Learning by Investing:

Entrepreneurial Spillovers from Venture Capital

Josh Lerner

Jinlin Li

Tong Liu*

October 2022

Abstract

This paper studies how investing in venture capital (VC) affects the entrepreneurial outcomes of individual limited partners (LPs). Using comprehensive administrative data on entrepreneurial activities and VC fundraising and investments in China, we first document that individual LPs, on average, contribute about 50% of capital of each fund in which they participate, and over 50% of them are entrepreneurs. We then exploit an identification strategy by comparing the entrepreneurial outcomes of individual LPs in funds that eventually launched with those in funds that failed to launch. The fraction of committed capital from corporate LPs in industries that subsequently encounter poor returns is used as an instrument for funds' launch failures. We find that after investing in a VC fund, individual LPs create significantly more ventures. These new ventures tend to be high-tech firms and file more patents. We find evidence consistent with venture investments being a channel through which individual LPs learn.

Key words: Entrepreneurship, learning-by-investing, limited partners, private capital.

JEL Codes: D83, G23, G24, L25, L26

*Harvard University and National Bureau of Economic Research; Harvard University; and MIT Sloan School of Management. Emails: josh@hbs.edu, jinlin_li@hks.harvard.edu, tongl@mit.edu. Lerner has received compensation for advising institutional investors in venture capital funds, venture capital groups, and/or governments designing policies relevant to venture capital. We thank Ruilin Cheng, Zijun Cheng, Songrui Liu, and Yiqing Mo for excellent research assistance. All errors and omissions are our own.

1 Introduction

The academic literature on entrepreneurial finance has largely treated investors and entrepreneurs as distinct groups. But the boundaries between investors and entrepreneurs have become increasingly blurred, reflecting the growing importance of angel groups, crowdfunding, and "super angel" venture funds (Bernstein et al., 2017; Lerner et al., 2018; Wallmeroth et al., 2018; Hellmann et al., 2021). While the numerous studies have highlighted how venture capitalists add value to portfolio firms (e.g., Bernstein et al., 2016; Kortum and Lerner, 2000; Hellmann and Puri, 2002), the potential impact of experience as a limited partner has received much less scrutiny.

This paucity of research is striking given the anecdotal evidence of the importance of this channel for venture capital influence. As highlighted on the website of AngelList Venture, "Aside from returns, benefits to becoming an LP (investing in VCs) might include... access to information ... [and an] expanded network." Both of these are key resources for entrepreneurs. This assertion can be corroborated by examining the trajectories of numerous entrepreneurs. For instance, Jitendra Gupta, an entrepreneur based in San Francisco, founded in 2009 Punchh, a loyalty platform for restaurants, groceries, retailers, and convenience stores. After seven years as CEO, he stepped aside (Punchh was acquired for one half billion dollars in 2021.) Among other activities, he invested in the KAE Capital Fund II in 2016, a fund that mainly focuses on investments in the consumer products, healthcare, and software sector. Two years later, he started a new venture, MyYogaTeacher, an online and interactive platform connecting students with Yoga experts.

In this paper, we study how being an LP in a VC fund affects an individual investor's subsequent entrepreneurial activity. While this is certainly not the only setting where we might expect knowledge transmission from investing, it is one where there are knowledgeable intermediaries that might facilitate learning, as opposed to settings such as crowdfunding.

It might be thought that identifying how investing in VC affects individual LPs would be empirically challenging. There are limited systematic data on the LPs of VC funds in the U.S. and many other nations, particularly when looking beyond the subset of public pension funds that have mandated disclosures. Moreover, comprehensive information about these LPs' entrepreneurial activities are often lacking, especially for the subset of firms that are not venture-backed.

We overcome this challenge by focusing on China, the second-largest venture market in the world and one with intense investor and policy interest (Cong et al., 2020; Huang and Tian, 2020). We assemble a unique dataset of that covers all firm creation and domestic VC activity in China. It combines the proprietary administrative business registry data (from the State Administration for Industry and Commerce, or SAIC) with the VC fundraising and investment records from Zero2IPO and Asset Management Association of China (AMAC). Our data contain the entirety of firm creation activities, the shareholders of these firms, VC equity investments, and the names and financial commitments of all limited partners from 1999 to 2018. The new, detailed data have rarely been used in previous studies, with the exceptions including Fei (2018) on the crowd-in effect of government programs on VC investments, Li (2022) on the role of government VC across business cycles, and Colonnelli et al. (2022) on private firms' aversion to VC investors with government ties.[1] Its availability can potentially expand the research agenda about limited partners in VC funds.

Another challenge is to address the endogeneity of the individuals' decision to invest in venture funds. An individual might become interested in biotechnology, and before launching the new venture, invest in such a start-up. But the two decisions need not bear a casual relationship. To address the interpretive challenge, we exploit two institutional features of the Chinese market. First, an aspiring fund has to register at the SAIC and obtain regulatory approval before it can launch in the market and make venture investments. There exist many "zombie" funds that registered at the SAIC and obtained the necessary approvals but failed to launch. This provides us with group of control funds that failed to reach the market.

Second, many funds rely on corporations as key investors. If corporate investors experience distress in a period prior to the formal approval of the funds' registration (but after they agreed to contribute capital), they are likely to default upon capital calls once the fund seeks to commence operations. These funds are unlikely to be launched. This allows us to construct a variable to predict funds' launch failures that is relatively exogenous to individual LPs' characteristics.

Our empirical investigation starts by comparing the entrepreneurial outcomes of individual LPs in

[1]The SAIC registration data have been recently used in a few other settings, including research on the impact of state ownership (Allen et al., 2019; Bai et al., 2020; Allen et al., 2021), firm creation (Bai et al., 2021; Barwick et al., 2022; Brandt et al., 2022), interregional investments (Shi et al., 2021), and share pledging (He et al., 2022).

VC funds that successfully launched to those of individual LPs in funds that failed to launch. Then we use the fraction of total committed capital from corporate LPs that encounter industry distress in the months before the fund's approval at the SAIC as an instrument for the fund's failure to launch. The economic rationale behind the instrumental variable is that if a fund receives more commitments from corporate LPs that experience financial distress, it is more likely that these corporate LPs will be unable to fulfill their financial obligations, hence leading to the failure of the fund.

We worry that poorer-quality entrepreneurs might invest in funds backed by worse managed corporations, which may introduce undesired heterogeneity. We thus only look at the component of financial distress that is unrelated to firm management. In particular, we define whether a corporate LP is in distress by examining its industry stock returns in the past six month prior to the approval of its SAIC registration. If the returns sharply underperform other industries, we define the corporate LP as being in distress. The main identification assumption is that the industry conditions experienced by corporate LPs in the six months prior to the approval of a fund's registration affect individual LPs' entrepreneurial activities only through whether the VC fund is successfully launched or not.

Using the IV approach, we first document a significant link between investing in a VC fund and individual LPs' entrepreneurial outcomes. After becoming an LP of a successfully launched VC fund, the average number of new ventures started by the individual LP per year will increase by about 0.07, which is about 17% of a standard deviation. Our estimate implies that on average an individual LP will create one more startup in 14 years after investing in VC, relative to their counterparts in the failed-to-launch funds. The result also obtains if we employ as a dependent variable the total number of ventures after becoming an LP .

We then examine the new ventures created by individual LPs. We compare the characteristics of ventures created after investing in a VC fund (new ventures) to those created prior to investing in VC (old ventures). We find about 30% of new ventures are in high-tech industries, as opposed to only about 20% of the old ventures. The new ventures are especially more likely to be in high-tech service (rather than high-tech manufacturing) industries. We find new ventures on average file more patents within three years after being founded compared to the old ones within the same period among individual LPs in the successfully launched funds relative to those in the failed-to-launch funds. However, we do not find they

hire more employees, suggesting a higher innovation efficiency within the new ventures.

Entrepreneurial spillovers occur both at the extensive and intensive margins. On the intensive margin, about half of individual LPs in the sample are entrepreneurs even before investing in any VC funds. We focus on this sub-sample of individual LPs (serial entrepreneurs) and adopt an alternative empirical strategy with the event study design using a matched sample. Thus, we employ a different empirical specification here, using a standard diff-in-diff framework without instrumental variables. In this analysis, we demonstrate a robust pattern that entrepreneurship increases after an individual invests in VC. We also show that the entrepreneurial spillover of being an LP is decaying over time: The incentive to create new ventures is strongest in the first two years after investing in VC and starts to decline afterwards.

What channels explain the presence of entrepreneurial spillovers to individual LPs? A learning channel might contribute because individual LPs access superior information about VCs' portfolio companies. Alternatively, a financial constraints channel can also explain the pattern. One might expect that investments in VCs can result in a substantial financial return to LPs. This would help ease the well-documented financial constraints facing entrepreneurs (e.g., Paulson et al., 2006; Adelino et al., 2015) and hence induce more firm creation. We find supporting evidence for the learning channel, but not for the financial constraints channel. Specifically, we find that the industry and patent classification codes of new ventures share more similarity to those of VCs' portfolio companies relative to the old ventures. The entrepreneurial spillover effect after investing in VC is strongest for first-time LPs, again consistent with learning. Inconsistent with the financial constraints channel, we do not find a significant increase in individual LPs' entrepreneurship in VCs with a successful exit in their portfolios.

We address various challenges to our identification strategy. One potential concern is that industry booms or busts directly affect the financial conditions of serial entrepreneurs' existing firms, changing their incentives to start new firms. Our main results remain to hold after excluding a sub-sample of affected LPs whose existing firms were in those boom-or-bust industries at the time of the approval of the VC fund's regstration. Another potential concern is that industry booms directly reveal new investment opportunities to LPs, leading them to create more new ventures aligned with these booming industries. We conduct a robustness test by excluding new ventures in booming industries, and our main results still hold.

Contribution to the Literature

This paper contributes to several strands of literature. First, our paper contributes to the literature on the roles of entrepreneurs and investors in financial markets. Previous studies largely treat entrepreneurs and investors as distinct, while in actuality, their identities overlap quite often. Gompers and Mukharlyamov (2022) find that transitions from startup founders to venture capitalists are quite common in the market, and successful founder-VCs enjoy a higher investment success rate compared to professional VCs. Even among institutions, sometimes LPs play different roles across market segments. Chernenko et al. (2021) study the recent trend of open-end mutual funds investing in private venture-backed firms. Also examining the Chinese market, He et al. (2022) find that the shareholders of listed firms are more likely to invest in VC/PE and start new firms due to the greater ability to pledge shares of publicly listed firms after the 2013 reforms. Unlike these papers, we show a transition from the role of investors to entrepreneurs in the market. It sheds light on the feedback effect across participants in the financial market and highlights the complementary experience and skills from investing in financial assets and entrepreneurship.

Second, our paper is related to the literature on LPs' returns from VC investments. The relative returns between the return of investing in VC and public equities have been extensively scrutinized. Prior work has focused on the direct financial returns (e.g., Kaplan and Schoar, 2005; Cochrane, 2005; Lerner et al., 2007; Harris et al., 2014; Korteweg and Nagel, 2016; Brown et al., 2021). We complement previous findings by documenting a non-pecuniary benefit of investing in VC funds, namely, the positive spillover to individual LPs' entrepreneurship after investing in a VC fund. Our results imply an indirect return to some LPs and uncover a new motivation for wealthy individuals to invest in VC.

Third, this paper speaks to the literature on the spillover effects of financial intermediaries. Prior work has shown that VCs facilitate exchanges of information and innovation resources (e.g., Lerner, 1995; Lindsey, 2008; González-Uribe, 2020; Li et al., 2021; Eldar et al., 2021) among their portfolio companies; corporate venture capital induces technological spillovers from invested startups to parent firms (e.g, Siegel et al., 1988; Hellmann, 2002; Gompers et al., 2005; Ma, 2020); and entrepreneurial spillovers from corporate R&D to their employees (e.g., Hellmann, 2007; Babina and Howell, 2018). In contrast, this paper adds to our understanding of how potential entrepreneurs learn. It uncovers that the

individual LPs - traditionally deemed as "passive" investors - proactively start new ventures after being exposed to VC investments.

Last, this paper contributes to the literature on information on entrepreneurial decision-making. In the setting of serial entrepreneurship, a number of prior studies have discussed the informational advantages of serial entrepreneurs (e.g., Gompers et al., 2010; Lafontaine and Shaw, 2016; Brandt et al., 2022). In another setting, Lerner and Malmendier (2013) identify informational spillovers from peers in entrepreneurial decisions and find that a higher share of entrepreneurial peers decreases entrepreneurship, mainly by reducing unsuccessful ventures. Sariri Khayatzadeh (2021) examines how entrepreneurs absorb information from angels, VCs, and their mentors to reduce the uncertainty in entrepreneurship. Wallskog (2022) investigates entrepreneurial spillovers across coworkers using the Census data. Supporting the role of information in entrepreneurial decision-making, she finds that an individual whose current coworkers have more prior entrepreneurship experience is more likely to become an entrepreneur in the future. Our paper adds to the literature by investigating a new mechanism through which entrepreneurs learn. Specifically, they strategically exploit financial intermediaries to "test the water" and pivot their new ventures to more innovative industries.

2 Data and Institutional Details

2.1 VC Data

We construct a novel dataset covering comprehensive records of VC fundraising, investments, and performance from 1999 to 2018 in China. The main data in our analysis come from the Business Registration Data (BRD), which are sourced from the administrative business registry at the SAIC in China. The BRD data seek to cover virtually all firms founded in China, as every company must register and obtain a commercial license from the SAIC before formally launching their operations. One advantage of the BRD data is that all firms' shareholders are reported when firms file their registrations. This implies that all funds' LPs (which are regarded as "shareholders" of the funds) are also documented in the data. Given the nature of the BRD data, our analysis focuses on LPs in VC funds which submitted registrations to the SAIC that were finally approved.

Besides the information on firms' registered capital and the respective ownership of their shareholders, the BRD data allow us to observe firms' names, their four-digit SIC industry code,[2] firms' scope of operation, their locations (street address, district, prefecture-level city, province, and Zipcode), firms' incorporation types, their organization codes and types,[3] at what time the firm obtained its SAIC registration approval (date), whether the firm is currently revoked or suspended, and if so when the revocation or suspension happened (date).

