) define equivalent functions in δ-θ space. I refer to this function as the entry condition. Substituting (A.22) into (A.23), we have

$$\frac{\rho + \phi p(\phi)}{\phi p(\phi)} c_e = \frac{q(\theta)}{\rho + q(\theta)} \frac{1-\gamma}{\rho+\delta}\pi - \frac{c(1-\gamma)}{\rho + q(\theta)}$$

where γ is given by (A.28). The LHS is a constant in the (δ, θ) space. Meanwhile, the RHS is decreasing in both θ and δ. If δ increases, $q(\theta)$ must increase to maintain equality, i.e., θ must fall. Therefore, the entry curve defines a downward sloping relationship between δ and θ. Hence, in order for a unique positive equilibrium to exist, the δ intercept of the entry curve at $\theta = 0$ must be strictly greater than 0.

From the Nash bargaining solution, $\tau \to \gamma\pi$ as $\theta \to 0$, meaning

$$c_e - \frac{\phi p(\phi)}{\rho + \phi p(\phi)} \frac{\pi(1-\gamma)}{\rho + \delta} \to 0.$$

Rearranging, this implies

$$\delta \to \frac{\phi p(\phi)\pi(1-\gamma)}{\rho + \phi p(\phi)} \frac{1}{c_e} - \rho.$$

Thus, the limit of δ as θ tends to 0 is positive if and only if

$$\frac{\phi p(\phi)(1-\gamma)}{\rho + \phi p(\phi)} \pi > \rho c_e.$$

The condition is intuitive and serves as a participation constraint for the entrepreneur. It says that the entrepreneur's share of profits accounting for the delay from having to match with a financier must be greater than the return on the entry cost at interest rate ρ.

Note that this inequality evaluated at the equilibrium ϕ necessarily implies that the analogous participation constraint holds for the VC. To see this, plug in for γ and ϕ in the numerator above:

$$\frac{\left(\frac{\eta}{1-\eta}\frac{c_e}{c_k}\right) p(\phi)(1-\eta)}{\eta(\rho + p(\phi)) + (1-\eta)(\rho + \phi p(\phi))} \pi > \rho c_e$$

which simplifies to

$$\frac{p(\phi)\gamma}{\rho + p(\phi)} \pi > \rho c_k.$$

To confirm that this is the VC's participation constraint, recall the entry condition for the VC (A.24). As $\theta \to 0$,

$$\delta \to \frac{p(\phi)}{\rho + p(\phi)} \frac{\gamma\pi}{c_k} - \rho$$

where the RHS is positive if and only if

$$\frac{p(\phi)\gamma}{\rho + p(\phi)} \pi > \rho c_k.$$

Hence, provided that the restrictions described in the proposition are met, a unique equilibrium in the positive quadrant exists at the intersection of the labor market identity and the entry curve. ■

A.6 Proof of Proposition 3

This section presents an analytical proof of Proposition 3. Let

$$A(\phi) = \frac{\phi p(\phi)}{\rho + \phi p(\phi)}, \quad B(\theta) = \frac{q(\theta)}{\rho + q(\theta)}.$$

We know by the properties of the matching technology that $A'(\phi) > 0$ and $B'(\theta) < 0$.

From (A.23) and (A.18), let

$$F_1(\delta, \theta, c_k) = A(\phi)B(\theta)\frac{\pi - \tau}{\rho + \delta} - c_e$$
$$F_2(\delta, \theta, c_k) = \frac{1}{\beta(\Lambda - 1)} + \frac{\delta}{M(\theta)} + \frac{\delta}{h} - 1$$

where $M(\theta) = \theta q(\theta)$, τ is given by (A.22), and ϕ is given by (A.25).

We have

$$\frac{\partial F_1}{\partial c_k} = \frac{B(\theta)}{\rho + \delta}\frac{\partial \phi}{\partial c_k}\left[A'(\phi)(\pi - \tau) - A(\phi)\frac{\partial \tau}{\partial \phi}\right] < 0 \tag{A.29}$$

where the inequality comes from the fact that $\partial\phi/\partial c_k < 0$, $A'(\phi) > 0$, and $\partial\tau/\partial\phi < 0$. Meanwhile,

$$\frac{\partial F_2}{\partial c_k} = 0.$$

Differentiation of F_1 and F_2 with respect to δ, θ, and the VC entry cost c_k gives:

$$J \cdot \begin{bmatrix} \frac{\partial \delta}{\partial c_k} & \frac{\partial \theta}{\partial c_k} \end{bmatrix}^\intercal = \begin{bmatrix} -\frac{\partial F_1}{\partial c_k} & 0 \end{bmatrix}^\intercal$$

where

$$J = \begin{bmatrix} -A(\phi)B(\theta)\left(\frac{\frac{\partial\tau}{\partial\delta}(\rho+\delta)+\pi-\tau}{(\rho+\delta)^2}\right) & A(\phi)B'(\theta)\frac{\pi-\tau}{\rho+\delta} \\ \frac{1}{M(\theta)} + \frac{1}{h} & -\frac{\delta M'(\theta)}{[M(\theta)]^2} \end{bmatrix}. \tag{A.30}$$

From this, we see that

$$\det(J) = A(\phi)B(\theta)\left(\frac{\frac{\partial\tau}{\partial\delta}(\rho + \delta) + \pi - \tau}{(\rho + \delta)^2}\right)\frac{\delta M'(\theta)}{[M(\theta)]^2} - A(\phi)B'(\theta)\left(\frac{\pi - \tau}{\rho + \delta}\right)\left(\frac{1}{M(\theta)} + \frac{1}{h}\right) > 0$$

which is strictly positive since $\partial\tau/\partial\delta > 0$, $M'(\theta) > 0$, and $B'(\theta) < 0$.

By Cramer's rule, we have:

$$\frac{\partial \delta}{\partial c_k} = \frac{1}{\det(J)} \left(\frac{\delta M'(\theta)}{[M(\theta)]^2} \right) \left(\frac{\partial F_1}{\partial c_k} \right) < 0 \tag{A.31}$$

which is negative given that $\det(J) > 0$, $M'(\theta) > 0$, and $\partial F_1 / \partial c_k < 0$.

Similarly,

$$\frac{\partial \theta}{\partial c_k} = \frac{1}{\det(J)} \left(\frac{\partial F_1}{\partial c_k} \right) \left(\frac{1}{M(\theta)} + \frac{1}{h} \right) < 0 \tag{A.32}$$

■

B Methods Appendix

B.1 Poisson Regression Estimation with Endogenous Regressors

This appendix provides additional details on the control function procedure used in Section 4, in which I estimate Poisson pseudo-maximum likelihood (PPML) regressions. The control function estimator obtains consistent estimates of the structural equation:

$$\mathbb{E}[y_{s,t} | \text{Ln VC Deals}_{s,t-1}, D_{s,t}, \varepsilon_{s,t}] = \exp(\beta \times \text{Ln VC Deals}_{s,t-1} + D'_{s,t}\alpha + \varepsilon_{s,t})$$

where $D_{s,t}$ is a vector of exogenous variables, Ln VC Deals$_{s,t-1}$ is the endogenous variable and $\varepsilon_{s,t}$ contains omitted variables that lead to the endogeneity of Ln VC Deals$_{s,t-1}$. $D_{s,t}$ contains at a minimum, market and year fixed effects, as well as time-interacted fixed effects by industry and location.

Let $z_{s,t}$ denote the IV. Consider the reduced form for Ln VC Deals$_{s,t-1}$:

$$\text{Ln VC Deals}_{s,t-1} = \pi z_{s,t} + D'_{s,t}\lambda + \nu_{s,t}. \tag{B.33}$$

By specifying

$$\mathbb{E}[\exp(\varepsilon_{s,t}) | \nu_{s,t}] = \exp(\eta + \rho \nu_{s,t})$$

(which holds, for example, under joint normality of $(\varepsilon_{s,t}, \nu_{s,t})$), and absorbing the constant η into the intercept, we obtain the estimating equation:

$$\mathbb{E}[y_{s,t} | \text{Ln VC Deals}_{s,t-1}, D_{s,t}, \nu_{s,t}] = \exp(\beta \times \text{Ln VC Deals}_{s,t-1} + D'_{s,t}\alpha + \rho \nu_{s,t}).$$

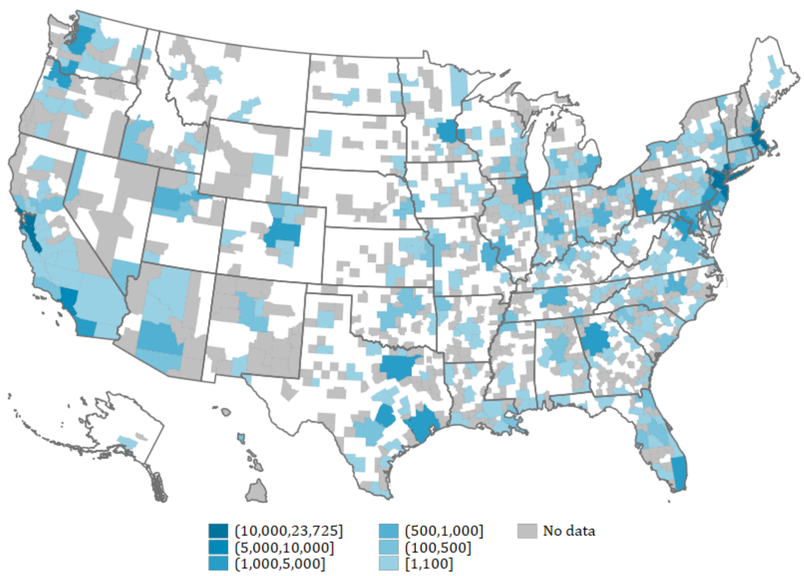
One can proceed in a two-step control function approach to obtain a consistent estimate of β (Wooldridge, 2010). (i) With the instrumental variable $z_{s,t}$, estimate the first-stage equation (B.33) via least squares to obtain residuals $\hat{\nu}_{s,t}$. (ii) Use the fixed effects Poisson estimator to estimate β, α, and ρ with $\hat{\nu}_{s,t}$ in place of $\nu_{s,t}$.

