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Learning by Investing: Entrepreneurial Spillovers from Venture Capital

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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 the 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 successfully launched VC fund, individual LPs create significantly more ventures than do LPs in funds which failed to launch. These new ventures tend to be high-tech firms and file more patents than do the LPs' prior ventures. 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

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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). For instance, in 2009 Jitendra Gupta, an entrepreneur based in San Francisco, founded Punchh, a loyalty platform for restaurants, groceries, retailers, and convenience stores. After seven years as CEO, he stepped aside (Punchh was acquired for 500 million 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.

While numerous studies have highlighted how venture capitalists (VCs) add value to portfolio firms (e.g., Kortum and Lerner, 2000; Hellmann and Puri, 2002; Bernstein et al., 2016), 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 (VC) influence. As highlighted on AngelList's website, "Aside from returns, benefits to becoming an LP [investing in VC funds] might include... access to information ... [and an] expanded network." Both of these are key resources for entrepreneurs.

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 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 the 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 entrepreneurial finance 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. (2023) on private firms' aversion to VC investors with government ties.[1] This dataset's availability can potentially expand the research agenda about limited partners in VC funds.

Another challenge is to address the endogeneity of the individuals' decisions to invest in venture funds. An individual might become interested in biotechnology, and before launching a new venture, invest in such a startup. But the two decisions need not bear a causal 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 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 launch failure of the fund.

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[1] The SAIC registration data have been recently used in a few other settings, including research on the impact of state ownership (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).

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's stock returns in the six months prior to the approval of its SAIC registration. If those 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 an instrumental variable (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 holds if we employ as a dependent variable the total number of ventures launched 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 that 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 or non high-tech) industries, an area more popular with venture investors. We find that 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 that they hire more employees, suggesting a higher innovation efficiency within the new ventures.

Entrepreneurial spillovers occur at both 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 an event-study design using a matched sample. Thus, we employ a different empirical specification here, using a standard difference-in-difference 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 decays 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. Other channels, including a financial constraints channel or a network channel, could 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. Alternatively, one might expect that interacting with GPs can lead to better connections with the VC world (e.g., Hochberg et al., 2007; Gompers et al., 2020), making it easier to obtain VC financing for LPs' own ventures and hence incentivizing more firm creation. We find supporting evidence for the learning channel, but not for the financial constraints channel or the network channel. Specifically, we find that the industry and patent classification codes of new ventures share more similarity, relative to the old ventures, to those of VCs' portfolio companies. The entrepreneurial spillover effect after investing in VC is strongest for LPs investing in funds managed by "better" quality GPs or 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 after investing in VC funds with a successful exit in their portfolios. Contrary to the prediction of the network channel, we do not find a significant increase in VC financing of the new ventures created by LPs.

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 continue 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 registration. 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. We also analyze potential concerns related to the matching between corporate LPs and GPs, the persistence of industry distress, and survival bias among GPs whose funds failed to launch.

Contribution to the Literature

This paper contributes to several strands of literature. The first is 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 founder to venture capitalist are quite common in the market, and successful founder-VCs enjoy a higher investment success rate compared to professional VCs. Even among institutions, LPs sometimes 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 venture capital and private equity (PE) and to 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 market role of investor to that of entrepreneur. This transition 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 investing in VC and in public equities have been extensively scrutinized. Prior work has focused on the direct financial returns (e.g., Cochrane, 2005; Kaplan and Schoar, 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 among their portfolio companies (e.g., Lerner, 1995; Lindsey, 2008; González-Uribe, 2020; Li et al., 2023; Eldar et al., 2021), 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, 2023). 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.

Finally, this paper contributes to the literature on information and 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) and Howell (2021) examine how entrepreneurs absorb information and feedback from angels, VCs, and venture competitions to reduce the uncertainty in entrepreneurship. Wallskog (2022) investigates entrepreneurial spillovers across coworkers using U.S. 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 for VC funds that registered with the SAIC.