To obtain a complete list of VC funds and firms, we employ the commercial VC dataset Zero2IPO and a hand-collected VC list from the Asset Management Association of China (AMAC). Rather than exclusively using Zero2IPO data, which focus more on larger and foreign GPs, the combination with the AMAC data allows better coverage on domestic VC funds and firms in China. We combine the BRD data with the Zero2IPO and AMAC data to identify portfolio companies in which VCs are shareholders. The data on VCs' portfolio company exits (e.g., M&A or IPO) come from Zero2IPO. We supplement our data with other company performance measures, including companies' patent data from China National Intellectual Property Administration (CNIPA), and online job postings data from various online recruiting platforms. The patents included in the sample are those filed and eventually awarded in China by the CNIPA between 1999 and 2021. The job postings data contain the total number of online postings and the total number of employees firms intended to hire between 2013 and 2021. In Section OA-1 of the Online Appendix, we discuss our sample construction process in detail.

We limit the sample in some ways to avoid potentially confounding cases. In our analysis, we exclude VC funds with registered capital less than 1 million RMB (about $144,800) or more than 4 billion RMB (about $579 million). For any funds with registered capital less than 1 million RMB, we are concerned that these are not typical VC funds focusing on equity investments in high-tech industries. For large-size funds with registered capital more than 4 billion RMB, we believe these are overwhelmingly either fund-of-funds or government-led VC funds, in which individual LPs would be unlikely to play an active role. These cutoffs, and those reported below, are adjusted to 2019 RMB using GDP deflators.

[2]All SIC codes and the industry classification, and those used below, follow the Standard Industrial Classification for National Economic Activities (SIC) issued by the Standardization Administration of the People's Republic of China in 2017.

[3]The organization codes and types are from the China Organization Code system, which was launched in 1989. Chinese government has made it compulsory for all businesses, public institutions, social organizations, trade unions, and non-governmental organizations to have an organization code. The code has been applied to many occasions including banking, tax, foreign trade and customs.

To be included in the analysis, we also require an individual LP to commit at least 10,000 RMB (about $1,448) to a fund, to eliminate investments that are likely to be inconsequential. This ensures that individual LPs in our sample are having a nontrivial exposure to VC investments. Our main results are robust even without this sample filter.

2.2 Individual LPs

Using this information, our analysis focuses on a final sample of 70,414 individuals committed capital to 11,120 VC funds that obtained the SAIC approval and successfully launched in the market with portfolio company investments between 1999 and 2018. Besides individual investors who directly committed capital to VC funds, who are straightforwardly identified as individual LPs, we also include individual investors investing in VCs indirectly via a financial vehicle.[4] The reason we penetrate through the ownership structure of financial vehicles to identify individual LPs is that some individual investors prefer forming a "shell" financial company to invest in VC funds due to regulatory or tax reasons.

Figure 1 exhibits the aggregate trend of individual LPs' investments across years. Both the total investment amounts and total number of funds invested by individual LPs take off in 2009 and reach their peaks around 2015 and 2016. For instance, the total commitments by individual LPs in 2015 were about 80 billion RMB (equivalent to $12 billion). In the sample, individual LPs on average committed about 50% of capital of a fund.[5] Each fund has around eight individual LPs on average, and each of them invested about 6.4 million RMB (equivalent to $0.93 million), as shown in Panel A of Table 1. These tabulations indicate that individual LPs are a significant funding source in the Chinese venture market. This contrasts with those mature VC markets: the US VC market heavily relies on funding from institutional investors, such as university endowments, pensions, and corporations. For instance, in 2020 the relative penetration of individual investors in North America private equity funds (including VC, buyout, and other private capital funds) is only 10.7% (Zakrzewski et al., 2022).

Figure 1 also indicates a big drop in individual LPs' investment activity in 2018. The crash, which

[4]Financial vehicles in the paper are defined as financial business entities whose four-digit industry code is 6740, 6760, 6900, 7212, or 7299. These four industry codes cover the majority of non-bank financial vehicles in China.

[5]This ratio is not equal to the total amount invested by individual LPs in a fund (50.991 million) divided by the fund size (165.79 million) since individual LPs are relatively concentrated in smaller-size funds. So when we average the total percent of capital invested by individual LPs across funds, it is higher than the ratio of the mean of total amount invested by individual LPs within a fund to the mean fund size.

was felt in Chinese venture fundraising as a whole, was mainly driven by the issuance of new Chinese regulations in April 2018, "Guiding Opinions on Regulating the Asset Management Business of Financial Institutions." This new regulation was a precursor of China's government tightened regulatory scrutiny over tech industries, including the crackdown on Internet giants and online tutoring sector in 2021. These regulatory changes altered the perception on high-tech ventures, reducing entrepreneurs' incentives to start new firms. To address the concern that this (and subsequent) regulation might contaminate our documented effects, in Table OA2.1 of the Online Appendix we conduct a robustness check for our main analysis (Table 3) by excluding any observations after April 2018.

We are particularly interested in the subset of individual LPs who are entrepreneurs. We define entrepreneurs as shareholders of another non-financial company with at least a 5% ownership stake. We require the non-financial company to have an initial registered capital between 200,000 RMB (about $29,000) and 200 million RMB (about $29 million). Imposing a lower bound on firms' registered capital is to exclude consulting/marketing businesses of individual LPs that could potentially be auxiliary companies to their main businesses. The upper bound helps us avoid huge public-private partnerships in the infrastructure and finance industries.[6] Though we use 5% as the cutoff, an average entrepreneur in our sample owns about 47% shares of a prior firm. One potential concern is that some angel investors may be mis-categorized as entrepreneurs. To address this concern, we conduct a robustness check by excluding potential angel investors, defined as shareholders of five or more startups and with equity stakes in each case below 25%. Our main results are robust, as shown in Table OA2.2 of the Online Appendix.

Among all individual LPs in the sample, we find 54.8% of them are entrepreneurs at any time during the sample period. 48% of them had already started a company before deploying any money in a VC fund as an LP. The median gap between the incorporation of their first company and their VC fund investment is 8.4 years conditional on having formed a company prior to the VC investment.

[6]Though the new version of the Company Law of the People's Republic of China removed the requirement in 2014, the old version imposed a minimum registered capital on newly-established firms across industries, which was in effect for most of our sample period. Based on the minimum registered capital requirement in the Company Law, our lower bound (200,000 RMB) only excludes a few types of firms in the consulting industry, including management consulting, trademark office, firm registration agency, market research agency, certification agency, etc. We think it is reasonable to exclude them as they might be auxiliary firms to individual LPs' main businesses. The upper bound (200 million RMB) only excludes a few types of firms in finance and telecommunications infrastructure industries, including insurance, banking, mobile networks, satellites, cables, etc. These businesses are largely controlled by the government and individual LPs could only participate through public-private partnerships, which are not regarded as typical entrepreneurship discussed in the literature.

These individual LPs founded 111,051 companies in total in the sample, 78,712 of which were established before or in the year when they first invested in a VC fund and 32,339 of which were new ventures created after becoming an LP. To eliminate cases of co-investment in VCs' portfolio companies, we exclude companies backed simultaneously by a VC fund and its individual LPs.

As for the background of individual LPs, Figure 2 shows the top 10 industries of their existing firms before investing in any VC. They are spread across wholesale/retail, manufacturing, R&D, leasing/commercial service, real estate, IT/software, construction, sports/entertainment, finance, and resident service.[7] For individuals owning business in multiple industries, we only consider the one in which they invested in most capital. In terms of the average invested amount per individual, LPs from the real estate and finance industries commit significantly more capital to funds, around 50% higher than LPs from other industries.

Regarding the demographic information of individual LPs, we use their first names to predict their gender, based on the 2010 Chinese Census Data. For a given name, we compute the probability of being a female in the sub-sample of individuals sharing the same name in the Census data. If the probability is greater than 0.5, we define the gender of an individual investor as female. Based on our calculation, we find that only 27.7% of these individual LPs are females.

We also make a simple comparison between those individual LPs who are entrepreneurs (so-called entrepreneur LPs) and those who are not (non-entrepreneur LPs). Table 2 shows that entrepreneur LPs generally invest in more VC funds (1.28 vs 1.22 funds per person), commit a higher ratio and a larger amount of capital per fund than non-entrepreneur LPs (7.4% vs. 4.8% and 8.02 million vs. 4.44 million RMB). The size of VC funds invested in by entrepreneur LPs are sightly smaller and these funds generally have more portfolio companies. Moreover, females are more represented among non-entrepreneurs LPs (33.1%) than entrepreneur LPs (23.2%). The entrepreneur LP have on average owned 3 ventures, with about 2.2 ventures created before investing in VC and 0.8 venture after becoming an LP. Their overall speed of venture creation is about 0.15 venture per year. Comparing the speed before and after investing in VC, it increases from 0.13 venture per year to 0.24 venture per year.

[7]Here we use the first-digit SIC code to define industries. For example, the industry of resident service includes the provision of residential care combined with either nursing, supervisory or other types of care as required by the residents and the repair and maintenance of computers peripheral equipment, communications equipment and consumer electronics, home and garden equipment, and other personal and household goods. The industry of R&D includes the activities of basic research, applied research, experimental development and the provision of other professional scientific and technical services.

3 Entrepreneurial Spillovers

3.1 Empirical Strategy

We wish to examine the consequences of venture investments by individual LPs on their decision to begin new businesses. But a naive analysis of this might pose a number of interpretative issues.

In particular, directly estimating ordinary least squares (OLS) might introduce bias due to endogeniety. For instance, an individual less interested in starting a new venture herself might be more willing to allocate her wealth to financial investments, including VC. As a consequence, the choice to invest in VC could be associated with a lower desire to create new ventures because of the inherent characteristics of individual investors, which is difficult to control for in OLS regressions. More generally, investors who chose not to invest in VC could be fundamentally different from individual LPs.

To overcome this concern, we adopt an empirical design similar to Seru (2014) and Bernstein (2015), in which we narrow the focus to individuals who aspired to become LPs in venture funds. In particular, we compare the entrepreneurial activity of individual LPs in funds that eventually launched with potential LPs in those funds that failed to launch. In the analysis, we define a VC fund that does not invest in any portfolio companies in the year after its registration is approved by the SAIC as one that failed to launch. This echos the fact that most VC funds in China already have a set of targets that they intend to invest in when registering at the SAIC, so that the very first capital call is typically made within a few months of the fund's approval. Figure 3 illustrates our empirical design.

All domestic VC funds must register at the SAIC before making the first capital call and launching investments in the market. The general process of VC fund registration in China is as follows. When VC firms decide to raise a fund, they will reach out to potential LPs, who then respond with their tentative commitments. After reaching the fundraising goal, VC firms then register the fund and list those potential LPs at the SAIC and AMAC. However, these commitments are subject to change due to LPs' idiosyncratic situations. As a result, not all funds whose registrations are approved launch successfully, as some LPs might be unable or unwilling to meet capital calls. For instance, the unexpected introduction of "Guiding Opinions on Regulating the Asset Management Business of Financial Institutions" in April 2018 stopped all bank LPs from deploying capital into the VC market, even if they have already made

capital commitments.

We compare the entrepreneurial activities of individual LPs in VC funds that successfully launched to individual LPs in funds which got registration approvals from the SAIC but ultimately failed to launch. We use a *cross-sectional* specification as follows:

$$Y_{ijt}^{post} = \alpha + \beta LaunchedVC_{ij} + Controls_{ijt} + \mu_j + \delta_t + \varepsilon_{ijt} \quad (1)$$

where Y_{ijt}^{post} is the average number of ventures per year (or the total number of ventures) created by individual LP i after investing in VC fund j that got the SAIC registration approval in year t, $LaunchedVC_{ij}$ is an indicator if VC fund j was successfully launched, μ_j are the fund manager fixed effects, and δ_t are the fund registry-year fixed effects. In the regression, we include LP i's gender, the total number of firms that LP i has started before investing in VC j, an indicator if LP i has invested in any other VC funds previously, the natural logarithm of fund j's size, and the ratio of LP i's committed capital to the total fund size in the VC fund as control variables. In our regressions, we winsorize our variables over the entire sample at the 0.5% level to remove extreme outliers. Table OA2.3 in the Online Appendix compares the characteristics of individual LPs in the successfully launched funds and these in the failed-to-launch funds.

However, whether a VC fund launches successfully is not entirely exogenous. If the launch outcome is related to VCs' unobserved features or individual LPs' inherent characteristics, then β might be biased. Therefore, we instrument for the launch success of a VC fund with the portion of total committed capital from corporate LPs that encounter industry distress in the fund. Our instrument exploits the theory of coordination frictions (e.g., Nanda and Rhodes-Kropf, 2019) between LPs. Typically, general partners (GPs) seek potential capital commitments from various sources: wealthy individuals and families, large institutional investors, and corporations (Gompers and Lerner, 2004). If a few prospective investors default on their commitments due to exogenous reasons, a VC fund would be unlikely to launch unless GPs can find other investors to fill the hole. For instance, *Weifang Mingcai Investment LLP* was a VC fund that obtained its registration approval from the SAIC in November 2017, with 79.8% of its committed capital from a corporate LP, *Zhaotong Yulong Construction Company*. The six-month average stock return of the real estate construction industry, in which *Zhaotong Yulong* is operating, was about

-22.18% between May and November 2017, underperforming most industries. Consistent with our hypothesis, this fund never launched operations. During the industry downturn, a corporate LP would be less likely to provide capital to *Weifang Mingcai*, leading to a failure to launch.

Thus, we hypothesize that a VC fund with more corporate LPs that experienced negative shocks during the fund registration process will be more likely to fail in the launch. Figure 4 illustrates how we construct the IV. Specifically, we create an instrument for the endogenous variable *Launched* VC_{ij} in Equation (1) as follows. For fund j, we compute the sum of the share of committed capital, h_{jk}, from corporate LP k that experienced financial distress. Let S_j denote the set of all corporate LPs in fund j. We define a corporate LP k as experiencing financial distress at time t (when the fund's registration is approved) if the past six month stock return of the two-digit SIC-code industry where corporate LP k is assigned to is at the bottom quintile among all two-digit SIC-code industries in the economy at time t. We use the industry instead of firm-level stock returns since we believe it is a component of financial distress that is unrelated to firm management. Firm-level stock returns might introduce undesired heterogeneity, as lower-ability entrepreneurs might invest worse companies. Therefore, given a fund obtaining its SAIC registration approval at time t (in months), we compute stock returns between $t-6$ and t for all two-digit SIC-code industries in the economy and identify a subset of bottom 20th percentile industries as the distressed ones. This period roughly corresponds to the gap between filing of registration with the SAIC and the registration approval (2nd and 3rd bars in Figure 4). Then we define the fraction of committed capital of any corporate LPs coming from these distressed industries as our IV.