Testing for endogeneity $H_0 : \rho = 0$ can be done using the standard t-statistic. For inference, one should adjust for the first-stage estimation of $\nu_{s,t}$, unless $\rho = 0$. Accordingly, I obtain clustered standard errors via bootstrap (1,000 replications).

C Supplementary Figures and Tables

C.1 Geography of VC Financing in Sample

Figure C2: Total VC Deals from 2002-2021 by Target Company MSA



Note. This figure presents the geographic dispersion of venture capital deals from Pitchbook data. The sample period is 2002 to 2021, and the unit of observation is a Metropolitan Statistical Area (MSA). The location of each VC deal is the MSA of the startup company's headquarters.

C.2 Funding Environment and Likelihood of Startup Failure

Table C1 shows that startups receiving their first financing round in hotter VC markets are more likely to fail, consistent with the findings of Nanda and Rhodes-Kropf (2013). The unit of observation is a startup receiving its first recorded round of VC financing between 2002 and 2018. I follow Hall and Woodward (2010) and Nanda and Rhodes-Kropf (2013) in the construction of two proxies for startup failure, described in the table notes. Panel A considers the first measure of failure, while Panel B considers the second measure. Columns (4) through (6) additionally control for firm age at the time of financing.

Column (4) shows that a doubling of local VC increases the likelihood of failure by 2.3 percentage points (from $0.033 \times \ln(2)$). This amounts to 10% of the mean failure rate as measured in Panel A and 5% of the mean failure rate as measured in Panel B. Interestingly, the shift-share IV used in the market- and individual-level analyses is weak in the firm-level regressions. Therefore, I present OLS regressions for this analysis.

Table C1: Funding Environment and Likelihood of Startup Failure

Panel A.	Dependent Variable: Startup Failure Measure 1					
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Ln VC Deals	0.037***	0.033***	0.039**	0.033***	0.029***	0.036**
	(0.011)	(0.009)	(0.016)	(0.011)	(0.009)	(0.016)
Firm Age				-0.014***	-0.013***	-0.013***
				(0.001)	(0.001)	(0.001)
Dependent Var. Mean	0.22	0.22	0.22	0.22	0.22	0.22
Panel B.	Dependent Variable: Startup Failure Measure 2					
Ln VC Deals	0.030***	0.025***	0.028*	0.031***	0.025***	0.028*
	(0.010)	(0.009)	(0.016)	(0.010)	(0.009)	(0.016)
Firm Age				0.001	0.001	0.001
				(0.001)	(0.001)	(0.001)
Dependent Var. Mean	0.48	0.48	0.48	0.48	0.48	0.48
FE: MSA $\times$ Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Year	Yes			Yes		
FE: Industry $\times$ Year		Yes			Yes	
FE: MSA $\times$ Year			Yes			Yes
R^2	0.08	0.08	0.11	0.08	0.08	0.11
Observations	38,482	38,482	38,482	38,482	38,482	38,482

Note. Each observation is a US startup in local market (MSA-industry pair) s receiving its first completed round of venture capital financing in year t. Startups receiving their first financing between 2002 and 2018, the sample period of the study, are considered. The dependent variable is an indicator for whether the startup fails, using two measures of failure following Hall and Woodward (2010) and Nanda and Rhodes-Kropf (2013). Specifically, in Panel A, the dependent variable is assigned a one if the Pitchbook variable OwnershipStatus is "Out of Business" or if the Pitchbook variable BusinessStatus indicates Bankruptcy. Panel B extends this measure and additionally assigns a one if the startup has not had an exit event (i.e., gone public or been acquired) and has not received a financing round since 2018. Ln VC Deals is the natural log of VC deals in year t and market s. Columns (4) through (6) additionally control for the age of the startup at financing. Standard errors are clustered by MSA-industry and reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

C.3 Balance Tables and Coefficient Stability

Table C2 presents the relationship between VC funding flows and worker characteristics. The specification is the same as Equation (4), but using the worker covariates as the dependent variable, and without controlling for other worker characteristics. There does not appear to be a clear relationship that holds across specifications.

Table C3 presents the analogous test between the instrument and worker characteristics. There is virtually no relationship between funding flows predicted by the shift-share IV and the observable characteristics of workers in those markets. While the IV appears to be negatively correlated with years of experience for Business workers, the implied magnitude is $< 1\%$ of the mean (from Table 1). Overall, the estimates indicate that neither the treatment variable nor the IV systematically predict differences in average ex-ante worker characteristics.

Consistent with the covariate balance shown above, Figure C3 demonstrates the stability of the estimates when gradually saturating the job-level specification with additional worker controls. The stability of these estimates provides evidence against the possibility of selection on unobservable characteristics (e.g., Oster, 2019).

Table C2: Balance Table: Initial Funding Environment and Worker Characteristics

	STEM Workers			Business Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Elite School						
Ln VC Deals ($t-1$)	0.006***	0.007***	0.001	0.001	0.002	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Panel B. Bachelor's Degree						
Ln VC Deals ($t-1$)	-0.001	0.003	-0.018***	0.006**	0.006**	0.003
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Panel C. Master's Degree						
Ln VC Deals ($t-1$)	-0.002	-0.003	0.008**	-0.003	-0.003	0.001
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Panel D. Doctoral Degree						
Ln VC Deals ($t-1$)	0.005**	0.001	0.011***	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
Panel E. Seniority ($t-1$)						
Ln VC Deals ($t-1$)	-0.039	-0.028	-0.013	-0.009	-0.013	-0.041
	(0.028)	(0.030)	(0.034)	(0.030)	(0.030)	(0.034)
Panel F. Years of Experience						
Ln VC Deals ($t-1$)	0.061	0.084	0.160**	-0.152***	-0.145**	-0.071
	(0.057)	(0.059)	(0.066)	(0.058)	(0.057)	(0.064)
Individual Controls	No	No	No	No	No	No
FE: MSA × Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Occupation × Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry × Year		Yes			Yes	
FE: MSA × Year			Yes			Yes
R^2	0.04	0.04	0.05	0.07	0.07	0.08
Observations	327,405	327,405	327,405	372,926	372,926	372,926

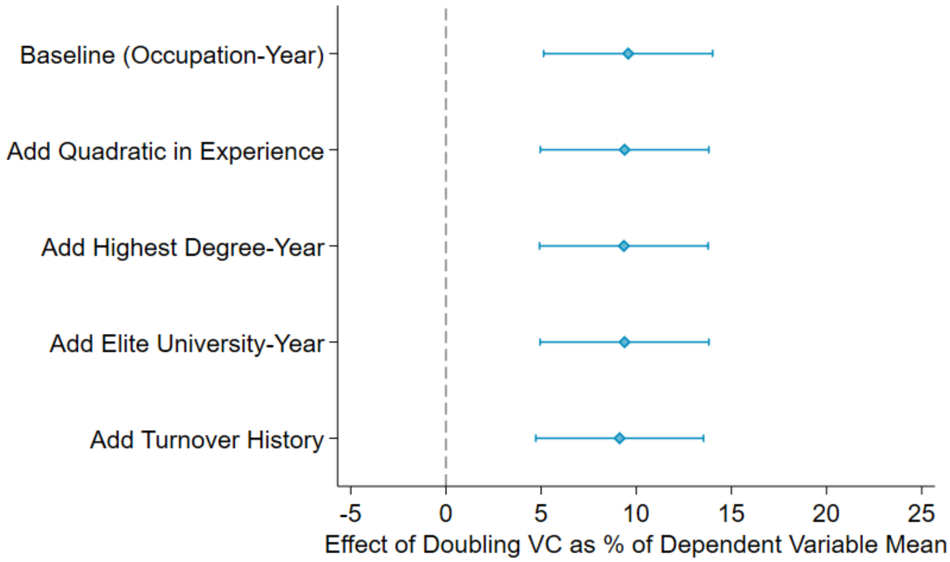
Note. This table tests for relationships between funding conditions at the time of hiring and worker characteristics. Each observation is an individual starting a job at a VC-backed startup in year t and MSA-industry pair s. Ln VC Deals ($t-1$) is the lagged natural log of VC deals in local market s. Each panel examines a different worker characteristic as the dependent variable. The regressions do not control for individual characteristics. Standard errors are clustered by MSA-industry-year and reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

