Venture Labor: A Nonfinancial Signal for Start-up Success *

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January 2024

Abstract

We explore the information value of labor market matching by examining the flow of talented employees from successfully exited entrepreneurial firms to less mature start-ups. Using restricted-access US Census data, we find that the presence of these "serial venture employees" positively predicts their new employers' future success in terms of exit likelihoods, size growth, and innovation productivity. Such predictive power is likely driven by the two-way selection/matching between serial venture employees and their new employers, and is stronger than the predictive power of other high-talent labor such as employees top-paid by their previous employers or those having prior VC-backing/public-firm experience. We further demonstrate the usefulness of this labor-based signal to venture capitalists and job seekers, especially when alternative information sources about the start-ups are limited. Overall, our findings highlight the importance of managerial information about labor market matching in the entrepreneurial world where there is a lack of accounting information.

Keywords: Venture Labor, Serial Venture Employees, Managerial Information about Labor Market Matching, Information Environments about Private Firms, Nonfinancial Signals of Start-up Performance

JEL number: G32, G34, J24, J63, M13

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* We gratefully acknowledge helpful comments from Vikas Agarwal, Reena Aggarwal, Ashwini Agrawal, Vladimir Atanasov, Tania Babina, Brad Barber, John Barrios, Asaf Bernstein, Utpal Bhattacharya, Oliver Binz, Elizabeth Blankespoor, Brian Bushee, Brian Cadman, Thomas Chemmanur, Lauren Cohen, Isil Erel, Michael Ewens, Janet Gao, Jillian Grennan, Thomas Hall, Kathleen Hanley, Camille Hebert, Po-Hsuan Hsu, Wei Jiang, Yongtae Kim, Eva Labro, Jongsub Lee, Yingxiang Li, Maria Loumioti, Mancy Luo, Song Ma, Maureen McNichols, Holger Mueller, Justin Murfin, Marina Niessner, Venky Nagar, Paige Ouimet, Raghu Rau, Kris Ramesh, Kelly Shue, Elena Simintzi, Wei-Ling Song, Denis Sosyura, Suraj Srinivasan, Jared Stanfield, Wim A Van der Stede, Melanie Wallskog, Wenyu Wang, Eric Weisbrod, Ting Xu, Sophia Jing Xue, Liu Yang, Ayako Yasuda, as well as participants at the 2024 FARS Midyear Meeting, the 2023 LBS Accounting Symposium, the 2023 Bretton Woods Accounting and Finance Ski Conference, the 2023 ITAM Finance Conference, the 2022 Napa/Sonoma Finance Conference, the 2023 European Finance Association Annual Meeting, and various other seminars and conferences. Any opinions and conclusions expressed herein are those of the authors and do not necessarily represent the views of the U.S. Census Bureau. This research was performed at a Federal Statistical Research Data Center under FSRDC Project Number 1091. All results have been reviewed to ensure that no confidential information is disclosed. CBDRB-FY20-147. Any errors and omissions are the responsibility of the authors.

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1. Introduction

A person's employment status and career trajectory are a result of equilibrium matching on the labor market, which reveals the preferences, information, and constraints of both the employee and her employer(s). On the one hand, talented employees possess private insights about the firms they work for (e.g., Hales, Moon Jr, and Swenson (2018), Huang, Li, and Markov (2020), Campbell and Shang (2022), deHaan, Li, and Zhou (2023)) and might use such information to identify and join firms with high unobservable quality. On the other hand, managers of high-quality firms might be able to extract useful information from job applicants' prior career trajectories and thus screen/hire talented employees who suit their needs (Merchant and Van der Stede (2007) and Campbell (2012)), leading to an equilibrium matching. To date, however, inadequate attention has been devoted to the information value contained in such labor market matching and its implication for the broader economy, especially small private firms that generate a significant proportion of the U.S. business activities yet are much harder to evaluate than publicly listed firms and thus suffer from information asymmetries and insufficient financing (Cassar (2004) and Cassar, Ittner, and Cavalluzzo (2015)).

In this paper, we examine the information value of labor market matching for private firms by exploiting a salient phenomenon in the entrepreneurial world – the flow of human capital from mature entrepreneurial firms that have just successfully "exited", in the form of initial public offerings (IPOs) or sell-outs, to less mature private start-ups.[1] As an example of such labor movement, shortly after Google went public in August 2004, 100 of the first 300 employees that were hired left the company. Many opted to continue their entrepreneurial pursuits by either

[1] Although there might be other ways to gauge the success of an entrepreneurial firm — such as its growth rate or the ability to obtain venture capital financing — we use its exit event (i.e., an IPO or sell-out) to determine whether it is mature/successful or not because such events are generally viewed as the clearest milestones of entrepreneurial success. See previous literature such as Poulsen and Stegemoller (2008), Bayar and Chemmanur (2012), Chemmanur et al. (2018), and Bowen, Fresard, and Hoberg (2023) for a more detailed discussion on why and when private firms choose to "exit," i.e., to change ownership structures to allow early equity investors such as entrepreneurs and venture capitalists to cash out.

starting their own businesses or joining other start-ups, rather than enjoying early retirement or moving to another public corporation for the sake of job stability or promotion.[2] The same pattern of labor flow also occurred at other successful entrepreneurial ventures such as PayPal, Facebook, and Uber, and thus become a part of Silicon Valley's culture.[3] This emerging trend in the private sector provides us a good opportunity to examine the information value of labor market matching, as both the job-movers and their new start-up employers would make use of their respective information sets to screen and match with each other.

Another important reason for focusing on private firms is that they have a relatively poorer information environment than publicly traded firms due to less regulation and limited accounting reporting (e.g., Ball and Shivakumar (2005), Armstrong et al. (2007), Cassar (2009), Hope, Thomas, and Vyas (2013), Minnis and Shroff (2017), Bernard, Burgstahler, and Kaya (2018)). Consequently, investors and stakeholders have been actively seeking other useful, non-financial-performance-based predictors for these firms' future performance and success. One potential predictor is the nature/quality of human capital a private firm accumulates.[4] In this paper, we aim to examine whether the above job-movers' career trajectory and their revealed job preferences can serve as such a nonfinancial signal. This analysis can also shed light on the potential role of managerial information about employer-employee matching (and more broadly, management

[2] https://www.sfgate.com/news/article/O-Googlers-where-art-thou-Some-employees-2624962.php

[3] For another example, Elon Musk left PayPal to join the newly established Tesla in 2004. Contrary to the popular belief that Musk was the founder of Tesla, he initially worked as Tesla's senior engineer (more specifically, product architect) and became its CEO in 2008 (see https://en.wikipedia.org/wiki/Elon_Musk).

[4] Anecdotal evidence suggests that job seekers on the entrepreneurial labor market tend to judge a start-up firm's potential by evaluating its human capital quality. For example, James Everingham, a famous Silicon Valley engineer and entrepreneur who worked for Netscape, Yahoo, Facebook, etc., once tweeted that "When you see a talent vortex, maybe you should jump in. I didn't join Netscape early because I knew how big the internet would become. I joined because that's where the smartest [people] in the industry were all going. I guess I'm better at judging talent than guessing the future."

control systems that incorporate such information) in shaping the performance of entrepreneurial firms, which are typically plagued by various forms of information frictions.[5]

We focus on employees who leave newly public or recently acquired entrepreneurial firms to join less mature start-ups. As these job-movers choose to work for young, pre-exit ventures repeatedly over the course of their life, we call them "serial venture employees". Similar to venture capitalists who have the ability to select high-quality start-ups to invest in, serial venture employees might also play a "screening" role in the entrepreneurial labor market. But instead of providing financial capital, they invest human capital, including their labor and knowledge/experience, in the start-ups. That is, these movers, by accompanying the growth of their previous employers and acquiring insights about the key ingredients for early entrepreneurial success, might be able to identify and join new start-ups with high potentials to succeed in the future. On the other hand, firms may actively select employees whose incentives/abilities are aligned with theirs (Merchant and Van der Stede (2007) and Campbell (2012)). Therefore, private firms with stronger incentives to grow and successfully exit might actively seek and poach these experienced workers with the necessary ambitions/abilities that can help the start-ups grow. That is, the "screening" can be performed by the firms/start-ups as well.[6] Taken together, the labor flow of serial venture employees into a start-up should positively predict the latter's future success.[7]

To explore the nature and value implications of the matching between serial venture employees and entrepreneurial firms, we need to overcome several empirical hurdles, most of which arise from data limitations. First, to examine the implication of serial venture employees for

[5] Existing literature (e.g., Cassar, Ittner, and Cavalluzzo (2015)) has found that alternative information sources (e.g., third party credit scores) can interact with accounting/financial reporting in reducing information frictions for small private businesses.

[6] In various places of the paper, we use the term "screening" to refer to this *mutual* (*two-way*) "matching/selection" to stay in line with the analogous terminology used in the venture capital literature.

[7] Note that if the two-way matching between serial venture employees and their new employers does not reflect active "screening/selection" by either party, then we should not be able to observe a significant association between venture labor and start-up success, which is our null hypothesis.

the success of their new start-up employers, we need to observe not only those start-ups that end up successfully exiting (and in the case of IPOs, becoming publicly traded) but also those that do not (which remain private and largely unobservable in most commercial databases). To tackle this problem, we make use of the Longitudinal Business Database (LBD) maintained by the U.S. Census Bureau, which covers virtually the entire universe of business establishments with employment in the U.S., both public and private. Second, we need person-level data on serial venture employees, especially their employment history. However, most commercial databases of person-level data only cover top executives or board directors. To overcome this difficulty, we exploit another dataset from the U.S. Census Bureau, namely, the Longitudinal Employer-Household Dynamics (LEHD) dataset, which contains individual employees' entire job histories, earnings from each job, and demographic information for over 95% of the private sector in the U.S. By matching the LEHD to the LBD, we are able to identify serial venture employees, as well as the firms they leave and the firms they subsequently join. Third, to understand the nature/quality of serial venture employees, we examine their past innovation behavior to gauge the degree of their creativity and risk-taking spirit, which are both essential qualities for one to excel in an entrepreneurial environment. To this end, we make use of the individual inventor data from the Harvard Business School (HBS) Patenting Database, which contains information about each inventor's patenting activities as well as where the inventor is employed when a given patent is filed. While both data sources (i.e., the Census data and the inventor data) have their own limitations, they perform complementary functions in our analysis.

Using the inventor data, we first find that the innovation productivity of serial venture employees — as measured by their patenting quantity, quality, originality, and exploratory nature — is higher than that of "stayers" (i.e., those inventors who choose to stay with newly exited firms), "leavers to public firms" (i.e., those who leave the exited firms for other public firms), or even new hires of the exited firms. Thus, serial venture employees seem to be the most innovative among all types of employees at newly exited firms. The loss of their talents cannot be easily replaced by hiring new employees. These results suggest that serial venture employees possess the creativity and the risk-taking spirit required for entrepreneurial activities, which helps explain their career choice to repeatedly work for pre-exit start-ups and the possible value implication of their labor movement.

Given that serial venture employees are more suited for entrepreneurial activities than other types of workers, we next turn to the Census data and examine whether and how the presence of these venture employees predicts the success of the new start-ups they join. Specifically, we match treatment private firms (i.e., those with at least one serial venture employee) to control ones (i.e., those without any serial venture employees) based on year, state, industry, size, age, VC-backing status, and whether they operate multiple establishments, and then compare their respective exit likelihoods and size (employment) growth over the next three years. Using the matched sample, we find that increasing the number of serial venture employees in a firm from zero to one is associated with a 0.15 percentage points increase in the firm's likelihood to successfully exit in the next three years. This magnitude is sizable given that the unconditional mean of the exiting likelihood in our sample is 0.4 percentage points. Likewise, private firms with more serial venture employees also exhibit considerably higher future size growth than similar control firms.[8] In all, these results indicate that the presence of serial venture employees in a private start-up can serve as a useful signal that positively predicts the latter's growth potential and future performance.

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[8] In untabulated analysis using a sample of manufacturing firms only, we also find that serial venture labor positively predicts startups' future sales growth and total factor productivity, which has been shown by the literature to capture private firms' profit margins and operating efficiency (e.g., Schoar 2002). In addition, using the inventor sample, we find that, in the five years after the joining of serial venture employees, these start-ups significantly outperform matched firms (with similar ex-ante characteristics but without such labor inflows) in terms of innovation output, quality, originality, and exploration. Interestingly, upon the hiring of these venture labor, the *original* inventors at these start-ups (i.e., those not moving from another firm) also begin to exhibit greater innovation productivity than matched inventors. To conserve space, we report these results in Section A1 of the Internet Appendix..

To further examine the “screening/matching” channel for our results, we explore the heterogeneous predictive power of venture labor based on their labor mobility restrictions. Contractual restrictions on labor mobility, such as noncompete agreements, may undermine the frictionless matching between serial venture employees and their next employers (Garmaise (2011); Samila and Sorenson (2011)). Constrained by such contractual features, serial venture employees might not be able to join their most preferred high-quality start-ups even if they can identify these firms. Similarly, high-quality start-ups might not be able to hire their most preferred serial venture employees under these restrictions. Therefore, if the positive association between serial venture employees and start-up success is driven by the “screening/matching” channel, we would expect the predictive power of venture labor to be weaker when labor is less mobile due to exogenous variations of such frictions (e.g., when the state-level Noncompetition Enforceability Index is higher). We find evidence consistent with this prediction.