Our IV for the variable *Launched* VC_{ij} is thus:

$$\text{Portion of Distressed Corporate LPs}_{ij} = \sum_{k \in S_j} \mathbf{1}\{k \in \text{Distressed Industries}\} \times h_{jk}. \tag{2}$$

We set the instrument to zero if the set S_j is empty. We compute a sum in Equation (2) because having more committed capital from corporate LPs in distressed industries make it less likely to that the VC fund managers will find other investors to fill the gap, leading to a higher probability of launch failure. In our analysis sample, for a fund having at least one corporate investor as an LP, corporate LPs on average contribute about 45% of its total capital. For a fund having at least one LP in distressed industries, on average the distressed corporate LPs contribute about 33% of the fund's capital. In total there are 939

funds containing distressed corporate LPs out of 20,519 funds, and 2,914 individual LPs among these funds out of 94,950 individual LPs.

Note that in constructing the IV, we use changes in stock returns prior to the approval of the funds' SAIC registrations (Time t in Figure 4). It captures the possible deterioration of corporate LPs' financial conditions during a period in which they could have already agreed to contribute capital to the fund (i.e., while the registration statement is being prepared and the statement is being reviewed at the SAIC). Six months is a reasonable time window to look at since on average it takes three to five months for a fund to complete fundraising and an additional two to three months for approval at the SAIC. If an industry shock hits during the six-month window, when the fund makes the first capital call after SAIC approval, the affected corporate investors are less likely to fulfill their commitments. We choose the bottom 20th percentile as the cutoff as it reflects a severe financial change: the industry at the cutoff has an average return of negative 22.11% and a median return of negative 16.53% in the six-month window.

Our main identifying assumption is that the instrument affects the outcome variable Y_{ij}^{post} only through its effects on funds' launch outcomes. Why is the exclusion restriction plausibly satisfied? Our IV test boils down to examining that, conditional on investing in a VC fund, an individual fund is less likely to start operations if a significant fraction of its capital is coming from corporate LPs that experienced industry distress. We believe the exclusion restriction plausibly holds because the LP industry-specific stock returns in the six months prior to the fund approval are unlikely to be correlated with unobserved shocks to individual LPs, including their entrepreneurial ability and unobserved quality differences across firms that they are about to create. We conduct more robustness checks to address possible identification challenges in Section 5. Our main results still hold.

At first glance, Equation (1) seems like a "difference-in-differences" analysis. It is worth highlighting that our specification is essentially a *cross-sectional* comparison, similar to Bernstein (2015), examining differences in entrepreneurship between two groups of individual LPs after committing to invest in VC funds. Recent critiques on staggered differences-in-differences analysis (e.g., Borusyak et al. 2021; Callaway and Sant'Anna 2021; Goodman-Bacon 2021; Sun and Abraham 2021; Baker et al. 2022; Athey and Imbens 2022) are less relevant in our analyses, as they do not involve dynamic timing issues commonly encountered with panel data. Furthermore, we conduct a robustness check by excluding individual LPs

with changing treatment statuses, e.g., those that first invest in a failed fund (control group) and later invest in a successful fund (treated control), or vice versa. Our main results still hold, as shown in Table OA2.4 of the Online Appendix, which helps alleviate the concerns about difference-in-differences analyses.

3.2 Empirical Results

We first report our OLS regression results from Equation (1) in columns (1) and (2) of Table 3. Columns (1) uses the total number of ventures created by individual LPs after committing to investing in a VC fund as the dependent variable. Though it does not provide a causal interpretation, the estimate provides useful suggestive evidence. The coefficient on *Launched VC*$_{ij}$ is positive and statistically significant at the 1% level. After becoming an LP in a successfully launched VC fund, the individual investor starts a total of 0.035 more ventures afterwards relative to LPs who invested in funds that failed to launch. One potential issue is that the dependent variable, total number of ventures, might suffer data truncation, as our sample ends in 2018. To this end, in column (2) we instead use the average number of ventures created per year after committing to invest in a VC fund as the dependent variable. The coefficient on *Launched VC*$_{ij}$ is consistently significantly positive, implying that individual LPs on average create 0.01 more ventures per year than LPs who invested in funds that failed to launch. Section 5 shows that our results also hold using the Cox proportional hazards model with panel data. We prefer the cross-sectional linear model because the Cox model does not easily accommodate fixed effects and the IV.

Our IV test is shown in columns (3) to (5) of Table 3. To have a valid IV, the relevance condition has to be satisfied. Column (3) presents the first-stage regression result. The dependent variable is equal to one if a VC fund is eventually launched and zero otherwise. We find that the coefficient on the portion of total committed capital from corporate LPs in distressed industries equals -0.272 and is significant at the 1% level. It indicates that a 10% increase in committed capital from corporate LPs in distressed industries is associated with a 2.72% decrease in the likelihood of VC funds' successful launch. A conservative version of the F-statistic, Kleibergen-Paap rk Wald F-statistic, is equal to 37.84 and greater than the threshold of 10, which strongly rejects the null that the instrument is a weak one. This supports

the relevance condition for our IV.

Figure 5 exhibits the non-parametric relation (local polynomials) between the portion of total committed capital from corporate LPs in distressed industries within a VC fund and the likelihood of a successful fund launch. It shows a robust negative correlation. The probability of successful launch drops from about 0.5 to 0.2 if the portion of total committed capital from corporate LPs in distressed industries increases from 0.1 to 0.9, again strongly supporting the relevance condition of our IV.

Columns (4) and (5) report the second-stage results. Column (4) uses the total number of ventures created after investing in a fund as the dependent variable. The coefficient on *Launched* VC_{ij} is significant at the 5% level and equals 0.315, implying that after becoming an LP in a successfully launched fund, the total number of newly created ventures by the individual LP on average increases by 0.315, which is 27% of the dependent variable's standard deviation (=0.315/1.169, where 1.169 is the standard deviation of the total number of newly created firms by investors included in the sample of Table 3). Column (5) uses the average number of ventures created per year as the dependent variable. The coefficient on the focal variable is still significant at the 5% level and equals 0.069, which is equivalent to 17% of the dependent variable's standard deviation (=0.069/0.409, where 0.409 is the standard deviation of the average number of ventures created annually by individual LPs in the sample included in Table 3). Alternatively, the coefficient indicates that individual investors on average start one more new venture in about 14 years (=1/0.069) after becoming LPs in VC funds. To have a better sense about the magnitude, the mean rate of new firm formation in the analysis sample is 0.133 venture per year, implying that an individual on average starts a new venture in about 7.5 years. These results suggest a strong positive entrepreneurial spillover from VCs to their individual LPs.

The magnitudes of our IV estimates exceed their OLS counterparts. It makes sense because our IV regressions potentially estimate a local average treatment (LATE), which could be larger than the population average treatment effect (Jiang, 2017). Notice that our IV-compliers are potentially those VC funds with closer ties to corporate LPs since they are more often to seek committed capital from corporations. Therefore, these VCs are more sensitive to the changes in their corporate LPs' financial situation and hence more responsive to our IV. Given their closer ties to the corporate world, this group of VCs is likely to exhibit larger LATEs. Why? They might be more attentive to industry trends, more acute

to potential investment opportunities and new technologies, and better equipped with industrial expertise and insights. When individual LPs invest in such VCs, LPs may gain more exposure to these skills and expertise through interactions with VCs. Hence we are expecting a larger entrepreneurial spillover to individual LPs in the IV estimation.

Another potential reason for the IV-OLS estimate gap in our paper could be measurement error in the regressor "*Launched* VC_{ij}". So our OLS regressions may be biased down due to the attenuation bias, while the IV regressions can potentially recover the true effect (Pancost and Schaller, 2021). To gauge how measurement error contributes to our IV-OLS estimate gap, we follow Pancost and Schaller (2021) in computing the measurement error ratio. This ratio, lying between zero and one, quantifies the extent to which measurement error bias dilutes the true effect. A ratio closer to one means that the attenuation bias due to measurement error is less severe in the OLS estimate. Specifically, by using the two IV-OLS pairs with the same regressor *Launched* VC_{ij} but different dependent variables in Table 3, we compute the measurement error ratio in our setting, which is equal to 0.896. Though this ratio is higher than the average measurement error ratios in the finance and economics literature surveyed by Pancost and Schaller (2021), it points to the direction that measurement error in *Launched* VC_{ij} partially explains the inflation of our IV estimates. One caveat is that we are using only two IV-OLS pairs to compute the measurement error ratio while Pancost and Schaller (2021) require a paper to have at least six pairs. So our calculation of the measurement error ratio may be noisy.

3.3 What Do the LPs' Newly Created Ventures Look Like?

Having shown that LPs in successfully launched funds are more likely to start new ventures than their counterparts, in this section we investigate what these newly created ventures look like. We compare the characteristics of companies created before investing in a VC fund (old ventures) to these of companies created afterwards (new ventures) by individual LPs in successfully launched funds relative to failed-to-launch funds along three different dimensions: industry, patents, and online hiring.

First, we find that the new ventures are more likely to be in high-tech industries. To facilitate the comparison, we focus on a sub-sample of ventures created by individual LPs in successfully launched VC funds (treated group). We define high-tech industries according to the Classification Criteria published

by the National Bureau of Statistics of China in 2017 and 2018. High-tech industries are divided into high-tech manufacturing and high-tech service industries.[8] As Figure 6 shows, the fraction of new ventures being in high-tech industries is 30%, significantly higher than that among old ventures (18%). This difference is mainly driven by the popularity of new ventures in the high-tech service rather than high-tech manufacturing industries.

In addition, we find that the new ventures file more patents than their old counterparts in the successfully launched funds relative to the failed-to-launch funds. Specifically, we construct a sample of ventures created by LPs. The unit of observation is each venture of an individual LP. We modify our Equation (1) and use the following cross-sectional specification:

$$\begin{aligned} V_{ijkt} = & \beta_1 \textit{Launched VC}_{ij} \times \textit{Post-LP Venture}_{ikt} + \beta_2 \textit{Launched VC}_{ij} + \beta_3 \textit{Post-LP Venture}_{ikt} \\ & + FEs + Control + \varepsilon_{ijkt} \end{aligned} \tag{3}$$

where V_{ijkt} are the outcome variables for venture k: the total number of patents filed (and eventually awarded) by a firm in two or three years after its formation and the total number of employees a firm intends to hire online within two or three years after their formation. $\textit{Launched VC}_{ij}$ is defined as the same way as in Equation (1). $\textit{Post-LP Venture}_{ikt}$ is an indicator equal to one if venture k was created after individual LP i invested in any fund at time t. The coefficient of interest is β_1, which measures the differences in outcomes of new ventures (relative to old ones) created by an individual LP in a successfully-launched fund compared to the difference for LPs in a failed-to-launch fund. In the regression, we control for the LP's gender, whether the LP has invested in any other funds before fund j, the fund size, the LP's committed capital as a share of fund size, venture k's size measured by the log of its registered capital, the location of the venture, and the LP's ownership stake in venture k. We control for the year in which the VC fund's registration was approved and GP fixed effects in Equation (1). We also include industry fixed effects and venture-founded year fixed effects to control the industry trends or policy changes regarding patenting (or hiring).

[8]The high-tech manufacturing industries include pharmaceutical manufacturing, aviation, spacecraft and equipment manufacturing, electronic and communication equipment manufacturing, computer and office equipment manufacturing, medical equipment and instrumentation manufacturing, and information chemical manufacturing. The high-tech service industries include information services, e-commerce services, inspection and testing services, high-tech services in the professional technical service industry, R&D and design services, scientific and technological achievements transformation services, intellectual property and related legal services, environmental monitoring and governance services, and other high-tech services.

The results are reported in Table 4. Columns (1) and (2) indicate that new ventures created by LPs in the successfully launched funds tend to file more patents. For example, column (1) shows that the new ventures on average file 0.01 more patents than old ventures in the two years after being founded by an individual LP in a successfully launched VC fund, compared to ventures by an LP in a failed-to-launch fund. This magnitude is equivalent to 2.9% of the dependent variable's standard deviation (=0.01/0.342, where 0.342 is the standard deviation of the average number of filed-and-eventually-granted patents of a venture within two years of being founded). Consistently, column (2) implies the difference for LPs of successful funds is 0.015 more patents within three years after being founded, again relative to LPs of successful funds. This pattern is consistent with the prior evidence that new ventures are more likely to be in high-tech industries.

Columns (3) and (4) exhibits the outcomes of online hiring in two and three years after a venture was founded. The number of observations shrink in the regressions of columns (3) and (4) because the online hiring data are only available after 2012. In contrast to the patent outcomes, the difference for new ventures of successful LPs is not significantly greater than that of LPs of unsuccessful funds. The coefficients on $\textit{Launched VC}_{ij} \times \textit{Post-LP Venture}_{ikt}$ are negative and insignificant, with a t-value of -0.25 and -0.30 in columns (3) and (4). Given the greater innovation output and the insignificant change in the number of employees, the table suggests that the innovation efficiency of new ventures of LPs in successful funds is higher.

3.4 Serial Entrepreneurs

In our sample, about a half of individual LPs are already entrepreneurs before investing in VC (Panel B of Table 1). This is an important group of individual LPs as they contribute about 72% of new venture creations after investing in VC among all the individual LPs in the sample. We call this group of individual LPs the serial-entrepreneur LPs. Given its prominence, we utilize this sub-sample to conduct an alternative set of empirical tests, which deviates from the IV analysis in Section 3.2 and uses the standard diff-in-diff techniques without IVs. It offers a different perspective on the impact of investing in VC. In addition, we can compare the old and new ventures created by this group of individual LPs before and after investing in any venture funds.

For the alternative empirical strategy, we adopt a standard difference-in-difference design using a matched sample rather than an instrumental variable. We construct a control group for the sub-sample of serial-entrepreneur LPs in successfully launched VC funds (treated group). A coarsened exact matching is implemented (Davis et al., 2014). To be considered as a potential control, we select from the universal sample of entrepreneurs in the BRD data who are owners of non-financial companies (at least 5%) and had never invested in any VC funds during our sample period. We drop those who are or used to be shareholders or executives of VC firms (GPs).

