Venture Capital Cycles and the Startup Labor Market

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Abstract

I show that venture capital market shocks have real consequences for high-skill knowledge 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 VC-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 Business workers are less affected. I show that differences in technology-skill specificity across occupations can explain this heterogeneity. The results indicate that shocks to risk capital can have lasting effects on knowledge worker careers.

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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). It has been well documented that flows of investment capital to high-growth businesses are highly volatile, often with large variation across industries and regions (Gompers and Lerner, 2004). Innovative firms not only require financial capital, but also rely crucially on the human capital of skilled workers. Inflows of financing may enable the movements of high-skill talent, including scientists, engineers, and business executives, towards emerging opportunities. While variation in financial returns over the investment cycle has been well studied (e.g., Nanda and Rhodes-Kropf, 2013), less is known about the returns to *human capital* for employees at innovative firms: what are the consequences of these movements for workers?

The answer is not obvious from theory alone. By nature, innovative firms engage in heavy experimentation and experience high rates of failure. This is reflected 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. As a result, these opportunities may come with significant career risks. In contrast, both conventional wisdom and related evidence suggest that returns to entrepreneurial workers may be positively skewed: the payoff is high if the startup succeeds, but long-term career consequences are minimal in the event of failure. Moreover, the experiences and skills gained from these roles may be valued in the labor market and accelerate career progress, regardless of the startup's outcome.[1]

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 shocks to the supply of risk capital have significant labor

[1]See, for example, related evidence on the returns to self-employment: 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

consequences. However, these consequences are not uniform across workers, but instead vary depending on the specificity of their human capital. I demonstrate this through the following steps: First, I document the role of financing for startup job creation and employment. Positive shocks to local VC increase skilled labor inflows into startups, while also generating substantial labor turnover. I then turn to understanding the characteristics of jobs induced by exogenous VC flows. I show that jobs created in "hotter" VC markets are shorter-lived, and that workers in these jobs are more likely to leave the VC-backed universe within two years. Next, I examine career consequences for workers. While the turnover effects highlighted above are similar across workers, I find that the effects on longer-term career progression differ by role. On average, science, technology, engineering, and math (STEM) workers advance slower in seniority in the two to five years after joining a startup in a hotter VC market. Meanwhile, workers in business, financial, and sales occupations (Business workers) are less affected. Finally, I show that this effect heterogeneity is consistent with the differential consequences of turnover by skill specificity: the negative effect on career advancement is driven by occupations that require more technology-specific skills.

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 first challenge by constructing a novel dataset of VC-backed firms from Pitchbook matched to public profiles of individuals who have reported working at these companies on LinkedIn, an online professional network with over one billion users worldwide as of 2024.[3] These profiles contain information on workers' employment and education histories. The job history data allow me to observe the timing of each worker-firm match and trace out each worker's career progression. My final 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" going forward.

A second challenge with the empirical exploration is that VC financing flows may be endogenous. For example, fundamental demand shocks such as changes in investment opportunities could both attract VC finance and increase startup hiring. Moreover, an improvement

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

[3]From https://about.linkedin.com/.

in technological opportunities could lead to estimates that understate the potential risks of hot financing markets to workers. I address the challenge of identifying the impact of VC using two approaches. First, in addition to including MSA-by-industry fixed effects to control for any time-invariant heterogeneity across local markets, I directly control for demand shocks by introducing industry-by-year fixed effects, absorbing any unobservable confounding variation that can be explained by industry-level shocks. I also introduce state-by-year or MSA-by-year fixed effects to control for any confounding channels that can be explained by regional economic shocks.

Next, I employ an instrumental variable (IV) approach to isolate shifts in the supply of venture capital. I use investor-level data from Pitchbook to construct an IV for VC flows at the MSA-industry-year level. I predict VC flows in a given MSA-industry-year using the weighted sum of each investor's nation-wide investment activity–excluding activity in that local market–where the weights are each investor's pre-period market share. For example, Softbank received a \$45 billion investment from the Saudi Public Investment Fund in 2017 before closing a \$93 billion fund in May 2017. According to the Pitchbook data, Softbank's total number of US VC investments grew 74% from 2016 to 2018. Meanwhile, deal volume of the VC firm New Enterprise Associates grew 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 five years prior to the shock would have experienced a larger increase in available capital over this period.

Using the constructed panel of MSA-industry-year financing and startup labor flows, I first document that risk capital shocks impact the allocation of high-skill workers in the economy, as exogenous inflows of VC attract workers to startups 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 findings demonstrate that increases in VC create new startup jobs and also induce job destruction, highlighting the role of risk capital for knowledge worker churn.

The identifying assumption for the instrument is that, conditional on observables, the pre-shock investor market shares are exogenous (Goldsmith-Pinkham, Sorkin, and Swift, 2020). I control for differential shocks to isolate the exogenous component of the market shares. In particular, the inclusion of industry-by-year fixed effects allows me to rely on *within-industry* comparisons. This alleviates concerns about potential confounds that can be explained by industry shocks, including the possibility that differential exposures could reflect differences in investment mandates. The inclusion of state-by-year or MSA-by-year fixed effects further controls for local economic conditions. The idea is that, purged of industry and location trends, the remaining variation in the exposures reflect investor idiosyncracies that do not predict changes in startup labor other than through realized VC flows.[4] I discuss further evidence for the identifying assumption in Section 4.

After establishing the role of increases in the supply of risk capital for job creation, I then turn to understanding the consequences for workers in these jobs using the individual-level data. To address the concern of selection given that financing flows are not randomly assigned, I employ the IV approach to isolate exogenous shocks to VC and recover their causal effect on workers. In addition, I make use of the rich résumé data to rely on increasingly strict sources of identifying variation at the individual level. I control for differential time trends by occupation, highest degree obtained, and university ranking, in addition to labor market experience to 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. Next, I make use of each worker's employment history to further account for ex-ante differences in worker types. I control for each individual's turnover propensity using their historical rate of job switching. Finally, when studying long-term career outcomes, I show that the effects are robust to the inclusion of *origin firm* fixed effects, absorbing any 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.

I show that jobs created in hotter VC markets are shorter-lived. Specifically, a doubling of local VC increases the likelihood of leaving the startup within two years by 3.5 percentage points, or 8.5% relative to the mean, and these effects are similar across occupations. A fall in job duration itself could reflect either improved outside options or increased job fragility. I find a collection of evidence consistent with an increase in job fragility by observing workers' subsequent employers, promotions, and the timing of the departures. First, I show that these departures are not explained by workers leaving successful startups after a startup exit. Next, I find that workers who enter hotter VC markets are more likely to leave the VC-backed and formerly VC-backed universe entirely (which includes tech giants such as Meta,

[4]The individual-level design further saturates this model by absorbing time-varying shocks by occupation, education, and prior experience.

Apple, Amazon, and Google) within two years. Specifically, a doubling of local VC reduces the likelihood of working at VC-backed universe in two years by 2.8 percentage points, or 9.2% relative to the mean. An increase in job fragility is also consistent with the findings of Nanda and Rhodes-Kropf (2013) that startups funded in hot markets are more likely to fail, which I also find in my data and sample period.

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 skills and experience that, if transferable, could lead to productivity gains and consequently faster advancement even in the event of startup closure. On the other hand, workers may face productivity losses from increased turnover, particularly if the human capital they gain in these positions is not general. I proxy for the returns to human capital for workers who take up a job with their change in seniority over the next two to five years. 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. Specifically, the measure calculates (over the full sample of employment) the median number of years it takes individuals to reach a job title at firms of any given industry and firm size quintile.

I find that while job duration in hot VC markets falls across occupations, effects on career advancement differ by role. STEM workers 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 average change. In other words, entering a hot VC market leads to a career setback for STEM workers of 9 months relative to the average career path over the next five years.

Meanwhile, the effect for Business workers is not distinguishable from zero. This heterogeneity is consistent with the hypothesis that the costs of job churn may be 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 skill requirements from job posting data. I find that the effects of hot VC markets are more negative on the advancement of workers in roles requiring more vintage-specific skills. A standard deviation increase in skill specificity increases the negative impact of doubling VC by 16% of the mean seniority progression.

Finally, I turn to estimating the distributional consequences of VC market shocks. I find that the effects are not uniform across the distribution; rather, the estimated slope coefficients are more (less) negative in lower (higher) quantiles for both STEM and Business workers. This indicates that the conditional distribution of seniority outcomes widens in booming financing markets. This is consistent with the theory that high capital supply periods facilitate VC risk-taking (Nanda and Rhodes-Kropf, 2017). As increases in the supply of capital lower the cost of experimentation for investors and facilitate investments into riskier firms, workers acquire skills related to these technologies. Higher rates of startup failure and increased turnover lead to slower average job ladder advancement for workers who acquire more specialized skills. However, these opportunities also offer potential upside, as the top-quantile effects suggest.

Related literature. This paper relates to a rich literature on the cyclicality of risk capital, including within private capital markets (Kaplan and Stein, 1993; Gompers and Lerner, 2000; Gompers et al., 2008; Inderst and Müller, 2004; Kaplan and Schoar, 2005; Nanda and Rhodes-Kropf, 2013; Opp, 2019; Janeway, Nanda, and Rhodes-Kropf, 2021), 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), and the financing of innovative firms more generally (DeMarzo, Kaniel, and Kremer, 2007; Johnson, 2007; Brown, Fazzari, and Petersen, 2009; Pastor and Veronesi, 2006, 2009; Kerr and Nanda, 2015; Haddad, Ho, and Loualiche, 2022). 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. 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 changes in the supply of equity finance: effects on skilled labor flows.