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 code,[2] their location(s) (street address, district, prefecture-level city, province, and zip code), firms' incorporation types, the date the firms obtained their SAIC registration approval, whether the firms are currently revoked or suspended, and if so, the dates the revocation or suspension happened.

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 the 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 the 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. We focus on invention patents rather than the utility or design patents. For each patent, we observe its applicant's name, application date, grant date, and classification codes. We match patents to companies based on the applicant or owner's names and remove the duplicated entries. The job postings data contain the total number of online postings and the total number of employees that the firms intended to hire between 2013 and 2021. In Section OA-1 in the Online Appendix, we discuss our sample construction process in detail.

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

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 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.

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, in order to eliminate investments that are likely to be inconsequential. This ensures that individual LPs in our sample have 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 who 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 VC funds indirectly via a financial vehicle.[3] The reason we penetrate 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 in 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 a fund's capital.[4] Each fund has around eight individual LPs on average, each of which 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 in mature VC markets: the U.S. 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).

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[3] 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.

Figure 1 also indicates a big drop in individual LPs' investment activity in 2018. The crash, which 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 the Chinese government's tightened regulatory scrutiny over tech industries, including the crackdown on Internet giants and the online tutoring sector in 2021. These regulatory changes altered the perception of 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 OA3.2 in the Online Appendix we conduct a robustness check for our main analysis (Table 3), excluding any observations after April 2018.

We are particularly interested in the subset of individual LPs who are entrepreneurs. Following He et al. (2022), 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.[5] Though we use 5% as the cutoff, an average entrepreneur in our sample owns about 47% of shares of a prior firm. One potential concern is that some angel investors may be miscategorized 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%. In another robustness check, we combine the information on firms' management teams and define entrepreneurs as shareholders of another company with (a) at least a 50% ownership stake or (b) at least a 5% ownership stake and an executive position within a firm (e.g., CEO, CFO, manager, board chairman) at the same time. Our main results are robust, as shown in Tables OA3.3 and OA3.4 in the Online Appendix.

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[4] 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.

[5] 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 amount 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

Among all individual LPs in the sample, we find that 54.8% of them are entrepreneurs at any time during the sample period, and 48% 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.

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.[6] For individuals owning businesses in multiple industries, we only consider the industry in which they invested the 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.

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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 very different from the typical entrepreneurship discussed in the literature.

[6] Here we use the one-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.

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) and commit a higher ratio and a larger amount of capital per fund than non-entrepreneur LPs do (7.4% vs. 4.8% and 8.02 million vs. 4.44 million RMB). VC funds invested in by entrepreneur LPs are slightly smaller and generally have more portfolio companies than those of non-entrepreneur LPs. Moreover, females are more represented among non-entrepreneur LPs (33.1%) than among entrepreneur LPs (23.2%). Entrepreneur LPs have on average owned 3 ventures, with about 2.2 ventures created before investing in VC and 0.8 ventures after becoming an LP. Their overall speed of venture creation is about 0.15 ventures per year, increasing from 0.13 ventures per year before their VC investment to 0.24 ventures per year after.

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 naïve analysis of this might pose a number of interpretative issues.

In particular, directly estimating ordinary least squares (OLS) might introduce bias due to endogeneity. For instance, an individual less interested in starting a new venture themself might be more willing to allocate their 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).

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 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 echoes the fact that most VC funds in China already have a set of targets they intend to invest in when registering at the SAIC, so 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 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 had already made capital commitments.

