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

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Abstract

We examine an emerging phenomenon that talented employees leave successful entrepreneurial firms to join less mature start-ups. Using proprietary person-level data and private firm 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, venture capital financing, and innovation productivity. Such predictive power is more likely driven by a screening/matching channel rather than venture labor's nurturing role. Our paper sheds light on an underexplored pattern of inter-firm labor flow, which provides a nonfinancial yet value-relevant signal about private firms for investors and stakeholders.

Key words: Venture Labor, Serial Venture Employees, Start-up Performance, Information Environments about Private Firms, Innovation

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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). To date, however, not adequate attention has been devoted to the information contained in employee job history records and its implication for the broader economy, despite the increasing availability of such data and the growing importance of efficient labor-capital matching in driving economic growth. In this paper, we aim to shed new light on the information value of employee job history by examining a prominent form of labor flow in the entrepreneurial world.

A salient phenomenon in Silicon Valley is 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] For instance, 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 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. For

[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 (2020) 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.

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

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.[3]

We explore the nature and value implications of such labor movement by focusing on employees who leave newly public or recently acquired entrepreneurial firms to join less mature private firms, and analyzing whether such human capital flow reveals value-relevant information about the newly joined 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. Therefore, the labor flow of serial venture employees into a start-up could positively predict the latter's future success.[4] Alternatively, 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,

[3] https://en.wikipedia.org/wiki/Elon_Musk

[4] Note that the "screening" can be performed by the firms/start-ups as well. In other words, the positive association between serial venture labor and firms' future performance might reflect a mutual selection process and the corresponding equilibrium matching. In various places of the paper, we use the term "screening" to refer to this two-way "matching/selection" to stay in line with the analogous terminology used in the venture capital literature.

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.[5] The "screening" and "nurturing" roles played by serial venture employees, like those by venture capitalists, are not mutually exclusive and may co-exist independent of each other.

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

[5] In certain cases, these venture employees might also benefit their new employers by bringing their personal wealth (capital) (e.g., becoming employee-investors or "human capitalists" as in Eisfeldt, Falato, and Xiaolan (2022)) 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.

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.[6] 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

[6] In untabulated analyses, we also find that the departure of serial venture employees from recently IPO firms contributes to the well-documented long-run IPO underperformance in both operating and stock returns, even after controlling for the effects of new hires or leavers to public.

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. Moreover, among private start-ups without venture capital (VC) backing, those with a larger number of serial venture employees are also more likely to obtain VC funding in the next three years. 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 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.[7]

To shed light on the relative importance of the "screening/matching" channel and the "nurturing" channel, we explore the heterogeneous predictive power of venture labor based on these employees' time spent with their new employers as well as contractual restrictions on their labor mobility. First, 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 relatively more important than the "screening" channel, we would expect the signal to be more informative when these employees work at the start-ups for a longer period. 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 join the start-ups *only recently*.

Second, contractual restrictions on labor mobility such as noncompete agreements may undermine a 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 "screening/matching" channel is relatively more important, we would expect the predictive power of venture labor to be weaker when labor is less mobile due to such frictions (e.g., when the state-level Noncompetition

[7] Note that if neither of the "screening/matching" or "nurturing" channels has a material effect, then we would not be able to observe a significant association between venture labor and start-up success, which is our null hypothesis.

Enforceability Index is higher). We find evidence consistent with this prediction. Taken together, these results suggest that the "screening/matching" channel of venture labor (i.e., their ability to match with high-quality start-ups) might have dominated the "nurturing" channel (i.e., their ability to improve the start-ups' operations and performance) in our sample, even if both channels may co-exist.[8]

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

[8] In untabulated analysis, 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 consistent with both channels.

suppliers, customers, and other employees) infer the quality and potential of entrepreneurial firms. In fact, we have shown that start-ups with more venture labor are more able to attract private equity investors (i.e., obtain VC financing for the first time) or to convince 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 *other* employees on the labor market. 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 able to attract and hire more new employees in the near future, especially those already having stable jobs (i.e., "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 the start-up is subject to a poorer information environment, e.g., when it is younger or operates in an R&D-intensive industry that highly values confidentiality and business secrets.

Next, we consider the implication of venture labor for another important performance metric for entrepreneurial firms, namely, their innovation productivity. 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.

In the final part of our paper, we explore one potential motive of serial venture employees to leave newly exited firms and join less mature start-ups, namely, their desire to work in an adventurous and creative environment that allows them to keep being entrepreneurial rather than work under the staid and mundane workplace culture of mature public firms.[9] Specifically, we examine inventors' *post-exit* (i.e., long-term future) innovation activities and find that, in the five years after their original employers' IPOs or sell-outs, serial venture employees file more patents and receive more citations per patent than their matched stayers and leavers to public firms. The patents filed by serial venture employees are also more original and more exploratory. These results suggest that, by moving to less mature firms, serial venture employees can keep engaging in innovation activities, which are explorative and risky in nature.

While previous literature on the importance of human capital identifies skilled labor largely based on their demographic attributes (e.g., immigration or visa status) or ranks along the corporate ladder, 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. Understanding the nature and implication of such labor flow is important because the information disclosure about private firms is less regulated and limited in relevance and

[9] It is worth noting that serial venture employees could also be driven by other motivations, such as their "monetary incentive" to make a big fortune by either having their labor income increased or enjoying the value appreciation in their stock/option compensation from the new start-ups. However, due to data limitation (e.g., a lack of detailed employee stock option granting information), we leave the exploration of these other motivations to future studies.

reliability compared to that about public firms, which calls for a search of nonfinancial predictors for their future performance. In this sense, our study 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.[10] The flow of serial venture labor facilitates the transfer of private, value-relevant information about start-ups to other entrepreneurial market participants (including both investors and stakeholders), which, together with the potential diffusion of their skills and knowledge, can enhance the welfare of the entire venture ecosystem.[11]

2. Related literature

Our paper is related to several strands of literature. First, it contributes to the literature on the importance of human capital for firms. For example, Eiling (2013), Donangelo (2014), Israelsen and Yonker (2017), Kuehn, Simutin, and Wang (2017), and Shen (2021) document that human capital adds critical value to publicly traded firms and thus influences asset prices.[12] In addition, recent studies have also started to explore the

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[10] 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.