In doing so, this paper contributes to a growing body of work understanding the mobility and allocation of knowledge workers, an important determinant of aggregate productivity growth (Murphy, Shleifer, and Vishny, 1991; Acemoglu et al., 2018; Bell et al., 2018; Hsieh et al., 2019; Celik, 2023; Akcigit, Pearce, and Prato, 2024). Within the entrepreneurial labor market, recent evidence sheds light on factors that affect mobility from incumbent firms to startups: Babina and Howell (2024) demonstrate the role of corporate R&D in spurring departures to startups. Babina, Ouimet, and Zarutskie (2022) show that worker departures to startups increase after a firm goes public. Akcigit and Goldschlag (2023) document that large incumbents pay high wages to attract inventors who then go on to produce less impactful innovations. Bernstein, Townsend, and Xu (2024) show that workers are less likely to search for jobs at startups during economic downturns. In this paper, I document that shifts in the supply of funding affect the allocation of knowledge workers to entrepreneurial firms and across local markets. These findings suggest that the mobility of skilled labor may be an important way in which financing shocks impact the real economy.

By documenting the role of funding shocks for longer-term career outcomes, this paper also relates to the literature studying the effect of initial labor market conditions on future earnings, which has shed light on aggregate conditions over the business cycle. Oyer (2008) finds that improved stock market conditions during one's MBA education increase the likelihood of a long-term career on Wall Street. Workers who graduate in a recession experience persistent earnings discounts (Oreopoulos, von Wachter, and Heisz, 2012; Altonji, Kahn, and Speer, 2016; Schwandt and von Wachter, 2019). While these studies demonstrate channels through which economic expansions may improve future earnings, this paper demonstrates the risks of entering booming risk capital markets, as these markets experience high levels of experimentation and labor market turnover. This relates to recent work by Hombert and Matray (2023), who document a long-term earnings discount of workers in high-skill occupations who joined the late 1990s ICT boom, and Blank and Maghzian (2023), who show that workers who join high-yield firms during credit booms earn initially higher wages, but this effect reverses in the long run. This paper contributes with an analysis of VC financing flows across markets and over 15 years of data. I show that supply shocks to equity finance impact knowledge workers, and that the risk of slowed career progression is higher for occupations requiring more technology-specific skills. In doing so, this paper also relates to the literature on vintage-specific human capital (Chari and Hopenhayn, 1991; Violante, 2002; Deming and Noray, 2020; Kogan et al., 2021, 2022; Braxton and Taska, 2023).

Finally, this work adds to the strand of the literature studying the real economic consequences of VC, which has identified a causal role for VC in stimulating innovation (Kortum and Lerner, 2000; Bernstein, Giroud, and Townsend, 2016) and aggregate employment (Samila and Sorenson, 2011). In this paper, I study the implications of VC financing shocks for startup worker outcomes.

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.

2 Theoretical Framework

2.1 Venture Capital, Labor, and Production in General Equilibrium

To theoretically motivate the linkages between the supply of venture capital financing and skilled labor flows, I offer an equilibrium model of VC financing, labor, and production 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; Silveira and Wright, 2016; Wasmer and Weil, 2004) 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 the labor market. This paper's focus is the empirical analysis of implications for the startup labor market. Therefore, the full model is developed in Appendix A and the main predictions are presented here.

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 also increases the rate of technical obsolescence, increasing 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 likelihood of separation 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 Knowledge Worker Career Progression

The model in Appendix A and summarized above predicts that a fall in the VC's entry cost increases the supply of VC in the economy, increasing capital market competition and reducing the time it takes for entrepreneurs to find an available financier. In other words, more "money chasing deals" leads to a "hot" VC funding environment, consistent with the empirical findings of Gompers and Lerner (2000). As the VC's equity stake falls and deal flow increases, the labor market is impacted as well: increased firm entry leads to more job openings. However, jobs created in hot VC markets are shorter lived as the rate of match destruction increases. I test the predictions of increased turnover and lower job duration in Sections 4 and 5.

Positive shocks to the supply of capital could have differing implications for longer-term career outcomes. On the one hand, workers who join startups in booming investment markets could acquire valuable skills in frontier technologies that improve their job advancement opportunities. These skills may be transferable across firms, enhancing productivity even in the event that the worker switches jobs. This implies that working in hot VC markets may lead to faster career advancement.

On the other hand, the model's prediction of increased turnover implies that workers in hotter markets could incur costs that slow productivity gains relative to their counterparts. Indeed, an established literature has shown that job displacement leads to earnings losses that persist beyond the period of unemployment (e.g., Jacobson, LaLonde, and Sullivan, 1993; Couch and Placzek, 2010), likely due to losses of accumulated firm-specific human capital (Becker, 1962; Lazear, 2009). Moreover, on-the-job investments include more than skill acquisition but also, reputation building and establishing familiarity that may be consequential for internal promotions. This suggests that these workers may face slowed job ladder progression as they work to re-establish themselves at new firms.

Moreover, the model's prediction of increased capital market competition and smaller VC equity stakes accords with anecdotal accounts of loosened investor discipline to compete for deals in hot markets, which may result in lower realized returns (Lerner and Nanda, 2020). Indeed, the nature of VC investments makes it likely for financing booms to be followed by busts. 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). Additionally, other documented phenomena in securities markets may be especially prevalent when investing in high-growth companies; these include systematic errors in expectations of future growth stemming from overreaction (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 may increase the likelihood that booming markets are followed by subsequent contractions and as a result, negative labor demand shocks. Workers may consequently need to find new jobs not only at different firms but also in different technological areas, or potentially at firms not financed by VC entirely. This suggests the possibility of slower career advancement even after accumulating valuable skills in a specific technology, as the opportunity to deploy these skills falls.

The third group of predictions involves hypotheses that imply that the effects on seniority progress may not be uniformly positive or negative across workers. The model predicts that easier financing increases new entry, thereby increasing competition and the rate of displacement. Increased competition may generate non-uniform effects across the conditional outcome distribution by increasing top quantile outcomes and reducing lower quantile outcomes in a "winner-takes-all" manner. Another possibility is a shift in the underlying distribution of funded firms, which translates to labor market outcomes. Nanda and Rhodes-Kropf (2013) provide evidence that hot funding markets mitigate perceived financing risk to VCs. As a result, more experimental and higher risk (and not necessarily lower quality) projects receive backing in hot markets.

These hypotheses are not mutually exclusive, but rather, generate a set of more nuanced predictions that include the potential for heterogeneous effects. In particular, (1) workers may gain valuable experiences from working in a hot financing environment. (2) However, increased turnover and the potential for market-wide contractions suggest that the accompanying risks of hot markets may be greater for workers who acquire more specialized skills. (3) In addition, heightened competition and risk-taking during periods of capital abundance may generate non-uniform effects across the conditional outcome distribution. 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 data 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 variable. I first obtain the full sample of US-headquartered firms 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 B2 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 sourced from public profiles on LinkedIn. LinkedIn is the largest online professional network with over one billion users worldwide as of May 2024. Users post their CVs and can additionally use the platform to network, share posts, and search for jobs. 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 on LinkedIn. 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.[5] 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 venture-backed startups by removing 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

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

2012. Some firms may remain privately-held even as they mature beyond the startup phase. Therefore, for the remaining companies, I also drop any positions beginning 15 years after the company's first observed VC financing round.

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 39,649 venture-backed firms and 860,794 startup jobs beginning from 2003 to 2018.

Data construction. After obtaining the matched sample of users, I then observe 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. I link this 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 B.1 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. The choice of the industry granularity does not impact the results.

The second dataset is an individual-level dataset in which each observation is a job (defined as a worker-firm match). I construct 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. The measurement of job duration takes into account a worker's full tenure at the firm.

I now describe the construction of the seniority outcome variable. 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 obtained 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 B.2 provides further details on the construction of seniority. Table B12 in the Appendix presents examples of the most common titles in the information technology industry. For these titles, the table shows the seniority value for the largest and smallest firm size quintiles. The table shows that in general, having a more senior title at a larger firm receives a higher seniority value than the same title at a smaller firm.

Descriptive statistics. The final sample consists of 860,794 jobs at 39,649 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.[6] 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 7 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 17%, as this group includes legal and medical professionals.

Figure 1 presents examples of VC investment flows and startup labor flows using the

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

Table 1: Startup Worker Descriptive Statistics

	N	Mean	p25	p50	p75	Std. Dev.
All						
Years of Experience	860,794	8.63	3.00	7.00	13.00	7.55
Seniority	860,794	7.58	4.00	7.00	10.00	4.44
Job Duration in Months	860,794	41.61	15.00	30.00	57.00	36.39
Elite School (Binary Variable)	860,794	0.10	0.00	0.00	0.00	0.30
Highest Degree: Bachelor (Binary Variable)	860,794	0.58	0.00	1.00	1.00	0.49
Highest Degree: Masters Level (Binary Variable)	860,794	0.31	0.00	0.00	1.00	0.46
Highest Degree: Doctoral Level (Binary Variable)	860,794	0.08	0.00	0.00	0.00	0.27
STEM Workers						
Years of Experience	358,050	8.35	3.00	7.00	12.00	7.29
Seniority	358,050	7.02	4.00	6.50	9.50	4.02
Job Duration in Months	358,050	42.34	15.00	32.00	58.00	36.53
Elite School (Binary Variable)	358,050	0.11	0.00	0.00	0.00	0.32
Highest Degree: Bachelor (Binary Variable)	358,050	0.54	0.00	1.00	1.00	0.50
Highest Degree: Masters Level (Binary Variable)	358,050	0.33	0.00	0.00	1.00	0.47
Highest Degree: Doctoral Level (Binary Variable)	358,050	0.10	0.00	0.00	0.00	0.30
Business & Management Workers						
Years of Experience	414,662	9.19	3.00	7.00	13.00	7.82
Seniority	414,662	8.36	5.00	7.00	11.00	4.66
Job Duration in Months	414,662	41.24	14.00	30.00	56.00	36.20
Elite School (Binary Variable)	414,662	0.10	0.00	0.00	0.00	0.30
Highest Degree: Bachelor (Binary Variable)	414,662	0.63	0.00	1.00	1.00	0.48
Highest Degree: Masters Level (Binary Variable)	414,662	0.30	0.00	0.00	1.00	0.46
Highest Degree: Doctoral Level (Binary Variable)	414,662	0.04	0.00	0.00	0.00	0.20
Other Workers						
Years of Experience	88,082	7.17	2.00	5.00	10.00	7.04
Seniority	88,082	6.16	3.00	5.00	8.00	4.34
Job Duration in Months	88,082	40.40	13.00	28.00	57.00	36.68
Elite School (Binary Variable)	88,082	0.08	0.00	0.00	0.00	0.27
Highest Degree: Bachelor (Binary Variable)	88,082	0.54	0.00	1.00	1.00	0.50
Highest Degree: Masters Level (Binary Variable)	88,082	0.25	0.00	0.00	0.00	0.43
Highest Degree: Doctoral Level (Binary Variable)	88,082	0.17	0.00	0.00	0.00	0.38