Table C3: Balance Table: Predicted Initial Funding Environment and Worker Characteristics

	STEM Workers			Business Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Elite School						
Ln Predicted VC $(t-1)$	0.002*	0.002	0.000	-0.001	0.001	-0.003**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Panel B. Bachelor's Degree						
Ln Predicted VC $(t-1)$	0.002	0.002	0.000	0.002	0.000	0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Panel C. Master's Degree						
Ln Predicted VC $(t-1)$	0.001	0.001	-0.001	-0.002	-0.002	-0.002
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Panel D. Doctoral Degree						
Ln Predicted VC $(t-1)$	-0.003*	-0.002	-0.000	-0.001	-0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Panel E. Seniority $(t-1)$						
Ln Predicted VC $(t-1)$	-0.029	-0.009	-0.036	-0.032	-0.026	-0.038
	(0.022)	(0.023)	(0.025)	(0.022)	(0.022)	(0.024)
Panel E. Years of Experience						
Ln Predicted VC $(t-1)$	-0.050	-0.028	-0.038	-0.113***	-0.102**	-0.118***
	(0.042)	(0.043)	(0.048)	(0.042)	(0.042)	(0.044)
Individual Controls	No	No	No	No	No	No
FE: MSA × Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Occupation × Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry × Year		Yes			Yes	
FE: MSA × Year			Yes			Yes
R^2	0.04	0.04	0.05	0.07	0.07	0.08
Observations	327,405	327,405	327,405	372,926	372,926	372,926

Note. This table tests for relationships between the instrumental variable for funding conditions at the time of hiring and worker characteristics. Each observation is an individual starting a job at a VC-backed startup in year t and MSA-industry pair s. Ln Predicted VC $(t-1)$ is the lagged natural log of predicted VC deals in local market s, constructed according to Equation (3). Each panel examines a different worker characteristic as the dependent variable. The regressions do not control for individual characteristics. Standard errors are clustered by MSA-industry-year and reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

Figure C3: Coefficient Stability with Worker Covariates



Note. This figure shows the effect of increased capital at the time of hiring on the likelihood of worker separation from the startup within two years. From top to bottom, each coefficient progressively adds an additional worker covariate to the specification. These covariates in order are: occupation-by-year fixed effects, quadratic polynomial in labor market experience, highest degree-by-year fixed effects, elite university-by-year fixed effects, and previous turnover history. The figure plots the effect of doubling VC as a percentage of the dependent variable mean, calculated as $\hat{\beta}\ln(2)/\text{Mean} \times 100\%$ where $\hat{\beta}$ is estimated from Equation (4) by 2SLS. Standard errors are clustered by MSA-industry-year and 90% confidence intervals are shown.

INTERNET APPENDIX

D Supplementary Data and Sample Details

D.1 Sample Construction

This section describes how I match US VC-backed companies in Pitchbook to the online professional profiles of individuals who have reported working there.

1. Retrieve US VC-backed companies.

- I restrict to firms headquartered in the US and founded after the year 1995.
- I restrict to companies with a completed round (DealStatus="Completed") of VC financing (DealClass="Venture Capital").
- I restrict to financing rounds where the deal type (DealType) is classified as "Early Stage VC," "Later Stage VC," "Seed Round," or "Accelerator/Incubator."
- I drop any cases where the date of the VC financing round is missing.

2. Produce set 1 of candidate matches. Once I obtain the set of firms to match to the employment data, I produce two sets of candidate matches. I obtain the first set of candidate matches by exact matching on the company page identifiers. Importantly, these identifiers are available for firms that are both currently in business and out of business. I also manually verify for a subset of firms that for companies that get acquired, the identifiers match to the profile of the original startup, and not the acquiring parent company.

I validate the matches from the identifiers by verifying that the company names listed on the worker's employment positions match the company names of the startups in Pitchbook. To do so, I pre-process the company names, which includes removing any special characters as well as removing corporate and legal suffixes such as "inc.," "llc," and "corp." I do the same for the former names of companies (CompanyFormerName) and any company alias (CompanyAlsoKnownAs), in cases where this is applicable. I then assess the string distance between the company name listed on the employment position and the Pitchbook data company name using two measures: the Jaro-Winkler similarity measure and the overlap coefficient.[26] For companies matched in Step 2a, 96% of total observed employment positions

[26] The overlap coefficient, otherwise known as the Szymkiewicz-Simpson coefficient, is given by $\text{overlap}(A, B) = \frac{|A \cap B|}{\min(|A|, |B|)}$. I assess the overlap coefficient because in many cases, the VC data name and employment data name differ in how fully the names are written out, for example, "Robinhood" vs. "Robinhood Markets," which removal of standard corporate and legal suffixes does not address. In cases like this, the overlap coefficient takes the value 1.

have a Jaro-Winkler similarity greater than 0.95 or an overlap coefficient of 1.

3. Produce set 2 of candidate matches. I obtain a second set of candidate matches after producing set 1. For companies that do not match in the first step, I exact match companies to employment positions using the company name and state.

4. Retrieve employment positions. Once I obtain both sets of candidate matches, I restrict the sample of workers and filter for employment positions. Specifically,

- I keep positions that indicate dates of employment, employment location, and job title.
- I drop workers who do not report their educational history.
- I keep college-educated workers. Additionally, I keep workers in occupations that typically require a bachelor's degree, obtained from the BLS data on education by occupation.
- I drop any positions not indicating full-time employment. This includes, for example, users who report experience from internships, experience on boards of directors or as board observers, as well as participation in professional development programs.

5. Impose date-based matching criteria. I restrict the set of candidate matches using a date-based criteria that compares the start dates of reported employment positions to the date we would expect the company to begin hiring workers. A small portion of companies have missing founding years in Pitchbook. For these, I instead use the year of the first VC financing round. I flag a candidate as a non-match if over 20% of the positions associated with a candidate match company begin three or more years before the firm's founding year, and there are at least ten such positions. I impose the criteria in both levels and shares given that, in some cases, founding members and early employees may legitimately have start dates that precede the company's official founding year or first year of VC financing.

6. Keep pre-exit observations. Among companies that pass the above filters, I observe the subset of companies that eventually go public or become acquired. For these companies, I keep positions up until the year prior to the exit event. For companies that take a long time to go public or for companies that stay private for a long time, I also drop any positions starting 15 years past the founding year.

Note: Tracking career progress. The above steps detail how I obtain the sample of VC-backed startup jobs. Importantly for the analyses in the paper, I also track the career progress of workers beyond their startup employment. That is, after identifying the workers in the startup job sample, I obtain the full employment histories of each these workers, including the years prior to and following their startup experience.

D.2 Sample Coverage Description and Validation Tests

I start with 42,735 firms that fit the criteria described in Step 1 of D.1. Of these, I match 34,859 (82%) to employment positions from workers' professional profiles. Among these firms, I identify 779,298 startup jobs, or worker-firm matches.

Table D4 compares the firms that are matched to the employment data to the firms that are not. First, matched and non-matched firms do not differ systematically in age, and have the same average founding year of 2009, around the midpoint of my sample. Similarly, the average year of first VC financing is the same (2011) for both groups of firms. Matched and non-matched firms also have a similar rate of acquisition of around 22%. Matched firms are more likely to have had an IPO.

I then evaluate the stage of the last recorded VC round for each startup, as measured by whether this last round was a Seed round, Series A, Series B, or Series C+. Not every startup has series information available. Columns (3) through (6) condition on firms that have series information in Pitchbook for the purposes of better understanding the stage distribution.

Table D4: Characteristics of Matched vs. Not Matched Firms

	Full Sample			Have Series Information		
	(1) All	(2) Matched	(3) Not Matched	(4) All	(5) Matched	(6) Not Matched
Average Founding Year	2009	2009	2009	2009	2009	2009
Average First Deal Year	2011	2011	2011	2011	2011	2011
Acquired	0.22	0.22	0.23	0.23	0.22	0.26
Publicly Held	0.03	0.03	0.01	0.03	0.03	0.01
Not Public or Acquired	0.76	0.75	0.76	0.74	0.74	0.73
Last Round Seed	0.22	0.20	0.31	0.28	0.24	0.48
Last Round Series A	0.22	0.23	0.19	0.29	0.29	0.30
Last Round Series B	0.15	0.16	0.08	0.19	0.20	0.12
Last Round Series C+	0.19	0.21	0.06	0.24	0.27	0.10
No Series Info	0.23	0.20	0.36	0.00	0.00	0.00
N	42,734	34,859	7,875	32,849	27,831	5,018

Note. This table compares firms matched to the worker resume data to firms that were not matched. The average founding year and average first deal year are rounded to the nearest integer year.

Among firms with this information, 48% of unmatched firms had their last financing round at the Seed stage, compared to 24% for matched firms. These unmatched firms are unlikely to have reached the expansion stage of hiring more workers, so their absence from the job data is unsurprising. Importantly, the results suggest that the matched sample is representative of VC-funded companies that would have employed workers, and consequently, of the broader population of startup employees.