Further, we also find that serial venture employees whose previous jobs are in the same state or the same industry as the newly joined start-ups have stronger predictive power for these firms’ future success, which is also consistent with the “screening/matching” channel.

One might wonder whether the predictive power for start-up success is simply driven by the exceptional talent possessed by serial venture employees, which enables them to match with high-quality start-ups through the mutual screening process. If so, other types of high-talent employees, such as those who are previously top paid within their employers and those who have prior working experience at VC-backed private firms, might also serve as value-relevant signals for entrepreneurial success. To examine this possibility, we run a horse race among these different types of high-talent labor and find that serial venture employees have the strongest predictive power for start-up success, indicating the importance of their unique career trajectory (i.e., the fact that they have witnessed and contributed to the recent successful exit of a start-up) in addition to their talent in explaining the value implication of their labor flow.

Our evidence so far suggests that the presence of serial venture employees can serve as a useful signal that picks up various informational aspects of the start-up firm via the workers' revealed preferences. Given the lack of hard information on such firms, the soft information gathered by serial venture employees, which is in turn reflected in their job-hopping actions, can help investors and important stakeholders (such as suppliers, customers, and other employees) infer the quality and potential of entrepreneurial firms. Note that the entrepreneurial community is closely connected due to the geographical and industry concentrations of both start-ups and private financiers (e.g., venture capital firms). Entrepreneurial market participants such as investors and workers should be able to easily gather the job-hopping (or job history) information about other workers without access to proprietary datasets such as the census data.[9] In fact, our baseline results have indicated that start-ups with more venture labor are more able to attract public market investors (i.e., become more likely to successfully go public or get acquired). To further assess the value of this nonfinancial signal, we examine whether the presence of serial venture employees helps attract VC investors and *other* job seekers on the entrepreneurial labor market. To the extent that job seekers pay close attention to their prospective employers' earnings announcements and financial condition (Brown and Matsa (2016), Choi, Choi and Malik (2023)), they should be incentivized to produce information about the labor force quality/background of their future employers and make decisions accordingly.

Indeed, using the same matching procedure described above (which controls for major firm attributes and thus the demand for labor), we find that firms with more serial venture labor are more likely to obtain VC funding in the next three years. In addition, these firms are able to attract and hire more new employees in the near future, especially those already having stable jobs (i.e.,

[9] For example, people living in the same neighborhood could exchange information about the job status of common friends/acquaintances; venture capitalists often screen the resumes of all the employees of a start-up company before making the investment decision; and modern social media such as LinkedIn also publicly provide such job history information to all subscribers.

"on-the-job" movers) as opposed to those currently unemployed. To the extent that on-the-job workers likely have a stronger need for job-related signals, as they have a higher opportunity cost of taking the job offers than the unemployed who have no labor income anyway, this finding illustrates the usefulness of the nonfinancial signal of venture labor to job seekers on the entrepreneurial labor market, particularly those information-sensitive ones. Furthermore, we find the signal to be more useful when there are fewer alternative information sources for the start-up, i.e., when it is subject to a poorer information environment and lower financial reporting quality (e.g., when it is younger or operates in an R&D-intensive industry that highly values confidentiality and business secrets).

One alternative but non-mutually-exclusive explanation for the predictive power of serial venture employees is a potential "nurturing" role played by these employees. That is, similar to venture capitalists who facilitate the start-ups' growth with funding and monitoring/advising, serial venture employees could diffuse the entrepreneurial culture, institutional wisdom, and technological know-how from their past employers to the new start-ups. For instance, they could serve as team leaders or mentors in their new employers, contributing to the latter's successful growth.[10] To examine this alternative explanation, we explore the heterogeneous predictive power of venture labor based on these employees' time spent with their new employers. It typically takes time for a new hire to exert ample influence on her employer's operations to help improve its future performance. Hence, if serial venture employees' "nurturing" role is important, we would expect the signal to be more informative when these employees work at the start-ups for a longer period of time. However, opposite to this prediction, we find the positive association between serial venture employees and their employers' future success to be more pronounced when these workers

[10] In certain cases, these venture employees might also benefit their new employers by bringing their personal wealth (capital) or their networks (such as personal/professional connections to venture capitalists, banks, potential acquirers, or other high-skilled workers). Hence, throughout the paper, we use the term "nurturing" to refer to a general "treatment effect" of venture labor on their new employers regardless of how they match.

join the start-ups *only recently* (when the task of predicting performance/success is easier). This result, which does not fully dismiss venture labor's nurturing role as a possible explanation, suggests that this "treatment" effect is unlikely the dominant channel for our results.[11]

Overall, our paper illustrates the value of managerial information about employer-employee matching in the entrepreneurial labor market. By identifying and attracting serial venture employees with prior successful entrepreneurial experience, founders and managers of small businesses can tap the full potential of such talented labor to promote future growth. Our study thus highlights the importance of management control systems (e.g., Merchant and Van der Stede (2007), Sandino (2007), Labro, Lang, and Omartian (2023)) for young entrepreneurial firms, which typically suffer from various forms of information asymmetry and lack of financing opportunities (e.g., Cassar (2004), Cassar, Ittner, and Cavalluzzo (2015)). Our study also extends the literature on private firm valuation by identifying a specific form of human capital flow that can serve as a useful signal of private firms' quality.[12] The flow of serial venture labor facilitates the transfer of private, value-relevant information about start-ups to other entrepreneurial market participants, which can enhance the welfare of the entire venture ecosystem.

2. Related literature

Our paper is related to several strands of literature. First, it contributes to the nascent studies on management control systems (e.g., Merchant and Van der Stede (2007), Sandino (2007), and Labro, Lang, and Omartian (2023)), especially those on managerial information and employee selection/retention/promotion (e.g., Campbell (2012), Li and Sandino (2018), Deller and Sandino

[11] We also examine how the departure of serial venture employees affects newly public firms' post-IPO accounting performance and stock returns. We find that the fraction of employees/inventors who leave a newly public firm after the IPO to join other private firms is negatively associated with the firm's post-IPO accounting performance and stock returns. These results illustrate the valuable human capital possessed by serial venture employees and the significant losses incurred when firms cannot retain such talents, which echoes the findings by Labro and Omartian (2023) that firms try hard to manage employee retention risk. To conserve space, we present these results in Section A2 of the Internet Appendix.

[12] In untabulated analysis of a subsample of manufacturing firms, we find that the predictive power of serial venture labor persists even after we control for common operational characteristics of the start-ups such as their sales, capital stock, total factor productivity, capital expenditures, capital intensity, market share, white-collar wage ratio, etc.

(2020), Chen and Li (2023), Choi, Choi, and Malik (2023), Choi, Gipper, and Malik (2023), and Labro and Omartian (2023)). Our paper adds to this literature by illustrating the importance of managerial information about the two-way labor market matching in the entrepreneurial world where there is a lack of accounting information. Accounting information can be limited under many circumstances and for many different reasons. The case of entrepreneurial firms is just one example. Our study thus has a broad implication for both the financial and managerial accounting literature. Although we show the importance of one specific type of managerial information, there are many other types of managerial information that can be explored to alleviate the undesirable impact of inadequate disclosure and limited accounting information. As such, our findings call for future research to further integrate the financial and managerial accounting literature and exploit the complementarities between the two.

Second, we add to the literature on the information environments of private firms, which are an important driver of economic growth. Researchers find that value-relevant information about private firms is crucial to the decision-making of various participants in the entrepreneurial market, such as venture capital investors (e.g., Hand (2005) and Baik, Berfeld, and Verdi (2020)), acquirers (e.g., Jansen (2020)), banks (e.g., Cassar, Ittner, and Cavalluzzo (2015), Berger, Minnis, and Sutherland (2017)), and competitors (e.g., Darmouni and Sutherland (2021)). Despite the high information demand for private firms, they often have more opaque information environments and lower financial reporting quality than public firms (e.g., Ball and Shivakumar (2005), Burgstahler, Hail, and Leuz (2006), and Hope, Thomas, and Vyas (2013)) due to the lack of consistent regulation (e.g., Minnis and Shroff (2017) and Bernard, Burgstahler, and Kaya (2018)) and the voluntary nature of disclosure by private firms (e.g., Armstrong et al. (2007) and Cassar (2009)). We add to this literature by showing that private firms' potential investors and stakeholders (such as job seekers on the entrepreneurial labor market) can partially rely on the nonfinancial signal of serial venture labor to infer the quality of private firms and make informative decisions when high-quality financial statement information is hard to come by. The identification and exploitation of such nonfinancial signals can potentially enhance the information environments of private firms and consequently contribute to economic growth.

Third, our paper contributes to the literature showing that rank-and-file employees possess value-relevant information about their employers (e.g., Brown and Matsa (2016), Babenko and Sen (2016), Hales, Moon Jr., and Swenson (2018), Green et al. (2019), Huang, Li, and Markov (2020), Baghai et al. (2021), Agrawal, Hacamo, and Hu (2021), He et al. (2022), and Campbell and Shang (2022)). While this literature focuses on whether rank-and-file employees possess valuable information about *public* firms, we examine whether the labor movement of such employees can serve as a useful performance signal for *private* startups, which are subject to a poorer information environment and whose investors/stakeholders are in greater need of such nonfinancial signals.[13]

Fourth, our paper is also related to the literature on the implication of labor mobility for IPO firms (e.g., Bernstein (2015), Borisov, Ellul, and Sevilir (2021), Babina, Ouimet, and Zarutskie (2022)). We differ from these studies in two important ways. First, while they focus on the post-IPO employment dynamics of firms that recently go public, we examine the future performance of *private* startups that hire talented employees from successful entrepreneurial firms. Second, our definition of successful entrepreneurial firms goes beyond those having IPOs: A large fraction of our sample consists of private firms exiting through sell-outs (acquisitions), which has become the predominant way of exits in recent decades (see, e.g., Chemmanur et al. (2022)).

[13] Our paper is also broadly related to the literature on the value of key employees for private entrepreneurial firms. While this literature identifies skilled labor largely based on their demographic attributes (e.g., immigration or visa status) or ranks along the corporate ladder (e.g., Ewens and Marx (2018), Chen, Hshieh, and Zhang (2021), Gu et al. (2020), and Dimmock, Huang, and Weisbenner (2022)), our paper exploits the job history information of start-up employees and finds that the joining of workers with immediate exposure to entrepreneurial success can positively predict a private start-up's future success.

Finally, the recent labor and accounting literature finds that labor mobility has important implications for various corporate policies, such as their employee incentive provision policies (Van der Stede , Wu, and Wu (2020)), patent filings (Armstrong, Glaeser, and Park (2020) and Kang and Lee (2022)), information disclosure (e.g., Aobdia (2018), Li, Lin, and Zhang (2018), Ali, Li, and Zhang (2019), and deHaan, Li, and Zhou (2023)), executive compensation (Erkens (2011)), earnings management (e.g., Dou, Khan, and Zou (2016) and Gao, Zhang, and Zhang (2018)), anti-takeover provisions (Dey and White (2021)), tax planning (Barrios and Gallemore (2023)), and wage and nonwage benefits (Labro and Omartian (2023)). We extend this literature by identifying a specific type of labor mobilization, namely, the labor flow from mature entrepreneurial firms to young start-ups, which positively predicts the future success of the latter.[14]

3. Data and Sample Construction

We obtain data on U.S. IPOs and private-target acquisitions (i.e., sell-outs) from the Securities Data Company (SDC) database.[15] We restrict our sample to IPOs and acquisitions completed during 1990-2007 because our data on individual employees (i.e., the Longitudinal Employer-Household Dynamics (LEHD) program from the U.S. Census Bureau) cover the period of 1990-2008, and we need at least one year to track employees' job status after deal completion.

[14] Our paper is also related to the broader literature on why and how entrepreneurs start their own businesses. In particular, this line of research finds that the decisions by entrepreneurs to start their own businesses can be shaped by venture capitalists (e.g., Hellmann and Puri (2002); Samila and Sorenson (2011)), social contacts (e.g., Lerner and Malmendier (2013); Guiso, Pistaferri, and Schivardi (2021)), family members (e.g., Lindquist, Sol, and Van Praag (2015); Laspita et al. (2012); Vladasel et al. (2020)), coworkers (Wallskog (2022)), takeover activities (Kim (2022)), or the entrepreneurs' previous entrepreneurial experience (e.g., Gompers et al. (2010); Zhang (2011); Parker (2013); Lafontaine and Shaw (2016); Nahata (2019)). Unlike these studies, we examine the value implication of rank-and-file employees who repeatedly work for entrepreneurial firms, rather than that of entrepreneurs themselves. Although untabulated, all our results continue to hold if we drop serial venture employees who are likely to be founders (i.e., those who join the start-ups during the first year of business and are among the top earners).