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. These different episodes correspond respectively to 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. The labor figures show the year-over-year change in startup employment as well as 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 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 Knowledge Worker Flows

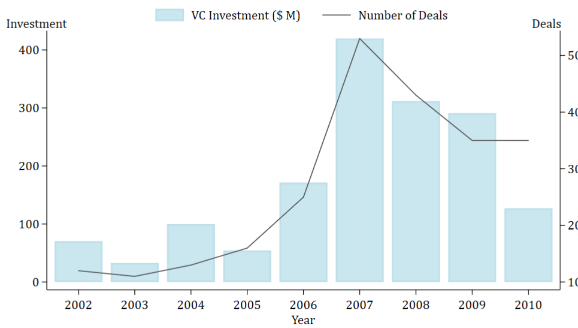
4.1 Empirical Design

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, TX, as a "local market." Consider the following model at the local market-by-year level:

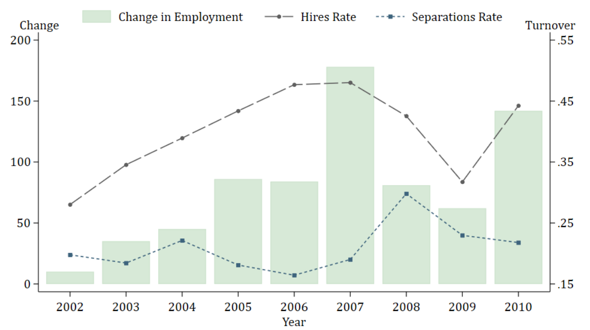
$$\mathbb{E}[y_{s,t} \big| \text{Ln VC Deals}_{s,t-1}, D_{s,t}, \varepsilon_{s,t}] = \exp(\beta \times \text{Ln VC Deals}_{s,t-1} + D'_{s,t}\alpha + \varepsilon_{s,t}) \qquad (2)$$

where $y_{s,t}$ is a nonnegative dependent variable such as startup hiring in market s and year t, and Ln VC 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. This model assumes that the conditional expectation

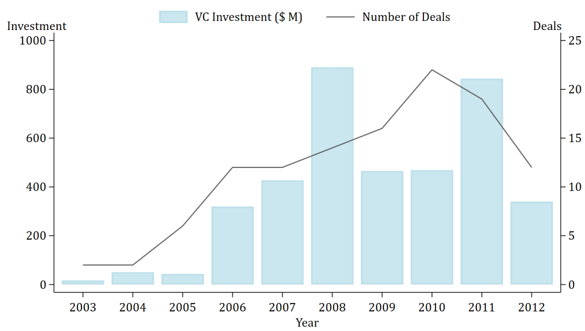
Figure 1: VC and Startup Labor Flows: Examples from Matched Data



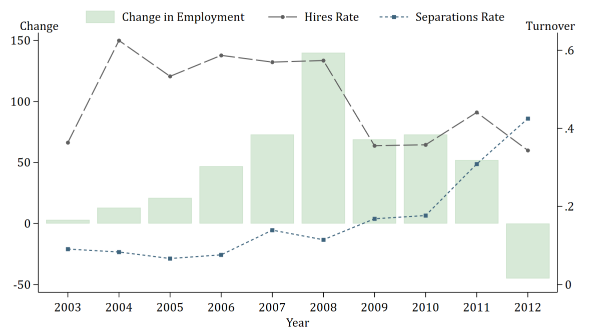
(a) VC Flows: Boston - B2C (Consumer)



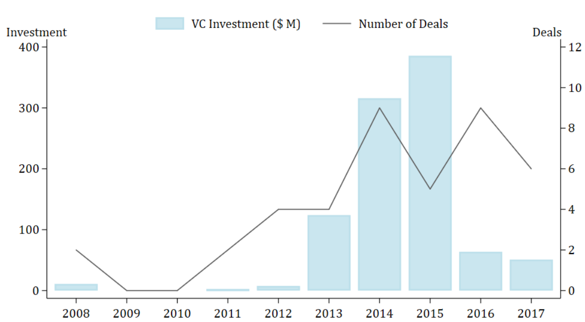
(b) Startup Labor Flows: Boston - B2C (Consumer)



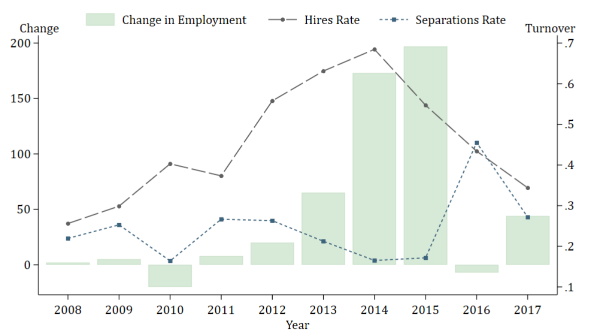
(c) VC Flows: San Jose - Energy



(d) Startup Labor Flows: San Jose - Energy



(e) VC Flows: Chicago - Financial Services



(f) Startup Labor Flows: Chicago - Financial Services of $y_{s,t}$ takes the exponential form. The coefficient of interest is β, the elasticity of hires with respect to VC investment, which I estimate using Poisson pseudo maximum likelihood. 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, for instance, 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 directly 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 any confounding variation that can be explained by broader regional shocks, or MSA-by-year fixed effects to control for changes in local economic conditions.

Next, I turn to an instrumental variable 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.3.

4.2 Constructing an Instrumental Variable for Local VC Flows

While much of the cyclical variation in VC deployments may coincide with changes in underlying investment opportunities, an increasing amount of research has shed light on 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).[7] In this section, I describe an approach that exploits heterogeneity across local markets in the exposure to common shocks through differential exposures to VC investors.

Why would shocks to different investors affect the total supply of VC in a local market? This would likely not be the case if entrepreneurs could costlessly substitute the funding of one investor for another. However, an established literature on the VC investment model suggests that this is not the case. VCs actively monitor and provide guidance to 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 portfolio companies (Admati and Pfleiderer, 1994; Townsend, 2015). As a result, capital supply shocks to VCs with investments in certain local markets are likely to affect the overall availability of funding in those markets.

These features motivate a shift-share-style approach (Bartik, 1991; Blanchard and Katz, 1992). Let $I_{s,j,t}$ be VC investments of investor j in market s, year t and $w_{s,j,t}$ be 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 the fund life of a VC fund 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. The instrument is relevant; across specifications, the smallest first-stage F-statistic is 39.7.

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

[7] 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.

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).[8] 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.[9] 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 $D_{s,t}$ narrow the identifying variation to isolate exogenous variation in the shares. Perhaps most importantly, I include industry-by-year fixed effects to rely on within-industry comparisons. This alleviates concerns about potential confounds that can be explained by industry shocks, including the possibility that differential exposures could reflect differences in investment mandates. Another concern might be that shares could be co-determined with local productivity shocks or local labor market shocks. I include state-by-year fixed effects to control for changes in statewide conditions or MSA-by-year fixed effects to absorb local economic conditions. The individual-level design described in Section 5 further saturates this model by accounting for differential shocks by occupation, quantity and quality of education, and prior labor market experience. Consequently, the identification exploits residual variation in the pre-shock exposures purged of industry, location, occupation, and education specific trends, and relies on the assumption that the residual variation does not predict differences in startup worker outcomes through channels other than realized VC investments.

This paper's empirical design also allows for an additional test, which I present in Appendix B.1. I verify that the estimates are similar when conducting the analyses at Pitchbook's more

[8]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.

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

granular industry designation and controlling for these granular industry shocks. These specifications rely on variation in the shares within specific technology groups, e.g., within Semiconductors, Healthcare Technology Systems, or Computer Hardware. The stability of the estimates across designs provides further support for the IV's validity.

4.3 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. Standard errors are clustered by MSA-industry, the level of the treatment variable. 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. Standard errors are clustered by MSA-industry.

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. These columns show that, consistent with the patterns illustrated in Figure 1, a doubling of local VC in the year prior increases startup hiring by 19% and startup separations by 21%.[10] The estimates suggest that VC financing plays a role in increasing skilled worker flows to startups and also increasing startup labor churn. Note that these regressions aim to recover the role of VC flows for job creation and job destruction at startups, and are not meant to estimate 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 elasticties are larger than those of Samila and Sorenson (2011).

[10]Since I am considering large percentage increases, I do not use the usual log-log approximation for a 1% increase. Instead, magnitude interpretations are obtained from $[\exp(\hat{\beta}\ln(2)) - 1] \times 100\%$.

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 ($t-1$)	0.295***	0.246***	0.289***	0.251***	0.328***	0.274***
	(0.037)	(0.030)	(0.043)	(0.036)	(0.042)	(0.033)
Panel B. IV PPML Estimates						
Ln VC Deals ($t-1$)	0.520***	0.479***	0.432***	0.391***	0.602***	0.523***
	(0.116)	(0.124)	(0.115)	(0.118)	(0.120)	(0.127)
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	250.64	228.19	250.64	228.19	250.64	228.19
Dependent Var. Mean	68.87	68.87	28.79	28.79	15.57	15.57
Observations	47,937	47,937	47,937	47,937	47,937	47,937

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. 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.