[11] 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 other predictors of entrepreneurial success. However, compared to financial information, which is often confidential/proprietary for private firms, information about inter-firm labor flow can be more easily obtained through workplace/neighborhood conversations, social contacts, or publicly available worker resume data such as LinkedIn, making serial venture labor a viable nonfinancial signal for many entrepreneurial market participants.

[12] Similarly, Chemmanur et al. (2019) and Liu, Mao, and Tian (2017) show that human capital is a key driving force of public firms' innovation productivity.

value of key employees for private entrepreneurial firms (e.g., Ewens and Marx (2018), Chen, Hshieh, and Zhang (2020), Gu et al. (2020), and Dimmock, Huang, and Weisbenner (2021)). While the above literature mostly identifies skilled labor based on their demographic attributes (e.g., immigration or visa status) or ranks along the corporate ladder, our paper exploits the job history information of start-up employees and finds that workers with immediate exposure to entrepreneurial success can be a form of valuable human capital. A recent paper by Agrawal, Hacamo, and Hu (2021) shows that the net labor outflow of public firms predicts the latter's abnormal stock returns. While they focus on the implication of labor flow for public firms' future performance (as well as investors' perception of such association), we examine whether the labor movement of venture labor 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.

Second, our paper is related to the literature on the employment dynamics of IPO firms. For example, Bernstein (2015) documents that the post-IPO departure of inventors partly contributes to the decline in innovation among newly public firms. Babina, Ouimet, and Zarutskie (2020) find that the departure of high-wage employees to start-ups after a successful IPO triggers the industrial diversification of the IPO firm. In addition, Borisov, Ellul, and Sevilir (2021) show that firms increase their employment after going public. 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 entrepreneurial exits in recent decades (see, e.g., Chemmanur et al. (2022)).

Third, our paper contributes 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 stakeholders, such as venture capital investors (e.g., Baik, Berfeld, and Verdi (2019)), debt holders (e.g., Minnis (2011)), banks (e.g., Cassar, Ittner, and Cavalluzzo (2015) and Minnis and Sutherland (2017)), and acquirers (e.g., Jansen (2020)). 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., Burgstahler, Hail, and Leuz (2006)) due to the lack of consistent regulation and the voluntary nature of disclosure by private firms. We add to this literature by showing that private firms' potential investors and stakeholders (such as job seekers on the entrepreneurial labor market) can rely on the nonfinancial signal of serial venture labor to infer the quality of private firms and make informative decisions in the absence of high-quality financial statement information. The identification and exploitation of such nonfinancial signals can potentially enhance the information environments of private firms and consequently contribute to economic growth.[13]

[13] Our paper is also broadly related to the recent literature on the interaction between mature firms and younger firms in the economy. For example, Ma, Murfin, and Pratt (2021) document a tangible asset channel through which younger firms benefit from older firms located in the same geographic area by purchasing vintage physical capital from the latter. We add to the above channels by showing that the flow of intangible assets (more specifically, human capital) might act as a new channel to facilitate the interaction between mature and younger firms without requiring geographical proximity.

Finally, our paper is also broadly related to the literature on the performance of serial entrepreneurs, i.e., those who repeatedly start new businesses (e.g., Gompers et al. (2010), Zhang (2011), Parker (2013), Lafontaine and Shaw (2016), and Nahata (2019)).[14] While this strand of studies exclusively focuses on entrepreneurs who repeatedly start new ventures as founders, we examine rank-and-file employees who repeatedly work for entrepreneurial firms.[15]

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. 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 restrict our sample to IPOs and acquisitions completed between 1990 and 2007 because our data on individual employees

[14] A contemporaneous paper by Wallskog (2022) also uses the LEHD data and shows that individuals whose current coworkers have more prior entrepreneurship experience are more likely to become entrepreneurs themselves. While this paper analyzes the causal effect of coworker influence on *individuals'* decisions to start new business, we focus on the predictive power of private *firms'* labor force composition (i.e., the presence of employees with recent IPO/sell-out experience) for their future performance.

[15] 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).

(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 the employees' job status after the deals' completion.

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. 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

[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.

data to the SDC data using the link files created in the first step. The matched sample contains about 289,000 employees from 1,200 IPO firms and about 642,000 employees from 3,300 acquired private firms.[19,20]

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. 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 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. We further require an IPO (acquired) firm to have at least one patent 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

[19] These numbers are rounded according to the disclosure requirement by the U.S. Census Bureau.

[20] 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.

individuals) after the exit dates.[21] The final inventor sample consists of 4,357 inventors from 814 IPO firms and 2,209 inventors from 524 acquired private firms.[22]

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

[21] 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.

[22] Note that both the Census and the inventor data have their own limitations but perform complimentary roles in our analyses. For example, although the serial venture employees identified from the Census data do not necessarily engage in innovation at the same level that inventors do, they may possess other talents such as technical, marketing, mentoring/advising, or management skills that could help them match with successful ventures in the first place and/or contribute to the growth of these start-ups. At the same time, using inventors' patenting activities to track their employment history might be imperfect, but it allows us to gauge the quality/talent of a subset of important, technologically-savvy venture employees.