[15] Following previous IPO literature (e.g., Chemmanur and He (2011); Chemmanur et al. (2018)), we remove all IPOs related to equity carve-outs, American depositary receipts, American depositary shares, global deposit receipts, global deposit shares, units, trust receipts, and trust units. For the sample of private-target acquisitions, we remove all deals that are reverse takeovers, spin-offs, recapitalizations, self-tenders, exchange offers, repurchases, minority stake purchases, acquisitions of remaining interest, privatizations, divestitures, asset sales, deals whose target and acquirer belong to the same parent company, and deals whose status is defined as "incomplete" by the SDC.

We obtain individual employee job history and demographic information from the LEHD program, which covers over 95% of those employed in the private sector in all 50 U.S. states.[16] Employees' quarterly earnings and employment information are obtained from the Employment History File (EHF).[17] Individual characteristics, including age, gender, ethnicity, and education, are obtained from the Individual Characteristics File (ICF). Our LEHD sample includes 26 participating states that have agreed to share their data with us as external (i.e., non-Census) researchers under the Local Employment Dynamics federal-state partnership.[18] Following a three-step process, we match employers in the LEHD data to IPO and acquired private firms from the SDC data.[19] The matched sample contains about 289,000 employees from 1,200 IPO firms and about 642,000 employees from 3,300 acquired private firms.[20, 21]

Data on inventors, including their employers, patents, and citations, are obtained from the Harvard Business School (HBS) Patenting Database constructed by Li et al. (2014). Following standard practice in the literature, we treat the assignee of an inventor's patent as her employer. We then adopt a two-step procedure to match IPO firms from the SDC database to assignees in the HBS patenting database.[22] We further require an IPO (acquired) firm to have at least one patent

[16] See Abowd et al. (2009) for a comprehensive overview of the LEHD data.
[17] See Tate and Yang (2015), Aldatmaz, Ouimet, and Van Wesep (2018), and He, Li, and Shu (2022) for more information about the detailed components of LEHD employee earnings.
[18] The 26 LEHD states in our sample are Arizona, California, Colorado, Delaware, Georgia, Hawaii, Idaho, Illinois, Indiana, Louisiana, Maryland, Maine, New Jersey, New Mexico, Nevada, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, Tennessee, Texas, Utah, Vermont, Washington, and Wisconsin.
[19] First, we match the IPO and acquired firms to firms in the LBD via a combination of name-and-address matching and manual checking, following Chemmanur et al. (2022). In the second step, we match employers in the LEHD database to LBD establishments by Employer Identification Number (EIN), industry, state, and county, using the Business Register Bridge (BRB) file maintained by the U.S. Census Bureau. We then aggregate employees of all establishments that belong to the same firm using LBD's firm identifier, "FIRMID." In the third step, we match the LEHD data to the SDC data using the link files created in the first step.
[20] These numbers are rounded according to the disclosure requirement by the U.S. Census Bureau.
[21] Following He et al. (2022), for empirical tests using the LEHD sample, we further require that at least 90 percent of a firm's workforce (measured by either the number of employees or total payroll in LBD) is covered by its establishments in the 26 states for which we have LEHD data. Relaxing this filter to 50 percent or 0 percent does not qualitatively change our results.
[22] First, we match an IPO firm's Committee on Uniform Securities Identification Procedures (CUSIP) number from the SDC database to the permanent identification numbers (PERMNO) using the link file provided by the Center for Research in Security Prices (CRSP). We then match the IPO firm's PERMNO to patent assignees using the link file

filed in the year before the IPO date (deal completion date). In addition, we drop the inventors whose employment records cannot be tracked after their employers' exit dates, including those who do not file any patents or only file patents for non-corporate assignees (i.e., governments, universities, and individuals) after the exit dates.[23] The final inventor sample consists of 4,357 inventors from 814 IPO firms and 2,209 inventors from 524 acquired private firms.

4. Variable Definitions

4.1 Identifying serial venture employees

To identify serial venture employees in the LEHD sample, we begin by identifying all full-time employees of private firms that had recently exited through IPOs or sell-outs during the period of interest. Following the literature (e.g., Babina et al. (2020)), we define an employee *i* as a full-time employee of firm *j* in quarter *t* if the employee's wage from firm *i* in quarter *t* is above or equal to the federal minimum wage in that quarter and the employee also receives non-zero wages from firm *i* in quarter *t-1* and *t+1*. Using this method, we identify, for a private firm exiting in quarter *t*, all of its full-time employees in quarter *t-1*. We then divide the pool of full-time employees into several categories based on their employment status after quarter *t* (i.e., the exiting quarter). For IPO firms, if an employee starts to work full-time for another private (public) firm in any quarter between *t+1* and *t+4*, we define her as a "serial venture employee" ("leaver to public firm"), meaning that she quits the job in the newly exited firm and moves to another private (public) firm during the one-year period after the exit.[24,25] If the employee still works for the IPO firm in

provided by Kogan et al. (2017). To match acquired private firms from the SDC database to patent assignees, we use a combination of name-matching algorithms and manual checking.

[23] We supplement the HBS Patenting Database with the PatentsView database (available at https://www.patentsview.org/download/), which contains additional information on the assignees' identities.

[24] Following Chemmanur et al. (2022), we identify public firms in the Census data by matching it to Compustat data and IPO data. Firms that are neither public nor exiting in a given year are treated as private firms.

[25] Note that the LEHD data do not provide information on whether an employee leaves the firm voluntarily or involuntarily. However, researchers often infer a job-to-job move as voluntary if a worker separates from a job and begins work at a new job within a short time period (e.g., Haltiwanger, Hyatt, and McEntarfer (2018) and Haltiwanger et al. (2018)). Given that serial venture employees, by construction, are those who start work for other firms shortly after leaving the exited firms, their movements are more likely to be voluntary rather than involuntary. In addition,

quarter *t+4*, we define her as a "stayer." For acquired firms, we define an employee as a serial venture employee (leaver to public firm) if she starts to work full-time for another private (public) firm other than the merged firm in any quarter between *t+1* and *t+4*. If the employee still works for the merged firm in quarter *t+4*, she is identified as a stayer. We focus on the employee's job record within one year after her original employer's exit rather than that further into the future to reduce the likelihood that the employee's employment choice is confounded by other factors unrelated to the exit event.

To study how the presence of serial venture employees is associated with private firms' future success, we construct a sample of private firms with serial venture employees and matched firms without such employees.[26] For each firm in year *t*, we calculate *LnSerialVE* as the natural logarithm of one plus the number of serial venture employees employed by the firm in the last quarter of year *t* and *PctSerialVE* as the fraction of serial venture employees in the firm's workforce in the last quarter of year *t*.

To identify serial venture employees in the inventor sample, we first find all the inventors who file at least one patent for an exited firm during the year prior to its exit date (i.e., the IPO date or the deal completion date for sell-outs). These inventors can be assumed to work for the exited firm prior to the exit. Then, for an IPO firm, we follow the spirit of Bernstein (2015) to define such inventors as serial venture employees (leavers to public firms) if they file at least one patent for another private (public) firm in the year after the IPO date.[27] For an acquired firm, we define its pre-exit inventors as serial venture employees (leavers to public firms) if they file at least one patent for another private (public) firm other than the merged firm in the year after the deal completion date. Stayers are defined as those inventors who are neither serial venture employees

our results remain qualitatively similar if we require that a serial venture employee's salary at her new employer is higher than that at her original employer, which is a stricter definition of voluntary turnover.

[26] Details of the matching procedure are discussed in Section 6.1.

[27] If the assignee of a patent has a valid PERMNO in the linking file provided by Kogan et al. (2017), we treat it as a public firm. Otherwise, it is treated as a private firm.

nor leavers to public firms, and who have not filed any patents for other firms before filing at least one patent for the exited firms after the exit date.[28] In addition, we identify an inventor as a new hire of an IPO firm if she has never filed a patent for the firm before the IPO date and files at least one patent for the IPO firm in the year after the IPO date. Similarly, we identify an inventor as a new hire of the merged firm after an acquisition if she has never filed a patent for the target or the acquirer before the deal completion date and files at least one patent for the merged firm in the year after the deal completion date.

4.2 Measuring private firms' future success

We construct two main empirical measures to gauge a private firm's future success. For a firm *i* in year *t*, *Exit* is defined as a dummy variable that equals one if the firm exits through going public or getting acquired in the next three years (i.e., $t+1$ to $t+3$), and zero otherwise. *SizeGrowth* is defined as the percentage change in the firm's total employment from year $t+1$ to $t+3$. For the firms that cease to exist by year $t+3$, *SizeGrowth* is set to be -1.[29]

4.3 Control variables in the LEHD sample

For regression analyses using the LEHD sample, we calculate the average employees' demographic characteristics at the firm level. *LnAvgEarn*, *LnAvgAge*, and *LnAvgEdu* are defined as the natural logarithm of average quarterly earnings, age, and education, of a firm's employees, respectively. *Gender* (*Ethnicity*) is defined as the fraction of male (white) employees in a firm. In addition, we control for the natural logarithm of the total number of employees (*LnEmp*) and the natural logarithm of firm age (*LnFirmAge*), measured as one plus the difference between a given year and the year when a firm's first establishment was founded.

4.4 Summary statistics

[28] Our results are robust to treating all inventors who are neither serial venture employees nor leavers to public firms as stayers.
[29] Our results are robust to dropping such deceased firms.

We first report summary statistics for our LEHD sample. Panel A of Table 1 presents the proportion of various employee categories for exited (i.e., IPO or acquired) firms. Among the 931,000 pre-exit full-time employees from exited private firms in our sample, 11.1 percent move to private firms within one year following the exits and thus become serial venture employees. Meanwhile, 4.8 percent of these employees move to public firms during the same window, and the rest (84.1 percent) stay.

Panel B of Table 1 presents summary statistics at the firm level for the LEHD sample. To minimize the effect of outliers on our regression analysis, we winsorize all continuous variables at their 1st and 99th percentiles. Among the firms in our sample, 0.4 percent exit through IPOs or sell-outs within the next three years. The average employment growth is -8.7 percent.[30] The measures for the presence of serial venture employees, *LnSerialVE* and *PctSerialVE*, have averages of 0.135 and 0.013, respectively.[31] Firms in this sample have an average of about 49.5 employees. The average age of the firms is about 13.0 years. The employees have average quarterly earnings of 9,470 dollars. The average age and education level of the employees are 41.2 years and 14.4 years, respectively. On average, 53.5 percent of a firm's employees are male, and 70.4 percent of a firm's employees are white.

5. Entrepreneurial Talent of Serial Venture Employees

Although the LEHD sample allows us to track the employment status of individual employees in newly exited firms and gauge the demographic characteristics of these employees, it is hard to infer the entrepreneurial talent (i.e., the essential characteristics required for entrepreneurial successes) of these employees based on the LEHD data alone. The inventor data, meanwhile, track the number of patents filed and citations received by individual inventors. Such

[30] The mean employment growth is negative because, as mentioned before, employment growth is set to -1 for the firms that cease to exist by the end of year *t+3*.

[31] The small means of the number and fraction of serial venture employees are mostly driven by the large fraction of start-ups without any such employees (i.e., the control firms), which is similar to the right-skewed distribution of innovation activities in the economy due to the large population of zero-patenting firms.

information can be used to infer their innovative behavior and thus their creativity and risk-taking spirit, which are both required talents for achieving entrepreneurial successes (see, e.g., Islam and Zein (2020)). Therefore, we turn to the inventor sample to examine the difference in talent/quality between serial venture employees and other employees of the exited firms.

To measure an inventor's innovation quantity and quality, we calculate her average number of patents filed per year (*Patents*) and the average number of citations received per patent (*CitePat*). In addition, we follow the prior literature (e.g., Levine, Lin, and Wei (2017), Hirshleifer, Hsu, and Li (2018), Gao, Hsu, and Li (2018), Brav et al. (2018), and Lin, Liu, and Manso (2021)) and measure the originality and explorative nature of an inventor's patents. Specifically, we calculate the originality score of the patents (*Originality*) as the average number of unique technological classes cited by an inventor's patents. A higher *Originality* score indicates that an inventor's patents deviate more from the current technology trajectories. We also calculate the average number of exploratory patents filed by an inventor per year (*Exploratory*). A patent is defined as "exploratory" if 80% or more of its citations are not based on the existing knowledge of the firm, i.e., all the patents filed by the firm and the patents that were cited by the firms' patents filed over the past five years. A larger number of exploratory patents filed by an inventor indicates that she is more capable of acquiring new knowledge. Both *Originality* and *Exploratory* capture an inventor's willingness and capacity to explore beyond her existing base of knowledge, which partially reflects her entrepreneurial ability and spirit.