We implement one-to-one matching for this analysis. Two matching scenarios, depending on the number of companies owned by an entrepreneur, are considered. In the first scenario, we focus on the serial entrepreneur LPs in the treated group who own only one company in the year that they first invest in a VC fund (we do not count companies that the entrepreneur has already exited). We match each of them with an entrepreneur in the control group who owns only one company in that year, whose company operates in the same two-digit SIC industry, belongs to the same incorporation type, is located, and, in the same city. Then, we divide two continuous variables-the share of the company's equity held by the entrepreneur and the registered capital of the company-into sixteen cells with roughly equal number of members in each. We require their holding shares of the company and the company's registered capital to be in the same cell for both the treated unit and the control. In the second scenario, we consider the sub-sample of serial-entrepreneur LPs who run two or more startups in the year that they first invest in a VC fund. We proceed as before, but divide three continuous variables-besides the two used beforehand, an extra variable is the number of companies owned by an entrepreneur-into sixty-four roughly equal cells. We then use the characteristics of the representative company in which they invested the most capital, and then repeat our matching process. Our matching procedure yields that 95.3% of serial entrepreneur LPs in the treated group can be matched to a control entrepreneur.

Correspondingly, our specification is as follows:

$$Y_{it} = \beta_1^{All} Post_{it} + \beta_2^{Real} Treated_i \times Post_{it} + \tau_t + \gamma_i + Control + \varepsilon_{it} \tag{4}$$

where Y_{it} is the number of ventures created by individual i in year t, $Post_{it}$ is an indicator variable equal to one if individual i (or her counterpart in the treated group when i is in the control group) has invested

in a VC fund by year t, and $Treated_i$ is a dummy equal to one if for individuals with $Launched\ VC = 1$.[9] We also include individual and year fixed effects in the specification. Note the variable $Treated_i$ itself is not included in Equation (4) since it is absorbed by the individual fixed effects γ_i.

We report our regression results of Equation (4) in Table 5. The coefficient of interest is β_2^{Real}, i.e., the interaction term. A positive β_2^{Real} suggests that individuals create more ventures after they become LPs of VC funds than the matched controls. Columns (1)-(5) report the OLS estimates with varied controls and fixed effects. The coefficient β_2^{Real} remains significantly positive and stable, ranging from 0.06 to 0.02, when we add controls gradually from column (1) to column (5). All estimates are statistically significant at the 5% or 1% levels. The coefficient estimates imply a large entrepreneurial spillover after investing in a successfully launched VC fund. For instance, column (5) of Table 5 indicates that, after investing in VC, individual LPs on average create 0.018 more ventures per year, which is equivalent to 4.4% of the dependent variable's standard deviation (=0.018/0.411, where 0.411 is the standard deviation of the number of firms created in a year by individual LPs or their matched control units within the sample period). This magnitude lies in between our OLS and IV estimates in columns (2) and (5) of Table 3.

To investigate the dynamic effects before and after an individual invests in a successfully launched VC fund, we use an event-study design following Jaravel et al. (2018). We employ a full set of leads and lags around the first year investing in a successful VC fund by individual LPs (L_{it}^{Real}) and the associated coefficients ($\left\{\beta^{Real}(k)\right\}_{k=-5}^{5}$), where k denotes the relative years before and after investing in a VC fund for the first time; a full set of leads and lags around the first-time VC investments in VC for both actual and placebo individual LPs (L_{it}^{All}) and the coefficients associated with them ($\left\{\beta^{All}(k)\right\}_{k=-5}^{5}$); year fixed effects ($\tau_t$); and individual fixed effects (γ_i). So the model of the event study is[10]:

$$Y_{it} = \sum_{k=-5}^{5} \beta^{Real}(k)\mathbf{1}\{L_{it}^{Real} = k\} + \sum_{k=-5}^{5} \beta^{All}(k)\mathbf{1}\{L_{it}^{All} = k\} + \tau_t + \gamma_i + Control + \varepsilon_{it}. \tag{5}$$

We report our event study estimation results of Equation (5) in Figure 3. We find the difference in the number of ventures created by individual LPs and their matched controls in a year, which is $\beta^{Real}(k)$ in

[9] In our research design, similar to Jaravel et al. (2018), the matching step implies that the placebo individual LPs in the control group inherit the counterfactual year of investing in VC with the corresponding real individual LPs in the treated group.

[10] We bin observations where k beyond 5 (-5) into $k = 5$ ($k = -5$). In the regression, we omit the lag dummies for $k = -1$ by benchmarking this year.

Equation (5), is not statistically significant before the event year. It suggests that our pre-trend assumption is largely satisfied and the entrepreneurial activity of the treated group is almost identical to that of the treated group. This is mechanical due to our exact matching procedure. After the event year, Figure 7 shows that the coefficients, $\beta^{Real}(k)$, have positive estimates up to two years after the event. This indicates that the number of ventures created by individual LPs is significantly larger than the control group in the first two years after investing in a venture fund. However, after peaking in the first two years, the coefficients gradually decay to zero and become insignificant in the third year and after. This closely matches Chinese funds' life cycle dynamics: venture funds in the first two years of their life actively identify and invest in portfolio companies.[11] Entrepreneurial spillovers from VCs to individual LPs flow when VC funds are actively investing.

4 Potential Channels

Our empirical findings unveil that individual LPs start more ventures after investing in a VC fund. These newly created ventures tend to be high-tech firms and to file more patents. In this section, we discuss two potential explanations for the findings. We find supporting evidence for the learning hypothesis but not for the financial constraints hypothesis.

4.1 Learning Hypothesis

One potential channel to explain individual LPs' entrepreneurial spillovers is the learning effect. Besides financial returns, investing in VC funds may enable LPs to interact with GPs and learn more about entrepreneurship. We thus expect that the characteristics of newly created ventures after becoming an LP should be more influenced by portfolio companies. Indeed, we find evidence supporting the learning hypothesis. Relative to the old ventures, the new ones more resemble VCs' portfolio companies in terms of the industry and technology fields,

First, we provide visual evidence that the industry distribution of new ventures are closer to that of VCs' portfolio companies than the old ventures. Figure 8 restricts our comparisons to a sample of

[11] By analyzing the universal venture investment records between 1999 and 2018 in China, we compute the median and mean time when a venture investment was made, which is at 18 months and 28 months after funds obtaining their SAIC registration approvals.

ventures created by individual LPs in successfully launched funds (the treated group). The fraction of portfolio companies in the R&D industry is relatively high (39%). We also find this ratio tends to be higher for new ventures by the LPs (21%) compared to the old ones (14%). Similarly, the percentage of portfolio companies in the wholesale and retail industry is relatively low (8%). We find that this percentage is lower for the new ventures (18%) relative to the old ones (28%).

Second, we examine whether the new ventures share more similarity with the portfolio companies in terms of four-digit industry codes and three-digit patent classification codes using primary assignments of the patents relative to the old ventures. The patent classification codes are from the International Patent Classification (IPC) system in 2021. Since we only focus on the ventures created by individual LPs in the treated group, we use the following specification:

$$V_{ikt} = \beta_1 \textit{Post-LP Venture}_{ikt} + FEs + Control + \varepsilon_{ikt}. \tag{6}$$

In our regressions, the unit of observation is a venture by an individual LP. The dependent variable V_{ikt} is an indicator equal to one if venture k created by individual LP i shares the same four-digit industry code with any portfolio company of the VC funds in which individual LP i invested.

Alternatively, the unit of observation is each patent by a venture of individual LP. We include all patents filed (and eventually awarded by the CNIPA) by firms after their formation between 1999 and 2021 in the analysis. The dependent variable V_{ikt} in this case is equal to one if a patent filed (and eventually granted) by venture k of individual LP i after k's formation shares the same three-digit patent classification code with any patents filed by portfolio companies of the same VC funds in which individual LP i invested. The independent variable *Post-LP Venture*$_{ikt}$ is an indicator whether venture k was created after individual LP i invested in any VC fund at time t.

Table 6 shows the regression results. In columns (1) and (2), the dependent variable is whether the new venture shares the same four-digit industry code with any portfolio companies. We use both the Probit and linear probability models to estimate β_1. The coefficients on *Post-LP Venture* in both columns are positively significant, implying that the new ventures are more likely to be in the same four-digit industry as the portfolio companies compared to the old ones. Similarly, columns (3) and (4) show that the patents filed by new ventures also have a higher chance to be of the same primary field as those

patents filed by VCs' portfolio companies. When comparing the industry overlap in columns (1) and (2), we control for the venture's size, location, if it ever received a VC investment, and industry and founded-year fixed effects. When examining the patent classification overlap in columns (3) and (4), in addition to the venture-level controls mentioned above, we include patents' primary field classification and patent application year fixed effects.

We also examine the extent to which the learning channel affects entrepreneurial outcomes of LPs in that invest in multiple funds. We would expect the marginal benefit of learning diminishes in the number of fund investments, simply because individual LPs would have more exposure to the venture process. We therefore predict a decreasing effect on entrepreneurship when individual LPs invest in multiple VC funds. To test this story, we adopt a variant of Equation (1) by including a dummy, *Veteran* LP_{ij}, equal to one if individual LP i has previously invested in VC funds before fund j and its interaction term with *Launched* VC_{ij}.

Regression results are reported in Table 7. The coefficient of interest is on our interaction term, *Launched* $VC_{ij} \times$ *Veteran* LP_{ij}. Column (1) shows that compared to a first-time LP, a veteran LP creates about 0.04 fewer total number of ventures after investing in VC, though the coefficient is not statistically significant. Column (2) shows that the average number of new firms created by a veteran LP is 0.02 fewer than a first-time LP, statistically significant at the 5% level. Both results are again consistent with the learning channel: there is a decreasing benefit from learning after investing in multiple VC funds.

4.2 Financial Constraints Hypothesis

Another possible channel is through relaxing the financial constraints of entrepreneurs (Evans and Jovanovic, 1989). Being an LP means a chance of cash windfall if the VC fund does successful transactions. The capital distributions from the VC fund can potentially relieve individual LPs' financial constraints, inducing more firm creation afterwards. If the financial constraints faced by individual LPs indeed hinder their entrepreneurship, we would expect the effect of investing in a VC fund on individual LPs' entrepreneurial outcomes are more pronounced for a fund having successful exits (namely, portfolio companies going public or being acquired).

To test this channel, we implement a similar specification as Equation (1), now including an indicator

variable *Portfolio Exit*$_{ij}$ equal to one if fund j invested by individual LP i has any successful exits in its portfolio companies between the time of the fund's establishment and 2018, and its interaction term with *Launched VC*$_{ij}$. For this channel to work, we predict the coefficient on *Launched VC*$_{ij}$ $\times$ *Portfolio Exit*$_{ij}$ should be significantly positive. However, our results go against this prediction, as shown in Table 8. Column (1) reports the estimated coefficient for the total number of ventures created after investing in a VC fund. We still have a positive slope, but it is statistically insignificant. Column (2) reports the result for the average number of ventures per year. The estimated coefficient on *Launched VC*$_{ij}$ $\times$ *Portfolio Exit*$_{ij}$ is negative and statistically insignificant. Both results go in the opposite direction of the prediction, suggesting that the observed entrepreneurial spillovers are not explained by the financial constraints hypothesis.

5 Robustness

In this section, we conduct several robustness checks to address potential concerns on our specification and identification strategies. First, our analysis is suitable for the Cox proportional hazards model to assess the tendency of starting ventures as the time passes. We show our results are robust to this alternative specification. Second, there are concerns that the industry shocks we used to define distressed corporate LPs at the time of VC obtaining its SAIC approval might impact the financial conditions of individual LPs' existing firms; the industry shocks could also reveal potential (un)attractive entrepreneurial opportunities. These hence affect individual LPs' entrepreneurial incentives and potentially explain our main findings. To address these concerns, we discuss several robustness tests in this section.

In our main analysis, we adopt a cross-sectional test by comparing individual LPs in the successfully launched funds to those in the failed-to-launch funds. For robustness, we expand our unit of observation from the LP-by-fund level to LP-by-year panel. Given an individual LP, the panel documents at which year the LP invests in VC and how many ventures are created every year. We then use the panel data to rerun our regression with the Cox proportional hazards model. We redefine *Launched VC* to be an indicator for whether a VC fund is successfully launched (treated dummy). We add another variable LP_{it} to indicate if individual i has already become an LP of a fund in year t (post dummy). The results, shown in Table OA2.5 of the Online Appendix, convey a quite similar and robust message as in our

main analysis. The coefficient on the interaction term, $Launched\,VC \times LP$, is positively significant at the 1% level, implying that it is more likely for an individual to start ventures after becoming an LP in a successfully launched fund.

Next, we address several identification challenges. One potential identification threat is that the individual LPs' existing firms (old ventures) experienced similar economic cycles to these corporate LPs in distressed industries at the time of the formation of the VC fund. These could be potential wealth shocks to individual LPs and change their entrepreneurial incentives. For instance, if their existing firms have experienced similar economic busts as those corporate LPs, the negative shock might induce them to "gamble" by starting new ventures.

To alleviate this concern, we exclude individual LPs whose existing firms (old ventures) were in the industries that experienced busts at the time of the VC fund was approved. We follow the same approach as above, defining an industry to be in distress if its past six month average stock return is in the bottom quintile among all two-digit industries in the economy at the time when the fund obtained its SAIC approval. Our main results still hold, as shown in Table OA2.6 of the Online Appendix. Though the 2SLS estimate for the dependent variable of total number of ventures in column (4) becomes statistically insignificant at the 10% level, the estimated coefficient still indicates a positive spillover effect of investing in VC on entrepreneurship. Consistent with our main results, all other OLS and IV regressions robustly produce significantly positive coefficients of *Launched VC*.

Conversely, a related concern is that individual LPs' existing firms experienced an economic boom at the time of the VC fund's SAIC approval. This positive financial shocks might increase their incentives to start new ventures. To address this concern, we exclude individual LPs whose existing firms (old ventures) were in the boom industries at the time of the VC fund's approval. A boom industry is defined as an industry whose past six month average stock return is in the top quintile among all industries at the time of VC fund's regulatory approval. As reported in Table OA2.7 of the Online Appendix, our main conclusions continue to hold. Overall, these results indicate that our instrument is not simply picking up the omitted incentives of individual LPs to start new ventures due to changing financial conditions of their existing firms.