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.[23,24] If the employee still works for the IPO firm in 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.

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.[25] 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

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[23] 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.

[24] 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, 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.

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

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.[26] 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 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.[27] 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 three 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

[26] 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.
[27] Our results are robust to treating all inventors who are neither serial venture employees nor leavers to public firms as stayers.

from year *t+1* to *t+3*. For the firms that cease to exist by year *t+3*, *SizeGrowth* is set to be -1.[28] *VC* is a dummy variable that equals one if the firm obtains VC financing for the first time (i.e., becomes VC backed) within the next three years, and zero otherwise.[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

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.

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[28] Our results are robust to dropping such deceased firms.

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

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] Roughly 0.2 percent of the non-VC-backed firms get their first VC investment within the next three years. 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

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[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.

citations received by individual inventors. Such 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., Chemmanur et al. (2019) and 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 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

[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.

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 two channels. First, 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). Meanwhile, high-quality start-ups might be able to screen and attract such talented employees, leading to an equilibrium matching. Second, serial venture employees possess valuable human capital and can pass on their skills, experience, and entrepreneurial spirit to the start-ups they join, which enhances the latter's performance and future prospects (i.e., play a "nurturing" role). These two channels are not mutually exclusive.

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

[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

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] 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 three measures for private firms' future success (in year *t+1* to *t+3*) discussed earlier: *Exit*, *SizeGrowth*, or *VC*. *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-pair fixed effects, which fully absorb industry, year, and state fixed effects as well as their multiplicative combinations as the matching is done at the 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

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.

[34] 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)).

likelihood of a successful exit. To account for possible correlations in errors of each matched pair, we cluster standard errors at the matched-pair 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). Columns (2) and (3) further show that the presence of serial venture employees in a firm's workforce is positively associated with both the firm's future employment growth (*SizeGrowth*) and its likelihood of obtaining first-time VC financing (*VC*).

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, employment growth, and the likelihood to obtain VC financing in the future.

In untabulated analysis, 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 (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.

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.[35]

6.2 Relative importance of the "screening/matching" channel and the "nurturing" channel

As discussed earlier, there are two potential explanations to the predictive power of serial venture labor, namely, the "screening/matching" channel and the "nurturing" channel. To gauge the relative importance of these two channels, we explore the heterogeneous predictive power of venture employees based on the time they spent with their new employers and the enforceability of contractual restrictions on these employees' labor mobility.

First, we examine how serial venture employees' predictive power for start-up success varies with their time spent with the new employers. Since it typically takes time for new hires to exert ample influence on their employer's operations, if the nurturing channel is relatively more important, we would expect the predictive power to be

[35] These results are currently untabulated due to the disclosure requirements of the Census Bureau.

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* (*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.[36] As shown in Table 4, the coefficients on *LnSerialVEJoinedRecently* are significantly larger than those on *LnSerialVEJoinedLongAgo* in all three 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.

We then examine 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.

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

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. In contrast, the nurturing channel is not affected by the restrictions on labor mobility because it takes effect only after the matching is done (i.e., conditional on a serial venture employee joining the next start-up). Hence, if the screening/matching channel is relatively more important than the nurturing one, we would 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.[37] As shown in Table 5, the coefficients on the interaction term are significantly negative in all 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.

In all, the analyses discussed in this section suggest that, although both channels are not mutually exclusive and might co-exist, the screening/matching one might be relatively more important than the nurturing one in explaining venture labor's predictive power for start-up success.

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

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.[38] *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 success than these other types of labor. For example, increasing the number of serial venture employees from zero to one in this regression

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[38] 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.

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 Serial venture employees and start-up firms' labor market attractiveness

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. Stakeholders such as job seekers could utilize this signal, i.e., the presence of serial venture employees, to select the firms they want to invest their human capital in. To further illustrate the value of this nonfinancial signal, 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 other workers on the entrepreneurial labor market.

Specifically, we identify a firm's new hires following the methodology developed by the Census Bureau's Job-to-Job Flow (J2J) program. 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*.[39] 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*.[40]

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. Panel A of Table 7 presents the results. Column (1) shows a significantly positive association between the presence 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

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[39] See https://lehd.ces.census.gov/doc/j2j_101.pdf for more details about the definition of new hires.

[40] 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.

status. Columns (2) and (3) 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. (2017)), this finding illustrates the value of the nonfinancial signal of serial venture employees to job seekers on the labor market.

In addition to the analyses discussed above, we further explore whether the signal is more useful when a start-up is subject to a poorer information environment, e.g., when the firm is younger or operates in an R&D-intensive industry that highly values confidentiality. First, we interact *LnSerialVE* with *LnFirmAge* in the regressions and present the results in Panel B of Table 7. As can be seen, the interaction term is significantly negative in all three regressions, indicating that the predictive power of serial venture labor is stronger 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 C of Table 7.[41] The significantly positive coefficients of the interaction term indicate that the predictive power of serial venture labor is more pronounced for firms in industries that attach greater value to confidentiality and business secrets. These findings suggest that the

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

signal of venture labor is indeed more useful when a private firm is subject to a more opaque information environment where financial signals are harder to obtain.

To sum up, the evidence presented in this section illustrates that job seekers on the entrepreneurial labor market, who are an important group of stakeholders, value the nonfinancial signal of serial venture labor and utilize this signal to choose their private employers especially when these start-ups are harder to value.

6.5 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.[42] 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 8 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 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 8 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

[42] 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.

originality than matched/similar inventors at other firms. These results are consistent with both the screening/matching channel and the nurturing channel.