Table 2 compares the innovation behaviors of serial venture employees (*SerialVE*) to those of employees in other categories.[32] On average, a serial venture employee files 1.68 patents per year before the exit date, which is significantly greater than those filed by leavers to public firms (*LeaverToPub*) or by stayers (*Stayer*), reflecting the higher innovation productivity of serial

[32] Among the 6,566 pre-exit inventors, 11.9 percent move to private firms and thus are defined as serial venture employees, 5.6 percent move to public firms, and 82.5 percent stay with the exited firms. This distribution is generally comparable to that of the LEHD sample.

venture employees. Similarly, the average number of citations received by the patents of serial venture employees (27.3) is also significantly larger than those received by the patents of stayers (22.2), which indicates that serial venture employees generate higher quality patents than those inventors who stay with the exited firms. Further, the patents by serial venture employees have significantly higher *Originality* (9.01) and are more exploratory (0.66) than those by leavers to public firms or stayers, suggesting that serial venture employees are more adventurous in nature and more capable than other inventors in exploring new technological domains. More importantly, although the newly exited firms hire a large number of inventors post-exit, the newly hired inventors (*NewHire*) have significantly worse track records in terms of innovation quantity/quality (i.e., fewer patents and fewer citations per patent) and innovative originality (i.e., patents with lower originality scores and fewer exploratory patents) than serial venture employees, further suggesting that the loss in exited firms' key human capital due to the departure of serial venture employees is hard to replace.

Taken together, these results indicate that serial venture employees possess the creativity and risk-taking spirit required for entrepreneurial activities, which explains their career choice to repeatedly work for private start-ups and the possible value implications of their labor movement.

6. Serial Venture Employees and Start-up Firms' Future Success

6.1 Baseline results

We hypothesize that private firms' future success is positively associated with the presence of serial venture employees among their workforces through a two-way screening/matching channel. On the one hand, serial venture employees might have the ability to identify and join start-ups with high unobservable quality to start with (i.e., play a "screening" role). On the other hand, high-quality start-ups might be able to screen and attract such talented employees, leading to an equilibrium matching.

To empirically examine this hypothesis, we match a sample of private firms with serial venture employees to the ones without such labor along several important dimensions. Specifically, for each firm *i* with at least one serial venture employee (i.e., the "treatment" firm) in the last quarter of year *t*, we find all the private firms in that year without any serial venture employees in the last quarter and are in the same three-digit NAICS industry, state, size group, and age group as the treatment firm.[33] We further require the matched "control" firms to have the same VC-backing status and multi-unit status (i.e., whether the firm is a single-establishment or multi-establishment firm) as the treatment firm.[34,35] Finally, for each treatment firm *i*, we retain up to five eligible matched firms that are the closest to firm *i* in terms of size (measured by the total number of employees). Then we estimate the following model using the final matched sample:

$$FutureSuccess_i = \alpha + \beta_1 SerialVE_i + \beta_2 LnEmp_i + \beta_3 LnFirmAge_i + \beta_4 LnAvgEarn_i + \beta_5 LnAvgAge_i + \beta_6 LnAvgEdu_i + \beta_7 Gender_i + \beta_8 Ethnicity_i + MatchedPair + \varepsilon_i, \quad (1)$$

where *FutureSuccess* is one of the two measures for private firms' future success (in year *t+1* to *t+3*) discussed earlier: *Exit* or *SizeGrowth*. *SerialVE* captures the presence of serial venture employees working for firm *i* at the end of year *t*, and can be one of the two measures discussed earlier: *LnSerialVE* or *PctSerialVE*. All other control variables, defined in Section 4.3, are measured either at year *t* (for firm characteristics) or the last quarter of year *t* (for employee characteristics). We include matched-group fixed effects, which fully absorb industry, year, and state fixed effects as well as their multiplicative combinations as the matching is done at the

[33] Following Davis et al. (2014), we classify firms into 12 size groups based on their employment: (1) 1-4 employees, (2) 5-9 employees, (3) 10-19 employees, (4) 20-49 employees, (5) 50-99 employees, (6) 100-249 employees, (7) 250-499 employees, (8) 500-999 employees, (9) 1,000-2,499 employees, (10) 2,500-4,999 employees, (11) 5,000-9,999 employees, and (12) 10,000 or more employees. We classify firms into five age groups: (1) 0-5 years, (2) 6-10 years, (3) 11-15 years, (4) 16-20 years, and (5) 21 or more years. Our results remain robust when we use a three-year band instead of a five-year band for the age groups and when we use six-digit NAICS industry instead of three-digit NAICS industry for the matching procedure.

[34] We obtain the data of venture-capital-backed firms from the Thomson One VentureXpert database.

[35] Ideally, we want to control for other observable firm quality measures (such as profitability) that are key determinants of private firms' success. However, such information is missing in most databases covering private firms including the LBD. Therefore, we make our best effort by matching on VC-backing status, which is commonly used as a comprehensive proxy for unobservable private firm quality (see, e.g., Hochberg, Ljungqvist, and Lu (2007), Kerr, Lerner, and Schoar (2014), and Dimmock, Huang, and Weisbenner (2021)).

industry-state-year level. These fixed effects also control for the effects of VC-backing status, age group, size group, and multi-unit status on the likelihood of a successful exit. We cluster standard errors at the matched-group level.

Table 3 presents the results of estimating Equation (1). For ease of interpretation, we multiply the dependent variables by 100. Column (1) of Panel A presents the regression using *Exit* as the measure for firms' future success and *LnSerialVE* as the measure for the presence of serial venture employees. We find that private firms with more serial venture employees are significantly more likely to successfully exit through IPOs or sell-outs. Increasing the number of serial venture employees from zero to one (i.e., increasing *LnSerialVE* from zero to 0.69) is associated with a 0.15 (=0.224×0.69) percentage points increase in a firm's likelihood to successfully exit in the next three years, which is approximately 38.6% of the mean unconditional exiting likelihood in our sample (i.e., 0.4 percentage points). Column (2) further shows that the presence of serial venture employees in a firm's workforce is positively associated with the firm's future employment growth (*SizeGrowth*).

Next, we repeat the regressions using *PctSerialVE* (the fraction of serial venture employees among a firm's workforce) instead of *LnSerialVE* as the independent variable. Panel B of Table 3 shows that the fraction of serial venture employees in a firm's workforce is positively associated with the firm's likelihood to successfully exit and its employment growth.[36]

In addition, we also apply the same matching procedure to a sample of private firms in the manufacturing sector using the Annual Survey of Manufacturers (ASM) and the Census of Manufacturing Firms (CMF). We find that the presence of serial venture labor positively predicts their employers' future three-year sales growth and three-year-average total factor productivity

[36] Our results remain robust when we use a dummy variable that equals one for firms with serial venture employees and zero for those without, instead of *LnSerialVE* or *PctSerialVE*, as the independent variable. We do not tabulate these results due to the disclosure requirement by the Census.

(TFP), which has been shown by the literature (e.g., Schoar (2002); Krishnan, Nandy, and Puri (2015)) to capture private firms' profit margins and operating efficiency.[37]

One might conjecture that serial venture employees, due to their risk tolerance and adventurous nature, could push their next employers to adopt excessively risky strategies, which increases these start-ups' performance volatility (along with an increase in average/mean performance) and ultimately leads to a higher probability of failure. However, opposite to this prediction, we find no evidence that serial venture labor significantly increases the probability of failure of their new employers.[38]

6.2 Analyses of the screening/matching channel

6.2.1 Heterogeneous predictive power of venture labor based on labor mobility restrictions

To further examine the two-way "screening/matching" channel for our main results, we perform two tests. First, we analyze whether labor market frictions such as contractual restrictions on human capital movement affect serial venture employees' predictive power for start-up success. Specifically, we follow the literature (e.g., Garmaise (2011), Samila and Sorenson (2011), Custodio, Ferreira, and Matos (2019)) and use the legal enforceability of employee noncompete agreements across U.S. states as a proxy for the labor market frictions that limit human capital mobility. Noncompete agreements are clauses in employment contracts that restrict workers from joining rival firms under certain circumstances. The enforceability of these agreements varies from state to state. In states where the enforceability of noncompete agreements is stronger, it is harder for serial venture employees to freely choose and join their most preferred next employers. Similarly, start-ups would also have more difficulty hiring their most preferred job candidates including serial venture employees, leading to a less perfect matching between the two. Hence, if the screening/matching channel plays an important role in driving our main results, we would

[37] We are not able to tabulate this analysis since the Census Bureau has a strict set of rules determining the maximum number of estimates that can be disclosed from a given sample and what specific estimates to be disclosed.
[38] These results are currently untabulated as well due to the disclosure requirements of the Census Bureau.

expect the predictive power of serial venture employees for start-up success to be significantly weaker in states with stronger enforceability of noncompete agreements.

To examine this hypothesis, we run a set of regressions similar to those specified by Equation (1), except that we interact *LnSerialVE* with *NEI*, the Noncompetition Enforceability Index of the state where a firm operates.[39] As shown in Table 4, the coefficients on the interaction term are significantly negative in both columns, suggesting that the predictive power of serial venture employees is weaker in states with stronger enforceability of noncompete agreements. This heterogeneity indicates that the matching between start-up quality and employee talent becomes less efficient if labor mobility is subject to more stringent contractual restrictions, which reduces the usefulness of serial venture employees as a start-up performance/quality signal. These results suggest that the screening/matching channel is important in driving the predictive power of venture labor.

6.2.2 Heterogeneous predictive power of venture labor based on their geographic location and industry background

Next, we analyze the heterogeneous predictive power of serial venture employees based on their geographic proximity to their new employers and their industry background.

We first examine whether serial venture employees who live closer to the newly joined start-ups (i.e., those who move from the same state that the start-ups operate in) have greater predictive power for these start-ups' future success. Existing literature has shown that local investors have information advantage over non-local ones (see, e.g., Coval and Moskowitz (1999, 2001), Ivkovic and Weisbenner (2005), and Baik, Kang, and Kim (2010)). Therefore, if the screening/matching channel plays an important role in explaining our baseline results, serial venture employees who live closer by should have better predictive power than those who live

[39] The Noncompetition Enforceability Index, ranging from 0 to 9, is provided by Garmaise (2011).

further away because one's local information advantage should have facilitated the screening of and the matching to her future employer.

To test the above prediction, we run a set of regressions similar to those specified by Equation (1), where we replace the key independent variable with *LnSerialVEInState* and *LnSerialVEOutState*. *LnSerialVEInState* is the natural logarithm of the number of serial venture employees whose previous employer (the exited firm) operates in the same state as their new employer (the private start-up). *LnSerialVEOutState* is the natural logarithm of the number of serial venture employees whose previous employer operates in a different state from their new employer. We report the regression results in Panel A of Table 5. As can be seen, the coefficients on *LnSerialVEInstate* are larger than those on *LnSerialVEOutState* in both columns. The F-test for the difference between the coefficients on *LnSerialVEInstate* and *LnSerialVEOutState* is significant at the 1% level for the regression using *Exit* as the dependent variable. These results suggest that the screening/matching channel is an important driver for venture labor's predictive power for start-up success.

We then explore the heterogeneous predictive power of serial venture employees based on their industry-specific knowledge about the start-ups (see, e.g., Cassar (2014)). Similar to the notion that local information could facilitate serial venture employees' screening of their future employers (and vice versa), industry-specific knowledge obtained by these employees from their previous employers could also help them determine the quality of the start-ups. Meanwhile, higher-quality start-ups might also be able to screen and poach venture employees with similar industry backgrounds. Therefore, if the screening/matching channel is important, the predictive power should be stronger for serial venture employees whose previous employers operate in the same industry as their new employers.

Panel B of Table 5 shows that, consistent with the above prediction, the coefficients on *LnSerialVESameInd*, the log number of serial venture employees whose previous employer operates in the same three-digit NAICS industry as their new employer, are larger than those on *LnSerialVEDiffInd*, the log number of serial venture employees whose previous employer operates in a different industry, in both regressions. The F-test for the difference between the coefficients of *LnSerialVESameInd* and *LnSerialVEDiffInd* is significant at the 10% level (5% level) for the regression using *Exit* (*EmpGrowth*) as the dependent variable. These results again suggest that the two-way screening/matching is an important underlying mechanism for our baseline results.

6.3 Horse race between serial venture employees and other types of high-talent labor

One might wonder whether the predictive power for start-up success is simply driven by the exceptional talent possessed by serial venture employees, which enables them to match with high-quality start-ups through the mutual screening process. If so, the presence of other types of high-talent employees, such as those who are top paid within their previous employers and those who have prior working experience at VC-backed private firms, might also serve as useful non-financial signals for entrepreneurial success. To compare the relative predictive power of these different types of high-talent labor, we run a horse race among them in this section.

Specifically, we add *LnEmpHighEarn*, *LnEmpVC*, and *LnEmpPublic* as key explanatory variables to regressions specified by Equation (1). *LnEmpHighEarn* is the natural logarithm of one plus the number of employees in a firm whose earnings at their previous employers are among the top deciles.[40] *LnEmpVC* (*LnEmpPublic*) is the natural logarithm of one plus the number of employees in a firm who have prior working experience at VC-backed private (public) firms.