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

$$Y_{ijt}^{post} = \alpha + \beta Launched\,VC_{ij} + Controls_{ijt} + \mu_j + \delta_t + \varepsilon_{ijt} \tag{1}$$

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 received its SAIC registration approval in year t, $Launched\,VC_{ij}$ is an indicator of whether VC fund j was successfully launched, μ_j is the fund manager fixed effects, and δ_t is 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 of whether 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 raised capital of 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 OA3.5 in the Online Appendix compares the characteristics of individual LPs in the successfully launched funds and those 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 the fund's corporate LPs that encounter industry distress. 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 to 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 that corporate LP k is assigned to is in the bottom quintile among all two-digit SIC-code industries at time t.[7]

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[7] The corporate LPs that encountered industry distress come from various industries. The two-digit industries in the sample most frequently encountering distress include Commercial Services (72), Wholesale Trade (51), Science and Technology

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 alongside 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 and identify a subset of the 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 the more committed capital from corporate LPs in distressed industries a VC fund has, the less likely it is that the fund's managers will find other investors to fill the gap, leading to a higher probability of launch failure. Our IV construction shares a similar flavor of the shift-share design (e.g., Adao et al., 2019). In the 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.[8]

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). This captures the possible deterioration of corporate LPs' financial conditions during a period in which they 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). The ideal time window for the IV construction, following Bernstein (2015), would be stock returns between the time of the VC fund starts to prepare the SAIC registration and the time when the fund obtains its

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Promotion and Application (75), Capital Markets Services (67), and Software and Information Technology Services (65).

[8] The number of individual LPs in the regression sample is different that of Table 1 because individual LPs with missing control variables and IVs are dropped.

approval. Unfortunately, we cannot use this range because we only have the information on the SAIC registration approval date. We hence choose to examine a fixed time window of six months. We believe that six months is a reasonable time window 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. Even though it might introduce some noise, as the industry distress shock might hit before the fund begins the process of seeking SAIC approval, our relevance condition still holds: If an industry shock hits during the six-month window before SAIC approval, then 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 to the corporate LPs: on average, industries at the cutoff of the bottom 20th percentile have a 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 LP is less likely to start a venture if the fund they invested in has a significant fraction of capital coming from corporate LPs that experienced industry distress. We believe that the exclusion restriction plausibly holds because the 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. One potential concern is that industry booms (distress) independently predict individual LPs (not) founding a startup in the industry. But this logic might not explain the gap between individual LPs of the treated and control groups in their entrepreneurial outcomes, because all investors should be equally affected by the industry shock. We conduct more robustness checks to address other possible identification challenges in Section 5. Our main results still hold.

At first glance, Equation (1) seems like a "difference-in-difference" 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, such as 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 OA3.6 in the Online Appendix, which helps alleviate the concerns about difference-in-difference analyses.

3.2 Empirical Results

We first report our OLS regression results from Equation (1) in columns (1) and (2) of Table 3. Column (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 $\textit{Launched VC}_{ij}$ 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 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 $\textit{Launched VC}_{ij}$ remains 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. This 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 a VC fund's successful launch. A conservative version of the F-statistic, Kleibergen-Paap rk Wald F-statistic, is equal to 37.84, much greater than the threshold of 10, strongly rejecting 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.[9]

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, relative to LPs in unsuccessfully launched 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 strong positive entrepreneurial spillovers from VCs to their individual LPs.

The economic magnitude of the entrepreneurial spillover after investing in VC funds documented in the paper is nontrivial. Benchmarking to prior studies, Evans and Leighton (1989) use data from the National Longitudinal Survey of Young Men (NLS) for 1966–1981 and the Current Population Surveys for 1968–1987 and find that the annual entry rate of wage workers into self-employment is about 4%, implying that an individual on average enters into self-employment in about 25 years (=1/0.04). Comparably, Nanda and Sørensen (2010) and Wallskog (2022) use Danish and U.S. data and find that a one standard deviation higher exposure to entrepreneurial coworkers predicts a 4% and an 8% higher likelihood of becoming an entrepreneur subsequently. Hombert et al. (2020) study the impact of unemployment insurance reform on entrepreneurship in France and find that following the reform, the monthly number of newly created firms increased by a significant 10% across all industries.

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[9] Figure 5 suggests that IV continuously predicts the likelihood of a successful fund launch. To show how it passes through continuously to the entrepreneurial outcomes, we run a reduced-form regression of new venture creation directly on the IV. Results are collected in Table OA3.1 in the Online Appendix. It confirms that our IV negatively predicts the total number of created ventures and the average number of created ventures after an investor investing in a venture fund at a significance level of 1%.