7. Serial Venture Employees' Incentive to Work in an Entrepreneurial Environment

In this section, we explore one potential incentive for serial venture employees to quit their original employers after a successful exit and move to other private firms, namely, their preference to work in an entrepreneurial environment. Previous literature has shown that people often pursue entrepreneurship for nonpecuniary reasons such as the desire for autonomy and the tolerance for risk (see, e.g., Hamilton (2000), Puri and Robinson (2013), Hvide and Panos (2014), Ouimet and Zarutskie (2014), Roach and Sauermann (2015), and Cassar and Meier (2018)). Further, after a private firm goes public or is acquired, it exhibits a decrease in creative activities such as innovation (see, e.g., Aggarwal and Hsu (2014), Bernstein (2015), Cunningham, Ederer, and Ma (2021), Gao, Hsu, and Li (2018), and Dambra and Gustafson (2021)), which might trigger the departure of talented employees who desire autonomy and entrepreneurial working environments. Hence, we hypothesize that, serial venture employees — who are more explorative, risk-tolerant, and adventurous in nature (see, e.g., Puri and Robinson (2013)) — might move to private firms in the pursuit of an environment that better nurtures these qualities, since their original employers come to focus more on routine businesses after successfully exiting.

To examine this motive, we use the inventor sample to study the association between the inventors' decisions to leave the exited firms and their post-exit (i.e., long-term future) innovation activities. Given that, as shown earlier, serial venture employees have higher pre-exit innovation productivity, we conduct a *matched-sample* analysis to control for their pre-exit innovation activities. Specifically, for each serial venture employee whose employer exits in year *t*, we find all the leavers to public firms and all the stayers whose employers also exit in year *t*, and whose average annual patent output in the five years before the exit is comparable (i.e., has a difference no greater than 1) to that of the serial venture employee. By doing so, we compare serial venture employees to inventors in other categories with similar levels of pre-exit innovation productivity. For those matched serial venture employees and other inventors, we first calculate each individual's average number of patents filed per year (*PatentsPostExit*), average number of citations received per patent (*CitePatPostExit*), average originality score per patent (*OriginalityPostExit*), and average number of exploratory patents filed per year (*ExploratoryPostExit*) in the five years post-exit. Then, for each serial venture employee, we calculate the differences between her four innovation activity measures (mentioned above) and the median values of these measures amongst her matched inventors.

Table 9 reports the results, which show that serial venture employees file 0.63 more patents annually than their matched leavers to public firms in the five years post-exit. The patents filed by serial venture employees have higher quality (measured as citations per patent) and are more original and more exploratory as well. All these four differences are significant at the 1% level. In addition, serial venture employees exhibit greater long-term innovation productivity than their matched stayers.

These results provide suggestive evidence that one incentive of serial venture employees to move to private firms is their desire to work in an adventurous and creative environment that can allow them to keep being entrepreneurial.

8. 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, venture capital financing, and innovation productivity.

This 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 channel for the signal to work. Meanwhile, the positive association between venture labor and start-up success is weaker in states with lower labor mobility, suggesting that the matching (mutual screening) between the two is a relatively more important channel than the nurturing channel. 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 job seekers on the entrepreneurial labor market as well as when this signal is most useful. Finally, we show that serial venture employees could be motivated by their desire to work in an entrepreneurial environment.

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 investors and stakeholders. The private information revealed through these employees' job-hopping actions, together with the potential diffusion of their skills/knowledge to private start-ups, enhances the welfare of the entire 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 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 relatively uninformed investors/stakeholders who do not have 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.

REFERENCES

Abowd, J.M., Stephens, B.E., Vilhuber, L., Andersson, F., McKinney, K.L., Roemer, M. and Woodcock, S., 2009. The LEHD infrastructure files and the creation of the Quarterly Workforce Indicators. In *Producer dynamics: New evidence from micro data* (pp. 149-230). University of Chicago Press.

Aggarwal, V.A. and Hsu, D.H., 2014. Entrepreneurial exits and innovation. *Management Science*, *60*(4), pp.867-887.

Agrawal, A., Hacamo, I. and Hu, Z., 2021. Information dispersion across employees and stock returns. *The Review of Financial Studies*, *34*(10), pp.4785-4831.

Aldatmaz, S., Ouimet, P. and Van Wesep, E.D., 2018. The option to quit: The effect of employee stock options on turnover. *Journal of Financial Economics*, *127*(1), pp.136-151.

Babina, T., Ma, W., Moser, C., Ouimet, P. and Zarutskie, R., 2020. Pay, employment, and dynamics of young firms. *Working paper*.

Babina, T., Ouimet, P. and Zarutskie, R., 2020. IPOs, human capital, and labor reallocation. *Working paper*.

Baik, B., Berfeld, N. and Verdi, R., 2019. Public financial statements and private firm equity financing. *Working paper*.

Bayar, O. and Chemmanur, T.J., 2012. What drives the valuation premium in IPOs versus acquisitions? An empirical analysis. *Journal of Corporate Finance*, *18*(3), pp.451-475.

Bernstein, S., 2015. Does going public affect innovation? *The Journal of Finance*, *70*(4), pp.1365-1403.

Blau, D.M. and Robins, P.K., 1990. Job search outcomes for the employed and unemployed. *Journal of Political Economy*, *98*(3), pp.637-655.

Borisov, A., Ellul, A. and Sevilir, M., 2021. Access to public capital markets and employment growth. *Journal of Financial Economics*, *141*(3), pp.896-918.

Bowen III, D.E., Frésard, L. and Hoberg, G., 2020. Rapidly evolving technologies and startup exits. *Swiss Finance Institute Research Paper*, (19-22).