As shown in Table 6, the coefficients on *LnSerialVE* remain significantly positive after the inclusion of these additional variables that capture the presence of other types of high-talent employees. More importantly, serial venture employees have greater predictive power for start-up

[40] For each current employee with an identifiable previous employer, we rank all employees of that employer in terms of earnings/wages for the second last quarter before she leaves the firm. This is to alleviate the concern that the last quarter of each employee with her previous employer might not be a full-employment quarter. Our results are robust to using the last quarter or using top quintiles or terciles to define top paid workers.

success than these other types of labor. For example, increasing the number of serial venture employees from zero to one in this regression setting is associated with a 0.12 (=0.172×0.69) percentage points increase in a firm's likelihood to successfully exit in the next three years, whereas increasing the number of top paid employees, the number of employees with prior VC-backed firm working experience, and the number of employees with prior public firm working experience from zero to one is associated with only a 0.01, 0.01, and 0.03 percentage points increase in the firm's exiting likelihood, respectively. Furthermore, the differences between the coefficients of *LnSerialVE* and those of other categories of employees are mostly significant at the 1% level. These results suggest that serial venture labor seems to be the most useful nonfinancial signal for start-up success among all types of high-talent labor that we consider here.

6.4 Who use the venture labor signal? Evidence from venture capital financing and new hires

So far, our results have shown that the presence of serial venture employees in private firms can be used as a signal for the firms' future success, even after controlling for observable firm quality using the matching procedure described in previous sections. But who are the potential users of this nonfinancial signal? We hypothesize that any entrepreneurial market participants with imperfect access to start-ups' accounting/financial information such as VC investors and job seekers could benefit from utilizing this signal. As noted before, the entrepreneurial community is closely connected due to the geographical and industry concentrations of both start-ups and private financiers (e.g., venture capital firms). Entrepreneurial market participants such as investors and workers should be able to easily gather the job-hopping (or job history) information about other workers without access to proprietary datasets such as the census data. We perform two tests in this section. First, we examine whether private firms with more serial venture employees are more likely to obtain VC funding. Then we exploit the uniqueness of the LEHD data, which allows us to observe the labor *inflows* of private firms and examine whether the presence of serial venture employees helps private firms attract job seekers on the entrepreneurial labor market.

To examine whether VC investors utilize the signal of serial venture employees, we run a regression similar to those specified in Equation (1), except that we replace the dependent variable with *VC*, a dummy variable that equals one if a firm obtains VC financing for the first time (i.e., becomes VC backed) within the next three years, and zero otherwise.[41] As shown in Column (1) of Table 7, the presence of serial venture employees is positively associated with the firm's likelihood of obtaining first-time VC financing, suggesting that even sophisticated investors like venture capitalists can utilize the signal of serial venture labor when selecting start-ups to invest in.

To examine the behavior of job seekers on the entrepreneurial labor market, we first identify a firm's new hires following the methodology developed by the Census Bureau's Job-to-Job Flow (J2J) program. Specifically, we define a worker *j* to be a new hire by firm *i* in quarter *t* if the worker is employed by the firm in quarter *t* but not in quarter *t-1*. We further separate the new hires into two categories: job-to-job hires and hires from nonemployment. A new hire is defined as a job-to-job hire by firm *i* in quarter *t* if the worker works for another firm in quarter *t* or *t-1*. A new hire is defined as a hire from nonemployment by firm *i* in quarter *t* if the worker does not have any jobs in quarter *t* or *t-1*.[42] At the firm-level, we calculate *LnHire*, *LnJ2JHire*, and *LnNEHire*, defined as the natural logarithm of one plus the total number of new hires, job-to-job hires, and hires from nonemployment, respectively, of a firm from year *t+1* to *t+3*.[43]

We then run a set of regressions similar to those specified in Equation (1), except that we now use one of the three new hire measures as the dependent variables. Columns (2) to (4) of Table 7 present the results. Column (2) shows a significantly positive association between the presence

[41] We conduct this test using a subsample of private firms not backed by VC in year *t*.
[42] See https://lehd.ces.census.gov/doc/j2j_101.pdf for more details about the definition of new hires.
[43] Note that the new hire variable used in this section is different from the size growth variable used in the previous sections. While size growth (change in total employment) captures both a firm's labor inflow and outflow, new hire focuses only on the labor inflow.

of serial venture employees and the total number of new employees hired by a firm (*LnHire*) in the next three years, suggesting that serial venture labor increases a private firm's attractiveness on the entrepreneurial labor market. However, although we have tried our best to control for observable characteristics of the private firms in this regression, one might argue that this result could simply reflect the stronger unobservable fundamentals of firms with serial venture labor and thus their greater labor *demand* for new hires.

To illustrate the role of labor *supply* decisions of job seekers in this setting, we further differentiate between the types of new hires based on their previous employment status. Columns (3) and (4) show that firms with greater serial venture labor are more able to attract and hire both new employees already having stable jobs (i.e., job-to-job hires) and those currently non-employed, but much more so with the former group (with a substantially larger coefficient on *LnSerialVE*). Given that on-the-job workers are likely to have a stronger need for job-related signals as they have a higher opportunity cost of taking new job offers than unemployed workers and thus consider more factors before joining a private firm (see, e.g., Blau and Robins (1990) and Faberman et al. (2022)), this finding illustrates the value of the nonfinancial signal of serial venture employees to job seekers on the labor market.

We further explore whether the signal is more useful to VC investors and job seekers when a start-up is subject to a poorer information environment and lower financial reporting quality, e.g., when the firm is a younger start-up (see, e.g., Hope, Thomas, and Vyas (2013)) or operates in an R&D-intensive industry that highly values confidentiality (see, e.g., Lobo, Xie, and Zhang (2018), Fu et al. (2020), and Simpson and Tamayo (2020)). First, we interact *LnSerialVE* with *LnFirmAge* in the regressions and present the results in Panel A of Table 8. As can be seen, the interaction term is significantly negative in all four regressions, indicating that the signal of serial venture labor is more useful for younger firms. We then interact *LnSerialVE* with *RDind*, the average R&D intensity (R&D expenses scaled by total assets) of the public firms in a private firm's three-digit

NAICS industry, and present the results in Panel B of Table 8.[44] The significantly positive coefficients of the interaction term indicate that the signal of serial venture labor is more useful for firms in industries that attach greater value to confidentiality and business secrets. Taken together, these findings suggest that the signal of venture labor is indeed more useful when there are fewer alternative information sources about the private start-ups.

6.5 Alternative explanation based on the nurturing role of serial venture employees

One might argue that the predictive power of serial venture employees for start-up success could also be explained by a "nurturing" role by these employees. That is, similar to venture capitalists who facilitate the start-ups' growth with funding and monitoring/advising, serial venture employees could also play a nurturing role by diffusing the entrepreneurial culture, institutional wisdom, and technological know-how from their past employers to the new start-ups. This alternative channel, though not mutually exclusive with the screening/matching channel, could affect the interpretation of our baseline results. To examine whether venture labor's nurturing role is a predominant channel through which the presence of serial venture employees predicts start-up success, we explore the heterogeneous predictive power of venture employees based on the time they spent with their new employers. Since it takes time for new hires to exert ample influence on their employer's operations/performance, if the nurturing channel is important, we would expect the predictive power to be stronger for those serial venture employees who have worked for the start-ups for a longer time (i.e., joined the start-ups long time ago rather than only recently).

To explore this heterogeneity, we run a set of regressions similar to those specified by Equation (1), except that we replace the key independent variable (*LnSerialVE*) with *LnSerialVEJoinedRecently* and *LnSerialVEJoinedLongAgo*. *LnSerialVEJoinedRecently*

[44] The coefficients on *RDind* itself in these regressions are absorbed by the matched-pair fixed effects since *RDind* is an industry-level variable.

(*LnSerialVEJoinedLongAgo*) is the natural logarithm of one plus the number of serial venture employees who joined their new employers within (prior to) the past one year.[45]

As shown in Table 9, the coefficients on *LnSerialVEJoinedRecently* are significantly larger than those on *LnSerialVEJoinedLongAgo* in both columns, with the F-tests for the difference being significant at the 1% or 5% level. These results suggest that the nurturing channel might not be the main underlying force that drives the predictive power of serial venture employees in our sample. While we acknowledge that this evidence alone cannot fully rule out the nurturing role played by serial venture employees in practice, the possibility of this alternative channel does not materially undermine this paper's main objective, which is to identify a useful nonfinancial performance signal for entrepreneurial market participants in the presence of limited information accessibility.

7. Conclusion

This paper studies an emerging phenomenon that talented employees leave successfully exited (via IPOs or sell-outs) entrepreneurial firms to join less mature start-ups. Using unique employee-level and private firm data, we find that such serial venture employees seem to be the most innovative and adventurous among all types of employees in the newly exited firms. The presence of such employees also positively predicts their new employers' future success in terms of exit likelihoods, size growth, and innovation productivity.

The positive association between venture labor and start-up success is weaker in states with lower labor mobility. In addition, serial venture employees whose previous jobs are in the same state or the same industry as the newly joined start-ups have stronger predictive power for these firms' future success. These results suggest that the matching (mutual screening) between the two is an important channel through which serial venture employees predict start-up success. Meanwhile, the positive predictive power is not stronger when serial venture employees work for the start-ups for a longer time, suggesting that their potential nurturing role is unlikely a main

[45] Our results are similar if we use two or three years as the cutoff.

channel for the signal to work. We also run a horse race among different types of high-talent labor and find that serial venture employees have the strongest predictive power for start-up success, indicating the importance of their unique job history (in addition to their talent) in explaining the value implication of their labor flow. Further, we demonstrate the usefulness of this nonfinancial signal to VC investors and job seekers on the entrepreneurial market, especially when there are limited alternative sources of information about the start-ups.

Overall, our study identifies a useful nonfinancial signal of private firms' quality, namely, the presence of serial venture employees, which can facilitate the decision-making of other entrepreneurial market participants such as managers, investors, and stakeholders. The private information revealed through these employees' job-hopping actions can enhance the welfare of the venture ecosystem.

We are not claiming that serial venture labor is the only or the most important nonfinancial predictor for start-up success. In fact, this predictor might be correlated with and complementary to other important attributes of entrepreneurial firms that also have value implications. What we document in the paper only illustrates the usefulness of this nonfinancial signal to some investors/stakeholders who have imperfect access to other performance predictors, especially those based on firms' financials or operations. Compared to such information, which is often confidential/proprietary, the information about the labor flow on the entrepreneurial market can be more easily obtained through workplace conversations, social contacts, or publicly available worker resume data such as LinkedIn or Burning Glass Technologies, making serial venture labor a viable nonfinancial signal for many entrepreneurial market participants.

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Appendix A: Variable Definition

Employee-level Variables:

Variable	Definition
SerialVE	A dummy variable that equals one if an employee of an IPO or acquired private firm moves to another private firm in the year after her original employer's exit date, and zero otherwise.
LeaverToPub	A dummy variable that equals one if an employee of an IPO or acquired private firm moves to another public firm in the year after her original employer's exit date, and zero otherwise.
Stayer	A dummy variable that equals one if an employee of an IPO or acquired private firm still works for her original employer in the year after the exit date, and zero otherwise.
NewHire	A dummy variable that equals one if an employee is hired by an IPO firm in the year after the IPO date or by a merged firm in the year after the merger completion date, and zero otherwise.
Patents	The average number of patents filed per year by an inventor from an exited firm in the five years before the exit date.
CitePat	The average number of citations received per patent by an inventor from an exited firm in the five years before the exit date.
Originality	The average originality of patents filed by an inventor from an exited firm in the five years before the exit date. Each patent's originality is calculated as the number of unique technological classes cited by the patent, following Hirshleifer, Hsu, and Li (2018).
Exploratory	The average number of exploratory patents filed per year by an inventor from an exited firm in the five years before the exit date. Following Gao, Hsu, and Li (2018), Brav et al. (2018), and Lin, Liu, and Manso (2021), a patent is defined as an exploratory patent if 80% or more of its citations are not cited by the assignee's existing patents or the citations made by those patents.

Firm-level Variables:

Variable	Definition
Exit	A dummy variable that equals one if a private firm exits through going public or getting acquired in year t+1 to t+3 , and zero if the firm remains private in these three years.
SizeGrowth	The percentage change in a firm's total employment from year t+1 to t+3.
VC	A dummy variable that equals one if a firm obtains VC investment in year t+1 to t+3, and zero otherwise.
LnSerialVE	The natural logarithm of the number of serial venture employees in a firm in the last quarter of a given year.
PctSerialVE	The fraction of serial venture employees in a firm's workforce in the last quarter of a given year.
LnEmp	The natural logarithm of the total number of employees in a firm.