Another concern is that individual LPs are tempted to start new ventures when they see better oppor-

tunities in the booming industries. Thus, the apparent spillovers we documented might not come from learning after investing in VC, but rather from entrepreneurs reacting to the same stimuli that drive the VC fund formation and investment choices. To alleviate this concern, we conduct another robustness check. We exclude any ventures created by individual LPs after becoming an LP that are in boom industries, defined by the past six-month stock returns at the time of the VC fund's approval. As Table OA2.8 in the Online Appendix shows, our main conclusions still hold in both OLS and 2SLS regressions. The coefficients of interest are positively significant at the 1% level.

6 Conclusions

This paper studies how investing in VC affects the entrepreneurial outcomes of individual limited partners (LPs). By constructing a comprehensive dataset on the firm creations, VC fundraising, and VC investment in China, we find a positive entrepreneurial spillover from investing in VC funds. Individual investors are more likely to create new ventures after becoming LPs of venture funds. These new ventures are more likely to be in high-tech industries and file more patents. The industry and patent fields of new ventures are more likely to overlap with those of VCs' portfolio companies, suggesting a learning-by-investing mechanism. Taken together, this paper provides a systematic and rigorous analysis about the consequences of blurring boundaries between investors and entrepreneurs.

An interesting question is whether such spillovers can occur in other ways. For instance, angel investments in start-ups appear to have increased sharply in recent years, as has crowdfunding and online investment groups. Understanding the relative learning form these different approaches to investing is a fertile avenue for future research.

References

Adelino, M., Schoar, A., and Severino, F. (2015). House prices, collateral, and self-employment. *Journal of Financial Economics*, 117(2):288–306.

Allen, F., Cai, J., Gu, X., Qian, J., Zhao, L., and Zhu, W. (2021). Centralization or decentralization? the evolution of state-ownership in China. Working paper, University of Pennsylvania.

Allen, F., Cai, J., Gu, X., Qian, J., Zhao, L., Zhu, W., et al. (2019). Ownership networks and firm growth: what do forty million companies tell us about the Chinese economy? Working paper, University of Pennsylvania.

Athey, S. and Imbens, G. W. (2022). Design-based analysis in difference-in-differences settings with staggered adoption. *Journal of Econometrics*, 226(1):62–79.

Babina, T. and Howell, S. T. (2018). Entrepreneurial spillovers from corporate R&D. Working paper, National Bureau of Economic Research.

Bai, C.-E., Hsieh, C.-T., Song, Z. M., and Wang, X. (2020). The rise of state-connected private owners in China. Working paper, National Bureau of Economic Research.

Bai, C.-E., Jia, R., Li, H., and Wang, X. (2021). Entrepreneurial reluctance: talent and firm creation in China. Working paper, National Bureau of Economic Research.

Baker, A. C., Larcker, D. F., and Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, 144(2):370–395.

Barwick, P. J., Chen, L., Li, S., and Zhang, X. (2022). Entry deregulation, market turnover, and efficiency: China's business registration reform. Working paper, Cornell University.

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

Bernstein, S., Giroud, X., and Townsend, R. R. (2016). The impact of venture capital monitoring. *Journal of Finance*, 71(4):1591–1622.

Bernstein, S., Korteweg, A., and Laws, K. (2017). Attracting early-stage investors: evidence from a randomized field experiment. *Journal of Finance*, 72(2):509–538.

Borusyak, K., Jaravel, X., and Spiess, J. (2021). Revisiting event study designs: robust and efficient estimation. Working paper, University College London.

Brandt, L., Dai, R., Kambourov, G., Storesletten, K., and Zhang, X. (2022). Serial entrepreneurship in China. Working paper, University of Toronto.

Brown, G., Harris, R., Hu, W., Jenkinson, T., Kaplan, S. N., and Robinson, D. T. (2021). Can investors time their exposure to private equity? *Journal of Financial Economics*, 139(2):561–577.

Callaway, B. and Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2):200–230.

Chernenko, S., Lerner, J., and Zeng, Y. (2021). Mutual funds as venture capitalists? Evidence from unicorns. *Review of Financial Studies*, 34(5):2362–2410.

Cochrane, J. H. (2005). The risk and return of venture capital. *Journal of Financial Economics*, 75(1):3–52.

Colonnelli, E., Li, B., and Liu, E. (2022). Investing with the government: a field experiment in China. Working paper, University of Chicago.

Cong, L. W., Lee, C. M., Qu, Y., Shen, T., et al. (2020). Financing entrepreneurship and innovation in China. In *Foundations and Trends® in Entrepreneurship*, volume 16, pages 1–64. Now Publishers, Inc.

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):3956–90.

Eldar, O., Grennan, J., and Waldock, K. (2021). Common ownership and startup growth. Working paper, Duke University.

Evans, D. S. and Jovanovic, B. (1989). An estimated model of entrepreneurial choice under liquidity constraints. *Journal of Political Economy*, 97(4):808–827.

Fei, C. Y. (2018). Can governments foster the development of venture capital? Working paper, University of North Carolina at Chapel Hill.

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

Gompers, P., Lerner, J., and Scharfstein, D. (2005). Entrepreneurial spawning: public corporations and the genesis of new ventures, 1986 to 1999. *Journal of Finance*, 60(2):577–614.

Gompers, P. A. and Lerner, J. (2004). *The venture capital cycle*. MIT press, Cambridge, MA.

Gompers, P. A. and Mukharlyamov, V. (2022). Transferable skills? Founders as venture capitalists. Working paper, National Bureau of Economic Research.

González-Uribe, J. (2020). Exchanges of innovation resources inside venture capital portfolios. *Journal of Financial Economics*, 135(1):144–168.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2):254–277.

Harris, R. S., Jenkinson, T., and Kaplan, S. N. (2014). Private equity performance: what do we know? *Journal of Finance*, 69(5):1851–1882.

He, Z., Liu, B., and Zhu, F. (2022). Share pledging in China: funding listed firms or funding entrepreneurship? Working paper, National Bureau of Economic Research.

Hellmann, T. (2002). A theory of strategic venture investing. *Journal of Financial Economics*, 64(2):285–314.

Hellmann, T. (2007). When do employees become entrepreneurs? *Management Science*, 53(6):919–933.

Hellmann, T. and Puri, M. (2002). Venture capital and the professionalization of start-up firms: empirical evidence. *Journal of Finance*, 57(1):169–197.

Hellmann, T., Schure, P., and Vo, D. H. (2021). Angels and venture capitalists: substitutes or complements? *Journal of Financial Economics*, 141(2):454–478.

Huang, Z. and Tian, X. (2020). China's venture capital market. In *The Handbook of China's Financial System*, pages 383–418. Princeton University Press.

Jaravel, X., Petkova, N., and Bell, A. (2018). Team-specific capital and innovation. *American Economic Review*, 108(4-5):1034–1073.

Jiang, W. (2017). Have instrumental variables brought us closer to the truth. *Review of Corporate Finance Studies*, 6(2):127–140.

Kaplan, S. N. and Schoar, A. (2005). Private equity performance: returns, persistence, and capital flows. *Journal of Finance*, 60(4):1791–1823.

Korteweg, A. and Nagel, S. (2016). Risk-adjusting the returns to venture capital. *Journal of Finance*, 71(3):1437–1470.

Kortum, S. and Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *RAND Journal of Economics*, 31(4):674–692.

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

Lerner, J. (1995). Venture capitalists and the oversight of private firms. *Journal of Finance*, 50(1):301–318.

Lerner, J. and Malmendier, U. (2013). With a little help from my (random) friends: success and failure in post-business school entrepreneurship. *Review of Financial Studies*, 26(10):2411–2452.

Lerner, J., Schoar, A., Sokolinski, S., and Wilson, K. (2018). The globalization of angel investments: Evidence across countries. *Journal of Financial Economics*, 127(1):1–20.

Lerner, J., Schoar, A., and Wongsunwai, W. (2007). Smart institutions, foolish choices: the limited partner performance puzzle. *Journal of Finance*, 62(2):731–764.

Li, J. (2022). Government as an equity investor: evidence from Chinese government venture capital through cycles. Working paper, Harvard University.

Li, X., Liu, T., and Taylor, L. A. (2021). Common ownership and innovation efficiency. Working paper, University of Pennsylvania.

Lindsey, L. (2008). Blurring firm boundaries: the role of venture capital in strategic alliances. *Journal of Finance*, 63(3):1137–1168.

Ma, S. (2020). The life cycle of corporate venture capital. *Review of Financial Studies*, 33(1):358–394.

Nanda, R. and Rhodes-Kropf, M. (2019). Coordination frictions in venture capital syndicates. In *The Oxford Handbook of Entrepreneurship and Collaboration*, pages 351–371. Oxford University Press.

Pancost, N. A. and Schaller, G. (2021). Measuring measurement error. Working paper, University of Texas at Austin.

Paulson, A. L., Townsend, R. M., and Karaivanov, A. (2006). Distinguishing limited liability from moral hazard in a model of entrepreneurship. *Journal of Political Economy*, 114(1):100–144.

Sariri Khayatzadeh, A. (2021). *Three essays on the role of information in the development of early-stage startups*. PhD thesis, University of Toronto.

Seru, A. (2014). Firm boundaries matter: evidence from conglomerates and R&D activity. *Journal of Financial Economics*, 111(2):381–405.

Shi, X., Xi, T., Zhang, X., and Zhang, Y. (2021). "Moving umbrella": bureaucratic transfers and the comovement of interregional investments in China. *Journal of Development Economics*, 153:102717.

Siegel, R., Siegel, E., and MacMillan, I. C. (1988). Corporate venture capitalists: autonomy, obstacles, and performance. *Journal of Business Venturing*, 3(3):233–247.

Sun, L. and Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, 225(2):175–199.

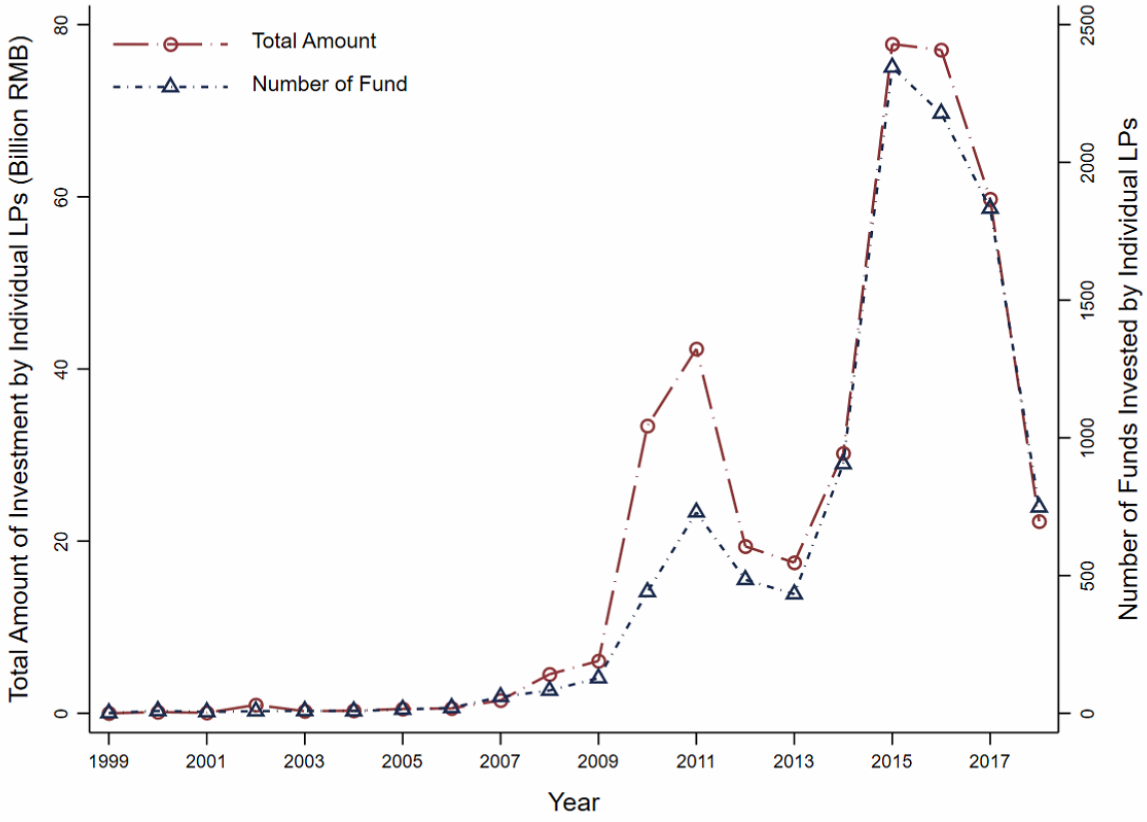
Wallmeroth, J., Wirtz, P., and Groh, A. P. (2018). Venture capital, angel financing, and crowdfunding of entrepreneurial ventures: a literature review. In *Foundations and Trends® in Entrepreneurship*, volume 14, pages 1–129. Now Publishers, Inc.

Wallskog, M. (2022). Entrepreneurial spillovers across coworkers. Working paper, Duke University.

Zakrzewski, A., Palmisani, E., Covazzi, G., Teixeira, B., Bacchetti, B., Bizzozero, M., Shah, K., Boehler, T., and Rizzato, F. (2022). The future is private: unlocking the art of private equity in wealth management. White paper, Boston Consulting Group and iCapital.