The magnitudes of our IV estimates exceed their OLS counterparts. This 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 more often 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 aware of potential investment opportunities and new technologies, and better equipped with industrial expertise and insights. Individual LPs investing in such VCs may gain more exposure to these skills and expertise through interactions with those VCs. Hence, we expect 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 $\textit{Launched VC}_{ij}$. In this case, our OLS regressions may be biased down due to 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 $\textit{Launched VC}_{ij}$ 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 suggests 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 are, 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.[10] 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

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[10] 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. In general, VC investors in China and the U.S. have favored funding high-tech services.

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. *Launched* VC_{ij} is defined the same as in Equation (1). *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 industry trends or policy changes regarding patenting (or hiring).

The results are reported in Table 4. Columns (1) and (2) indicate that new ventures created by LPs in 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 that 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) exhibit 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 than for those of LPs in unsuccessful funds.

3.4 Serial Entrepreneurs

In our sample, about 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 creation after investing in VC among all the individual LPs in the sample. We call this group of individual LPs the serial-entrepreneur LPs. Given their 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 difference-in-difference techniques without IVs. This 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 (i.e., 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 these LPs with an entrepreneur in the control group who owns only one company in that year and whose company operates in the same two-digit SIC industry, belongs to the same incorporation type, and is located 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 into sixty-four roughly equal cells. Besides the two variables used previously (using the characteristics of the company in which they invested the most capital), we add an extra variable measuring the number of companies owned by an entrepreneur. We then repeat our matching process. 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 their 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 an indicator equal to one for individuals with $Launched\ VC = 1$.[11] We also include individual and year fixed effects in the specification. Note that 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}—the interaction term. A positive β_2^{Real} suggests that individuals create more ventures after they become LPs of VC funds than do 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.

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[11] 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 of the corresponding real individual LPs in the treated group.

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 of investing in a successful VC fund by individual LPs (L_{it}^{Real}) and the associated coefficients ($\{\beta^{Real}(k)\}_{k=-5}^{5}$), 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 for both actual and placebo individual LPs (L_{it}^{All}) and the coefficients associated with them ($\{\beta^{All}(k)\}_{k=-5}^{5}$); year fixed effects ($\tau_t$); and individual fixed effects (γ_i). So, the model of the event study is[12]

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

We report our event-study estimation results of Equation (5) in Figure 7. We find that the difference in the number of ventures created by individual LPs and their matched controls in a year, which is $\beta^{Real}(k)$ in Equation (5), is not statistically significant before the event year. This suggests that our pre-trend assumption is largely satisfied and the entrepreneurial activity of the treated group is almost identical to that of the control 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.[13] Entrepreneurial spillovers from VCs to individual LPs flow when VC funds are actively investing.

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

[13] 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.

4 Potential Channels

Our empirical findings reveal 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 three potential explanations for the findings—learning, financial constraints, and networking. We find supporting evidence for the learning hypothesis but not for the financial constraints or the network hypotheses.

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 entrepreneurial opportunities. We thus expect that the characteristics of newly created ventures of entrepreneurs after becoming an LP should be 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 is closer to that of VCs' portfolio companies than of the old ventures. Figure 8 restricts our comparisons to a sample of ventures created by individual LPs in successfully launched funds (the treated group). In each panel, we tabulate the industry share of companies within the respective group. The three panels represent three groups of companies considered: a set of old ventures created by individual LPs before investing in VC, a set of portfolio companies invested in by VC, and a set of new ventures created by individual LPs after investing in VC. Specifically, we find that the fraction of VC portfolio companies in the R&D industry is relatively high (39%). Consistent with the learning hypothesis, this ratio turns out to be higher for the new venture group (21%) compared to the old venture group (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, relative to the old ventures, with the portfolio companies in terms of four-digit industry codes and three-digit patent classification codes using primary assignments of the patents. 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:

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

In this regression, 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 an 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 $\mathit{Post\text{-}LP\ Venture}_{ikt}$ is an indicator of 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 positive and 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 have 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, whether it ever received a VC investment, and industry and founding 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 the patent's primary field classification and patent application year fixed effects.