LnFirmAge	The natural logarithm of a firm's age in year t, measured as one plus the difference between t and the year when the firm's first establishment was founded.
LnEarn	The natural logarithm of employees' average quarterly earnings.
LnAvgAge	The natural logarithm of employees' average age (in terms of years).
LnAvgEdu	The natural logarithm of employees' education level (in terms of years).
Gender	The fraction of male employees in a firm.
Ethnicity	The fraction of white employees in a firm.
LnSerialVEJoinedRecently	The natural logarithm of the number of serial venture employees who joined their new employers within the past one year.
LnSerialVEJoinedLongAgo	The natural logarithm of the number of serial venture employees who joined their new employers prior to the past one year.
NEI	The Noncompetition Enforceability Index of the state where a firm operates.
LnSerialVEInState	The natural logarithm of the number of serial venture employees whose previous employer (the exited firm) operates in the same state as their new employer (the private start-up).
LnSerialVEOutState	The natural logarithm of the number of serial venture employees whose previous employer operates in a different state from their new employer.
LnSerialVESameInd	The natural logarithm of the number of serial venture employees whose previous employer operates in the same three-digit NAICS industry as their new employer.
LnSerialVEDiffInd	The natural logarithm of the number of serial venture employees whose previous employer operates in a different three-digit NAICS industry from their new employer.
LnEmpHighEarn	The natural logarithm of one plus the number of employees in a firm whose earnings at their previous employers for their second last quarter with these firms are among the top deciles.
LnEmpVC	The natural logarithm of one plus the number of employees with prior working experience at VC-backed firms.
LnEmpPublic	The natural logarithm of one plus the number of employees with prior working experience at public firms.
LnHire	The natural logarithm of the total number of new hires by a firm in year t+1 to t+3. New hires are identified following the methodology developed by the Census Bureau's Job-to-Job Flow (J2J) program.
LnJ2JHire	The natural logarithm of the total number of job-to-job hires by a firm in year t+1 to t+3. Job-to-job hires are identified following the methodology developed by the Census Bureau's Job-to-Job Flow (J2J) program.
LnNEHire	The natural logarithm of the total number of hires from nonemployment by a firm in year t+1 to t+3. Hires from nonemployment are identified following the methodology developed by the Census Bureau's Job-to-Job Flow (J2J) program.
RDind	The average R&D intensity (R&D expenses scaled by total assets) of the public firms in a private firm's three-digit NAICS industry.

Table 1: Summary Statistics

This table reports the summary statistics of variables for the LEHD sample. Panel A reports the fraction of various employee categories for exited (i.e., IPO or acquired) firms. *SerialVE*, *LeaverToPub*, and *Stayer* refer to an exited firm's employees who move to private firms, those who move to other public firms, and those who stay, respectively. The sample includes about 931,000 employees from IPO firms and acquired private firms. Panel B reports the summary statistics at the firm-level for firms with serial venture employees and their matched private firms with no serial venture employees. The statistics are rounded following the disclosure requirement by the U.S. Census Bureau. The definitions of all variables are presented in Appendix A.

Panel A: Fraction of Employees for Exited Firms

Employee Category	Fraction (%)
SerialVE	11.1
LeaverToPub	4.8
Stayer	84.1

Panel B: Summary Statistics at the Firm Level

Variables	Mean	Std	N
Exit	0.004	0.060	582,000
SizeGrowth	-0.087	0.570	582,000
LnSerialVE	0.135	0.290	582,000
PctSerialVE	0.013	0.048	582,000
LnEmp	3.902	1.676	582,000
LnFirmAge	2.562	0.854	582,000
LnAvgEarn	9.156	0.546	582,000
LnAvgAge	3.719	0.148	582,000
LnAvgEdu	2.670	0.072	582,000
Gender	0.535	0.293	582,000
Ethnicity	0.704	0.285	582,000

Table 2: Innovation Quality of Serial Venture Employees and Other Inventors

This table reports and compares the innovation quality of serial venture employees, leavers to public firms, stayers, and new hires. *Patents* is the average number of patents filed per year by an inventor. *CitePat* is the average number of citations received per patent. *Originality* is the average number of unique technological classes cited per patent. *Exploratory* is the average number of exploratory patents filed per year. All variables are calculated over the five-year window before the exit event (IPO or acquisition). In addition, we report the differences among inventor categories along with the associated t-statistics. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	SerialVE	*LeaverToPub*	*Stayer*	*NewHire*	*Difference (t-statistics)*		
	(1)	(2)	(3)	(4)	(1)-(2)	(1)-(3)	(1)-(4)
Patents	1.678	1.287	0.829	0.085	0.391***	0.849***	1.593***
					(5.278)	(17.328)	(33.468)
CitePat	27.300	26.545	22.197	3.309	0.755	5.102***	23.991***
					(0.402)	(4.391)	(21.929)
Originality	9.010	8.241	8.141	1.065	0.769**	0.869***	7.945***
					(1.990)	(3.380)	(32.830)
Exploratory	0.664	0.587	0.361	0.046	0.077**	0.303***	0.618***
					(2.572)	(15.955)	(33.579)

Table 3: Serial Venture Employees and Private Firms' Future Success

This table presents the regressions of private firms' future success on the presence of serial venture employees. For each private firm with at least one serial venture employee in the last quarter of year *t*, we find all the private firms with no serial venture employees in the same quarter and are in the same three-digit NAICS industry, state, size group, and age group as the firm with serial venture employees (i.e., the focal firm). We further require the matched firms to have the same VC-backing status and multi-unit status as the focal firm. Finally, for each focal firm *i*, we retain five eligible matched firms that are the closest to firm *i* in terms of size. $Exit_{(t+1,t+3)}$ is a dummy variable that equals one if a private firm exits through IPO or sell-out between year *t+1* and year *t+3*, and zero otherwise. $SizeGrowth_{(t+1,t+3)}$ is the percentage change in a firm's total employment from year *t+1* to year *t+3*. $LnSerialVE_t$ is the natural logarithm of one plus the number of serial venture employees in a firm in the last quarter of year *t*. $PctSerialVE_t$ is the fraction of serial venture employees in a firm's workforce in the last quarter of year *t*. All other variables are defined in Appendix A. Each regression includes a separate intercept. We include matched-group fixed effects in all regressions. T-statistics based on standard errors clustered by matched group are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Number of Serial Venture Employees and Start-up Success

Dep. Var.	$Exit_{(t+1,t+3)}$	$SizeGrowth_{(t+1,t+3)}$
	(1)	(2)
$LnSerialVE_t$	0.224***	0.075***
	(6.628)	(28.450)
$LnEmp_t$	0.161	0.039***
	(1.526)	(4.309)
$LnFirmAge_t$	-0.053	-0.003
	(-1.287)	(-0.670)
$LnAvgEarn_t$	0.265***	0.105***
	(14.040)	(48.000)
$LnAvgAge_t$	-0.284***	-0.201***
	(-6.097)	(-27.900)
$LnAvgEdu_t$	0.367***	-0.118***
	(4.021)	(-7.537)
$Gender_t$	-0.005	-0.017***
	(-0.169)	(-3.920)
$Ethnicity_t$	-0.006	-0.019***
	(-0.198)	(-4.931)
Matched-Group Fixed Effects	Yes	Yes
Observations	582,000	582,000
R-squared	0.276	0.260

Panel B: Fraction of Serial Venture Employees and Start-up Success

Dep. Var.	$Exit_{(t+1,t+3)}$	$SizeGrowth_{(t+1,t+3)}$
	(1)	(2)
$PctSerialVE_t$	0.178*	0.147***
	(1.867)	(7.362)
$LnEmp_t$	0.211**	0.056***
	(1.998)	(6.208)
$LnFirmAge_t$	-0.052	-0.003
	(-1.265)	(-0.570)
$LnAvgEarn_t$	0.280***	0.109***
	(14.700)	(49.980)
$LnAvgAge_t$	-0.306***	-0.207***
	(-6.520)	(-28.620)
$LnAvgEdu_t$	0.386***	-0.113***
	(4.214)	(-7.236)
$Gender_t$	-0.004	-0.016***
	(-0.129)	(-3.824)
$Ethnicity_t$	-0.011	-0.021***
	(-0.370)	(-5.370)
Matched-Group Fixed Effects	Yes	Yes
Observations	582,000	582,000
R-squared	0.276	0.259

Table 4: Differential Predictive Power of Serial Venture Employees by State-level Noncompetition Enforcement Index

This table presents the regressions of private firms' future success on the interaction between the presence of serial venture employees and the Noncompetition Enforcement Index of the state where a private firm operates. $LnSerialVE_t$ is the natural logarithm of one plus the number of serial venture employees in a firm in the last quarter of year *t*. NEI_t is the Noncompetition Enforcement Index of the state where a firm operates in year *t*. Control variables similar to those in Table 3 are included but not reported. Each regression includes a separate intercept. We include matched-group fixed effects in all regressions. T-statistics based on standard errors clustered by matched group are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	$Exit_{(t+1,t+3)}$	$SizeGrowth_{(t+1,t+3)}$
	(1)	(2)
$LnSerialVE_t \times NEI_t$	-0.094***	-0.003**
	(-5.179)	(-2.458)
$LnSerialVE_t$	0.538***	0.089***
	(6.529)	(17.31)
Controls	Yes	Yes
Matched-Group Fixed Effects	Yes	Yes
Observations	582,000	582,000
R-squared	0.276	0.260

Table 5: Differential Predictive Power of Venture Labor Based on Their Geographic Location and Industry Background

This table presents the analysis on the heterogeneous predictive power of venture labor based on their geographic location and industry background. Panel A presents the regressions using serial venture employees who live closer to or further away from their new employers. $LnSerialVEInState_t$ ($LnSerialVEOutState_t$) is the natural logarithm of one plus the number of serial venture employees in a firm *i* in the last quarter of year *t* whose original employer and new employer operate in the same state (different states). Panel B presents the regressions using serial venture employees who have or do not have experience in their new employers' industries. $LnSerialVESameInd_t$ ($LnSerialVEDiffInd_t$) is the natural logarithm of one plus the number of serial venture employees in a firm *i* in the last quarter of year *t* whose original employer and new employer operate in the same three-digit NAICS industry (different three-digit NAICS industries). We report the F-statistics and the associated P-values for the difference between the coefficients of the two types of serial venture employees in each regression. All other variables are defined in Appendix A. Each regression includes a separate intercept. We include matched-group fixed effects in all regressions. Standard errors are clustered by matched groups. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: In-state/Out-of-state Serial Venture Employees and Start-ups' Future Success

Dep. Var.	$Exit_{(t+1,t+3)}$	$EmpGrowth_{(t+1,t+3)}$
	(1)	(2)
$LnSerialVEInState_t$	0.437***	0.080***
	(6.368)	(16.780)
$LnSerialVEOutState_t$	0.077**	0.072***
	(2.250)	(22.530)
F-statistics	22.400	1.892
P-value	<0.001	0.169
Matched-Group Fixed Effects	Yes	Yes
Observations	582,000	582,000
R-squared	0.276	0.260

Panel B: Same-industry/Different-industry Serial Venture Employees and Start-ups' Future Success

Dep. Var.	$Exit_{(t+1,t+3)}$	$EmpGrowth_{(t+1,t+3)}$
	(1)	(2)
$LnSerialVESameInd_t$	0.383***	0.091***
	(3.579)	(13.030)
$LnSerialVEDiffInd_t$	0.185***	0.072***
	(5.373)	(24.670)
F-statistics	3.139	6.178
P-value	0.076	0.013
Matched-Group Fixed Effects	Yes	Yes
Observations	582,000	582,000
R-squared	0.276	0.260

Table 6: Horse Race between Serial Venture Employees and Other Types of High-Talent Labor

This table presents the regressions of private firms' future success on the presence of serial venture employees and other types of high-talent employees. $LnSerialVE_t$ is the natural logarithm of one plus the number of serial venture employees in a firm in the last quarter of year t. $LnEmpHighEarn_t$ is the natural logarithm of one plus the number of employees with high salary at their previous employers. $LnEmpVC_t$ ($LnEmpPublic_t$) is the natural logarithm of one plus the number of employees who have prior working experience at VC-backed firms (public firms). We report the F-statistics and the associated P-values for the difference between the coefficients of *LnSerialVE* and that of each type of other high-talent employees. Detailed definitions of the variables are provided in Appendix A. Control variables similar to those in Table 3 are included but not reported. Each regression includes a separate intercept. We include matched-group fixed effects in all regressions. T-statistics based on standard errors clustered by matched group are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	$Exit_{(t+1,t+3)}$	$SizeGrowth_{(t+1,t+3)}$
	(1)	(2)
$LnSerialVE_t$	0.172***	0.058***
	(4.988)	(11.15)
$LnEmpHighEarn_t$	0.021***	0.022***
	(6.897)	(27.83)
$LnEmpVC_t$	0.015**	0.037***
	(2.510)	(15.08)
$LnEmpPublic_t$	0.041***	0.062***
	(7.056)	(21.34)
F-statistics (*LnSerialVE* - *LnEmpHighEarn*)	19.090	50.380
P-value (*LnSerialVE* - *LnEmpHighEarn*)	<0.001	<0.001
F-statistics (*LnSerialVE* - *LnEmpVC*)	18.750	13.540
P-value (*LnSerialVE* - *LnEmpVC*)	<0.001	<0.001
F-statistics (*LnSerialVE* - *LnEmpPublic*)	14.020	0.420
P-value (*LnSerialVE* - *LnEmpPublic*)	<0.001	0.518
Controls	Yes	Yes
Matched-Group Fixed Effects	Yes	Yes
Observations	582,000	582,000
R-squared	0.276	0.260