I now turn to the estimates using the IV. I use the control function estimator obtained from a two-step estimation procedure as described in Wooldridge (2010). Appendix B.3 provides additional details on this approach. Standard errors are clustered by MSA-industry and are obtained via bootstrap. Column (4) shows that a doubling of local VC increases startup hiring 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 job creation 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%.

While the IV estimates are larger than the PPML estimates in magnitude, the PPML estimates are 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 job destruction.

The larger IV magnitudes for startup employment and hires is consistent with two potential explanations.[11] 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. Appendix Table B2 shows the stability of the estimates when conducting the analysis at the MSA-industry group (granular industry) level and controlling for granular industry shocks.

Overall, the estimates show that positive shocks to local venture capital increase knowledge worker flows into startups in these markets. However, as the examples of Figure 1 suggest, 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 that startup separations also rise 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.

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

5 VC Markets and Startup Worker Outcomes

The previous section documents that venture capital 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 VC market shocks for worker outcomes.

5.1 Individual-Level Empirical Strategy

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

$$y_{i,t+2} = \beta \times \text{Ln VC Deals}_{s,t-1} + \gamma_s + x'_{i,t}\delta + \theta_{s,t} + \varepsilon_{i,t} \tag{4}$$

As before, β is the coefficient on lagged venture capital investments in market s and is the estimand of interest. The specification includes MSA-industry fixed effects γ_s to absorb time-invariant differences across local markets. Here, $y_{i,t+2}$ is a worker-level dependent variable such as seniority in year $t+2$. However, the possibility of selection presents an identification concern in this setting. That is, 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, the shift-share IV described in Section 4 is used as an instrument for the treatment variable of interest Ln VC $\text{Deals}_{s,t-1}$. This allows me to isolate exogenous shifts in the availability of venture funding across markets. In addition, the specification 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 degree-by-year fixed effects. 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.

Next, a unique benefit provided by the résumé data is the ability to observe the school attended by each worker. I additionally introduce 1{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.

Workers may 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 total months in the labor force at the time of joining the startup. This allows me to account for each worker's ex-ante propensity to change employers.

Finally, when studying long-term career outcomes, I further 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.

These controls restrict the identifying variation to comparisons of workers exposed to similar labor market shocks when beginning their startup employment. For example, we may want to compare software engineers who attended top universities joining startups in the same industry but in cities with exogenously different capital supply that year. Alternatively, I present specifications where the identifying variation compares software engineers going to the same city (e.g., San Francisco), but exploiting differences in capital supply across industries. When using the shift-share 2SLS estimator, these differences in capital supply are driven by idiosyncratic differences in initial investor exposures.

I test for observable relationships between the worker covariates and VC flows in Appendix Tables B3 and B4. 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 B3 investigates the relationships between worker characteristics and realized VC flows, while Table B4 investigates the relationships with predicted VC flows (used as the instrument). The estimates reveal no clear relationships between either realized or predicted VC flows and observable characteristics of workers in those markets. In particular, Table B4 shows that the variation isolated by the shift-share instrument does not relate to worker attributes–including university ranking, educational attainment, years of experience or initial seniority–in a statistically or economically significant way. This provides further support for the validity of the IV.

Consistent with the covariate balance shown above, I find that controlling for additional worker characteristics does not impact the estimates. Figure B3 in the Appendix 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 increased funding 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 doubling local VC increases the likelihood that the worker leaves the startup within two years by 3.5 percentage points.[12] The mean departure rate within two years is 0.41. Thus, this corresponds to an 8.5% 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 B5.

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. I investigate this by observing workers' subsequent employment positions. For example, if workers are leaving their startups for

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

different startups or for Big Tech firms with more senior job titles, this might be suggestive of an improvement in the outside option. I examine this in Table 3 Panel B, where the dependent variable is an indicator equal to one if the worker has left the VC-backed universe within two years, and zero otherwise. The VC-backed universe includes both VC-backed firms and formerly VC-backed firms, which include tech giants such as Meta, Apple, Amazon, and Google.

The estimated regression coefficients show that workers who enter hotter VC markets are more likely to leave the VC-backed and formerly VC-backed universe entirely within two years. A doubling of local VC reduces the likelihood of working at VC-backed universe in two years by 2.8 percentage points. The mean departure rate from the VC-backed universe is 31%. Thus, this corresponds to a 9.2% effect relative to the mean.

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

	Dependent Variable: Leave Startup $(t+2)$					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A.	OLS	OLS	OLS	2SLS	2SLS	2SLS
Ln VC Deals $(t-1)$	0.016***	0.015***	0.013***	0.050***	0.054***	0.051**
	(0.002)	(0.002)	(0.003)	(0.015)	(0.021)	(0.020)
Dependent Var. Mean	0.41	0.41	0.41	0.41	0.41	0.41
Panel B.	Dependent Variable: Leave VC-Backed Universe $(t+2)$					
Ln VC Deals $(t-1)$	0.004*	0.005**	0.007***	0.041***	0.048**	0.037*
	(0.002)	(0.002)	(0.002)	(0.014)	(0.020)	(0.019)
Dependent Var. Mean	0.31	0.31	0.31	0.31	0.31	0.31
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				134.92	73.17	90.77
Observations	860,791	860,791	860,791	860,791	860,791	860,791

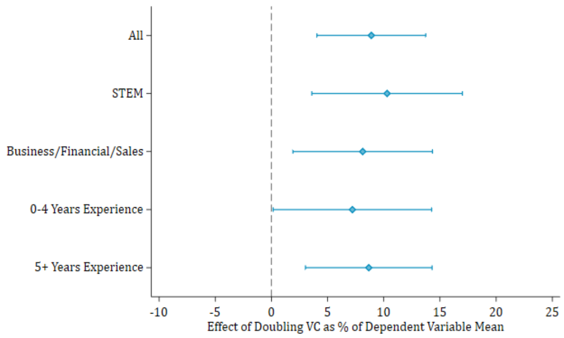
Note. This table shows the effect of increased capital at the time of hiring on the likelihood of worker departure from the firm and from the venture-backed universe. Each observation is an individual starting a job in year t at a VC-backed startup in MSA-industry pair s. In Panel A, the dependent variable 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 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), while 2SLS estimates using a shift-share instrumental variable 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.

Figure 2 plots the effects by subgroup. I consider workers in different occupations (STEM versus Business) as well as workers of different experience levels (0-4 years of experience or greater than 5 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 not concentrated among a specific subgroup of workers but are instead similar across groups. The increase in separations across worker types is consistent with the finding of Nanda and Rhodes-Kropf (2013) that startups funded in hot VC markets are more likely to close down. In Appendix Table B1, I show that this finding also holds in my sample period and empirical design.

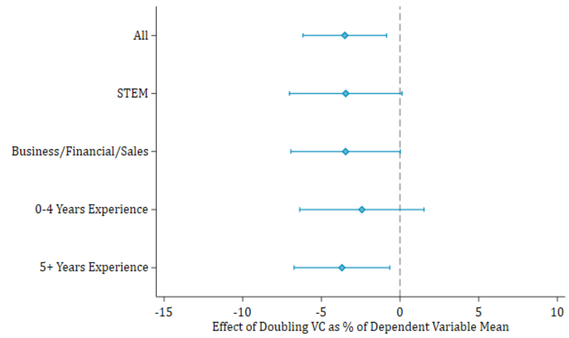
The 2SLS estimates are larger than the OLS estimates. This suggests that when high VC deployments are driven by exogenous increases in capital rather than a market-specific fundamental shock, jobs are increasingly shorter-lived and workers are more likely to leave the VC-backed universe. This is also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

One question may be whether departures could be related to the startup exiting through going public or becoming acquired. Appendix Table B6 replicates the result but dropping, for startups that have an exit, an additional two years of jobs prior to the startup's exit. For the remaining workers, any departures from the firm within two years must have occurred prior to the startup's exit. The stability of the estimates shows that the finding of shorter-lived jobs is not explained by departures after an acquisition or IPO date. This is especially indicative of job fragility in the startup setting, where workers earn submarket salaries but have the potential for large payoffs in the event of a successful firm exit through their equity compensation (Hall and Woodward, 2010).

Figure 2: Worker Departure 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 departure from the startup and VC-backed universe by subgroup: STEM workers, Business workers, workers with 0 to 4 years of experience, and workers with at least 5 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). 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 in two years and zero otherwise. Additional details on the regression model can be found in Table 3. Standard errors are clustered by MSA-industry-year and 95% confidence intervals are shown.

6 VC Markets and Startup Worker Career Progression

6.1 Measuring Career Progression

I now turn to studying the career progression of startup workers. Even given an increase in job fragility, it is not obvious how periods of capital abundance ultimately affect progression along the job ladder. Workers who join startups in hot funding markets could gain valuable skills and experience that, if transferable, could lead to productivity gains and faster seniority advancement regardless of whether they stay at the startup. On the other hand, workers may experience productivity losses from increased turnover, especially if the human capital gained in the position is highly firm or technology specific.

When studying job ladder progression, a question that arises is how to take into account differences in titles and organizational hierarchies across firms. I address this by constructing seniority following the methodology of Amornsiripanitch et al. (2023) as described in Section 3 and Appendix B.2. The measure accounts 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 of "Vice President" typically denotes a different seniority level at financial services firms compared to technology corporations. I obtain a seniority value for each job title by firm industry by 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 B12 shows that in general, 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 is addressed by the fact that seniority is calculated for each possible job title with a sufficient number of observations over the full sample of employment. Over a large distribution, various job titles that denote similar levels should ultimately receive similar seniority scores.