Third, we explore the heterogeneity in learning under the "mentorship" of GPs with various qualities.

If the learning hypothesis is true, we expect that individual LPs are able to learn more via the interaction with "better quality" GPs. We hence predict an increasing effect of entrepreneurial spillover when individual LPs invest in venture funds managed by more experienced GPs or GPs with better investment records. To test the story, we construct three proxies for "better quality" GPs. *GP with More Deals* is an indicator equal to one if the number of VC deals made by a GP prior to the focal fund's SAIC approval is in the top quintile among all GPs; *GP with More Successful Exits* is defined as an indicator equal to one if the rate of successful exits, defined as the number of deals exited through IPOs or M&As divided by the total number of deals ever made by the GP prior to the focal fund's SAIC approval, is in the top quintile; and *Older GP* is an indicator for whether the age of a GP at the time when the fund's SAIC registration was approved is in the top quintile. We modify the specification in Equation (1) by including an interaction term between these proxies and $Launched\ VC_{ij}$. We expect that the interaction term to have a positive coefficient.

Regression results are collected in Table 7. Column (1) shows that compared to a GP who engaged with fewer deals in the past, an individual LP creates about 0.08 more ventures after investing in a fund managed by a more experienced GP. Column (4) uses the average number of ventures created per year as the dependent variable, and the coefficient estimate conveys a similar message: interacting with more experienced GPs induces an individual LP to create about 0.03 more ventures per year. The estimated slopes in both columns are statistically significant at the 5% level. In columns (2) and (5), we use the number of GPs' successful exits as a proxy for their quality. Consistently, the estimation results show that an individual LP significantly creates more ventures after investing in a fund managed by "better quality" GPs. Estimates in columns (3) and (6) demonstrate that interacting with GPs with a longer history in the market would lead to a more pronounced effect in venture creation. All these results reveal the heterogeneous effects by GP's characteristics, aligned with the learning hypothesis.

We also examine the extent to which the learning channel affects entrepreneurial outcomes of LPs that invest in multiple funds. We would expect that 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 an indicator, *Veteran* LP_{ij}, that is 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 8. 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 cash windfall is possible if the VC fund undertakes 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 that the effect of investing in a VC fund on individual LPs' entrepreneurial outcomes to be more pronounced for funds 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 in by individual LP i has any successful exits among its portfolio companies between the time of the fund's establishment and 2018, and its interaction term with *Launched* VC_{ij}. Ideally, we could use the IRR of VC funds to proxy for their performance and the amount of capital distributions to LPs. Unfortunately, we do not have the IRR data for these funds. We use instead the successful exits of VC investments as a crude measure of returns. For this channel to work, we predict that 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 9. 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. Neither result supports the prediction, suggesting that the observed entrepreneurial spillovers are not explained by the financial constraints hypothesis.

4.3 Network Hypothesis

Networking plays an important role in the process of VC fundraising, deal sourcing, syndication, and exit (e.g., Hochberg et al., 2007; Gompers et al., 2020). After investing in VC, the interaction between GPs and LPs may enable individual LPs to be better connected to the venture world. It is possible that they can access venture financing for their own companies, leading to more firm creation after investing in VC. We denote this channel as the network channel. If true, we should expect that it will be easier for individual LPs' own ventures to receive VC funding, in particular funding from the GPs they are connected with.