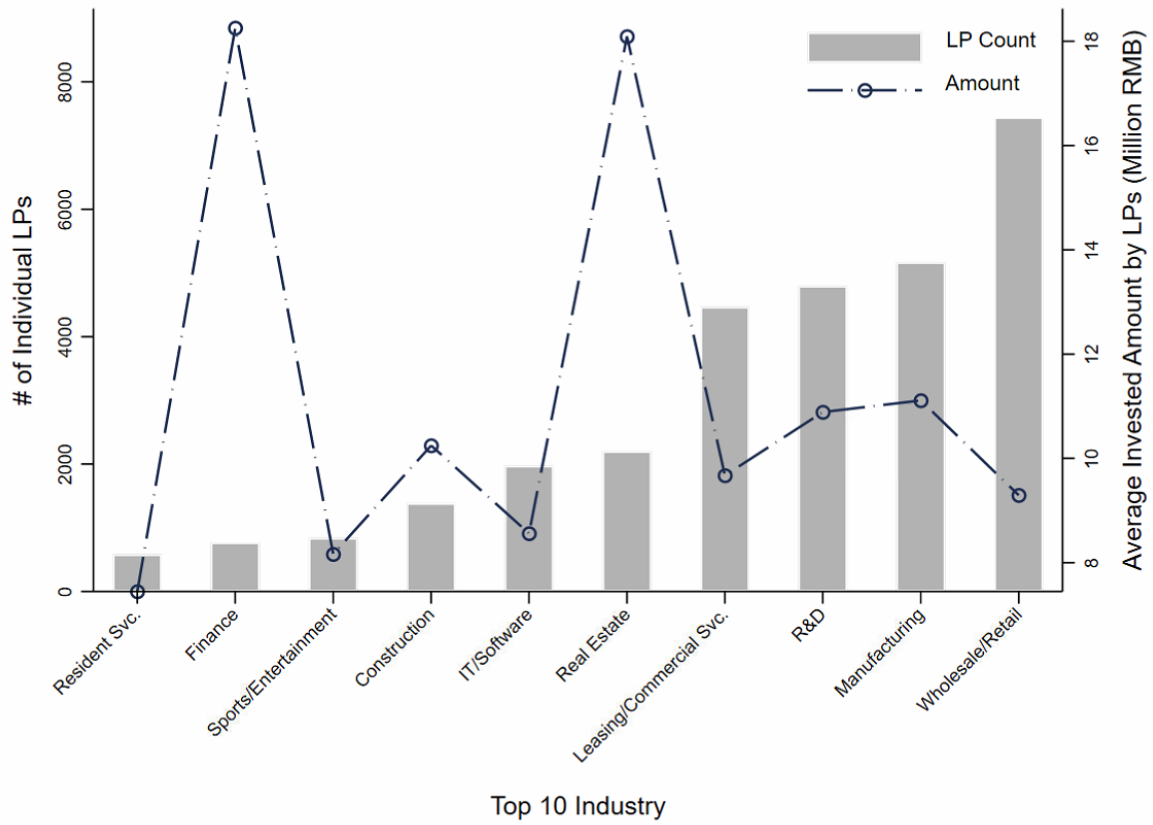
Figures

Figure 1: Individual LPs' Investments by Year



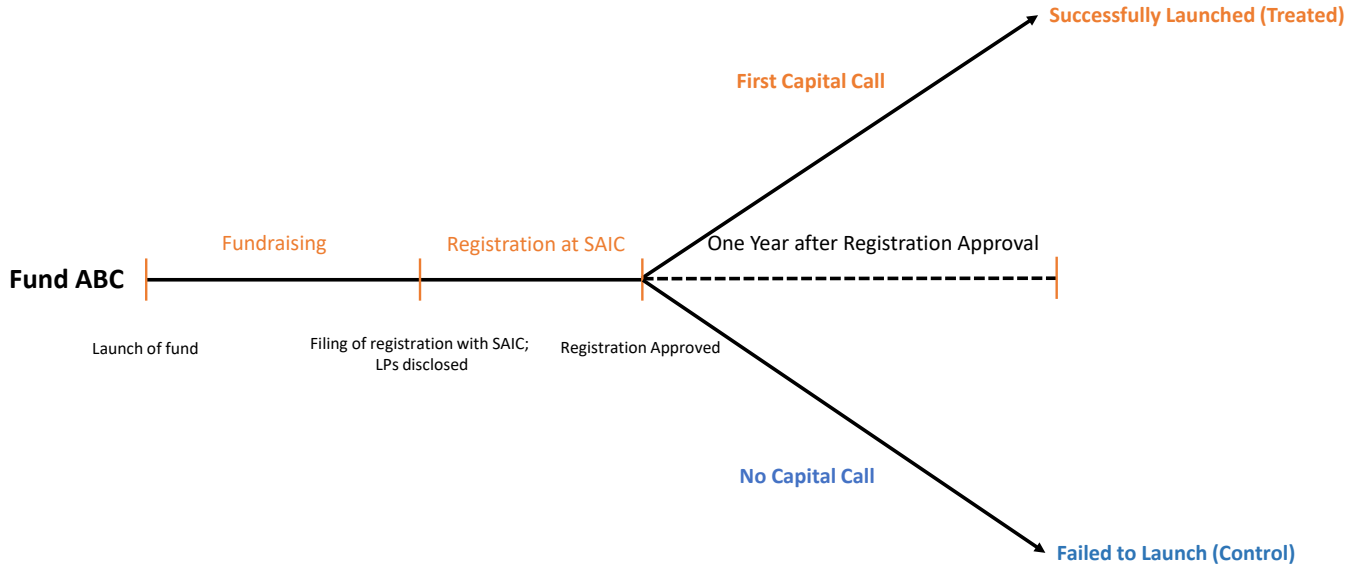
This figure shows the total capital commitments and total number of VC funds invested by individual LPs from 1999 to 2018. RMB values are adjusted to 2019 by GDP deflators.

Figure 2: Industry Focus of Individual LPs before Investing in VCs



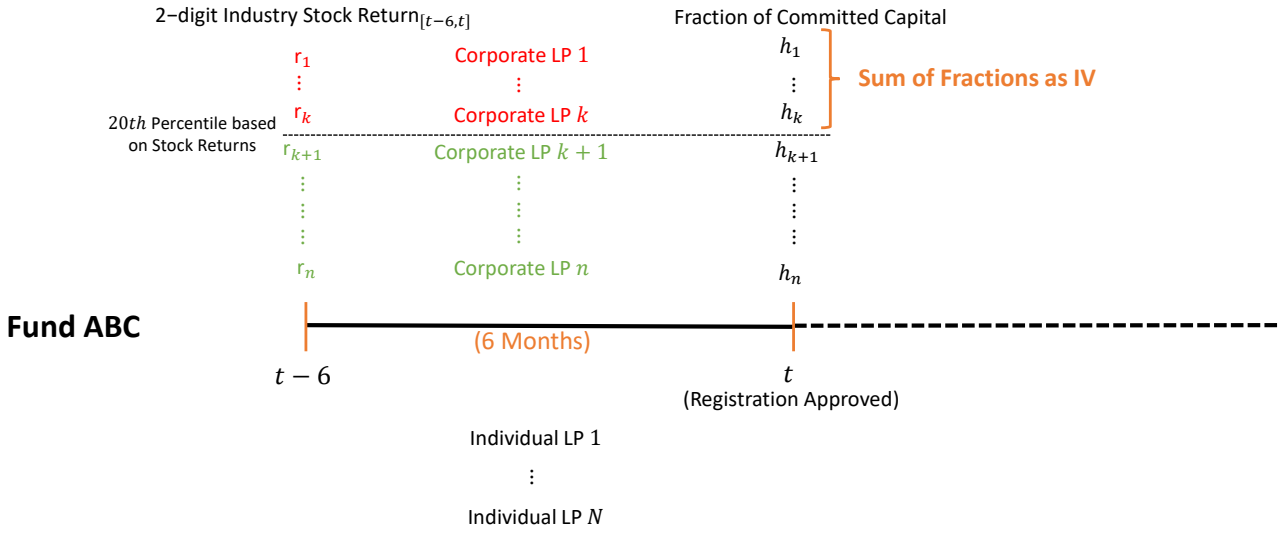
This figure shows the top 10 industry focuses of individual LPs' existing businesses before they investing in VC, and the average invested amounts in VC funds per individual LP across industries. For individual LPs whose existing businesses span across multiple industries, we define the main industry focus as the one where they had invested the most. RMB values are adjusted to 2019 by GDP deflators.

Figure 3: Empirical Design



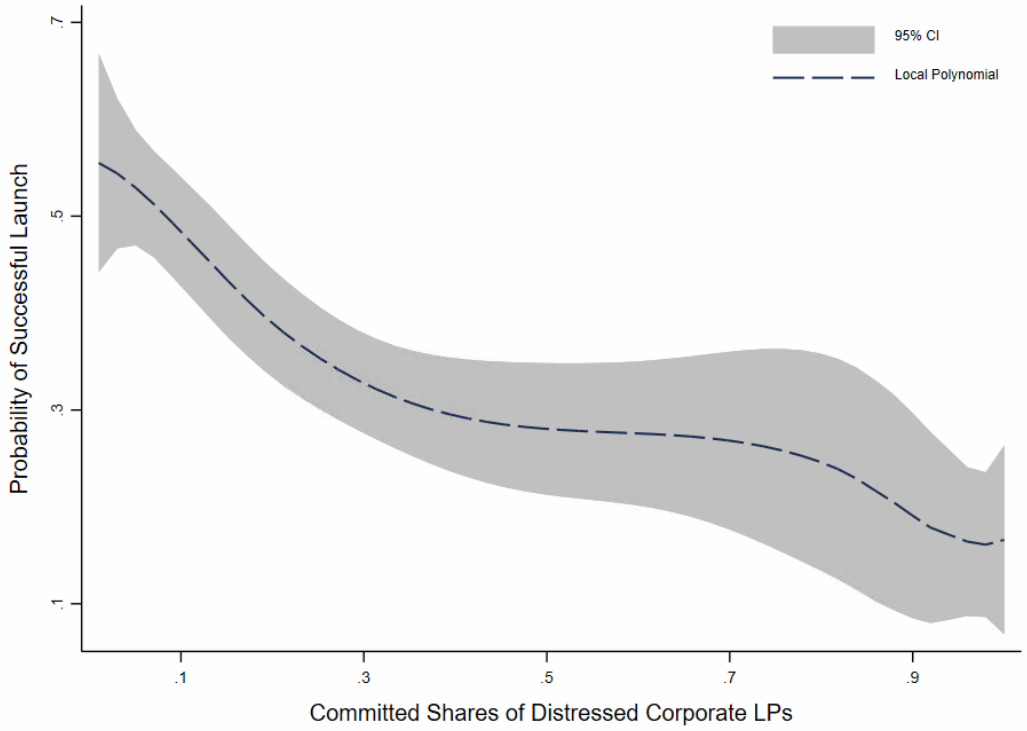
This figure illustrates the empirical design used in the paper. It compares entrepreneurial outcomes of individual LPs in the successfully launched funds to those in the funds that failed to launch.

Figure 4: IV Construction



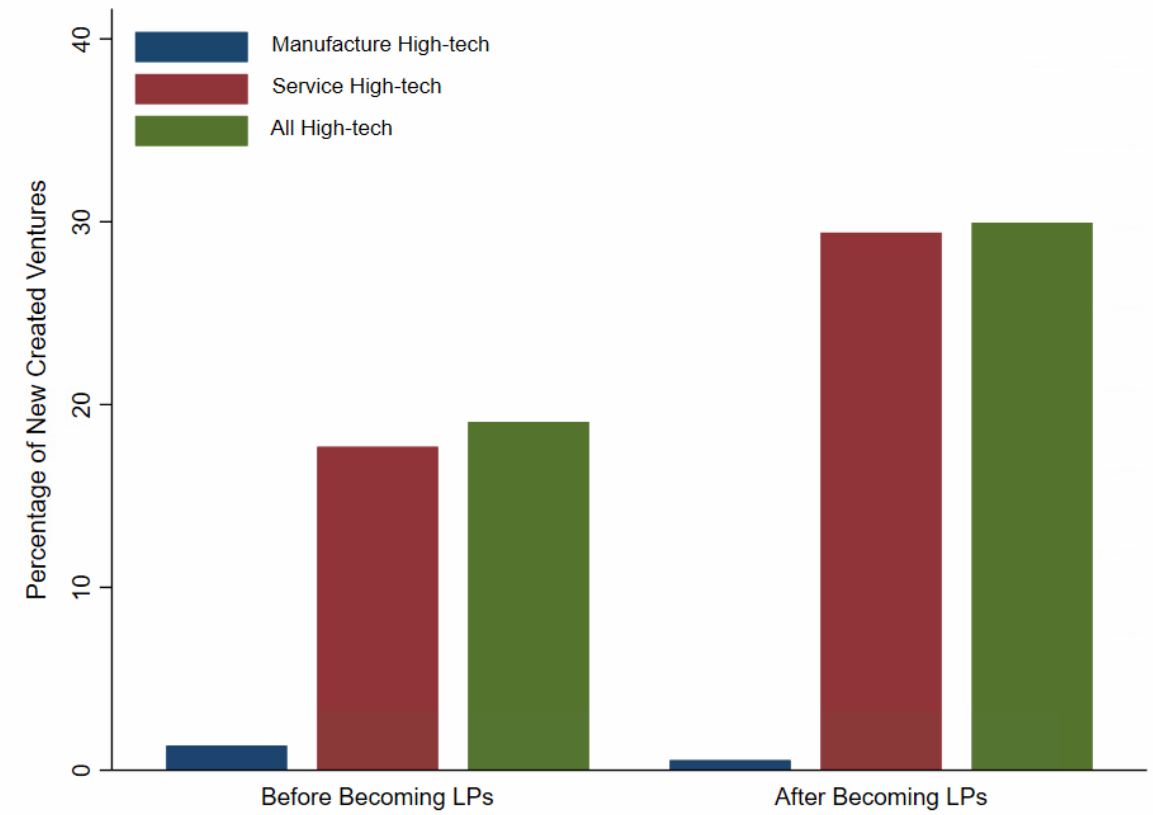
This figure illustrates the process on how we construct the IV for *Launched* VC_{ij} in Equation (1). The bottom 20th percentile is defined based on past six month stock returns across all two-digit SIC code industries in the economy at time t.