Table 7: Use of the Venture Labor Signal by Investors and Stakeholders

This table presents the tests on the use of venture labor signal by entrepreneurial market participants, namely, VC investors and job seekers. $VC_{(t+1,t+3)}$ is a dummy variable that equals one if a non-VC-backed firm gets VC financing between year $t+1$ and year $t+3$, and zero otherwise. $LnHire_{(t+1,t+3)}$ is the natural logarithm of the number of new employees hired by firm i between year $t+1$ and year $t+3$. $LnJ2JHire_{(t+1,t+3)}$ is the natural logarithm of the number of new employees hired from other firms by firm i between year $t+1$ and year $t+3$. $LnNEHire_{(t+1,t+3)}$ is the natural logarithm of the number of employees hired from nonemployment by firm i between year $t+1$ and year $t+3$. All other variables are defined in Appendix A. Column (1) uses the sample of firms not backed by VC in year t, while Columns (2) to (4) use the full sample. Control variables similar to those in Table 3 are included but not reported. Each regression includes a separate intercept. We include matched-group fixed effects in all regressions. T-statistics based on standard errors clustered by matched group are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	$VC_{(t+1,t+3)}$	$LnHire_{(t+1,t+3)}$	$LnJ2JHire_{(t+1,t+3)}$	$LnNEHire_{(t+1,t+3)}$
Sample	Non-VC-backed		Full	
	(1)	(2)	(3)	(4)
$LnSerialVE_t$	0.242***	0.165***	0.207***	0.089***
	(8.417)	(21.200)	(30.410)	(12.850)
Controls	Yes	Yes	Yes	Yes
Matched-Group Fixed Effects	Yes	Yes	Yes	Yes
Observations	573,000	582,000	582,000	582,000
R-squared	0.222	0.510	0.536	0.520

Table 8: Use of the Venture Labor Signal by Investors and Stakeholders: Cross-sectional Analyses Based on Information Availability

This table presents the cross-sectional analyses on the use of venture labor signal based on start-ups' information availability. $VC_{(t+1,t+3)}$ is a dummy variable that equals one if a non-VC-backed firm gets VC financing between year $t+1$ and year $t+3$, and zero otherwise. $LnHire_{(t+1,t+3)}$ is the natural logarithm of the number of new employees hired by firm i between year $t+1$ and year $t+3$. $LnJ2JHire_{(t+1,t+3)}$ is the natural logarithm of the number of new employees hired from other firms by firm i between year $t+1$ and year $t+3$. $LnNEHire_{(t+1,t+3)}$ is the natural logarithm of the number of employees hired from nonemployment by firm i between year $t+1$ and year $t+3$. Panel A presents cross-sectional tests based on $LnFirmAge_t$, the natural logarithm of a firm's age. Panel B presents cross-sectional tests based on $RDind_t$, the average R&D expenses scaled by total assets of the public firms in a private firm's three-digit NAICS industry. All other variables are defined in Appendix A. In both panels, Column (1) uses the sample of firms not backed by VC in year t, while Columns (2) to (4) use the full sample. Control variables similar to those in Table 3 are included but not reported. Each regression includes a separate intercept. We include matched-group fixed effects in all regressions. T-statistics based on standard errors clustered by matched group are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cross-sectional Analysis Based on Firm Age

Dep. Var.	$VC_{(t+1,t+3)}$	$LnHire_{(t+1,t+3)}$	$LnJ2JHire_{(t+1,t+3)}$	$LnNEHire_{(t+1,t+3)}$
Sample	Non-VC-backed	Full		
	(1)	(2)	(3)	(4)
$LnSerialVE_t \times LnFirmAge_t$	-0.254***	-0.110***	-0.111***	-0.075***
	(-6.006)	(-12.540)	(-14.290)	(-9.660)
$LnSerialVE_t$	0.906***	0.450***	0.494***	0.283***
	(7.331)	(20.810)	(25.490)	(14.830)
$LnFirmAge_t$	-0.061*	-0.051***	-0.056***	-0.026***
	(-1.743)	(-6.047)	(-7.585)	(-3.602)
Controls	Yes	Yes	Yes	Yes
Matched-Group Fixed Effects	Yes	Yes	Yes	Yes
Observations	573,000	582,000	582,000	582,000
R-squared	0.222	0.510	0.536	0.520

Panel B: Cross-sectional Analysis Based on Industry-level R&D Expenses

Dep. Var.	$VC_{(t+1,t+3)}$	$LnHire_{(t+1,t+3)}$	$LnJ2JHire_{(t+1,t+3)}$	$LnNEHire_{(t+1,t+3)}$
Sample	Non-VC-backed	Full		
	(1)	(2)	(3)	(4)
$LnSerialVE_t \times RDind_t$	2.315***	0.327***	0.337***	0.193**
	(3.849)	(2.946)	(3.424)	(1.991)
$LnSerialVE_t$	0.161***	0.153***	0.195***	0.082***
	(5.502)	(16.710)	(24.390)	(10.070)
Controls	Yes	Yes	Yes	Yes
Matched-Group Fixed Effects	Yes	Yes	Yes	Yes
Observations	573,000	582,000	582,000	582,000
R-squared	0.222	0.510	0.536	0.520

Table 9: Differential Predictive Power of Serial Venture Employees by Time Spent with Their New Employers

This table presents the regressions of private firms' future success on the presence of serial venture employees who joined the start-ups recently (within one year) or long time ago (more than one year ago). $LnSerialVEJoinedRecently_t$ ($LnSerialVEJoinedLongAgo_t$) is the natural logarithm of one plus the number of serial venture employees in a firm in the last quarter of year t if these employees joined the firm within (prior to the beginning of) year t. We report the F-statistics and the associated P-values for the difference between the coefficients of the two types of serial venture employees in each regression. All other variables are defined in Appendix A. Each regression includes a separate intercept. We include matched-group fixed effects in all regressions. T-statistics based on standard errors clustered by matched group are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	$Exit_{(t+1,t+3)}$	$SizeGrowth_{(t+1,t+3)}$
	(1)	(2)
$LnSerialVEJoinedRecently_t$	0.382***	0.136***
	(4.922)	(21.410)
$LnSerialVEJoinedLongAgo_t$	0.166***	0.053***
	(4.558)	(18.600)
$LnEmp_t$	0.162	0.040***
	(1.535)	(4.350)
$LnFirmAge_t$	-0.047	-0.001
	(-1.151)	(-0.188)
$LnAvgEarn_t$	0.265***	0.105***
	(14.040)	(47.990)
$LnAvgAge_t$	-0.278***	-0.199***
	(-5.979)	(-27.570)
$LnAvgEdu_t$	0.369***	-0.117***
	(4.039)	(-7.501)
$Gender_t$	-0.004	-0.016***
	(-0.142)	(-3.851)
$Ethnicity_t$	-0.007	-0.020***
	(-0.245)	(-5.071)
F-statistics	6.407	136.200
P-value	0.011	<0.001
Matched-Group Fixed Effects	Yes	Yes
Observations	582,000	582,000
R-squared	0.276	0.260

Internet Appendix For

Venture Labor: A Nonfinancial Signal for Start-up Success

January 2024

A1. Innovation quality of the firms joined by serial venture employees

In this section, we consider the implication of serial venture employees for another important performance metric for private entrepreneurial firms, namely, their innovation productivity. We use the inventor data for this analysis.

To mitigate selection concerns, we again adopt a matching approach by constructing a matched sample of firms with similar innovation productivity but without an influx of serial venture employees. Specifically, for each treatment firm *i* (i.e., each private firm *i* with at least one serial venture employee joining the firm on date *t*), we find all the private firms who share the same major patent class with firm *i* (i.e., the technology class in which a firm files the largest number of patents) and whose total number of patents filed in the five-year period before year *t* is between 0.8 and 1.2 times of that of firm *i*. For each treatment firm *i* and its matched firms, we calculate the average number of patents filed per year (*FirmPatentsPostJoin*), the average number of citations received per patent (*FirmCitePatPostJoin*), the patents' average originality score (*FirmOriginalityPostJoin*), and the average number of exploratory patents filed per year (*FirmExploratoryPostJoin*) in the five-year period after *t*.[46] Then, for each treatment firm *i*, we calculate the differences between its four innovation activity measures and the median values of these measures of its matched firms.

Panel A of Table A1 reports the average of the above differences after the serial venture employees join the firm. As can be seen, treatment firms file 4.21 more patents annually than matched firms that did not have serial venture employees. The patents filed by treatment firms also have higher quality, as their average number of citations per patent is 6.51 higher than that of the

[46] We examine the innovation output in the five-year period after the joining of serial venture employees as innovation is a long-term investment of which the outcome might not be observable in the short term.

matched firms. In addition, patents filed by treatment firms are more original and more exploratory compared to matched firms. All these differences are significant at the 1% level.

We further explore whether serial venture employees can predict the innovation productivity of the *existing* inventors in their new employers (i.e., their new colleagues). To explore this possibility, we compare the innovation productivity of serial venture employees' new colleagues in the treatment firms and ex-ante similar inventors in the matched firms. Specifically, for each existing inventor j who works for treatment firm i (with at least one serial venture employee joining the firm on date t), we find all the inventors who work for firm i's matched firms on date t, and whose average annual number of patents filed in the five-year period before t differs no more than one from that of inventor j. We then compare the innovation productivity of inventor j and the median of her matched inventors in the five-year period after t.

Panel B of Table A1 shows that in the five years after serial venture employees join a firm, their new colleagues produce more patents and patents with higher quality and originality than matched/similar inventors at other firms.

A2. Venture Labor and Their Original Employers' Post-IPO performance

In this section, we investigate the association between the departure of serial venture employees and their original employers' post-IPO performance.[47] Using the LEHD sample, we estimate the following OLS regression:

$$\begin{aligned} PostIPOPerformance_i &= \alpha + \beta_1 PctSVELeft_i + \beta_2 PctLeaverToPub_i + \\ &\beta_3 PctNewHire_i + \beta_4 LnProceeds_i + \beta_5 IR_i + \beta_6 VC_i + \beta_7 TobinQ_i + \beta_8 LnMV_i + \\ &\beta_9 RDadj_i + \beta_{10} IndVCPct_i + \beta_{11} LnIndIPOVol_i + \beta_{12} IndRFOption_i + \beta_{13} LnEmp_i + \\ &\beta_{14} LnFirmAge_i + \beta_{15} LnAvgTenure_i + \beta_{16} LnAvgAge_i + \beta_{17} LnAvgEdu_i + \\ &\beta_{18} LnAvgEarn_i + Industry + Year + \varepsilon_i, \end{aligned} \tag{A1}$$

where $PostIPOperformance_i$ is either firm *i*'s buy-and-hold abnormal return (*BHAR*) or its average *ROA* in the one-, three-, or five-year windows after its IPO. *PctSVELeft* is the fraction of a firm's pre-exit employees who move to private firms within one year after the IPO (i.e., the serial venture employees). *PctLeaverToPub* is the fraction of a firm's pre-exit employees who move to public firms within one year after the IPO. All other variables are as defined in Appendix A. $LnProceeds$ and *IR* are measured at the time of the IPO; other firm-level characteristics are measured at the end of the first year post-IPO; and employee characteristics are measured at quarter *t-1*. We include industry fixed effects (at the three-digit NAICS level) and year fixed effects in the model. Standard errors are clustered at the industry level.

Panel A of Table A2 reports the results. Columns (1)-(3) use one-, three-, and five-year post-IPO *BHAR* as the dependent variables, respectively. Columns (4)-(6) use one-, three-, and five-year post-IPO average annual *ROA* as the dependent variables, respectively. We redact the regression coefficients of control variables in Columns (4)-(6) due to the disclosure restriction of

[47] We only study IPOs rather than acquired private firms in this section for two reasons. First, after sell-outs, the exited firms will be integrated into the acquirers, which are typically much larger. Thus, their combined performance after the acquisition will be largely determined by the acquirers rather than the acquired start-ups that lose entrepreneurial diffusers. Second, the IPO sample allows us to control for various firm characteristics that might be correlated with post-exiting performance, whereas there are no readily available financial data on the characteristics of acquired private firms.

the U.S. Census Bureau. The results show that both post-exit *BHAR* and *ROA* are negatively associated with the fraction of entrepreneurial diffusers that leave an IPO firm. Moreover, the economic magnitude of this impact increases over time, especially for abnormal returns. For example, a one standard deviation increase in the fraction of serial venture employees (i.e., 0.046) is associated with a 0.11 (=0.046×6.126/2.679) standard deviation decrease in the five-year post-IPO *BHAR* but only a 0.06 (=0.046×1.114/0.813) standard deviation decrease in the one-year post-IPO *BHAR*. Meanwhile, the fraction of leavers to public firms is not significantly associated with post-IPO performance, except for the one-year *BHAR*, suggesting that the departure of leavers to public firms is not as costly to the newly exited firms as that of serial venture employees. Interestingly, the fraction of new hires is insignificantly related to post-IPO *BHAR* but has a significantly negative association with post-IPO *ROA*, which possibly reflects the higher labor expenses but no greater labor productivity following the post-IPO expansion.