Brav, A., Jiang, W., Ma, S. and Tian, X., 2018. How does hedge fund activism reshape corporate innovation?. *Journal of Financial Economics*, *130*(2), pp.237-264.

Burgstahler, D.C., Hail, L. and Leuz, C., 2006. The importance of reporting incentives: Earnings management in European private and public firms. *The Accounting Review*, *81*(5), pp.983-1016.

Cassar, G., Ittner, C.D. and Cavalluzzo, K.S., 2015. Alternative information sources and information asymmetry reduction: Evidence from small business debt. *Journal of Accounting and Economics*, *59*(2-3), pp.242-263.

Cassar, L. and Meier, S., 2018. Nonmonetary incentives and the implications of work as a source of meaning. *Journal of Economic Perspectives*, *32*(3), pp.215-38.

Chemmanur, T.J. and He, J., 2011. IPO waves, product market competition, and the going public decision: Theory and evidence. *Journal of Financial Economics*, *101*(2), pp.382-412.

Chemmanur, T.J., He, J., He, S. and Nandy, D., 2018. Product market characteristics and the choice between IPOs and acquisitions. *Journal of Financial and Quantitative Analysis*, *53*(2), pp.681-721.

Chemmanur, T.J., He, J., Ren, X. and Shu, T., 2022. The disappearing IPO puzzle: New insights from proprietary US Census data on private firms. *Working Paper*.

Chemmanur, T.J., Kong, L., Krishnan, K. and Yu, Q., 2019. Top management human capital, inventor mobility, and corporate innovation. *Journal of Financial and Quantitative Analysis*, *54*(6), pp.2383-2422.

Chen, J., Hshieh, S. and Zhang, F., 2020. The role of high-skilled foreign labor in startup performance: Evidence from two natural experiments. *Journal of Financial Economics, 142*(1), pp.430-452.

Cunningham, C., Ederer, F. and Ma, S., 2021. Killer acquisitions. *Journal of Political Economy, 129*(3), pp.649-702.

Custódio, C., Ferreira, M.A. and Matos, P., 2019. Do general managerial skills spur innovation?. *Management Science*, *65*(2), pp.459-476.

Dambra, M. and Gustafson, M., 2021. Do the burdens to being public affect the investment and innovation of newly public firms?. *Management Science*, *67*(1), pp.594-616.

Davis, S.J., Haltiwanger, J., Handley, K., Jarmin, R., Lerner, J. and Miranda, J., 2014. Private equity, jobs, and productivity. *American Economic Review*, *104*(12), pp.3956-90.

Dimmock, S.G., Huang, J. and Weisbenner, S.J., 2021. Give me your tired, your poor, your high-skilled labor: H-1B lottery outcomes and entrepreneurial success. *Management Science.*

Donangelo, A., 2014. Labor mobility: Implications for asset pricing. *The Journal of Finance*, *69*(3), pp.1321-1346.

Eiling, E., 2013. Industry-specific human capital, idiosyncratic risk, and the cross-section of expected stock returns. *The Journal of Finance*, *68*(1), pp.43-84.

Eisfeldt, A., Falato, A., and Xiaolan, M.Z., 2022. Human capitalists. *NBER Macroeconomics Annual*, forthcoming.

Ewens, M. and Marx, M., 2018. Founder replacement and startup performance. *The Review of Financial Studies*, *31*(4), pp.1532-1565.

Faberman, R.J., Mueller, A.I., Şahin, A. and Topa, G., 2017. Job search behavior among the employed and non-employed (No. w23731). National Bureau of Economic Research.

Gao, H., Hsu, P.H. and Li, K., 2018. Innovation strategy of private firms. *Journal of Financial and Quantitative Analysis*, *53*(1), pp.1-32.

Garmaise, M.J., 2011. Ties that truly bind: Noncompetition agreements, executive compensation, and firm investment. *The Journal of Law, Economics, and Organization*, *27*(2), pp.376-425.

Gompers, P., Kovner, A., Lerner, J. and Scharfstein, D., 2010. Performance persistence in entrepreneurship. *Journal of Financial Economics*, *96*(1), pp.18-32.

Gu, L., Huang, R., Mao, Y. and Tian, X., 2020. How does human capital matter? Evidence from venture capital. *Journal of Financial and Quantitative Analysis,* pp.1-64.

Hamilton, B.H., 2000. Does entrepreneurship pay? An empirical analysis of the returns to self-employment. *Journal of Political Economy*, *108*(3), pp.604-631.

Haltiwanger, J.C., Hyatt, H.R., Kahn, L.B. and McEntarfer, E., 2018. Cyclical job ladders by firm size and firm wage. *American Economic Journal: Macroeconomics*, *10*(2), pp.52-85.

Haltiwanger, J., Hyatt, H. and McEntarfer, E., 2018. Who moves up the job ladder?. *Journal of Labor Economics*, *36*(S1), pp.S301-S336.

He, J., Shu, T., Ren, X, and Yang, H., 2022. The employee clientele of corporate leverage: Evidence from family labor income diversification. *Working Paper*.

He, J., Li, L. and Shu, T., 2022. Workplace inequality in the U.S.: Evidence from pay growth. *Working Paper*.

Hirshleifer, D., Hsu, P.H. and Li, D., 2018. Innovative originality, profitability, and stock returns. *The Review of Financial Studies*, *31*(7), pp.2553-2605.

Hochberg, Y.V., Ljungqvist, A. and Lu, Y., 2007. Whom you know matters: Venture capital networks and investment performance. *The Journal of Finance*, *62*(1), pp.251-301.

Hvide, H.K. and Panos, G.A., 2014. Risk tolerance and entrepreneurship. *Journal of Financial Economics*, *111*(1), pp.200-223.