Figure 5: Committed Shares from Distressed Corporate LPs and Fund Launch Likelihood



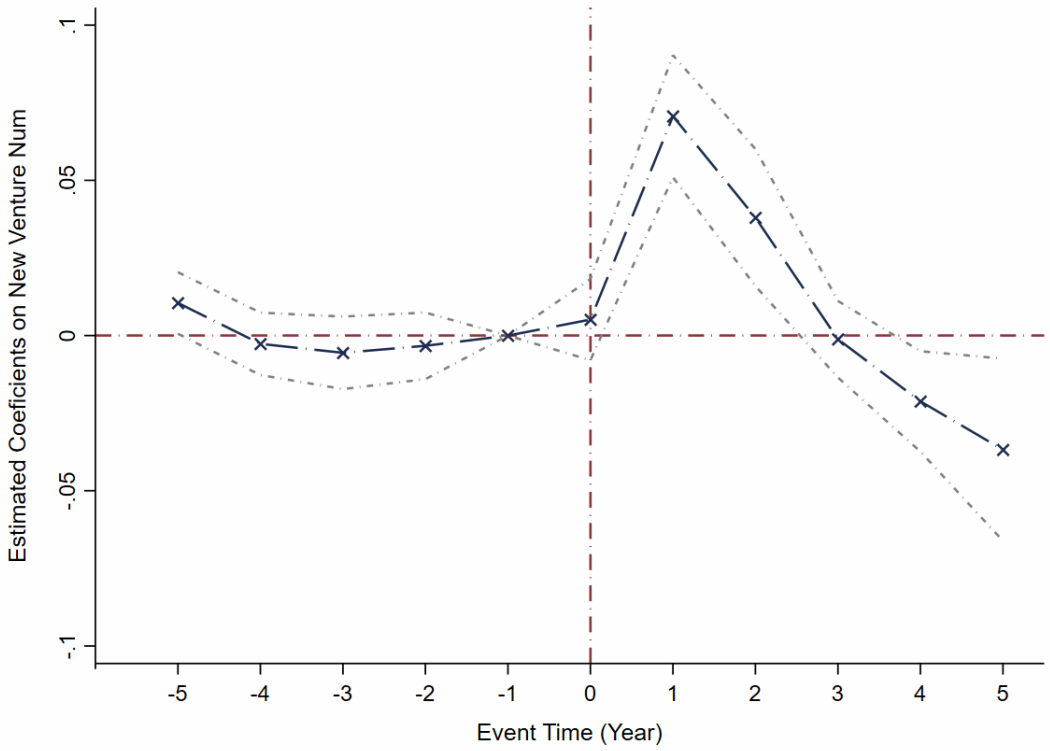
This figure presents the kernel-weighted local polynomial regression of the likelihood of VC's successful launch on the portion of its total committed capital from corporate LPs in distressed industries in the sample. We define a corporate LP is in distress industries at the time when the fund's SAIC registration was approved if the past six month stock return of the two-digit SIC code industry where the corporate LP assigned to is at the bottom quintile among all industries in the economy. The gray shaded area represents the 95% confidence interval.

Figure 6: High-tech Fraction of New Ventures vs Old Ventures



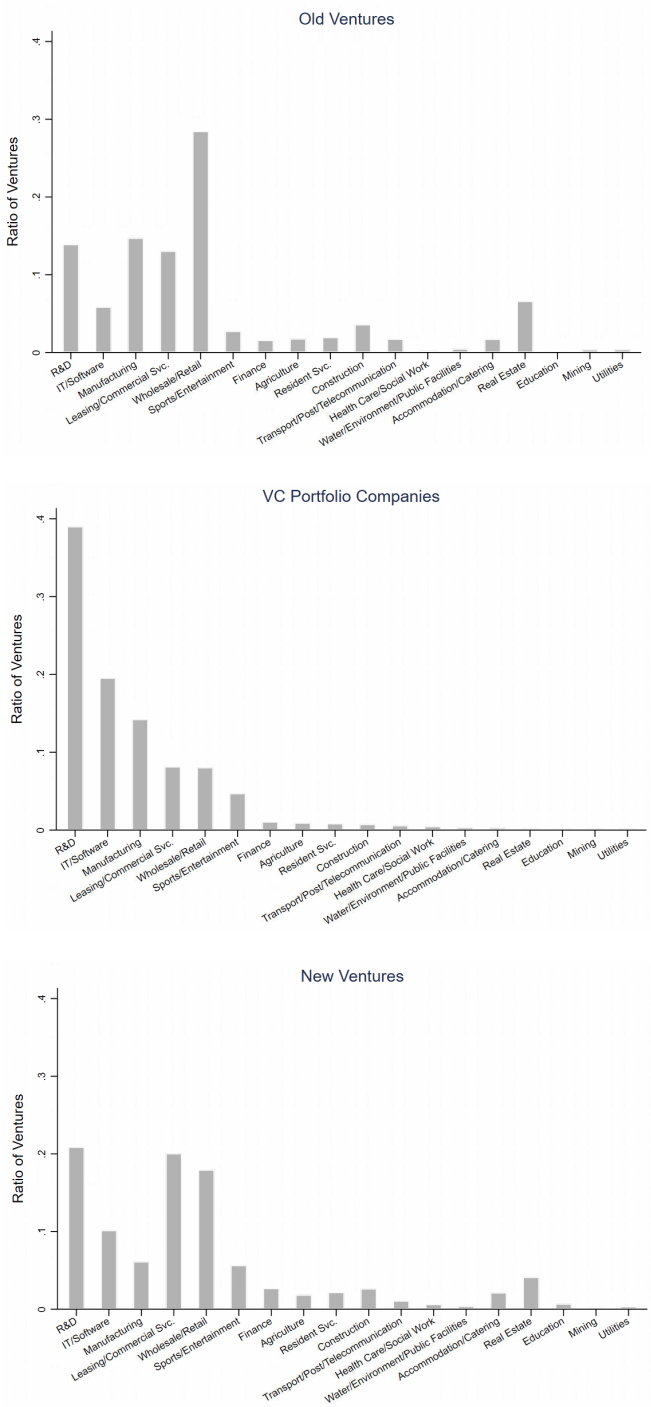
This figure shows the fraction of companies in manufacture and service high-tech industries. Specifically, we look into companies created by individual LPs before investing in VC (old ventures) and those created after investing in VC (new ventures). The first three bars under "Before Becoming LPs" represent the percentages of old ventures' industry distribution. The last three bars under "After Becoming LPs" represent the percentages of new ventures' industry distribution. The dark blue bars represent the percentage of companies in the manufacture high-tech industries. The red bars represent the percentage of companies in the service high-tech industries. The green bars are the sum of percentages in the manufacture and service high-tech industries within each group. We define the high-tech industries according to the Classification Criteria published by the National Bureau of Statistics of China in 2017 and 2018.

Figure 7: Event Study



This figure shows the event study results of Equation (5) . The y axis is the estimate of β^{Real} in Equation (5), which represents the dynamic effects of investing in VC on individual LPs' entrepreneurial outcomes. We show the effects from five years before the event year, i.e. becoming an LP for the first time (Year = 0), to five years after the event. The benchmark year is $t-1$, one year right before investing in VC. Gray dashed lines represent the 95% confidence interval.

Figure 8: Industry Distribution across Groups



This figure shows the industry distribution of individual LPs' own ventures and VCs' portfolio companies. Specifically, we examine three groups of companies: individual LPs' old ventures that are created before investing in VC (Panel A), individual LPs' new ventures that are created after investing in VC (Panel C), and VCs' Portfolio companies that have ever received VC investments (Panel B). The industry classification is based on the first-digit SIC industry code from the Standard Industrial Classification for National Economic Activities (SIC) issued by the Standardization Administration of the People's Republic of China in 2017.

Tables

Table 1: Summary Statistics

This table reports the summary statistics of a sample of individual LPs who invested in VC funds that obtained the registration approvals from the SAIC and successfully launched in the market with venture investments. Panel A shows the fund-level characteristics. Panel B exhibits the individual-LP-level characteristics. Panel C is at the LP by fund level. Among all variables, most of which are self-explained, *Already Entrepreneur* is an indicator equal to one if an individual LP already owned any ventures before investing in a VC fund. *Year Gap*$(t_{LP} - tEnt)$ is the year gap between the time of an individual LP starting the first venture and the time of her investing in a VC fund, conditional *Already Entrepreneur* equal to one. *Total# Ventures* represents the number of ventures created by an individual LP between 1999 and 2018. *Total# Ventures Before VC Investment* counts the number of ventures created by an LP between 1999 and the year when she invested in a VC fund (included). *Total# Ventures After VC Investment* is the difference between *Total# Ventures* and *Total# Ventures Before VC Investment*.

Panel A: Fund Level

Variable	Mean	Median	SD	*N*
Num. Individual LPs	7.928	4.000	18.580	11,120
Total Percent of Capital Invested by Individual LPs	0.496	0.487	0.340	11,120
Total Amount Invested by Individual LPs (Million RMB)	50.991	19.149	110.844	11,120
Fund Size (Million RMB)	165.790	54.635	356.554	11,120

Panel B: LP Level

Variable	Mean	Median	SD	*N*
Female	0.277	0.000	0.447	70,414
Entrepreneur	0.548	1.000	0.498	70,414
Num. Fund Invested	1.252	1.000	0.853	70,414
Total Amount Invested (Million RMB)	8.053	2.105	34.672	70,414

Panel C: LP by Fund Level

Variable	Mean	Median	SD	*N*
Percent of Capital Invested by Individual LPs	0.063	0.025	0.121	88,161
Amount Invested (Million RMB)	6.432	1.701	28.193	88,161
Already Entrepreneur	0.483	0.000	0.500	88,161
Year Gap $(t_{LP} - t_{Ent})$	8.368	9.000	5.067	42,615
Total# Ventures	1.665	1.000	3.164	88,161
Avg.# Ventures per Year	0.083	0.050	0.158	88,161
Total# Ventures Before VC Investment	1.224	0.000	2.757	88,161
Total# Ventures After VC Investment	0.440	0.000	1.073	88,161
Avg.# Ventures per Year Before VC Investment	0.075	0.000	0.160	88,161
Avg.# Ventures per Year After VC Investment	0.133	0.000	0.438	88,161

Table 2: Compare Entrepreneur and Non-entrepreneur LPs

This table shows the differences between the entrepreneur LPs and non-entrepreneur LPs. An individual LP is classified as either an entrepreneur LP or a non-entrepreneur LP depending on whether she owns at least 5% shares in other non-financial companies. Panel A shows the comparison of their characteristics at the LP by fund level, while panel B presents the comparison of their characteristics at the LP level.

Panel A: LP by Fund Level

	Entrepreneur LP		Non-entrepreneur LP		
Variable	Mean	SD	Mean	SD	Diff
Percent of Committed Capital	0.074	0.130	0.048	0.108	0.026***
Amount Invested (Million RMB)	8.016	29.800	4.438	25.892	3.578***
Fund Size (Million RMB)	215.204	397.694	226.589	412.511	-11.385***
Total# Ventures	2.988	3.745	0.000	0.000	2.988***
Avg.# Ventures per Year	0.149	0.187	0.000	0.000	0.149***
Total# Ventures Before VC Investment	2.198	3.392	0.000	0.000	2.198***
Total# Ventures After VC Investment	0.790	1.338	0.000	0.000	0.790***
Avg.# Ventures per Year Before VC Investment	0.134	0.196	0.000	0.000	0.134***
Avg.# Ventures per Year After VC Investment	0.239	0.566	0.000	0.000	0.239***

Panel B: LP Level

	Entrepreneur LP		Non-entrepreneur LP		
Variable	Mean	SD	Mean	SD	Diff
Female	0.232	0.422	0.331	0.471	-0.099***
Num. Fund Invested	1.275	0.819	1.224	0.891	0.051***
Total Amounts Invested (Million RMB)	10.223	38.232	5.432	29.600	4.791***

Table 3: New Venture Creation of Individual LPs: Failed vs Launched Funds

This table reports the regression results of Equation (1) in OLS and IV specifications. Columns (1) and (2) present the OLS estimates. Column (3) shows the first stage results of the 2SLS regression. Columns (4) and (5) present the second-stage estimates. The dependent variable in column (1) and column (4) is the total number of ventures created by individual i after investing in VC fund j that obtained its SAIC registration approval in year t. The dependent variable in column (2) and column (5) is the average number of ventures per year created by individual i after investing in VC fund j that obtained its SAIC registration approval in year t. The independent variable *Launched* VC_{ij} is an indicator if VC fund j was successfully launched. Control variables include LP i's gender, the total number of companies started by LP i before investing in VC j, an indicator if LP i has invested in any other VC funds before investing in fund j, the natural logarithm of fund j's size, and the ratio of LP i's committed capital in fund j. Fixed effects are indicated at the bottom row. Standard errors are clustered by year. ***, **, and * represent the statistical significance level are at 1%, 5%, and 10% respectively.

	(1)	(2)	(3)	(4)	(5)
	OLS Total# Firms	**OLS Avg# Firms**	**1st Stage Launched VC**	**2SLS Total# Firms**	**2SLS Avg# Firms**
Launched VC	0.035***	0.010***		0.315**	0.069**
	(0.012)	(0.002)		(0.124)	(0.032)
Portion of Corporate LPs in Distressed Industries			−0.272***		
			(0.044)		
1st stage F-stat			37.84		
			(0.000)		
Controls	Y	Y	Y	Y	Y
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.137	0.085	0.557		
Observations	93,920	93,920	93,870	93,870	93,870

Table 4: Differences between the Old and New Ventures

This table compares the characteristics of old and new ventures created by individual LPs. The unit of observation is each venture by individual LP. A venture is defined as an old venture if it was created by an individual LP before investing in any VC funds. Otherwise, it is defined as a new venture. The dependent variable in columns (1) and (2) is the number of filed patents that eventually granted in two and three years after venture k's formation. The dependent variable in columns (3) and (4) is the number of online job hiring in two and three years after venture k's formation. *Launched* VC_{ij} is an indicator if VC fund j in which individual LP i invested was successfully launched in the market. *Post-LP* $Venture_{ikt}$ is an indicator if venture k was founded after individual LP i invested in any fund at time t. We control for LP i's gender, an indicator if LP i has invested in any other VC funds before fund j, the log of fund j's size, the ratio of LP i's committed capital in fund j, venture k's size measured by the log of its registered capital, and LP i's shares in venture k. Fixed effects are indicated at the bottom row. Standard errors are clustered by venture's founded year. ***, **, and * represent the statistical significance level are at 1%, 5%, and 10% respectively.