I additionally conduct several validation checks to check for the possibility of survivorship bias in the results. First, I estimate a firm-level test on the sample of startups and an individual-level test on sample of matched workers. Table D5 shows there is no relationship between the likelihood that a startup is matched to the résumé data and this paper's treatment variable. Therefore, even if some firms are not observed, non-observability is not correlated with hot VC markets.

Table D5: Treatment Variable Does Not Predict Likelihood of Match

	Dependent Variable: Match to Résumé Data					
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Ln VC Deals	-0.001	-0.012	0.009	0.003	-0.008	0.011
	(0.009)	(0.009)	(0.011)	(0.009)	(0.009)	(0.011)
FE: MSA × Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Year	Yes			Yes		
FE: Industry × Year		Yes			Yes	
FE: MSA × Year			Yes			Yes
Firm Age Control				Yes	Yes	Yes
R^2	0.05	0.06	0.09	0.06	0.06	0.09
Dependent Var. Mean	0.79	0.79	0.79	0.79	0.79	0.79
Observations	38,482	38,482	38,482	38,482	38,482	38,482

Note. Each observation is a US startup receiving its first completed round of venture capital financing between 2002 and 2018. The dependent variable is an indicator for whether the startup in local market (MSA-industry pair) s receiving its first financing in year t is matched to the worker resume data. Ln VC Deals is the natural log of VC deals in year t and MSA-industry s. Columns (4) through (6) additionally control for the age of the startup at financing. Standard errors are clustered by MSA-industry and reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

Another potential concern is whether, conditional on the set of observed jobs, the rate of attrition from the employment data could be related to funding market conditions. Table D6 shows that this is not the case. The table reports estimates from the individual-level specification of Equation (4), where the dependent variable is an indicator for whether the worker does not have an observed employment position two calendar years after joining the startup. The baseline rate of attrition over two years is only 3%, and importantly, shows no systematic relationship with VC market conditions.

In summary, the matching rate between startups and worker employment data is high, and the evidence supports that the matched sample is representative of the population of startup employees. The likelihood of matching is not correlated with VC market conditions. Worker attrition from the employment data is minimal and likewise unrelated to funding conditions. Together, these results support the representativeness of the matched sample for analyzing labor outcomes in venture-backed startups.

Table D6: Treatment Variable Does Not Predict Worker Attrition

	Dependent Variable: Attrition from Data ($t+2$)					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Ln VC Deals ($t-1$)	0.000	0.000	0.000	0.003	0.001	0.011*
	(0.001)	(0.001)	(0.001)	(0.004)	(0.006)	(0.006)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: MSA × Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Occupation × Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry × Year		Yes			Yes	
FE: MSA × Year			Yes			Yes
Dependent Var. Mean	0.03	0.03	0.03	0.03	0.03	0.03
Observations	779,298	779,298	779,298	779,298	779,298	779,298

Note. Individual Controls include initial seniority in year t, a quadratic polynomial in labor market experience at job start, the worker's historical job turnover rate, highest degree-by-year fixed effects, and elite university-by-year fixed effects. Further definitions and data construction details can be found in Section 3. OLS estimates are shown in columns (1) through (4), while 2SLS estimates using a shift-share instrumental variable are shown in columns (5) through (8). Standard errors are clustered by MSA-industry-year and reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

D.3 Details on Seniority Construction

This appendix section outlines the seniority construction procedure in more detail. Seniority is constructed following the methodology of Amornsiripanitch et al. (2023).

Following their paper, the first step is to assign size quintiles to each firm-year based on employee headcount, where each quintile is based on shares of aggregate employment as opposed to shares of total firms. For example, firms in the top (largest) size quintile in a given year are the largest firms that comprise 20% of total employment that year. Firms in the second largest size quintile in a given year are the next firms that make up the next 20% of total employment that year, and so on. This makes it so that each quintile contains an equal portion of workers. (In contrast, assigning quintiles based on percentages of firms would make it so that the firms in the largest quintile would contain a disproportionately large amount of workers). As the authors recommend, I measure firm headcounts at one point in time (specifically, at the end of each year) rather than by the number of unique employees over the year so that higher employee turnover is not mistaken for larger headcount.

Job title strings are obtained from each user's reported employment experience. I first remove any reported positions that do not indicate full-time employment at a firm. This includes internships, participation in professional development programs, or experience on boards of directors. I then clean and standardize the job titles across workers. This includes standardizing commonly abbreviated descriptors (examples: sr. to senior, jr. to junior, assoc. to associate) as well as commonly abbreviated positions (examples: CEO for chief executive officer, CFO for chief financial officer, VP for vice president). If a user reports more than one title, I take the first listed title, with exceptions for if the first title describes a founding role (e.g., if founder and CEO, assign the title as CEO).

Seniority is computed as the median number of years required to reach a given job title for a given firm size quintile and industry. Importantly, this distribution is calculated over the full employment sample, not just over the sample of startup positions. This value is assigned as the seniority if all variables in the title-industry-firm size combination are non-missing and there are at least 10 observations in the combination. Following Amornsiripanitch et al. (2023), if one of the requirements is not satisfied, I move sequentially down the following list until a combination satisfies both requirements:

(i) Job title × industry × firm size quintile

(ii) Job title × firm size quintile

(iii) Job title × industry.

Once I have calculated seniority values for the job title-industry-firm size combinations, I turn to linking each worker-year observation with its seniority value. Starting from my matched worker-firm panel, I merge in the size quintile of the firm in that given year. I then merge in the seniority values using the title, industry, and size quintile. Ultimately, 4% of startup jobs remain unlinked to a seniority value. I exclude these observations from the seniority analysis.

Table D7 presents examples of job titles and their seniority values from the data. The first panel reports examples from the information technology (IT) industry while the second panel reports examples from the healthcare industry. For both industries, the table shows the most common job titles found in the largest firms (i.e., firms in the top size quintile), and sorts by these seniority values in descending order. Unsurprisingly, some titles are more prevalent in certain industries than others; for example, Software Engineer, Senior Software Engineer, and Product Manager are among the common titles in IT, while titles such as Research Associate, Scientist, and Senior Scientist are among the most common in healthcare.

Table D7: Seniority Examples from Most Common Job Titles

Industry	**Title**	**Seniority**	
		Top Size Quintile	Bottom Size Quintile
IT	Vice President	19	15
IT	Senior Director	17	14
IT	Director	15	11
IT	Principal	13	12
IT	Senior Manager	12	9
IT	Manager	10	8
IT	Staff Engineer	9	9
IT	Staff Software Engineer	9	9
IT	Project Manager	8	7
IT	Product Manager	8	6
IT	Senior Analyst	7	6
IT	Senior Software Engineer	7	8
IT	Account Executive	7	6
IT	Account Manager	5	5
IT	Software Engineer	4	3
IT	Specialist	3	3
Healthcare	Vice President	19	18
Healthcare	Executive Director	17	18
Healthcare	Senior Director	17	17
Healthcare	Director	15	13
Healthcare	Associate Director	14	12
Healthcare	Senior Project Manager	13	12
Healthcare	Principal	12	13
Healthcare	Senior Manager	12	12
Healthcare	Manager	10	9
Healthcare	Senior Scientist	9	9
Healthcare	Project Manager	9	7
Healthcare	Senior Analyst	8	7
Healthcare	Scientist	7	7
Healthcare	Registered Nurse	6	5
Healthcare	Associate Scientist	4	5
Healthcare	Research Associate	3	3

Note. This table shows examples of the seniority measure constructed for the analysis following the methodology of Amornsiripanitch et al. (2023). Seniority varies by industry, firm size quintile, and job title. This table presents examples from the Information Technology and Healthcare industries, showing the most common job titles in firms of the largest size and their corresponding seniority values for the largest (top quintile) and smallest (bottom quintile) firms. The table is sorted in descending order of seniority within each industry.

The table also shows that among large firms, the same job titles have generally similar seniority in both Healthcare and IT. For example, Vice President, Senior Director, Director, Senior Manager, and Manager all have the same seniority value in both industries for the largest firms. Though this is more apparent in IT, the same job title at larger firms generally obtains a higher seniority score than at smaller firms.

D.4 Explanatory Variable Transformation Robustness

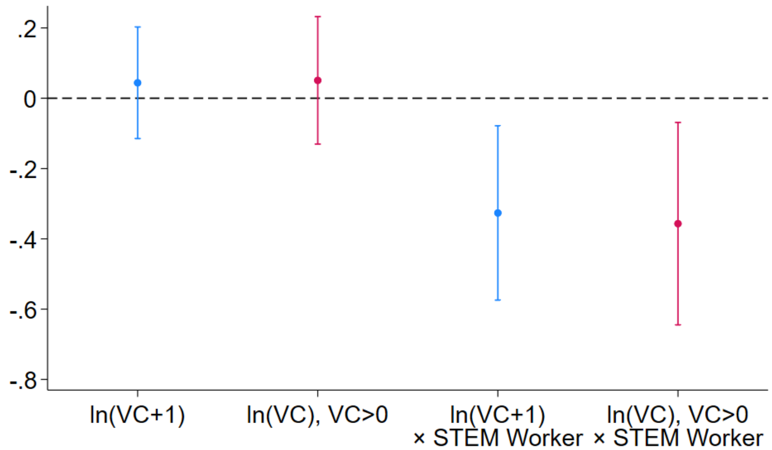
This section demonstrates the robustness of the results to different transformations of the treatment variable. Specifically, I estimate effects using two approaches: (i) taking the natural log of one plus VC Deals (preserving zeroes) and (ii) taking the natural log of VC Deals, dropping observations in which VC Deals takes the value zero.