Islam, E. and Zein, J., 2020. Inventor CEOs. *Journal of Financial Economics*, *135*(2), pp.505-527.

Israelsen, R.D. and Yonker, S.E., 2017. Key human capital. *Journal of Financial and Quantitative Analysis*, *52*(1), pp.175-214.

Jansen, M., 2020. Resolving information asymmetry through contractual risk sharing: The case of private firm acquisitions. *Journal of Accounting Research*, *58*(5), pp.1203-1248.

Kerr, W.R., Lerner, J. and Schoar, A., 2014. The consequences of entrepreneurial finance: Evidence from angel financings. *The Review of Financial Studies*, *27*(1), pp.20-55.

Kogan, L., Papanikolaou, D., Seru, A. and Stoffman, N., 2017. Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, *132*(2), pp.665-712.

Krishnan, K., Nandy, D.K. and Puri, M., 2015. Does financing spur small business productivity? Evidence from a natural experiment. *The Review of Financial Studies*, *28*(6), pp.1768-1809.

Kuehn, L.A., Simutin, M. and Wang, J.J., 2017. A labor capital asset pricing model. *The Journal of Finance*, *72*(5), pp.2131-2178.

Lafontaine, F. and Shaw, K., 2016. Serial entrepreneurship: Learning by doing?. *Journal of Labor Economics*, *34*(S2), pp.S217-S254.

Levine, R., Lin, C. and Wei, L., 2017. Insider trading and innovation. *The Journal of Law and Economics*, *60*(4), pp.749-800.

Li, G.C., Lai, R., D'Amour, A., Doolin, D.M., Sun, Y., Torvik, V.I., Amy, Z.Y. and Fleming, L., 2014. Disambiguation and co-authorship networks of the US patent inventor database (1975–2010). *Research Policy*, *43*(6), pp.941-955.

Lin, C., Liu, S. and Manso, G., 2021. Shareholder litigation and corporate innovation. *Management Science, 67(6),* pp.3346-3367.

Liu, T., Mao, Y. and Tian, X., 2017. The role of human capital: Evidence from patent generation. *Working paper*.

Ma, S., Murfin, J. and Pratt, R., 2021. Young firms, old capital. *Journal of Financial Economics*.

Wallskog, M., 2022. Entrepreneurial spillovers across coworkers. *Working paper*.

Minnis, M., 2011. The value of financial statement verification in debt financing: Evidence from private US firms. *Journal of Accounting Research*, *49*(2), pp.457-506.

Minnis, M. and Sutherland, A., 2017. Financial statements as monitoring mechanisms: Evidence from small commercial loans. *Journal of Accounting Research*, *55*(1), pp.197-233.

Nahata, R., 2019. Success is good but failure is not so bad either: Serial entrepreneurs and venture capital contracting. *Journal of Corporate Finance*, *58*, pp.624-649.

Ouimet, P. and Zarutskie, R., 2014. Who works for startups? The relation between firm age, employee age, and growth. *Journal of Financial Economics*, *112*(3), pp.386-407.

Parker, S.C., 2013. Do serial entrepreneurs run successively better-performing businesses?. *Journal of Business Venturing*, *28*(5), pp.652-666.

Poulsen, A.B. and Stegemoller, M., 2008. Moving from private to public ownership: Selling out to public firms versus initial public offerings. *Financial Management*, *37*(1), pp.81-101.

Puri, M. and Robinson, D.T., 2013. The economic psychology of entrepreneurship and family business. *Journal of Economics & Management Strategy*, *22*(2), pp.423-444.

Roach, M. and Sauermann, H., 2015. Founder or joiner? The role of preferences and context in shaping different entrepreneurial interests. *Management Science*, *61*(9), pp.2160-2184.

Samila, S. and Sorenson, O., 2011. Noncompete covenants: Incentives to innovate or impediments to growth. *Management Science*, *57*(3), pp.425-438.

Schoar, A., 2002. Effects of corporate diversification on productivity. *The Journal of Finance*, *57*(6), pp.2379-2403.

Shen, M., 2021. Skilled labor mobility and firm value: Evidence from a natural experiment. *Review of Financial Studies, 34(10),* pp.4663–4700.

Tate, G. and Yang, L., 2015. The bright side of corporate diversification: Evidence from internal labor markets. *The Review of Financial Studies*, *28*(8), pp.2203-2249.

Zhang, J., 2011. The advantage of experienced start-up founders in venture capital acquisition: evidence from serial entrepreneurs. *Small Business Economics*, *36*(2), pp.187-208

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), ad 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.
PatentsPostJoin	The average number of patents filed per year by a serial venture employee's new colleague or her matched inventor

	in the five years after the joining of the serial venture employee.
CitePatPostJoin	The average number of citations received per patent by a serial venture employee's new colleague or her matched inventor in the five years after the joining of the serial venture employee.
OriginalityPostJoin	The average originality of patents filed by a serial venture employee's new colleague or her matched inventor in the five years after the joining of the serial venture employee.
ExploratoryPostJoin	The average number of exploratory patents filed per year by a serial venture employee's new colleague or her matched inventor in the five years after the joining of the serial venture employee.
PatentsPostExit	The average number of patents filed per year by an inventor from an exited firm in the five years after the exit date.
CitePatPostExit	The average number of citations received per patent by an inventor from an exited firm in the five years after the exit date.
OriginalityPostExit	The average originality of patents filed by an inventor from an exited firm in the five years after the exit date.
ExploratoryPostExit	The average number of exploratory patents filed per year by an inventor from an exited firm in the five years after the exit date.