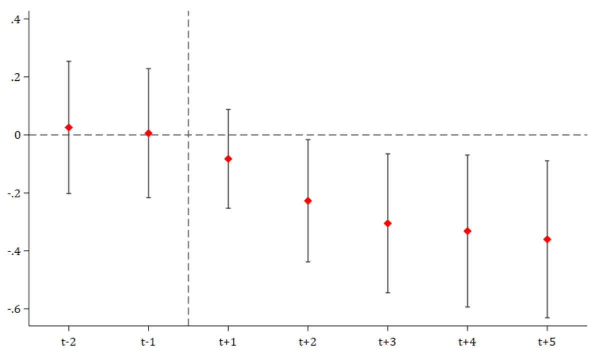
In this analysis, I consider each worker's first entry into a startup in calendar year t. I then measure seniority as of the worker's latest employment position in calendar year $t+2$. I estimate Equation (4) with the worker's seniority in $t+2$ as the dependent variable and also controlling for initial 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 again, in each year seniority is measured from the last employment position observed that year.

6.2 Effects on Seniority

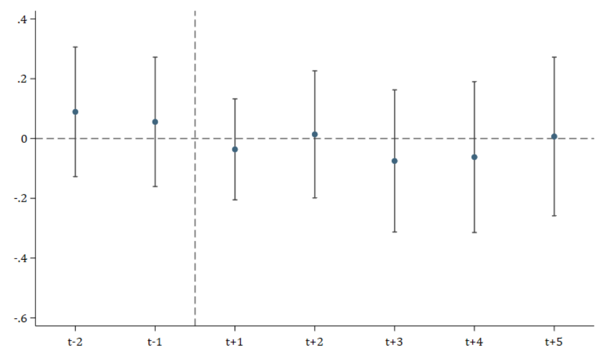
Figure 3 plots the 2SLS coefficient estimates of β in Equation (4) estimated separately for STEM and Business workers. Panel (a) shows that for STEM workers, the effect of hotter VC markets on seniority progression is not distinguishable from zero one year later, but negative two years following the entry year. Note that the negative coefficient estimates do not necessarily mean that workers in hot VC markets are falling in seniority; they imply that STEM workers who enter hotter VC markets advance slower in seniority after joining relative to their counterparts in less hot markets. The coefficient estimate for $t+2$ is -0.23, meaning that a doubling of local VC lowers two-year seniority progress by $\hat{\beta}\ln(2) = 0.16$ units. This amounts to 20% of the average two-year seniority change of 0.80 for STEM workers. The effect size implied by the coefficient is persistent and becomes 0.25 seniority units in year $t+5$. The average five-year seniority change for STEM workers is 1.68. 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 effectively 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.

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 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. 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 $t-1$. Additional details on the regression model can be found in Table 4. Standard errors are clustered by MSA-industry-year and 95% confidence intervals are shown.

Table 4 Panel A quantifies the difference in the effect for STEM workers versus non-STEM workers (including Business and Other workers). 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. 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. Columns (1) through (4) report the OLS estimates, while Columns (5) through (8) report the 2SLS estimates. Each column controls for a different set of industry and location fixed effects.

In all specifications, the effect of increased capital on seniority progression is more negative for STEM workers than other workers, and the difference is statistically significant. While the OLS estimates also imply a negative total effect for STEM workers, the 2SLS estimates are more negative than OLS (though the OLS estimates fall within the 95% confidence intervals of the 2SLS estimates). This is consistent with the more positive IV estimates when investigating worker departure probabilities; when high VC deployments are driven by increases in supply rather than market-specific fundamental shocks, jobs are both shorter-lived and subsequent seniority advancement is slower. Column (6) shows that in the IV regression, the effect of initial VC is statistically indistinguishable from zero for non-STEM workers, though the standard errors are also larger. Table B9 in the Appendix shows that the effects are similar when additionally controlling for origin firm fixed effects.

One concern could be that STEM workers who join hotter VC markets are on different seniority trajectories prior to joining the startup. I check for this by plotting dynamics in Figure 3. 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. This rules out the concern that STEM workers who enter hotter VC markets are on a downward trajectory even prior to joining the startup. Rather, the effects begin after joining the startup, and specifically after two calendar years.

Do seniority effects translate to earnings effects? Marinescu and Wolthoff (2020) provide strong evidence in favor of this possibility: using a dataset of US job postings, they find that job titles explain more than 90% of the variance in posted firm wages. Even conditional on six-digit SOC codes, jobs with more senior or managerial titles tend to offer higher wages. Their findings indicate that differences in seniority very likely translate to differences in earnings. That said, there are two reasons to believe that the seniority estimates here may even understate the long-term earnings discount of STEM workers who join hot market startups. First, as the literature on executive compensation suggests, the relationship between wages and seniority is likely nonlinear, in that the wage gains from an incremental promotion escalate at higher levels of the job ladder. Second, the foregone potential earnings from an increased probability of firm failure are especially high at a startup, where workers receive lower cash salaries but are compensated with firm equity (Hall and Woodward, 2010).

A related question about the relationship between seniority and earnings is whether cash-constrained firms might offer higher titles as a substitute for pay. However, given that

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 $(t-1)$	0.039***	0.035**	0.034**	0.031*	0.083	0.023	0.027	0.191
	(0.015)	(0.015)	(0.016)	(0.016)	(0.091)	(0.121)	(0.173)	(0.119)
Ln VC Deals $(t-1)$	-0.061***	-0.061***	-0.062***	-0.065***	-0.312**	-0.317**	-0.286**	-0.246*
× *STEM Worker*	(0.023)	(0.023)	(0.023)	(0.023)	(0.138)	(0.139)	(0.139)	(0.139)
Panel B.								
Ln VC Deals $(t-1)$	0.012	0.008	0.006	0.003	-0.042	-0.105	-0.108	0.100
	(0.011)	(0.012)	(0.013)	(0.014)	(0.073)	(0.112)	(0.181)	(0.105)
Ln VC Deals $(t-1)$	-0.023**	-0.022**	-0.023**	-0.027**	-0.175**	-0.166**	-0.163**	-0.171**
× *Skill Specificity*	(0.011)	(0.011)	(0.011)	(0.011)	(0.071)	(0.071)	(0.071)	(0.072)
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
R^2	0.56	0.56	0.56	0.57	0.50	0.50	0.50	0.50
First Stage F-Stat					136.45	74.38	39.68	92.34
Observations	708,314	708,314	708,314	708,314	708,314	708,314	708,314	708,314

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), 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.

startups financed in hot markets are less likely to be successful on average, if this hypothesis were true, this would work against the estimated effect, leading workers who join startups in hot VC markets to receive higher titles on average.

An additional question is whether differences in the subsequent employers of STEM workers could explain the result. For example, do STEM workers who enter hotter VC markets join more competitive firms two years later? In the previous section, I show that workers who enter hot VC markets are more likely to leave the VC-backed universe, which includes the formerly VC-backed technology giants. This effect holds for both STEM and Business workers, meaning that it alone cannot explain the occupational differences. In addition, Appendix Table B8 estimates Equation (4) with the natural log of firm headcount in year $t+2$ as the dependent variable. I do not find a statistically significant difference in the size of worker's firms in two years.

A remaining question is whether potential differences in the properties of the seniority distribution between STEM and non-STEM workers could explain the result. For example, one question might be whether there is more variation in the job ladder for STEM versus Business workers, which leads to more observable differences across STEM workers. Table 1 presents summary statistics separately for both groups. The standard deviation for Business workers is similar but slightly larger than that of STEM workers. Overall, the seniority distributions of STEM and Business workers are similar.

Therefore, it is unlikely that any of these alternative explanations could drive the result. It is also unlikely that selection can explain the observed effects. Using a shift-share IV approach, I isolate exogenous shocks to VC across markets to identify their causal effect on workers. Appendix Tables B3 and B4 test for relationships between VC flows and the characteristics of workers in a given market. The estimates of Table B4 show that the IV does not predict characteristics of workers in those markets for either STEM or Business workers. In addition to the IV approach, the set of granular individual-level controls further restricts the identifying variation to comparisons of observably similar individuals at the same point in time. Finally, it is not clear how selection alone could explain the observed "triple-difference" by occupation.

Taken together with the strong turnover effects shown in the previous section and 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, it is likely that reduced job stability leads 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-specific 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 likely 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. 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 $0.166 \times \ln(2) = 0.11$ seniority units. This amounts to 16% of the overall average two-year change of 0.72. Appendix Table B9 shows that the results continue to hold after controlling for origin firm fixed effects.

The results suggest that workers in roles with rapidly changing skill requirements where skill is more vintage-specific take on higher risk when joining startups in booming VC markets. These workers face higher expected reallocation costs in hotter capital markets where turnover is more likely. The findings suggest that the increased experimentation that takes place when capital is abundant leads to higher risk that is borne by workers who make more specialized human capital investments.

Distributional Effects. Thus far, the analyses have estimated the effects of increased capital on the means of outcome distributions. I now turn to estimating the quantile treatment effects of VC market shocks on seniority advancement (Koenker and Bassett, 1978).

The specification and empirical design are the same as that of Equation (4), except I now estimate quantile models of the form:

$$Q_{y|\text{Ln VC Deals},D}(\tau) = \beta(\tau) \times \text{Ln VC Deals}_{s,t-1} + D'_{i,t}\alpha(\tau) \tag{5}$$

for $\tau \in [0.05, 0.95]$ at intervals of 0.05, where $D_{i,t}$ is the vector of individual controls described in Section 5 and Ln VC Deals$_{s,t-1}$ represents lagged deal volume in market s. Because VC flows may be endogenous, this variable is instrumented for by predicted VC flows as described in Section 4. I obtain standard errors clustered at the MSA-industry-year level via bootstrap.