We further estimate a similar model to Equation (A1) using the inventor sample to explore the impact of the departure of serial venture employees on firms' post-IPO performance. *PctSVELeft*, *PctLeaverToPub*, and *PctNewHire* are now calculated using inventors instead of the LEHD employees. We control for *LnInventor*, the natural logarithm of the number of inventors (instead of employees), and drop employee demographics from the control list as these variables cannot be calculated for the inventor sample.

Consistent with the results using the LEHD sample, Panel B of Table A2 shows that the fraction of serial venture inventors (i.e., those leaving for private firms) also has a significantly negative association with their original employers' post-IPO performance, especially over the long run. In terms of economic magnitudes, a one standard deviation increase in the fraction of serial venture inventors (i.e., 0.213) is associated with a 0.09 (=0.213×0.934/2.127) standard deviation decrease in the five-year post-IPO *BHAR* and a 0.11 (=0.213×0.169/0.332) standard deviation decrease in the five-year average annual *ROA*. Again, the fraction of inventors leaving to public firms is not significantly associated with post-IPO performance. However, the fraction of newly hired inventors now positively predicts post-IPO *ROA*.

Taken together, the results in this section suggest that the departure of serial venture employees is costly to their original employers, which justifies why firms adopt various approaches to manage their employee retention risk (Labro and Omartian (2023)). In addition, the loss of talented employees with entrepreneurial experience and spirit might be one underexplored explanation for the well-known IPO long-run underperformance puzzle (e.g., Ritter (1991), Jain and Kini (1994), Teoh, Welch, and Wong (1998), and Chemmanur and Paeglis (2005)).

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Table A1: Future Innovation Productivity of Private Firms Joined by Serial Venture Employees

This table presents the analyses on the future innovation productivity of the firms (or their existing inventors) after the joining of serial venture employees. Panel A presents the average differences in post-joining innovation productivity between treatment firms (i.e., the firms that serial venture employees newly join) and matched firms. Specifically, for each treatment firm *i*, i.e., private firm *i* with at least one serial venture employee joining the firm on date *t*, we find all the private firms who share the same major patent class (i.e., the technology class in which a firm files the largest number of patents) with firm *i* and whose total number of patents filed in the five years before *t* is between 0.8 and 1.2 times of that of firm *i*. We then calculate these firms' average number of patents filed per year (*FirmPatentsPostJoin*), the average number of citations received per patent (*FirmCitePatPostJoin*), the patents' average originality score (*FirmOriginalityPostJoin*), and the average number of exploratory patents filed per year (*FirmExploratoryPostJoin*) in the five years after *t*. For each treatment firm *i*, we report the differences between its four innovation activity measures and the median values of these measures of its matched firms. Panel B reports the average differences in innovation productivity between serial venture employees' new colleagues (i.e., the existing inventors in the treatment firms who are not serial venture employees) and their matched inventors in the matched firms. Specifically, for each inventor *j* who works for treatment firm *i* (with at least one serial venture employee joining the firm on date *t*) and who is not a serial venture employee, we find all the inventors who work for firm *i*'s matched firms on date *t*, and whose average annual number of patents filed in the five-year period before *t* differs no more than one from that of inventor *j*. We then compare the innovation productivity (i.e., *PatentsPostJoin*, *CitePatPostJoin*, *OriginalityPostJoin*, and *ExploratoryPostJoin*) of inventor *j* and the median of her matched inventors in the five-year period after *t*. In addition, we report the t-statistics on whether the differences are significantly different from zero. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Difference in Future Innovation Productivity between Treatment Firms Joined by Serial Venture Employees and Matched Firms

Difference	Variable	N	Mean	t-statistics
Firms joined by serial venture employees - Matched firms	*FirmPatentsPostJoin*	1,430	4.208***	9.540
	FirmCitePatPostJoin	1,430	6.514***	20.496
	FirmOriginalityPostJoin	1,430	6.437***	29.544
	FirmExploratoryPostJoin	1,430	1.448***	7.344

Panel B: Difference in Future Innovation Productivity between Serial Venture Employees' New Colleagues (Peer Inventors) and Matched Inventors in Matched Firms

Difference	Variable	N	Mean	t-statistics
Peer inventors - Matched inventors	*PatentsPostJoin*	42,414	0.186***	67.202
	CitePatPostJoin	42,414	3.507***	73.233
	OriginalityPostJoin	42,414	2.277***	76.134
	ExploratoryPostJoin	42,414	0.028***	23.010

Table A2: Serial Venture Employees and Their Original Employers' Post-IPO Performance

This table presents the regressions on the association between the departure of serial venture employees and their original employers' post-IPO performance. Panel A reports the results in the LEHD sample. We redact the regression coefficients of control variables in Columns (4)-(6) due to the disclosure restriction by the U.S. Census Bureau. Panel B reports the results in the inventor sample. Columns (1)-(3) in both panels report the regressions using firms' buy-and-hold abnormal returns in the one, three, and five years after IPO (*AR1yr*, *AR3yr*, and *AR5yr*, respectively) as the measure of post-IPO performance. Columns (4)-(6) in both panels report the regressions using firms' average *ROA* in the one, three, and five years after IPO (*ROA1yr*, *ROA3yr*, and *ROA5yr*, respectively) as the measure of post-IPO performance. *PctSVELeft* (*PctLeaverToPub*) is the fraction of a firm's pre-exit employees who move to private (public) firms within one year after IPO. *PctNewHire* is the number of employees hired by an IPO firm in the year after the IPO date scaled by the number of employees working for the IPO firm in the quarter before the IPO date. *IR* is the percentage difference between the closing price on the IPO day and the offering price. *LnProceeds* is the natural logarithm of IPO proceeds (in terms of million dollars). *VC* is a dummy variable that equals one if a firm is backed by venture capital at the time of the IPO, and zero otherwise. *TobinQ* is the market value of equity (PRCC_F×CSHO) plus book value of assets (AT) minus book value of equity (CEQ) minus deferred taxes (TXDB) divided by the book value of assets (AT) at the first fiscal year end post the IPO. *LnMV* is the natural logarithm of the market value of equity (PRCC_F×CSHO) at the first fiscal year end post the IPO. *RDadj* is an IPO firm's R&D expenses (XRD) scaled by total assets (AT) in the first fiscal year post the IPO subtracting the mean R&D expenses scaled by total assets in the firm's three-digit NAICS industry over the same window. *IndVCPct* is the fraction of firms in an IPO firm's three-digit NAICS industry that are backed by venture capital. *LnIndIPOVol* is the natural logarithm of the total IPO volume in a firm's three-digit NAICS industry in its IPO year. *IndRFOption* is the number of shares in options granted to rank-and-file employees scaled by the total number of shares outstanding of a firm, averaged to the three-digit NAICS industry level. *LnAvgTenure* is the natural logarithm of average tenure (in terms of quarters) of a firm's employees. *LnAvgEarn* is the natural logarithm of quarterly earnings (in terms of 2007 dollars), of a firm's employees. *LnInventor* is the natural logarithm of the total number of inventors in a firm. Each regression includes a separate intercept. We include industry fixed effects (at the three-digit NAICS level) and year fixed effects in the regressions. Standard errors are clustered by three-digit NAICS industry. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Serial Venture Employees and Original Employers' Post-IPO Performance in the LEHD Sample

Dep. Var.	*AR1yr*	*AR3yr*	*AR5yr*	*ROA1yr*	*ROA3yr*	*ROA5yr*
	(1)	(2)	(3)	(4)	(5)	(6)
PctSVELeft	-1.114*	-4.343***	-6.126**	-0.885***	-1.068***	-0.951***
	(-1.942)	(-3.530)	(-2.301)	(-3.327)	(-5.094)	(-4.125)
PctLeaverToPub	-2.670***	-1.689	3.099	-0.171	-0.548	-0.405
	(-2.925)	(-1.241)	(0.996)	(-0.425)	(-1.357)	(-1.291)
PctNewHire	-0.002	0.027	-0.006	-0.024*	-0.027*	-0.037***
	(-0.052)	(0.185)	(-0.032)	(-1.690)	(-1.827)	(-3.100)
IR	-0.227***	-0.178***	0.123	+*	+	+**
	(-5.595)	(-2.726)	(0.445)			
LnProceeds	0.244	-0.755	0.196	+	+	+
	(0.959)	(-0.896)	(0.323)			
VC	0.078	0.173*	-0.148	-	-	-
	(1.112)	(1.723)	(-0.507)			
TobinQ	0.071***	0.025	0.014	+	+**	+*
	(9.373)	(0.930)	(0.703)			
LnMV	-0.182**	-0.013	-0.244	-	-	-
	(-2.624)	(-0.062)	(-1.398)			
RDadj	-0.055	-0.336	0.769	-***	-***	-***
	(-0.413)	(-1.322)	(0.721)			
IndVCPct	-13.360***	-23.930**	-65.860**	-***	-***	-***
	(-4.044)	(-2.019)	(-2.540)			
LnIndIPOVol	-0.026	-0.078	0.110	+	+	+
	(-0.624)	(-0.655)	(0.618)			
IndRFOption	7.515	13.860	-67.160	-	-	-
	(0.583)	(0.463)	(-0.794)			
LnEmp	0.130***	0.512***	0.736***	+***	+***	+***
	(3.186)	(3.830)	(2.911)			
LnFirmAge	0.006	-0.230	-0.676*	+**	+***	+***
	(0.173)	(-1.259)	(-1.903)			
LnAvgTenure	-0.065	0.306	0.691**	+	+*	+*
	(-1.493)	(1.342)	(2.328)			
LnAvgAge	0.531*	1.648*	2.801*	-	+	+
	(1.901)	(1.759)	(1.975)			
LnAvgEdu	-0.791	-0.543	-1.038	-	-	-
	(-1.286)	(-0.245)	(-0.204)			
LnAvgEarn	0.377***	0.316	0.541	+***	+***	+***
	(3.981)	(0.935)	(1.351)			
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	550	550	550	550	550	550
R-squared	0.365	0.244	0.223	0.632	0.61	0.592

Panel B: Serial Venture Employees and Original Employers' Post-IPO Performance in the Inventor Sample

Dep. Var.	*AR1yr*	*AR3yr*	*AR5yr*	*ROA1yr*	*ROA3yr*	*ROA5yr*
	(1)	(2)	(3)	(4)	(5)	(6)
PctSVELeft	-0.188	-0.695**	-0.934**	-0.138*	-0.152**	-0.169**
	(-1.701)	(-2.473)	(-2.479)	(-1.989)	(-2.299)	(-2.629)
PctLeaverToPub	0.274	-0.498	-0.979	-0.121	-0.097	-0.068
	(0.584)	(-0.560)	(-0.846)	(-0.991)	(-1.218)	(-0.885)
PctNewHire	0.010	0.022	0.042	0.025**	0.019**	0.013
	(0.493)	(0.591)	(0.731)	(2.620)	(2.155)	(1.533)
IR	-0.481***	-0.330***	-0.244***	-0.014	-0.017	-0.010
	(-3.672)	(-3.603)	(-4.188)	(-0.976)	(-1.152)	(-1.087)
LnProceeds	-0.023	-0.161	-0.189	0.076	0.062	0.050
	(-0.137)	(-0.611)	(-0.485)	(1.492)	(1.554)	(1.643)
VC	-0.063	0.190	0.286	-0.056	-0.039	-0.027
	(-0.609)	(1.234)	(1.103)	(-1.308)	(-1.174)	(-0.903)
TobinQ	0.076***	0.014	0.010	-0.001	-0.005**	-0.003
	(7.164)	(0.886)	(0.863)	(-0.650)	(-2.907)	(-1.698)
LnMV	0.050	0.291	0.191	-0.041	-0.008	0.004
	(0.335)	(1.284)	(0.604)	(-0.807)	(-0.195)	(0.155)
RDadj	-0.618	-0.569	-0.876	-1.146***	-0.990***	-1.014***
	(-1.682)	(-0.664)	(-1.521)	(-7.258)	(-8.496)	(-8.863)
IndVCPct	-0.242	-0.882*	-0.958	-0.060	-0.108	-0.130
	(-1.264)	(-1.818)	(-1.529)	(-0.630)	(-1.143)	(-1.282)
LnIndIPOVol	-0.033	-0.273**	-0.028	0.023	0.010	0.006
	(-0.683)	(-2.455)	(-0.164)	(1.485)	(0.618)	(0.304)
IndRFOption	6.968	-11.664	-17.984	-5.665*	-4.314*	-3.888*
	(1.355)	(-0.962)	(-1.098)	(-2.072)	(-1.933)	(-2.048)
LnInventor	0.044	0.031	0.133	0.054**	0.041*	0.033*
	(0.834)	(0.290)	(1.041)	(2.507)	(2.139)	(1.988)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	697	697	697	697	697	697
R-squared	0.297	0.141	0.092	0.370	0.364	0.370