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.
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.
FirmPatentsPostJoin	The average number of patents filed per year by a firm joined by a serial venture employee or its matched firms in the five years after the joining of the serial venture employee.
FirmCitePatPostJoin	The average number of citations received per patent by a firm joined by a serial venture employee or its matched firms in the five years after the joining of the serial venture employee.
FirmOriginalityPostJoin	The average originality of patents filed by a firm joined by a serial venture employee or its matched firms in the five years after the joining of the serial venture employee.
FirmExploratoryPostJoin	The average number of exploratory patents filed per year by a firm joined by a serial venture employee or its matched firms in the five years after the joining of the serial venture employee.

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
VC	0.002	0.047	573,000
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*. $VC_{(t+1,t+3)}$ 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. $LnSerialVE_t$ 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-pair fixed effects in all regressions. T-statistics based on standard errors clustered by matched pair 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.	$Exit_{(t+1,t+3)}$	$SizeGrowth_{(t+1,t+3)}$	$VC_{(t+1,t+3)}$
	(1)	(2)	(3)
$LnSerialVE_t$	0.224***	0.075***	0.242***
	(6.628)	(28.450)	(8.417)
$LnEmp_t$	0.161	0.039***	0.357***
	(1.526)	(4.309)	(4.417)
$LnFirmAge_t$	-0.053	-0.003	-0.091**
	(-1.287)	(-0.670)	(-2.553)
$LnAvgEarn_t$	0.265***	0.105***	0.248***
	(14.040)	(48.000)	(14.430)
$LnAvgAge_t$	-0.284***	-0.201***	-0.458***
	(-6.097)	(-27.900)	(-10.710)
$LnAvgEdu_t$	0.367***	-0.118***	0.559***
	(4.021)	(-7.537)	(7.137)
$Gender_t$	-0.005	-0.017***	0.025
	(-0.169)	(-3.920)	(0.902)
$Ethnicity_t$	-0.006	-0.019***	0.075***
	(-0.198)	(-4.931)	(2.874)
Matched-Pair Fixed Effects	Yes	Yes	Yes
Observations	582,000	582,000	573,000
R-squared	0.276	0.260	0.222

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

Dep. Var.	*Exit*$_{(t+1,t+3)}$	*SizeGrowth*$_{(t+1,t+3)}$	*VC*$_{(t+1,t+3)}$
	(1)	(2)	(3)
PctSerialVE$_t$	0.178*	0.147***	0.318***
	(1.867)	(7.362)	(3.423)
LnEmp$_t$	0.211**	0.056***	0.411***
	(1.998)	(6.208)	(5.067)
LnFirmAge$_t$	-0.052	-0.003	-0.090**
	(-1.265)	(-0.570)	(-2.514)
LnAvgEarn$_t$	0.280***	0.109***	0.263***
	(14.700)	(49.980)	(15.110)
LnAvgAge$_t$	-0.306***	-0.207***	-0.478***
	(-6.520)	(-28.620)	(-11.120)
LnAvgEdu$_t$	0.386***	-0.113***	0.576***
	(4.214)	(-7.236)	(7.359)
Gender$_t$	-0.004	-0.016***	0.026
	(-0.129)	(-3.824)	(0.946)
Ethnicity$_t$	-0.011	-0.021***	0.070***
	(-0.370)	(-5.370)	(2.663)
Matched-Pair Fixed Effects	Yes	Yes	Yes
Observations	582,000	582,000	573,000
R-squared	0.276	0.259	0.222

Table 4: 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-pair fixed effects in all regressions. T-statistics based on standard errors clustered by matched pair are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	$Exit_{(t+1,t+3)}$	$SizeGrowth_{(t+1,t+3)}$	$VC_{(t+1,t+3)}$
	(1)	(2)	(3)
$LnSerialVEJoinedRecently_t$	0.382***	0.136***	0.410***
	(4.922)	(21.410)	(6.019)
$LnSerialVEJoinedLongAgo_t$	0.166***	0.053***	0.161***
	(4.558)	(18.600)	(5.180)
$LnEmp_t$	0.162	0.040***	0.361***
	(1.535)	(4.350)	(4.472)
$LnFirmAge_t$	-0.047	-0.001	-0.084**
	(-1.151)	(-0.188)	(-2.372)
$LnAvgEarn_t$	0.265***	0.105***	0.248***
	(14.040)	(47.990)	(14.480)
$LnAvgAge_t$	-0.278***	-0.199***	-0.452***
	(-5.979)	(-27.570)	(-10.580)
$LnAvgEdu_t$	0.369***	-0.117***	0.562***
	(4.039)	(-7.501)	(7.176)
$Gender_t$	-0.004	-0.016***	0.026
	(-0.142)	(-3.851)	(0.936)
$Ethnicity_t$	-0.007	-0.020***	0.073***
	(-0.245)	(-5.071)	(2.795)
F-statistics	6.407	136.200	10.640
P-value	0.011	<0.001	0.001
Matched-Pair Fixed Effects	Yes	Yes	Yes
Observations	582,000	582,000	573,000
R-squared	0.276	0.260	0.222

Table 5: 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-pair fixed effects in all regressions. T-statistics based on standard errors clustered by matched pair are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	$Exit_{(t+1,t+3)}$	$SizeGrowth_{(t+1,t+3)}$	$VC_{(t+1,t+3)}$
	(1)	(2)	(3)
$LnSerialVE_t \times NEI_t$	-0.094***	-0.003**	-0.046***
	(-5.179)	(-2.458)	(-2.963)
$LnSerialVE_t$	0.538***	0.089***	0.410***
	(6.529)	(17.31)	(6.220)
Controls	Yes	Yes	Yes
Matched-Pair Fixed Effects	Yes	Yes	Yes
Observations	582,000	582,000	573,000
R-squared	0.276	0.260	0.222