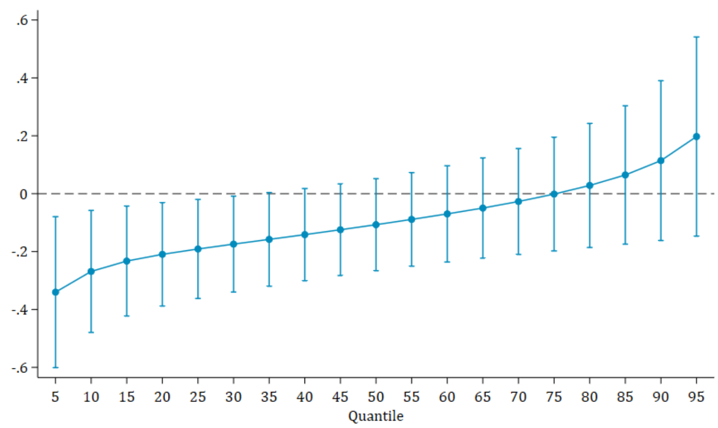
Table 5: Distributional Effects of Increased Capital at Worker Entry on Seniority Advancement

	(1) $\tau = 0.1$ IQR	(2) $\tau = 0.25$ IQR	(3) $\tau = 0.5$ IQR	(4) $\tau = 0.75$ IQR	(5) $\tau = 0.9$ IQR
Panel A. All Workers					
Ln VC Deals ($t-1$)	-0.269**	-0.191*	-0.107	-0.001	0.114
	(0.128)	(0.104)	(0.097)	(0.119)	(0.168)
Panel B. STEM Workers					
Ln VC Deals ($t-1$)	-0.365**	-0.321**	-0.271*	-0.197	-0.117
	(0.174)	(0.150)	(0.150)	(0.201)	(0.289)
Panel C. Business Workers					
Ln VC Deals ($t-1$)	-0.257	-0.139	-0.019	0.116	0.265
	(0.183)	(0.152)	(0.153)	(0.190)	(0.256)

Note. This table shows the quantile treatment effects of increased capital at the time of hiring on seniority advancement. Each observation is an individual beginning their first startup job in year t at a VC-backed startup in MSA-industry pair s. Equation (5) is estimated separately for all workers, STEM workers, and Business workers, and for $\tau \in \{0.1, 0.25, 0.5, 0.75, 0.9\}$. Ln VC Deals$_{s,t-1}$ is the natural log of VC deals in local market s in year $t-1$ and is instrumented for by a shift-share IV. The dependent variable is seniority in year $t+2$. Control variables are described in Table 4 and include industry-by-year fixed effects. Standard errors reported in parentheses are obtained via bootstrap and clustered by MSA-industry-year. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

Table 5 presents the estimates. Consistent with the result from estimating conditional means, increased capital at the time of worker entry lowers median future seniority for STEM workers. The figure also shows an interesting pattern: the effects of capital supply shocks are not uniform across the worker distribution, but become less negative as the quantile index

Figure 4: Distributional Effects of Increased Capital at Worker Entry on Seniority Advancement



Note. This figure shows the quantile treatment effects of increased capital at the time of hiring on seniority advancement. The figure reports the estimates of the coefficient on Ln VC Deals$_{s,t-1}$ in Equation (5) for quantiles $\tau \in [0.05, 0.95]$ at intervals of 0.05. Ln VC Deals$_{s,t-1}$ is the natural log of VC deals in local market s in year $t-1$ and is instrumented for by a shift-share IV. 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 seniority in year $t+2$. Individual control variables are described in Table 4 and include industry-by-year fixed effects. Standard errors are clustered by MSA-industry-year and obtained via bootstrap. 90% confidence intervals are shown.

increases. The effects at the 10th and 25th quantiles are more strongly negative than the effects at the median, and the effects become closer to zero above the quantile of 0.75.

A possible interpretation of the quantile treatment effect is the treatment effect for workers of a given rank in an innate productivity distribution (Chernozhukov and Hansen, 2004, 2005). That is, conditional on observed characteristics such as education and industry, workers who rank higher in the conditional seniority distribution are less affected by the initial funding environment. However, the effect is still negative for the majority of STEM workers, highlighting the risk of joining venture-backed firms in hot funding markets. An increase in dispersion is apparent for workers in non-STEM roles as well. For Business workers, the effect of capital supply shocks are negative at the 10th and 25th percentiles and positive at the 90th percentile (but not statistically significant). Ultimately, when considering all workers together, Figure 4 shows that the effect of initial funding market conditions is negative and statistically significant for quantiles $\tau = 0.3$ and below. Meanwhile, the point estimates are positive above $\tau = 0.8$ but not distinguishable from zero. Taken together, the estimates of $\beta(\tau)$ indicate that the conditional distribution of seniority outcomes widens in hotter VC markets.

7 Conclusion

The availability of risk capital 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 over 700 thousand knowledge 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 a trade-off between long-term productivity gains and short-term costs incurred by knowledge 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 An Equilibrium Model of VC, Labor, and Production

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

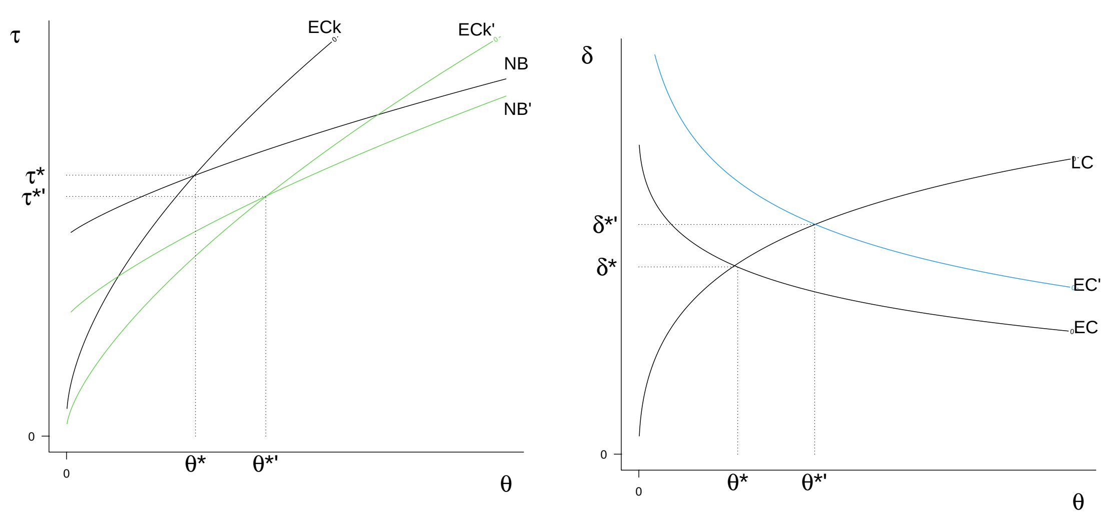
I now turn to studying the equilibrium effects of an exogenous shock to the financial sector. Specifically, I consider a shock that loosens the financial market while holding the other model primitives constant: a reduction in the VC's entry cost c_k. A fall in c_k induces more VC entry, increasing the 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.[13]

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.

[13] 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.

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 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

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

or

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

To confirm that this is the VC's participation constraint, recall that the VC's entry condition is

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

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

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

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:

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

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,

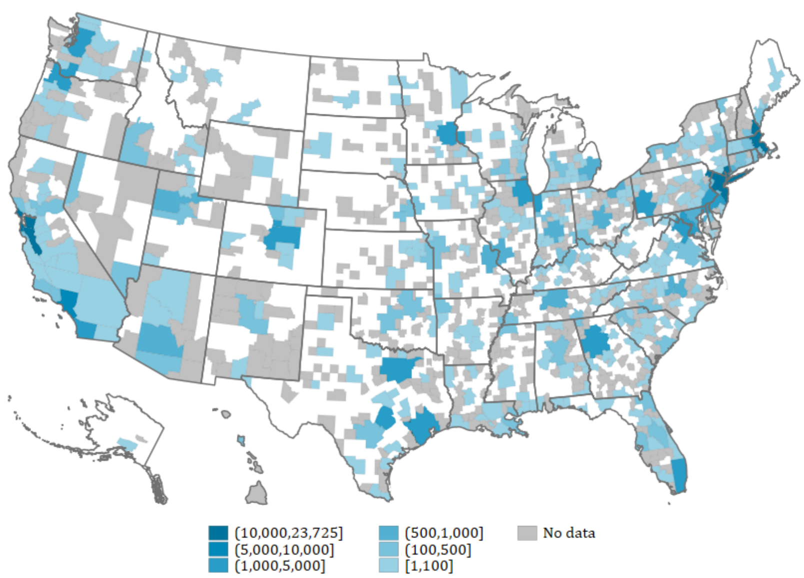
$$\frac{\partial \theta}{\partial c_k} = \frac{1}{\det(J)} \left(\frac{\partial F_1}{\partial c_k} \right) \left(\frac{1}{M(\theta)} + \frac{1}{h} \right) < 0 \tag{A.32}$$

■

B Empirical Analysis Appendix

B.1 Additional Figures and Tables

Figure B2: 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.

Table B1: Funding Environment and Likelihood of Startup Failure

	Startup Failure: Measure 1			Startup Failure: Measure 2		
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS
Ln VC Deals	0.035***	0.030***	0.041***	0.031***	0.027***	0.031**
	(0.011)	(0.008)	(0.016)	(0.010)	(0.009)	(0.016)
FE: MSA-Industry	Yes	Yes	Yes	Yes	Yes	Yes
FE: Year	Yes			Yes		
FE: Industry × Year		Yes			Yes	
FE: MSA × Year			Yes			Yes
R^2	0.07	0.07	0.10	0.08	0.08	0.11
Mean	0.21	0.21	0.21	0.47	0.47	0.47
Observations	39,317	39,317	39,317	39,317	39,317	39,317

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 MSA-industry pair s receiving its first reported financing in year t fails. In columns (1) through (3), this is measured using Pitchbook's variables, assigning a one if the variable OwnershipStatus is "Out of Business" or if the variable BusinessStatus indicates bankruptcy. In columns (4) through (6), this is measured by assigning 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 venture capital investments in year t and MSA-industry s. Standard errors are clustered by MSA-industry and reported in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

Table B2: 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 $(t-1)$	0.282***	0.251***	0.271***	0.254***	0.298***	0.269***
	(0.020)	(0.016)	(0.021)	(0.018)	(0.021)	(0.016)
Panel B. IV PPML Estimates						
Ln VC Deals $(t-1)$	0.559***	0.532***	0.439***	0.414***	0.652***	0.622***
	(0.089)	(0.089)	(0.089)	(0.087)	(0.098)	(0.096)
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	19.96	19.96	8.34	8.34	4.51	4.51
Observations	165,395	165,395	165,395	165,395	165,395	165,395

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. 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.