Figure D4 displays the coefficient estimates for the seniority analysis, corresponding to the estimates of Table 4. The estimates are nearly identical across both transformations. This holds for both the main effect of Ln VC Deals and its interaction with STEM worker in Panel (a), as well as its interaction with the occupation-level skill specificity measure in Panel (b).

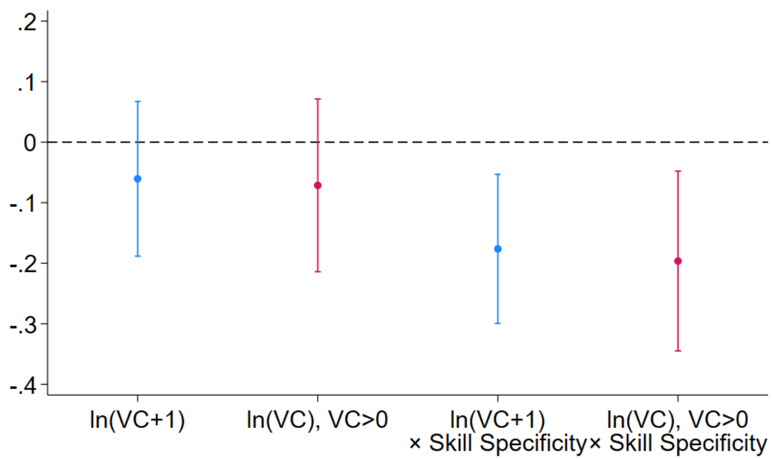
Figure D5 presents the coefficient estimates for the worker separation and reallocation analysis, corresponding to the estimates of Table 3. Once again, the estimates are almost identical across the two transformations, with slightly larger standard errors after dropping zeroes.

Figure D6 plots the coefficient estimates for the market-level analysis. The confidence intervals widen in the approach that drops all zeroes. This is expected given that there are more zeroes at the MSA-industry-year level than there are at the individual-level. The estimated magnitudes also appear to increase when considering intensive margin effects under approach (ii), though the point estimate still falls within the 90% confidence intervals of approach (i). This difference is intuitive, and indicates that the effects of "hot VC markets" are stronger along the intensive margin (i.e., conditional on the presence of VC activity) than the extensive margin, which reflect shifts from no activity to some activity.

Figure D4: Coefficient Comparison under Different Transformations of Treatment: Seniority



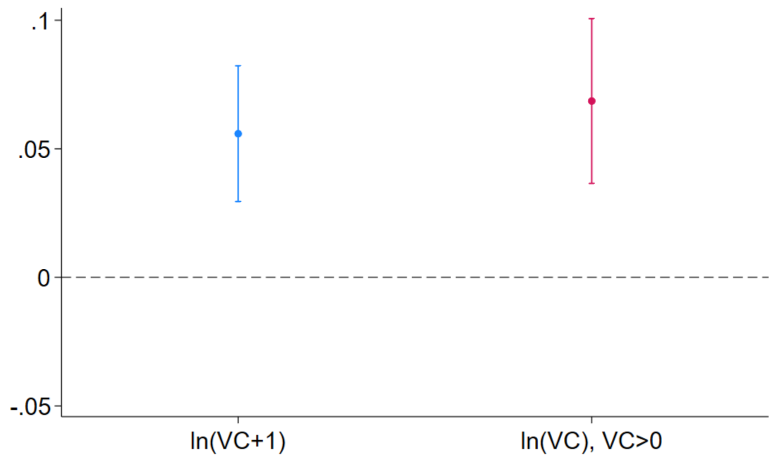
(a) Seniority $(t + 2)$: STEM Interaction



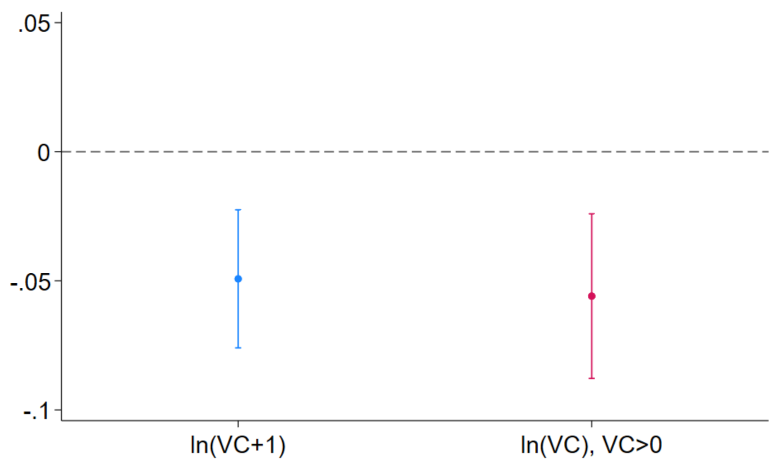
(b) Seniority $(t + 2)$: Specificity Interaction

Note. This figure shows the 2SLS estimates of the effect of increased capital at the time of hiring on seniority progress. The dependent variable is the worker's seniority two years after joining their first startup. See Table 4 for a description of the regression specification. Panels (a) and (b) are analogous to Panels A and B of Table 4, respectively. In both figures, the first and third coefficients (in blue) are analogous to Column (5) of Table 3. The second and fourth coefficients (in red) show robustness to an alternative transformation: taking the natural log of VC Deals and dropping observations where VC Deals is zero. Standard errors are clustered by MSA-industry-year and 90% confidence intervals are shown.

Figure D5: Coefficient Comparison under Different Transformations of Treatment: Job Duration and Reallocation



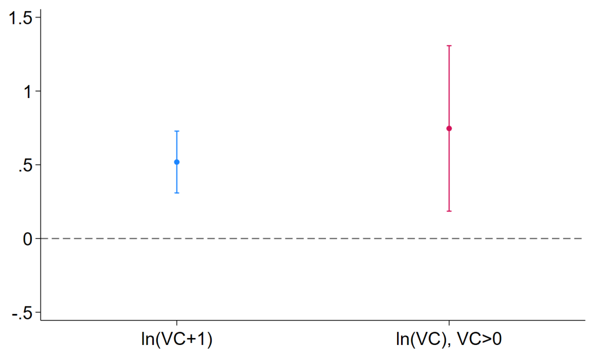
(a) Leave Firm within Two Years



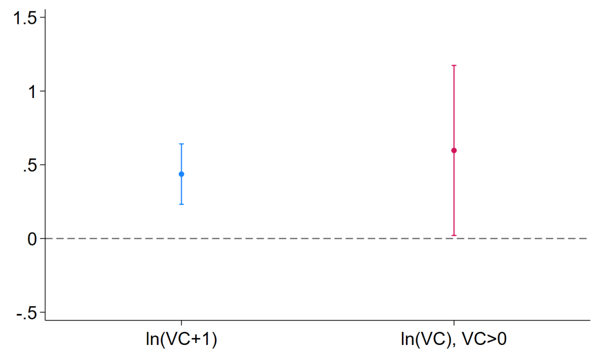
(b) Work in VC-Backed Universe ($t + 2$)

Note. This figure shows the 2SLS coefficient estimates of the effect of increased capital at the time of hiring on worker separation and reallocation. In panel (a), the dependent variable is an indicator for whether the worker separates from the startup within 24 months of joining. In panel (b), the dependent variable is an indicator for whether the worker is employed by the VC-backed universe at the end of calendar year $t + 2$, where year t is the year the worker joins the startup. In both figures, the coefficient on the left (in blue) is analogous to Column (4) of Table 3. The coefficient on the right (in red) shows robustness to an alternative transformation: taking the natural log of VC Deals and dropping observations where VC Deals is zero. Standard errors are clustered by MSA-industry-year and 90% confidence intervals are shown.

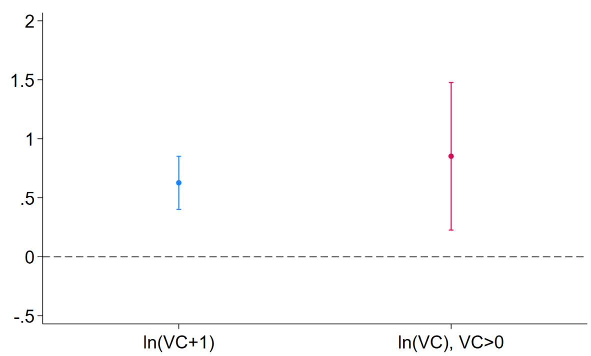
Figure D6: Coefficient Comparison under Different Transformations of Treatment: Market-Level



(a) Workers



(b) Hires



(c) Separations

Note. This figure shows the IV PPML estimates of the effect of increased capital on market-level startup job creation, destruction, and net employment. See Table 2 for a description of the regression model. In each panel, the coefficient on the left (in blue) is analogous to Panel B of Table 2. The coefficient on the right (in red) shows robustness to an alternative transformation: taking the natural log of VC Deals and dropping observations where VC Deals is zero. Standard errors are clustered by MSA-industry and 90% confidence intervals are shown.