	Total# Patents in 2 Years	***Total# Patents in 3 Years***	***Total# Hires in 2 Years***	***Total# Hires in 3 Years***
	(1)	(2)	(3)	(4)
Launched VC×Post-LP Venture	0.010**	0.015*	-0.581	-0.856
	(0.004)	(0.007)	(2.359)	(2.848)
Launched VC	0.003	0.001	0.520	0.774
	(0.002)	(0.002)	(1.427)	(1.364)
Post-LP Venture	-0.011**	-0.020***	-2.185	-3.960
	(0.005)	(0.007)	(2.768)	(4.078)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Firm Founded Year FE	Y	Y	Y	Y
Firm District FE	Y	Y	Y	Y
VC Fund Registered Year FE	Y	Y	Y	Y
GP FE	Y	Y	Y	Y
Adj. R^2	0.031	0.027	0.000	0.023
Observations	287,628	287,628	134,847	134,847

Table 5: New Venture Creation of Individual LPs: Matched Sample

This table reports the regression results of Equation (4) using the diff-in-diff specification with the matched control units. The dependent variable is the number of ventures created by individual i in year t. The independent variable $Post_{it}$ is an indicator whether individual i (or her counterpart in the treated group when i is in the control group) has ever invested in VC by year t. $Treated_i$ denotes the treatment group dummy, which is equal to one if individual i is a real individual LP (rather than a matched control). We present the results in columns (1) to (5) by varying controls and fixed effects. Control variables include individual i or her matched individual LP i's gender, the total number of firms that individual i has started before individual i (or her counterpart in the treated group when i is in the control group) investing in VC j, an indicator if individual i (or her counterpart in the treated group when i is in the control group) has invested in any other VC funds before investing in fund j, the natural logarithm of fund j's size, and the ratio of individual i's (or her counterpart in the treated group when i is in control group) committed capital in the fund. Standard errors are two-way clustered at individual and year levels. ***, **, and * represent the statistical significance level are at 1%, 5%, and 10% respectively.

	# Firms Created by an Individual in a Year				
	(1)	(2)	(3)	(4)	(5)
Treated×*Post*	0.061***	0.029**	0.020**	0.028**	0.018**
	(0.010)	(0.011)	(0.007)	(0.010)	(0.007)
Post	-0.008	-0.028***	-0.020**	-0.044***	-0.013
	(0.006)	(0.006)	(0.008)	(0.005)	(0.008)
Treated	0.013***	0.011***		0.014***	
	(0.002)	(0.002)		(0.002)	
Controls	N	Y	Y	Y	Y
Individual FE	N	N	Y	N	Y
Year FE	N	N	N	Y	Y
Adj. R^2	0.005	0.054	0.103	0.057	0.106
Observations	649,785	626,634	625,080	626,634	625,080

Table 6: Correlation between New Ventures and Portfolio Companies

This table shows the correlation of characteristics between ventures created by individual LPs and portfolio companies of VC funds. Columns (1) and (3) report the Poisson estimates. Columns (2) and (4) present the OLS estimates. The dependent variable in columns (1) and (2) is an indicator whether a venture created by an individual LP (no matter before or after she investing in any VC funds) has the same four-digit industry code as any portfolio companies of VC funds she ever invested in. The dependent variable in columns (3) and (4) is a dummy variable indicating whether the filed-and-eventually-granted patents of a venture after its formation have the identical three-digit classification code to any patents filed by portfolio companies of VC funds she ever invested in. Standard errors are two-way clustered at four-digit industry and established year levels for columns (1) and (2), and two-way clustered at three-digit patent classification code and application year levels for columns (3) and (4). ***, **, and * represent the statistical significance level are at 1%, 5%, and 10% respectively.

	Same 4-digit Industry Code		***Same 3-digit Patent Class Code***	
Specification	Poisson	OLS	Poisson	OLS
	(1)	(2)	(3)	(4)
Post-LP Venture	0.305***	0.021**	0.356***	0.101***
	(0.046)	(0.008)	(0.117)	(0.031)
Controls	Y	Y	Y	Y
Industry FE	Y	Y	N	N
Founded Year FE	Y	Y	N	N
Patent Field FE	N	N	Y	Y
Patent App. Year FE	N	N	Y	Y
Adj. R^2		0.202		0.235
Observations	74,613	104,138	10,208	11,244

Table 7: Veteran LPs and Entrepreneurship Spillovers

This table tests whether the learning channel would decay over time by comparing the entrepreneurial outcomes of first-time LPs and veteran LPs. *Launched* VC_{ij} is an indicator if VC fund j in which individual LP i invested was successfully launched, *Veteran* LP_{ij} is an indicator if individual LP i has previously invested in any other funds before fund j. Fixed effects are indicated at the bottom row. Standard errors are clustered by year. ***, **, and * represent the statistical significance level are at 1%, 5%, and 10% respectively.

	Total# Firms	***Avg# Firms***
	(1)	(2)
Launched VC×*Veteran LP*	−0.038	−0.024**
	(0.033)	(0.011)
Launched VC	0.033**	0.010**
	(0.014)	(0.004)
Veteran LP	0.081***	0.036***
	(0.021)	(0.007)
Controls	Y	Y
GP FE	Y	Y
Year FE	Y	Y
Adj. R^2	0.137	0.085
Observations	93,920	93,920

Table 8: Entrepreneurship Spillovers with Successful Portfolio Exits

This table tests the financial constraints hypothesis by examining individual LPs' entrepreneurial outcomes in VC funds having any successful exit. *Launched* VC_{ij} is an indicator if VC fund j in which individual LP i invested was successfully launched. *Portfolio* $Exit_{ij}$ is an indicator if VC fund j invested by individual LP i has any successful exits in its portfolio companies. Fixed effects are indicated at the bottom row. Standard errors are clustered by year. ***, **, and * represent the statistical significance level are at 1%, 5%, and 10% respectively.

	Total# Firms	***Avg# Firms***
	(1)	(2)
Launched VC×*Portfolio Exit*	0.115	-0.045
	(0.263)	(0.081)
Launched VC	0.042***	0.011***
	(0.014)	(0.003)
Portfolio Exit	-0.161	0.039
	(0.276)	(0.085)
Controls	Y	Y
GP FE	Y	Y
Year FE	Y	Y
Adj. R^2	0.137	0.085
Observations	93,920	93,920

Online Appendix
"Learning by Investing: Entrepreneurial Spillovers from Venture Capital"

Josh Lerner

Jinlin Li

Tong Liu

October 2022

This Online Appendix explains the sample construction process in detail and presents additional robustness checks mentioned in the paper.

OA-1 Data Appendix

OA-2 Additional Tables

Table OA2.1: Venture Creation after Excluding Observations after April 2018

This table replicates Table 3 except that we exclude LP-fund observations after April 2018 when the "Guiding Opinions on Regulating the Asset Management Business of Financial Institutions" was issued. Other details are the same as in Table 3.

	(1)	(2)	(3)	(4)	(5)
	OLS Total# Firms	**OLS Avg# Firms**	**1st Stage Launched VC**	**2SLS Total# Firms**	**2SLS Avg# Firms**
Launched VC	0.035***	0.010***		0.315**	0.069**
	(0.012)	(0.002)		(0.124)	(0.032)
Portion of Corporate LPs in Distressed Industries			−0.272***		
			(0.044)		
1st stage F-stat			37.83		
			(0.000)		
Controls	Y	Y	Y	Y	Y
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.137	0.085	0.557		
Observations	93,920	93,920	93,870	93,870	93,870

Table OA2.2: Venture Creation after Excluding Angel Investors

This table repeats the estimation in Table 3, except that we exclude potential angel investors defined as shareholders of five or more startups and their owned shares are below 25%. All other details are the same as Table 3.

	(1) **OLS Total# Firms**	(2) **OLS Avg# Firms**	(3) **1st Stage Launched VC**	(4) **2SLS Total# Firms**	(5) **2SLS Avg# Firms**
Launched VC	0.036***	0.010***		0.323**	0.066*
	(0.012)	(0.003)		(0.127)	(0.023)
Portion of Corporate LPs in Distressed Industries			−0.274***		
			(0.046)		
1st stage F-stat			35.71		
			(0.000)		
Controls	Y	Y	Y	Y	Y
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.138	0.085	0.557		
Observations	93,599	93,599	93,550	93,550	93,550

Table OA2.3: Compare Entrepreneur and Non-entrepreneur LPs

This table shows the summary statistics of individual LPs in the successfully launched funds and the failed-to-launch funds included in the regression sample in Table 3. Panel A shows the comparison of their characteristics at the LP by fund level, while panel B presents the comparison of their characteristics at the LP level. The number of individual LPs in successfully launched funds in Panel A (43,208 LP-by-fund observations) is smaller than that reported in Panel C of Table 1 (88,161 LP-by-fund observations) since the observations with any missing controls or instrumental variables are dropped from the main analysis sample.

Panel A: LP by Fund Level

	Successfully Launched Funds		Failed-to-Launch Funds		
Variable	Mean	SD	Mean	SD	Diff
Percent of Committed Capital	0.072	0.125	0.111	0.206	-0.039***
Amount Invested (Million RMB)	8.186	29.073	8.721	56.510	-0.535
Fund Size (Million RMB)	224.426	407.441	135.209	251.450	89.217***
Total# Ventures	3.006	3.869	2.687	2.383	0.319***
Avg.# Ventures per Year	0.150	0.193	0.134	0.119	0.016***
Total# Ventures Before VC Investment	2.157	3.497	2.008	2.024	0.149***
Total# Ventures After VC Investment	0.849	1.377	0.679	1.166	0.170***
Avg.# Ventures per Year Before VC Investment	0.134	0.202	0.119	0.118	0.015***
Avg.# Ventures per Year After VC Investment	0.254	0.588	0.242	0.469	0.012***
# Observation	43,208	·	51,742	·	·

Panel B: LP Level

	Successfully Launched Funds		Failed to Launch Funds		
Variable	Mean	SD	Mean	SD	Diff
Female	0.232	0.422	0.270	0.444	-0.038***
Num. Fund Invested	1.574	1.442	1.539	1.616	0.035***
Total Amount Invested (Million RMB)	13.399	51.637	13.451	117.428	-0.052
# Observation	31,214	·	35,551	·	·

Table OA2.4: Venture Creation after Excluding LPs with Treatment Status Changes

This table repeats the estimation in Table 3, except that we exclude LPs who first invested in a failed-launch fund and then invested in a successfully launched fund, or first invested in a successfully launched fund and then a failed-launched fund. All other details are the same as Table 3.

	(1) **OLS Total# Firms**	(2) **OLS Avg# Firms**	(3) **1st Stage Launched VC**	(4) **2SLS Total# Firms**	(5) **2SLS Avg# Firms**
Launched VC	0.042*	0.012**		0.489**	0.153**
	(0.020)	(0.005)		(0.222)	(0.055)
Portion of Corporate LPs in Distressed Industries			−0.280***		
			(0.048)		
1st stage F-stat			33.84		
			(0.000)		
Controls	Y	Y	Y	Y	Y
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.136	0.081	0.627		
Observations	69,377	69,377	69,334	69,334	69,334

Table OA2.5: Venture Creation with Cox Proportional-Hazards Specification

This table replicates Table 3 except that we expand the data into an LP by year panel and rerun the regression with Cox Proportional-Hazards model. The dependent variable is the number of new ventures created by individual LPs in a year. Other details are the same as in Table 3.

	(1)
	Cox
	New Venture
Launched VC× LP	0.065***
	(0.017)
Launched VC	0.282***
	(0.008)
LP	0.481***
	(0.050)
Female	−0.336***
	(0.008)
Log(VC Fund Size)	−0.080***
	(0.005)
Log(Invested Shares)	1.186***
	(0.035)
GP FE	N
Year FE	N
Log-likelihood	−932,280.68
Observations	2,419,898

Table OA2.6: Venture Creation after Excluding LPs with Existing Firms in Distress

This table replicates Table 3 except that we exclude individual LPs whose existing firms (old ventures) are in the distressed industries at the time when the VC fund obtained its SAIC registration approval. An industry is defined to be in distress if its past six month average stock return is in the bottom quintile among all two-digit industries in the economy at the time of funds' regulatory approval. Other details are the same as in Table 3.

	(1)	(2)	(3)	(4)	(5)
	OLS	**OLS**	**1st Stage**	**2SLS**	**2SLS**
	Total# Firms	**Avg# Firms**	**Launched VC**	**Total# Firms**	**Avg# Firms**
Launched VC	0.034**	0.009***		0.306	0.082**
	(0.012)	(0.002)		(0.180)	(0.030)
Portion of Corporate LPs in Distressed Industries			−0.252***		
			(0.068)		
1st stage F-stat			14.33		
			(0.002)		
Controls	Y	Y	Y	Y	Y
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.134	0.083	0.564		
Observations	78,790	78,790	78,739	78,739	78,739

Table OA2.7: Venture Creation after Excluding LPs with Existing Firms in Boom

This table replicates Table 3 except that we exclude individual LPs whose existing firms (old ventures) are in the boom industries at the time when the VC fund obtained its SAIC registration approval. An industry is defined to be a booming industry if its past six month average stock return is at the top quintile among all two-digit industries in the economy at the time of funds' regulatory approval. Other details are the same as in Table 3.

	(1) **OLS Total# Firms**	(2) **OLS Avg# Firms**	(3) **1st Stage Launched VC**	(4) **2SLS Total# Firms**	(5) **2SLS Avg# Firms**
Launched VC	0.025**	0.007***		0.389**	0.091***
	(0.010)	(0.002)		(0.133)	(0.029)
Portion of Corporate LPs in Distressed Industries			−0.264***		
			(0.050)		
1st stage F-stat			29.67		
			(0.000)		
Controls	Y	Y	Y	Y	Y
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.139	0.087	0.555		
Observations	82,385	82,385	82,335	82,335	82,335

Table OA2.8: Venture Creation after Excluding Newly Created Ventures in the Boom Industries

This table replicates Table 3 except that we exclude new ventures created by individual LPs after investing in VC, in which these new ventures lie in a set of boom industries. A boom industry is defined as the one whose past-six-month return is at the top quintile among all two-digit industries in the economy at the time of funds' regulatory approval. Other details are the same as in Table 3.

	(1) **OLS Total# Firms**	(2) **OLS Avg# Firms**	(3) **1st Stage Launched VC**	(4) **2SLS Total# Firms**	(5) **2SLS Avg# Firms**
Launched VC	0.024***	0.007***		0.416***	0.136***
	(0.008)	(0.002)		(0.067)	(0.033)
Portion of Corporate LPs in Distressed Industries			−0.253***		
			(0.034)		
1st stage F-stat			57.12		
			(0.000)		
Controls	Y	Y	Y	Y	Y
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.137	0.078	0.558		
Observations	86,016	86,016	85,974	85,974	85,974