Table B3: 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 $(t-1)$	0.007**	0.007**	0.002	0.002	0.003	-0.000
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Panel B. Bachelor's Degree						
Ln VC Deals $(t-1)$	-0.000	0.003	-0.017***	0.006	0.006*	0.002
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)
Panel C. Master's Degree						
Ln VC Deals $(t-1)$	-0.001	-0.001	0.009**	-0.002	-0.003	0.002
	(0.004)	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)
Panel D. Doctoral Degree						
Ln VC Deals $(t-1)$	0.004	0.000	0.009**	-0.001	-0.000	-0.001
	(0.003)	(0.002)	(0.004)	(0.001)	(0.001)	(0.002)
Panel E. Years of Experience						
Ln VC Deals $(t-1)$	0.051	0.081	0.195**	-0.148	-0.159*	-0.033
	(0.086)	(0.091)	(0.078)	(0.104)	(0.089)	(0.086)
Panel F. Initial Seniority						
Ln VC Deals $(t-1)$	-0.018	-0.016	0.015	-0.005	-0.024	-0.063
	(0.044)	(0.045)	(0.040)	(0.044)	(0.042)	(0.047)
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
Observations	358,049	358,049	358,049	414,660	414,660	414,660

Note. This table tests for relationships between initial deal volume and observable worker characteristics. Each observation is an individual starting a job in year t and MSA-industry pair s at a VC-backed startup. Ln VC Deals $(t-1)$ is the lagged natural log of VC deals in local market s. 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 B4: 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	0.001	-0.000	0.001	-0.002*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Panel B. Bachelor's Degree						
Ln Predicted VC ($t-1$)	0.003	0.002	0.001	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Panel C. Master's Degree						
Ln Predicted VC ($t-1$)	0.000	0.001	-0.001	-0.000	0.000	-0.000
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Panel D. Doctoral Degree						
Ln Predicted VC ($t-1$)	-0.002	-0.002	-0.000	-0.000	0.000	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Panel E. Years of Experience						
Ln Predicted VC ($t-1$)	-0.033	-0.010	-0.031	-0.086	-0.080	-0.081
	(0.051)	(0.050)	(0.056)	(0.057)	(0.055)	(0.057)
Panel F. Initial Seniority						
Ln Predicted VC ($t-1$)	-0.029	0.006	-0.040	-0.032	-0.040	-0.043
	(0.025)	(0.024)	(0.028)	(0.028)	(0.027)	(0.030)
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
Observations	358,049	358,049	358,049	414,660	414,660	414,660

Note. This table tests for relationships between the instrumental variable for initial deal volume and observable worker characteristics. Each observation is an individual starting a job in year t and MSA-industry pair s at a VC-backed startup. Ln Predicted VC ($t-1$) is the lagged natural log of predicted VC deals in local market s, constructed according to Equation (3). 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.

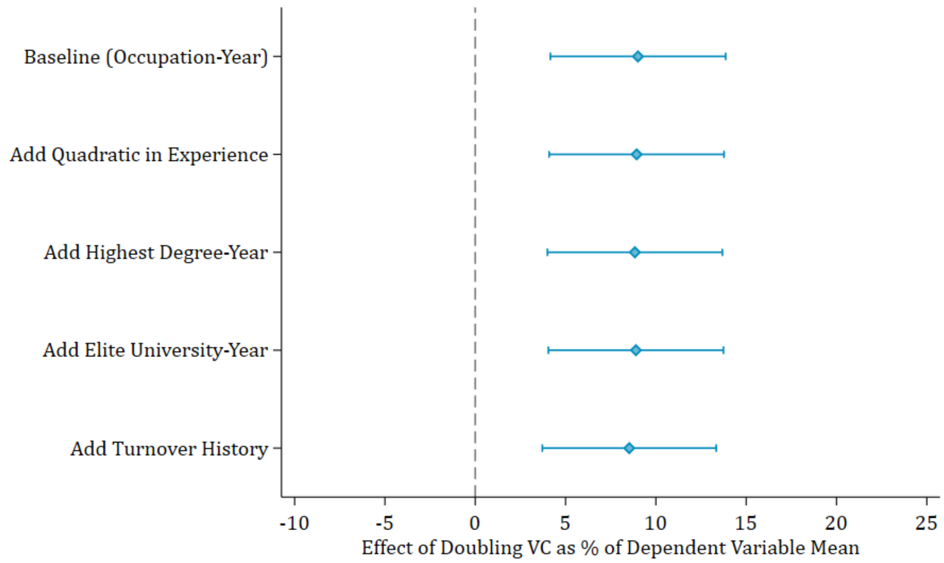


Figure B3: Coefficient Stability with Worker Covariates

Note. This figure shows the effect of increased capital at the time of hiring on the likelihood of worker departure 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). Standard errors are clustered by MSA-industry-year and 95% confidence intervals are shown.

Table B5: The Effect of Increased Capital at Worker Entry on Startup Job Duration

	Dependent Variable: Ln Job Duration					
	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Ln VC Deals ($t-1$)	-0.027***	-0.024***	-0.026***	-0.137***	-0.138***	-0.141***
	(0.005)	(0.005)	(0.005)	(0.030)	(0.043)	(0.042)
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	3.35	3.35	3.35	3.35	3.35	3.35
Observations	860,791	860,791	860,791	860,791	860,791	860,791

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), while 2SLS estimates using a shift-share instrumental variable 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.

Table B6: The Effect of Increased Capital at Worker Entry on Departure 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 ($t-1$)	0.014***	0.013***	0.013***	0.039***	0.042**	0.039*
	(0.002)	(0.002)	(0.003)	(0.015)	(0.021)	(0.020)
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	0.40	0.40	0.40	0.40	0.40	0.40
Observations	785,549	785,549	785,549	785,549	785,549	785,549

Note. This table shows robustness to dropping an additional two years prior to a startup's exit (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 sample contains jobs starting between 2003 and 2018. 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), while 2SLS estimates using a shift-share instrumental variable 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.

Table B7: The Effect of Increased Capital at Worker Entry on Departures with Granular Industry Controls

	Dependent Variable: Leave Startup ($t+2$)					
Panel A.	(1) OLS	(2) OLS	(3) OLS	(4) 2SLS	(5) 2SLS	(6) 2SLS
Ln VC Deals ($t-1$)	0.016***	0.015***	0.013***	0.050***	0.051**	0.051**
	(0.002)	(0.002)	(0.003)	(0.015)	(0.021)	(0.020)
Dependent Var. Mean	0.41	0.41	0.41	0.41	0.41	0.41
Panel B.	Dependent Variable: Leave VC-Backed Universe ($t+2$)					
Ln VC Deals ($t-1$)	0.004*	0.005**	0.007***	0.041***	0.044**	0.037*
	(0.002)	(0.002)	(0.002)	(0.014)	(0.020)	(0.019)
Dependent Var. Mean	0.31	0.31	0.31	0.31	0.31	0.31
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE: MSA-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
Observations	860,791	860,791	860,791	860,791	860,791	860,791

Note. This table shows the effect of increased capital at the time of hiring on the likelihood of worker departure from the firm and from the venture-backed universe. 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), while 2SLS estimates using a shift-share instrumental variable 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.

Table B8: Funding Environment at Worker Entry and Firm Size Change

	Dependent Variable: Ln Firm Size $(t+2)$							
	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) 2SLS	(6) 2SLS	(7) 2SLS	(8) 2SLS
Ln VC Deals $(t-1)$	-0.001	-0.009	0.009	0.037***	-0.016	-0.075	-0.077	-0.075
	(0.009)	(0.010)	(0.010)	(0.011)	(0.055)	(0.080)	(0.124)	(0.080)
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: MSA-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
R^2	0.23	0.23	0.23	0.23	0.18	0.18	0.18	0.18
Observations	791,095	791,095	791,095	791,095	791,095	791,095	791,095	791,095

Note. 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 size of the worker's firm, as measured by employee headcount, at the end of calendar year $t+2$. Ln VC Deals is the natural log of VC deals in local market s in year $t-1$. Individual Controls include initial firm size 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.

Table B9: 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 $(t-1)$	0.039**	0.036**	0.038**	0.032*	0.104	0.037	0.080	0.261**
	(0.016)	(0.017)	(0.017)	(0.018)	(0.100)	(0.133)	(0.195)	(0.131)
Ln VC Deals $(t-1)$	-0.074***	-0.074***	-0.076***	-0.075***	-0.355**	-0.363**	-0.346**	-0.311**
× *STEM Worker*	(0.025)	(0.025)	(0.025)	(0.026)	(0.154)	(0.156)	(0.156)	(0.156)
Panel B.								
Ln VC Deals $(t-1)$	0.007	0.005	0.003	-0.002	-0.026	-0.091	-0.041	0.181
	(0.013)	(0.013)	(0.014)	(0.015)	(0.080)	(0.125)	(0.208)	(0.115)
Ln VC Deals $(t-1)$	-0.032***	-0.031***	-0.032***	-0.035***	-0.226***	-0.217***	-0.214***	-0.213***
× *Skill Specificity*	(0.012)	(0.012)	(0.012)	(0.012)	(0.079)	(0.079)	(0.079)	(0.080)
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
R^2	0.62	0.62	0.62	0.62	0.48	0.48	0.48	0.48
Observations	708,314	708,314	708,314	708,314	708,314	708,314	708,314	708,314

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), 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.