E Supplementary Job Creation and Destruction Analysis

Table E8 shows the robustness of the IV estimates to different variants of the shift-share instrument. Recall that a market is a defined as an MSA-industry pair (m, k). Let $I_{m,k,j,t}$ denote VC investments of investor j in market (m, k) in year t, and let $w_{m,k,j,t}$ denote the share of investor j in that market and year. Recall that the IV is constructed as:

$$\text{Predicted VC}_{m,k,t} = \sum_{j} \left(w_{m,k,j,t_0} \sum_{(m,k)' \neq (m,k)} I_{(m,k)',j,t} \right) \tag{E.34}$$

where the inner summation runs over all MSA–industry pairs $(m, k)'$ other than the local market (m, k). Each panel in Table E8 implements a different, broader leave-out category for the inner summation:

(i) Panel A leaves out all markets with MSA m.

(ii) Panel B leaves out all markets with industry k.

(iii) Panel C leaves out all markets with either MSA m OR industry k.

The table shows that the estimates are robust across the different variants, providing further support for the validity of the IV.

Table E9 shows that the results are robust to dropping Silicon Valley. Specifically, it replicates the analysis of Table 2, but dropping the San Jose-Sunnyvale-Santa Clara MSA.

Table E10 shows that the IV estimates are robust to the specification with fully saturated fixed effects, i.e., including MSA-by-Industry, Industry-by-Year, and MSA-by-Year fixed effects, presented in Columns (2), (4) and (6). Panel B shows that the estimates are robust, but unsurprisingly, the standard errors increase due the reduced degrees of freedom in the fully saturated regression.

Table E11 shows that the results are robust to conducting the analyses at the level of Pitchbook's more granular industry classification (IndustryGroup).

E.1 Variants of Shift-Share Instrument

Table E8: The Effect of Increased Capital on Startup Labor Market Turnover with Alternative IV Leave-Out Groups

	Startup Employment		Startup Hires		Startup Separations	
	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML
Panel A. All MSA						
Ln VC Deals ($t-1$)	0.519***	0.431***	0.442***	0.353***	0.622***	0.505***
	(0.133)	(0.139)	(0.130)	(0.136)	(0.142)	(0.149)
First Stage F-Stat	225.88	206.44	225.88	206.44	225.88	206.44
Panel B. All Industry						
Ln VC Deals ($t-1$)	0.570***	0.471***	0.501***	0.419***	0.653***	0.545***
	(0.133)	(0.124)	(0.131)	(0.118)	(0.142)	(0.127)
First Stage F-Stat	244.12	221.72	244.12	221.72	244.12	221.72
Panel C. All MSA or Industry						
Ln VC Deals ($t-1$)	0.573***	0.453***	0.503***	0.394***	0.643***	0.517***
	(0.142)	(0.139)	(0.137)	(0.133)	(0.147)	(0.141)
First Stage F-Stat	212.96	192.76	212.96	192.76	212.96	192.76
FE: MSA-Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: State × Year		Yes		Yes		Yes
Mean	61.07	61.07	26.63	26.63	13.91	13.91
Observations	47,253	47,253	47,253	47,253	47,253	47,253

Note. This table shows the effect of increased capital on startup job creation, destruction, and net employment, using three variants of the shift-share IV. Each panel in the table implements a different, broader leave-out category for the inner summation in Equation (E.34): Panel A leaves out all markets with MSA m, Panel B leaves out all markets with industry k, and Panel C leaves out all markets with either MSA m OR industry k. The sample includes college-educated workers at US VC-backed startups. Each observation is an MSA-industry-year. The dependent variable in columns (1) and (2) is total employment of VC-backed startups as of year end. The dependent variable in columns (3) and (4) is the number of startup hires. The dependent variable in columns (5) and (6) the number of worker separations from startups. Ln VC Deals ($t-1$) is the natural log of VC deals in the MSA-industry in the year prior. The IV PPML estimates are obtained from a two-step control function approach, described in Appendix B.1. Standard errors reported in parentheses are clustered by MSA-industry, and are obtained by bootstrap in Panel B. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

E.2 Dropping Silicon Valley

Table E9: The Effect of Increased Capital on Startup Labor Market Turnover Dropping Silicon Valley

	Startup Employment		Startup Hires		Startup Separations	
	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML
Panel A. PPML Estimates						
Ln VC Deals ($t-1$)	0.299***	0.232***	0.268***	0.213***	0.329***	0.258***
	(0.034)	(0.019)	(0.033)	(0.019)	(0.036)	(0.023)
Panel B. IV PPML Estimates						
Ln VC Deals ($t-1$)	0.550***	0.490***	0.470***	0.418***	0.649***	0.558***
	(0.126)	(0.128)	(0.119)	(0.121)	(0.136)	(0.138)
FE: MSA × Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: State × Year		Yes		Yes		Yes
First Stage F-Stat	244.91	223.55	244.91	223.55	244.91	223.55
Mean	58.20	58.20	25.45	25.45	13.23	13.23
Observations	47,120	47,120	47,120	47,120	47,120	47,120

Note. This table shows the effect of increased capital on startup job creation, destruction, and net employment, while dropping the San Jose-Sunnyvale-Santa Clara MSA. The sample includes college-educated workers at US VC-backed startups. Each observation is an MSA-industry-year. The dependent variable in columns (1) and (2) is total employment of VC-backed startups as of year end. The dependent variable in columns (3) and (4) is the number of startup hires. The dependent variable in columns (5) and (6) the number of worker separations from startups. Ln VC Deals ($t-1$) is the natural log of VC deals in the MSA-industry in the year prior. Panel A presents the PPML estimates while Panel B presents IV PPML estimates using the shift-share instrumental variable. The IV PPML estimates are obtained from a two-step control function approach, described in Appendix B.1. Standard errors reported in parentheses are clustered by MSA-industry, and are obtained by bootstrap in Panel B. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

E.3 Specification with Fully Saturated Fixed Effects

Table E10: The Effect of Increased Capital on Startup Labor Market Turnover

	Startup Employment		Startup Hires		Startup Separations	
	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML
Panel A. PPML Estimates						
Ln VC Deals $(t-1)$	0.273***	0.161***	0.268***	0.159***	0.308***	0.178***
	(0.035)	(0.016)	(0.041)	(0.017)	(0.038)	(0.018)
Panel B. IV PPML Estimates						
Ln VC Deals $(t-1)$	0.440***	0.367*	0.364***	0.359*	0.521***	0.524**
	(0.129)	(0.217)	(0.125)	(0.217)	(0.138)	(0.221)
FE: MSA × Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry × Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: State × Year	Yes		Yes		Yes	
FE: MSA × Year		Yes		Yes		Yes
First Stage F-Stat	228.00	159.40	228.00	159.40	228.00	159.40
Mean	61.07	61.07	26.63	26.63	13.91	13.91
Observations	47,253	47,253	47,253	47,253	47,253	47,253

Note. This table shows the effect of increased capital on startup job creation, destruction, and net employment. Columns (2), (4), and (6) include the set of MSA-by-industry, industry-by-year, and MSA-by-year fixed effects. The sample includes college-educated workers at US VC-backed startups. Each observation is an MSA-industry-year. The dependent variable in columns (1) and (2) is total employment of VC-backed startups as of year end. The dependent variable in columns (3) and (4) is the number of startup hires. The dependent variable in columns (5) and (6) the number of worker separations from startups. Ln VC Deals $(t-1)$ is the natural log of VC deals in the MSA-industry in the year prior. Panel A presents the PPML estimates while Panel B presents IV PPML estimates using the shift-share instrumental variable. The IV PPML estimates are obtained from a two-step control function approach, described in Appendix B.1. Standard errors reported in parentheses are clustered by MSA-industry, and are obtained by bootstrap in Panel B. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

E.4 Granular Industries

Table E11: The Effect of Increased Capital on Startup Labor Flows at the Industry Group Level

	Startup Employment		Startup Hires		Startup Separations	
	(1) PPML	(2) PPML	(3) PPML	(4) PPML	(5) PPML	(6) PPML
Panel A. PPML Estimates						
Ln VC Deals ($t-1$)	0.298***	0.265***	0.281***	0.264***	0.315***	0.284***
	(0.023)	(0.017)	(0.023)	(0.019)	(0.023)	(0.018)
Panel B. IV PPML Estimates						
Ln VC Deals ($t-1$)	0.504***	0.461***	0.400***	0.364***	0.646***	0.600***
	(0.098)	(0.098)	(0.095)	(0.096)	(0.114)	(0.112)
FE: MSA × Industry Group	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry Group × Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: State × Year		Yes		Yes		Yes
Mean	18.14	18.14	7.91	7.91	4.13	4.13
Observations	159,068	159,068	159,068	159,068	159,068	159,068

Note. This table shows the effect of increased capital on startup job creation, destruction, and net employment. The sample includes college-educated workers at US VC-backed startups. Each observation is an MSA-industry group-year. The dependent variable in columns (1) and (2) is total employment of VC-backed startups as of year end. The dependent variable in columns (3) and (4) is the number of startup hires. The dependent variable in columns (5) and (6) the number of worker separations from startups. Ln VC Deals ($t-1$) is the natural log of VC deals in the MSA-industry group in the year prior. Panel A presents the PPML estimates while Panel B presents IV PPML estimates using the shift-share instrumental variable. The IV PPML estimates are obtained from a two-step control function approach, described in Appendix B.1. Standard errors reported in parentheses are clustered by MSA-industry group, and are obtained by bootstrap in Panel B. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

F Supplementary Worker Separation and Reallocation Analysis

Table F12 shows that the increase in worker separations is not explained by the firm undergoing an acquisition or going public. Specifically, while all of the main text analyses already drop any jobs starting after the firm has "exited," in this robustness check, I additionally drop any jobs within the three years prior to the startup's exit date, if applicable. This way, any separations within two years are sufficiently far away from the date of acquisition or IPO. The decrease in job duration continues to hold, showing that changes in ownership do not explain the effect.