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-pair fixed effects in all regressions. T-statistics based on standard errors clustered by matched pair are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Dep. Var.	$Exit_{(t+1,t+3)}$	$SizeGrowth_{(t+1,t+3)}$	$VC_{(t+1,t+3)}$
	(1)	(2)	(3)
$LnSerialVE_t$	0.172***	0.058***	0.199***
	(4.988)	(11.15)	(6.813)
$LnEmpHighEarn_t$	0.021***	0.022***	0.022***
	(6.897)	(27.83)	(7.868)
$LnEmpVC_t$	0.015**	0.037***	0.028***
	(2.510)	(15.08)	(4.793)
$LnEmpPublic_t$	0.041***	0.062***	0.011**
	(7.056)	(21.34)	(2.051)
F-statistics (*LnSerialVE - LnEmpHighEarn*)	19.090	50.380	36.590
P-value (*LnSerialVE - LnEmpHighEarn*)	<0.001	<0.001	<0.001
F-statistics (*LnSerialVE - LnEmpVC*)	18.750	13.540	30.780
P-value (*LnSerialVE - LnEmpVC*)	<0.001	<0.001	<0.001
F-statistics (*LnSerialVE - LnEmpPublic*)	14.020	0.420	40.000
P-value (*LnSerialVE - LnEmpPublic*)	<0.001	0.518	<0.001
Controls	Yes	Yes	Yes
Matched-Pair Fixed Effects	Yes	Yes	Yes
Observations	582,000	582,000	573,000
R-squared	0.276	0.260	0.222

Table 7: Serial Venture Employees and Start-ups' Labor Market Attractiveness

This table presents the regressions of private firms' future new hires on the presence of serial venture employees. $LnHire_{(t+1,t+3)}$ 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 baseline regressions of the new hire measures on $LnSerialVE_t$, the natural logarithm of one plus the number of serial venture employees in a firm in the last quarter of year *t*. Panel B presents cross-sectional tests based on $LnFirmAge_t$, the natural logarithm of a firm's age. Panel C 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. Control variables similar to those in Table 3 are included but not reported. Each regression includes a separate intercept. We include matched-pair fixed effects in all regressions. T-statistics based on standard errors clustered by matched pair are in parentheses. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Serial Venture Employees and New Hires

Dep. Var.	$LnHire_{(t+1,t+3)}$	$LnJ2JHire_{(t+1,t+3)}$	$LnNEHire_{(t+1,t+3)}$
	(1)	(2)	(3)
$LnSerialVE_t$	0.165***	0.207***	0.089***
	(21.200)	(30.410)	(12.850)
Controls	Yes	Yes	Yes
Matched-Pair Fixed Effects	Yes	Yes	Yes
Observations	582,000	582,000	573,000
R-squared	0.510	0.536	0.520

Panel B: Cross-sectional Analysis Based on Firm Age

Dep. Var.	$LnHire_{(t+1,t+3)}$	$LnJ2JHire_{(t+1,t+3)}$	$LnNEHire_{(t+1,t+3)}$
	(1)	(2)	(3)
$LnSerialVE_t \times LnFirmAge_t$	-0.110***	-0.111***	-0.075***
	(-12.540)	(-14.290)	(-9.660)
$LnSerialVE_t$	0.450***	0.494***	0.283***
	(20.810)	(25.490)	(14.830)
$LnFirmAge_t$	-0.051***	-0.056***	-0.026***
	(-6.047)	(-7.585)	(-3.602)
Controls	Yes	Yes	Yes
Matched-Pair Fixed Effects	Yes	Yes	Yes
Observations	582,000	582,000	573,000
R-squared	0.510	0.536	0.520

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

Dep. Var.	$LnHire_{(t+1,t+3)}$	$LnJ2JHire_{(t+1,t+3)}$	$LnNEHire_{(t+1,t+3)}$
	(1)	(2)	(3)
$LnSerialVE_t \times RDind_t$	0.327***	0.337***	0.193**
	(2.946)	(3.424)	(1.991)
$LnSerialVE_t$	0.153***	0.195***	0.082***
	(16.710)	(24.390)	(10.070)
Controls	Yes	Yes	Yes
Matched-Pair Fixed Effects	Yes	Yes	Yes
Observations	582,000	582,000	573,000
R-squared	0.510	0.536	0.520

Table 8: 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 9: Post-exit Innovation Productivity of Serial Venture Employees and Other Types of Labor

This table presents the difference in post-exit innovation productivity between serial venture employees and their matched inventors in other categories. For each serial venture employee whose employer exits in year *t*, we find all the leavers to public firms and stayers whose employers also exit in year *t*, and whose difference from the serial venture employee in terms of past patenting output is no more than one. We then calculate the average number of patents filed per year (*PatentsPostExit*), the average number of citations received per patent (*CitePatPostExit*), the patents' average originality score (*OriginalityPostExit*), and the average number of exploratory patents filed per year (*ExploratoryPostExit*) by each inventor in the five years after exits. We report the average differences between a serial venture employee's innovation productivity measures mentioned above and those of her matched inventors in other categories. 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.

Difference	Variable	N	Mean	t-statistics
SerialVE - LeaverToPub	*PatentsPostExit*	753	0.631***	12.749
	CitePatPostExit	753	3.098***	5.604
	OriginalityPostExit	753	1.670***	5.556
	ExploratoryPostExit	753	0.210***	10.686
SerialVE - Stayer	*PatentsPostExit*	781	0.908***	19.978
	CitePatPostExit	781	5.860***	11.417
	OriginalityPostExit	781	2.010***	7.171
	ExploratoryPostExit	781	0.411***	22.310