Table B10: 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 ($t-1$)	0.039***	0.035**	0.034**	0.031*	0.083	-0.005	-0.020	0.191
	(0.015)	(0.015)	(0.016)	(0.016)	(0.091)	(0.121)	(0.174)	(0.119)
Ln VC Deals ($t-1$)	-0.061***	-0.059***	-0.060***	-0.065***	-0.312**	-0.274*	-0.242*	-0.246*
× *STEM Worker*	(0.023)	(0.023)	(0.023)	(0.023)	(0.138)	(0.140)	(0.140)	(0.139)
Panel B.								
Ln VC Deals ($t-1$)	0.012	0.009	0.006	0.003	-0.042	-0.123	-0.150	0.100
	(0.011)	(0.012)	(0.012)	(0.014)	(0.073)	(0.113)	(0.183)	(0.105)
Ln VC Deals ($t-1$)	-0.023**	-0.018*	-0.018*	-0.027**	-0.175**	-0.140*	-0.137*	-0.171**
× *Skill Specificity*	(0.011)	(0.011)	(0.011)	(0.011)	(0.071)	(0.072)	(0.072)	(0.072)
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 Group × Year		Yes	Yes			Yes	Yes	
FE: State × Year			Yes				Yes	
FE: MSA × Year				Yes				Yes
FE: Origin Firm	No	No	No	No	No	No	No	No
R^2	0.56	0.56	0.56	0.57	0.50	0.50	0.50	0.50
Observations	708,314	708,314	708,314	708,314	708,314	708,314	708,314	708,314

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), 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.

Table B11: The Effect of Increased Capital at Worker Entry on Seniority Advancement with Granular Industry Controls and 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 $(t-1)$	0.039**	0.038**	0.038**	0.032*	0.104	0.007	0.028	0.261**
	(0.016)	(0.017)	(0.017)	(0.018)	(0.100)	(0.134)	(0.197)	(0.131)
Ln VC Deals $(t-1)$	-0.074***	-0.074***	-0.076***	-0.075***	-0.355**	-0.317**	-0.298*	-0.311**
× *STEM Worker*	(0.025)	(0.025)	(0.025)	(0.026)	(0.154)	(0.157)	(0.157)	(0.156)
Panel B.								
Ln VC Deals $(t-1)$	0.007	0.006	0.003	-0.002	-0.026	-0.108	-0.082	0.181
	(0.013)	(0.013)	(0.014)	(0.015)	(0.080)	(0.126)	(0.210)	(0.115)
Ln VC Deals $(t-1)$	-0.032***	-0.027**	-0.028**	-0.035***	-0.226***	-0.194**	-0.190**	-0.213***
× *Skill Specificity*	(0.012)	(0.012)	(0.012)	(0.012)	(0.079)	(0.080)	(0.080)	(0.080)
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 Group × 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
R^2	0.62	0.62	0.62	0.62	0.48	0.48	0.48	0.48
Observations	708,314	708,314	708,314	708,314	708,314	708,314	708,314	708,314

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 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.

B.2 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 LinkedIn profile. 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 $\times$ industry $\times$ firm size quintile

(ii) Job title $\times$ firm size quintile

(iii) Job title $\times$ industry.

Once I have calculated seniority values for all of 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. Approximately 80% of worker-years have a seniority value from the most granular combination of title-industry-quintile. Approximately another 10% match using title-quintile, and a remaining 10% using title-industry.

Tables B12 and B13 present examples of job titles and their seniority values from the data. Table B12 reports examples from the information technology (IT) industry while Table B13 reports examples from the healthcare industry. Both tables show 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.

The tables show 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.

Table B12: Seniority Examples from Most Common Job Titles: Information Technology

Title	**Seniority**	
	Top Quintile Firms	Bottom Quintile Firms
Vice President	19	15
Senior Director	17	14
Director	15	11
Principal	13	12
Senior Manager	12	9
Manager	10	8
Staff Engineer	9	9
Staff Software Engineer	9	9
Project Manager	8	7
Product Manager	8	6
Senior Analyst	7	6
Senior Software Engineer	7	8
Account Executive	7	6
Account Manager	5	5
Software Engineer	4	3
Specialist	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 industry and shows 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 for top quintile firms.

Table B13: Seniority Examples from Most Common Job Titles: Healthcare

Title	**Seniority**	
	Top Quintile Firms	Bottom Quintile Firms
Vice President	19	18
Executive Director	17	18
Senior Director	17	17
Director	15	13
Associate Director	14	12
Senior Project Manager	13	12
Principal	12	13
Senior Manager	12	12
Manager	10	9
Senior Scientist	9	9
Project Manager	9	7
Senior Analyst	8	7
Scientist	7	7
Registered Nurse	6	5
Associate Scientist	4	5
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 Healthcare industry and shows 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 for top quintile firms.

B.3 Estimating Poisson Regressions with Endogenous Regressors and Many Fixed Effects

This appendix provides additional details on the control function procedure used in Section 4. The control function estimator obtains consistent estimates of the structural equation:

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

where $D_{s,t}$ is a vector of exogenous variables, Ln VC $\text{Deals}_{s,t}$ is the endogenous variable and $\varepsilon_{s,t}$ contains omitted variables that lead to the endogeneity of Ln VC $\text{Deals}_{s,t}$. $D_{s,t}$ 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 $\text{Deals}_{s,t}$:

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

By specifying

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

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

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

One can proceed in a two-step control function approach to obtain a consistent estimate of β (Wooldridge, 2010). (i) Given a valid instrumental variable $z_{s,t}$, I first use the fixed effects Poisson estimator to estimate (B.33) and obtain $\hat{\nu}_{s,t}$. (ii) I then use the fixed effects Poisson estimator to estimate β, α, and ρ with $\hat{\nu}_{s,t}$ as a regressor.

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).

B.4 Estimating Quantile Regressions with Endogenous Regressors and Many Fixed Effects

This appendix section details how I estimate quantile treatment effects with both endogenous regressors and high-dimensional fixed effects. I adopt the approach of Machado and Santos Silva (2019) in estimating a parametric quantile model that assumes that the conditional distribution of the outcome variable belongs to the location-scale family. While this approach requires the former assumption, it is also flexible in allowing the fixed effects to affect the entire conditional distribution (as opposed to being location shifters only).[14]

I modify this approach to take into account endogenous regressors and multiple fixed effects. Consider the following parametric quantile model where $y_{i,t}$ is the dependent variable (e.g., worker seniority):

$$y_{i,t} = \theta_{s,t} + \beta \times \text{Ln VC Deals}_{s,t} + x'_{i,t}\delta + \left(\gamma_{s,t} + \gamma \times \text{Ln VC Deals}_{s,t} + x'_{i,t}\gamma_1\right)\varepsilon_{i,t} \tag{B.34}$$

where $\theta_{s,t}$ contains the fixed effects in the location part of the model, $\gamma_{s,t}$ represents the fixed effects in the scale portion of the model, and $x_{i,t}$ is a vector of individual controls. Assume the scale function $(\gamma_{s,t} + \gamma \text{Ln VC Deals}_{s,t} + x'_{i,t}\gamma_1) > 0$. The error term is normalized such that $\mathbb{E}[\varepsilon_{i,t}] = 0$ and $\mathbb{E}|\varepsilon_{i,t}| = 1$. Note that both the mean and scale contain endogenous regressors and a large number of fixed effects.

The parameter of interest in the quantile estimation is the coefficient on Ln VC Deals$_{s,t}$ and is given by

$$\beta + \gamma \times Q_\varepsilon(\tau) \tag{B.35}$$

where $Q_\varepsilon(\tau)$ is the τth quantile of $\varepsilon_{i,t}$. However, if Ln VC Deals$_{s,t}$ is endogenous and correlated with $\varepsilon_{i,t}$, a standard quantile regression of $y_{i,t}$ on the covariates will not yield a consistent estimate of the conditional quantiles. For the specified model, consistent estimation of the structural quantile effects requires obtaining consistent estimates of the location and scale parameters $(\theta_{s,t}, \beta, \delta, \gamma_{s,t}, \gamma, \gamma_1)$. I modify the procedure of Machado and Santos Silva (2019) to handle a large number of fixed effects and endogenous regressors. Given a valid instrument, I estimate the quantile effects through the following computationally simple procedure:

Step 1. Use 2SLS to obtain a consistent estimate of the location parameters and the

[14] Canay (2011) provides an alternative method to control for quantile-invariant fixed effects.

corresponding residuals $\hat{R}_{i,t} = y_{i,t} - \hat{\theta}_{s,t} - \hat{\beta} \times \text{Ln VC Deals}_{s,t} - x'_{i,t}\hat{\delta}$

Step 2. Use 2SLS to obtain a consistent estimate of the scale parameters from the following estimating equation:

$$|\hat{R}_{i,t}| = \gamma_{s,t} + \gamma \times \text{Ln VC Deals}_{s,t} + x'_{i,t}\gamma_1 + \nu_{i,t} \tag{B.36}$$

Step 3. Estimate $Q_\epsilon(\tau)$ by solving

$$\min_q \sum_{i,t} \rho_\tau \left(\hat{R}_{i,t} - (\hat{\gamma}_{s,t} + \hat{\gamma} \times \text{Ln VC Deals}_{s,t} + x'_{i,t}\hat{\gamma}_1)q \right) \tag{B.37}$$

where $\rho_\tau(x) = x[\tau 1(x > 0) - (1 - \tau)1(x \leq 0)]$ is the check function. Letting $\hat{q}_\tau$ denote the estimate of q in step 3, the final estimated structural quantile effect of the endogenous regressor is:

$$\hat{\beta} + \hat{\gamma} \times \hat{q}_\tau \tag{B.38}$$

I then use the bootstrap to obtain standard errors, clustering by MSA-industry-year.