Table F13 demonstrates the robustness of the worker separation result to directly examining the natural log of job duration in months as the dependent variable. The estimate in Column (5) indicates that a doubling of local VC reduces startup job duration by $[\exp(-0.155 \ln(2)) - 1] \times 100\% = 11\%$, in line with the estimates in the main text.

Table F14 demonstrates the robustness of the results to controlling for each individual's turnover rate prior to joining the startup. Specifically, I calculate each worker's annualized historical rate of job switching:

$$\frac{\text{Number of Past Firms}}{\text{Total Number of Months in Labor Force}} \times 12 \tag{F.35}$$

and include this as a control variable in the regression. The coefficient estimates are intuitive: in general, a higher rate of pre-startup turnover predicts shorter job duration. However, the effect of VC market conditions is highly robust, and the estimates are unimpacted by the addition of this control variable.

Table F15 shows robustness to controlling for industry-level shocks using Pitchbook's more granular industry classification (IndustryGroup).

F.1 Separations not Driven by Firm Acquisition or IPO

Table F12: The Effect of Increased Capital at Worker Entry on Separation within Two Years: Robustness

	Dependent Variable: Leave Startup $(t+2)$					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Ln VC Deals $(t-1)$	0.016***	0.015***	0.016***	0.045***	0.049**	0.045**
	(0.003)	(0.003)	(0.003)	(0.016)	(0.023)	(0.022)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: MSA $\times$ Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Occupation $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry $\times$ Year		Yes			Yes	
FE: MSA $\times$ Year			Yes			Yes
First Stage F-Stat				133.41	71.04	92.98
Dependent Var. Mean	0.41	0.41	0.41	0.41	0.41	0.41
Observations	657,963	657,963	657,963	657,963	657,963	657,963

Note. This table shows robustness to dropping any jobs starting three years prior to a startup's exit date (acquisition or IPO), if applicable. Each observation is an individual starting a job in year t and MSA-industry pair s at a VC-backed startup. The dependent variable is an indicator equal to one if the worker leaves the startup within 24 months and zero otherwise. Ln VC Deals $(t-1)$ is the lagged natural log of VC deals in local market s. Individual Controls include a quadratic polynomial in labor market experience at job start, the worker's historical job turnover rate, highest degree-by-year fixed effects, and elite university-by-year fixed effects. OLS estimates are shown in columns (1) through (3) and 2SLS estimates are shown in columns (4) through (6). Standard errors are clustered by MSA-industry and reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

F.2 Alternative Measure: Job Duration in Months

Table F13: The Effect of Increased Capital at Worker Entry on Job Duration

	Dependent Variable: Ln Job Duration					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Ln VC Deals $(t-1)$	-0.034***	-0.032***	-0.031***	-0.155***	-0.160***	-0.146***
	(0.005)	(0.005)	(0.006)	(0.033)	(0.047)	(0.045)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: MSA $\times$ Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Occupation $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry $\times$ Year		Yes			Yes	
FE: MSA $\times$ Year			Yes			Yes
First Stage F-Stat				131.31	69.85	90.30
Observations	779,298	779,298	779,298	779,298	779,298	779,298

Note. Each observation is an individual starting a job in year t and MSA-industry pair s at a VC-backed startup. The dependent variable is the natural log of job duration measured in months. Durations of jobs not yet ended by October 2022 are censored at this month. Ln VC Deals $(t-1)$ is the lagged natural log of VC deals in local market s. Individual Controls include a quadratic polynomial in labor market experience at job start, the worker's historical job turnover rate, highest degree-by-year fixed effects, and elite university-by-year fixed effects. OLS estimates are shown in columns (1) through (3) and 2SLS estimates are shown in columns (4) through (6). Standard errors are clustered by MSA-industry and reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

F.3 Controlling for Turnover History

Table F14: The Effect of Increased Capital at Worker Entry on Job Duration and Reallocation with Turnover History Control

	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
	Dependent Variable: Leave Startup $(t+2)$					
Ln VC Deals $(t-1)$	0.017***	0.017***	0.015***	0.054***	0.058**	0.049**
	(0.002)	(0.002)	(0.003)	(0.016)	(0.023)	(0.022)
Past Turnover Rate	0.097***	0.097***	0.096***	0.096***	0.096***	0.096***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dependent Var. Mean	0.41	0.41	0.41	0.41	0.41	0.41
	Dependent Variable: Work in VC-Backed Universe $(t+2)$					
Ln VC Deals $(t-1)$	-0.005*	-0.005**	-0.011***	-0.048***	-0.048**	-0.040*
	(0.003)	(0.003)	(0.003)	(0.016)	(0.023)	(0.022)
Past Turnover Rate	-0.074***	-0.073***	-0.073***	-0.073***	-0.073***	-0.073***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Dependent Var. Mean	0.62	0.62	0.62	0.62	0.62	0.62
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: MSA × Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Occupation × Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry × Year		Yes			Yes	
FE: MSA × Year			Yes			Yes
First Stage F-Stat				131.30	69.85	90.29
Observations	779,298	779,298	779,298	779,298	779,298	779,298

Note. This table shows the effect of increased capital at the time of hiring on the likelihood that (i) the worker separates from the firm and (ii) the worker remains in the universe of venture-backed firms. Each observation is an individual starting a job in year t at a VC-backed startup in MSA-industry pair s. In Panel A, the dependent variable is an indicator equal to one if the worker leaves the startup within 24 months and zero otherwise. In Panel B, the dependent variable is an indicator equal to one if the worker leaves the VC-backed universe within two years and zero otherwise. Both panels control for the worker's rate of job switching prior to joining the startup, given by (F.35). Ln VC Deals is the natural log of VC deals in local market s in year $t-1$. Individual Controls include a quadratic polynomial in labor market experience at job start, the worker's historical turnover rate, highest degree-by-year fixed effects, and elite university-by-year fixed effects. OLS estimates are shown in columns (1) through (3) and 2SLS estimates are shown in columns (4) through (6). Standard errors are clustered by MSA-industry-year and are reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

F.4 Controlling for More Granular Industry Shocks

Table F15: The Effect of Increased Capital at Worker Entry on Job Duration and Reallocation with Granular Industry Controls

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	2SLS	2SLS	2SLS
	Dependent Variable: Leave Startup ($t+2$)					
Ln VC Deals ($t-1$)	0.018***	0.018***	0.015***	0.056***	0.055**	0.051**
	(0.002)	(0.002)	(0.003)	(0.016)	(0.023)	(0.022)
Dependent Var. Mean	0.41	0.41	0.41	0.41	0.41	0.41
	Dependent Variable: Work in VC-Backed Universe ($t+2$)					
Ln VC Deals ($t-1$)	-0.005**	-0.005*	-0.011***	-0.049***	-0.043*	-0.042*
	(0.003)	(0.003)	(0.003)	(0.016)	(0.023)	(0.022)
Dependent Var. Mean	0.62	0.62	0.62	0.62	0.62	0.62
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: MSA $\times$ Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Occupation $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry Group $\times$ Year		Yes			Yes	
FE: MSA $\times$ Year			Yes			Yes
First Stage F-Stat				131.31	70.46	90.30
Observations	779,298	779,298	779,298	779,298	779,298	779,298

Note. This table shows the effect of increased capital at the time of hiring on the likelihood that (i) the worker separates from the firm and (ii) the worker remains in the universe of venture-backed firms. Each observation is an individual starting a job in year t at a VC-backed startup in MSA-industry pair s. In Panel A, the dependent variable is an indicator equal to one if the worker leaves the startup within 24 months and zero otherwise. In Panel B, the dependent variable is an indicator equal to one if the worker leaves the VC-backed universe within two years and zero otherwise. Ln VC Deals is the natural log of VC deals in local market s in year $t-1$. Individual Controls include a quadratic polynomial in labor market experience at job start, the worker's historical turnover rate, highest degree-by-year fixed effects, and elite university-by-year fixed effects. OLS estimates are shown in columns (1) through (3) and 2SLS estimates are shown in columns (4) through (6). Standard errors are clustered by MSA-industry-year and are reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

G Supplementary Seniority Analysis

Table G16 shows that the seniority effects are highly robust to controlling for the worker's rate of job switching prior to joining the startup (as given by Equation (F.35)). The coefficient estimates are intuitive: in general, a higher past turnover rate predicts lower future seniority. However, the inclusion of the turnover history control has no impact on the importance of funding market conditions.

Table G17 shows robustness to controlling for industry-level shocks using Pitchbook's more granular industry classification (IndustryGroup).

Table G18 shows that the seniority results are robust to including fixed effects for each worker's *origin firm*, that is, their employer before joining the VC-backed startup.

G.1 Controlling for Turnover History

Table G16: The Effect of Increased Capital at Worker Entry on Seniority Advancement with Turnover History Control

	Dependent Variable: Seniority $(t+2)$							
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) 2SLS	(6) 2SLS	(7) 2SLS	(8) 2SLS
Panel A.								
Ln VC Deals $(t-1)$	0.031**	0.035**	0.035**	0.020	0.044	0.004	0.019	0.169
	(0.016)	(0.016)	(0.017)	(0.018)	(0.097)	(0.127)	(0.190)	(0.126)
Ln VC Deals $(t-1)$	-0.060**	-0.062***	-0.064***	-0.064***	-0.326**	-0.339**	-0.310**	-0.271*
× *STEM Worker*	(0.024)	(0.024)	(0.024)	(0.024)	(0.151)	(0.153)	(0.152)	(0.152)
Past Turnover Rate	-0.029***	-0.030***	-0.030***	-0.028***	-0.029***	-0.029***	-0.030***	-0.028***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Panel B.								
Ln VC Deals $(t-1)$	0.007	0.009	0.007	-0.007	-0.060	-0.097	-0.061	0.094
	(0.012)	(0.013)	(0.013)	(0.015)	(0.078)	(0.120)	(0.203)	(0.111)
Ln VC Deals $(t-1)$	-0.024**	-0.023**	-0.025**	-0.028**	-0.176**	-0.171**	-0.171**	-0.169**
× *Skill Specificity*	(0.011)	(0.011)	(0.011)	(0.011)	(0.075)	(0.075)	(0.075)	(0.077)
Past Turnover Rate	-0.027***	-0.027***	-0.028***	-0.026***	-0.026***	-0.026***	-0.027***	-0.026***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: MSA × Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Occupation × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry × Year		Yes	Yes			Yes	Yes	
FE: State × Year			Yes				Yes	
FE: MSA × Year				Yes				Yes
First Stage F-Stat					129.48	67.39	32.35	89.73
Observations	627,312	627,312	627,312	627,312	627,312	627,312	627,312	627,312

Note. This table shows the effect of increased capital at the time of hiring on subsequent job ladder progression. Each observation is an individual beginning their first job at a VC-backed startup in year t and MSA-industry pair s. The dependent variable is the worker's seniority at the end of calendar year $t+2$. Ln VC Deals$_{s,t-1}$ is the natural log of VC deals in local market s in year $t-1$. Panel A includes an interaction term between this variable and an indicator for whether a worker is a STEM worker. Panel B includes an interaction term between Ln VC Deals and the rate of skill change measure from Deming and Noray (2020). Both panels control for the worker's rate of job switching prior to joining the startup, given by (F.35). Individual Controls include initial seniority in year t, a quadratic polynomial in labor market experience at job start, the worker's historical job turnover rate, highest degree-by-year fixed effects, and elite university-by-year fixed effects. OLS estimates are shown in columns (1) through (4) and 2SLS estimates are shown in columns (5) through (8). Standard errors are clustered by MSA-industry-year and reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

G.2 Controlling for More Granular Industry Shocks

Table G17: The Effect of Increased Capital at Worker Entry on Seniority Advancement with Granular Industry Controls

	Dependent Variable: Seniority ($t+2$)							
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) 2SLS	(6) 2SLS	(7) 2SLS	(8) 2SLS
Panel A.								
Ln VC Deals ($t-1$)	0.031**	0.035**	0.034**	0.019	0.044	-0.016	-0.019	0.169
	(0.016)	(0.016)	(0.017)	(0.018)	(0.097)	(0.128)	(0.191)	(0.126)
Ln VC Deals ($t-1$)	-0.060**	-0.062***	-0.064***	-0.063***	-0.326**	-0.316**	-0.288*	-0.272*
$\times$ *STEM Worker*	(0.024)	(0.024)	(0.024)	(0.024)	(0.151)	(0.154)	(0.153)	(0.152)
Panel B.								
Ln VC Deals ($t-1$)	0.006	0.009	0.005	-0.007	-0.060	-0.117	-0.112	0.093
	(0.012)	(0.013)	(0.013)	(0.015)	(0.078)	(0.121)	(0.204)	(0.111)
Ln VC Deals ($t-1$)	-0.024**	-0.021*	-0.022**	-0.028**	-0.176**	-0.157**	-0.156**	-0.169**
$\times$ *Skill Specificity*	(0.011)	(0.011)	(0.011)	(0.011)	(0.075)	(0.076)	(0.076)	(0.077)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: MSA $\times$ Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Occupation $\times$ Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry Group $\times$ Year		Yes	Yes			Yes	Yes	
FE: State $\times$ Year			Yes				Yes	
FE: MSA $\times$ Year				Yes				Yes
First Stage F-Stat					129.49	67.97	32.68	89.73
Observations	627,312	627,312	627,312	627,312	627,312	627,312	627,312	627,312

Note. This table shows the effect of increased capital at the time of hiring on subsequent job ladder progression. Each observation is an individual's first startup job in year t at a VC-backed startup in MSA-industry pair s. The dependent variable is the worker's seniority at the end of calendar year $t+2$. Ln VC Deals is the natural log of VC deals in local market s in year $t-1$. Panel A includes an interaction term between this variable and an indicator for whether a worker is a STEM worker. Panel B includes an interaction term between Ln VC Deals and the rate of skill change measure from Deming and Noray (2020). Individual Controls include initial seniority in year t, a quadratic polynomial in labor market experience at job start, the worker's historical turnover rate, highest degree-by-year fixed effects, and elite university-by-year fixed effects. Further definitions and data construction details can be found in Section 3. OLS estimates are shown in columns (1) through (4) and 2SLS estimates are shown in columns (5) through (8). Standard errors are clustered by MSA-industry-year and reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

G.3 Controlling for Origin Firm Fixed Effects

Table G18: The Effect of Increased Capital at Worker Entry on Seniority Advancement with Origin Firm Fixed Effects

	Dependent Variable: Seniority $(t+2)$							
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) 2SLS	(6) 2SLS	(7) 2SLS	(8) 2SLS
Panel A.								
Ln VC Deals $(t-1)$	0.026	0.030*	0.030	0.015	0.075	0.033	0.103	0.271*
	(0.018)	(0.018)	(0.019)	(0.020)	(0.109)	(0.144)	(0.222)	(0.143)
Ln VC Deals $(t-1)$	-0.061**	-0.063**	-0.064**	-0.061**	-0.361**	-0.377**	-0.368**	-0.334**
× *STEM Worker*	(0.026)	(0.026)	(0.026)	(0.027)	(0.168)	(0.171)	(0.171)	(0.170)
Panel B.								
Ln VC Deals $(t-1)$	0.001	0.005	0.002	-0.012	-0.039	-0.076	0.001	0.178
	(0.013)	(0.014)	(0.015)	(0.017)	(0.086)	(0.135)	(0.240)	(0.123)
Ln VC Deals $(t-1)$	-0.029**	-0.028**	-0.028**	-0.031**	-0.241***	-0.235***	-0.240***	-0.245***
× *Skill Specificity*	(0.012)	(0.013)	(0.013)	(0.013)	(0.085)	(0.085)	(0.085)	(0.087)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: MSA × Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Occupation × Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Industry × Year		Yes	Yes			Yes	Yes	
FE: State × Year			Yes				Yes	
FE: MSA × Year				Yes				Yes
FE: Origin Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First Stage F-Stat					132.92	66.89	30.81	96.93
Observations	627,312	627,312	627,312	627,312	627,312	627,312	627,312	627,312

Note. This table shows the effect of increased capital at the time of hiring on subsequent job ladder progression. Each observation is an individual beginning their first job at a VC-backed startup in year t and MSA-industry pair s. The dependent variable is the worker's seniority at the end of calendar year $t+2$. Ln VC Deals$_{s,t-1}$ is the natural log of VC deals in local market s in year $t-1$. Panel A includes an interaction term between this variable and an indicator for whether a worker is a STEM worker. Panel B includes an interaction term between Ln VC Deals and the rate of skill change measure from Deming and Noray (2020). Individual Controls include initial seniority in year t, a quadratic polynomial in labor market experience at job start, the worker's historical job turnover rate, highest degree-by-year fixed effects, and elite university-by-year fixed effects. OLS estimates are shown in columns (1) through (4) and 2SLS estimates are shown in columns (5) through (8). Standard errors are clustered by MSA-industry-year and reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.