To examine the channel, we revisit the specification in Equation (3). The dependent variable measures whether a venture receives VC financing within two and three years after its formation. We distinguish the sources of venture funding: from connected GPs—those whose funds the individual LP ever invested in—or from any other (non-connected) GPs. Table 10 exhibits the regression results. Columns (1) and (2) report the estimates for the log of total VC funding received by a venture within two or three years of its formation. Inconsistent with the prediction of the network hypothesis, we do not find that the new ventures created by individual LPs after investing in successfully launched venture funds receive more VC financing. Furthermore, columns (3) and (4) look at the amount of VC financing from the connected GPs. Again, the results strongly reject the prediction that the new ventures in the treated group receive more VC funding from the connected GPs. The estimated coefficients have negligible economic and statistical significance. The last two columns examine the amount of VC financing from other GPs. It seems that the other GPs do not fill the hole to provide more capital to the newly created ventures. All the above results suggest that the observed entrepreneurial spillovers cannot be explained by the network hypothesis.

5 Robustness

In this section, we conduct several robustness checks to address potential concerns about our specification and identification strategies. First, we use the Cox proportional hazards model to assess the tendency of starting ventures as time passes. We show that our results are robust to this alternative specification. Second, the industry shocks that we use to define distressed corporate LPs might also impact the financial conditions of individual LPs' existing firms and could also reveal potential (un)attractive entrepreneurial opportunities. These could affect individual LPs' entrepreneurial incentives and potentially explain our main findings. Third, the matching between corporate LPs and GPs may introduce challenges. If a venture fund had more capital commitments from corporate LPs than other funds had, that fund might differ in other ways. Fourth, the industries of the corporate LPs might overlap with the industries to which VCs' portfolio companies belong. 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. In this robustness check, we undertake this analysis at the LP-by-year panel. We note the year the LP invests in a VC fund and how many ventures that LP creates every year. We then use the panel data to rerun our regression with a 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 whether individual i has already become an LP of a fund in year t (post dummy). The results, shown in Table OA3.7 in the Online Appendix, convey a quite similar and robust message as in our main analysis. The coefficient on the interaction term, $\textit{Launched VC} \times \textit{LP}$, is positive and 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 VC fund's formation. These could be potential wealth shocks to individual LPs and change their entrepreneurial incentives. For instance, if their existing firms experience similar economic busts to those of the 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 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 at the time when the fund obtained its SAIC approval. Our main results still hold, as shown in Table OA3.8 in the Online Appendix. Though the 2SLS estimate for the dependent variable of total number of ventures in column (4) becomes statistically insignificant, 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 produce significantly positive coefficients for *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 shock 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 OA3.9 in the Online Appendix, our main conclusions continue to hold. Overall, these results indicate that our instrument is not simply picking up the decisions 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 opportunities 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 OA3.10 in the Online Appendix shows, our main conclusions still hold in both OLS and 2SLS regressions. The coefficients of interest are positive and significant at the 1% level.

There is another concern that venture funds having a larger portion of capital commitments from corporate LPs might exhibit heterogeneous characteristics. For example, VC funds with more corporate

LPs are more likely to experience financing shocks in our IV analysis and also may be more sensitive to industry trends. To alleviate this concern, we run a robustness check by directly controlling for the portion of capital commitments from corporate LPs in each fund. The results are collected in Table OA3.11 and indicate that our conclusions are robust. All estimates are positively significant at the 1% level in both OLS and 2SLS specifications.

The industries of corporate LPs may be highly correlated with those invested in by the VCs. In this case, LPs might learn from the corporate LPs, rather than from the VCs. To alleviate this concern, we compute the average Jaccard similarity index by taking an average of the Jaccard indices across VC funds. For each fund, the Jaccard index is computed by comparing the industries of the corporate LPs and the industries of the fund's portfolio companies.[14] The average Jaccard index in the sample is equal to 0.011. The low index indicates that the corporate LPs' industries are quite different from the industries of VCs' portfolio companies.

The industries experiencing booms or busts might be persistent across years. In this case, the distress shock we used to construct our IVs might not be random. In Figure OA2.1 in the Online Appendix, we exhibit the distribution of industry booms and busts across time. The figure shows that industries experiencing economic cycles are quite variable over time. Table OA3.12 in the Online Appendix tests the persistence of boom and bust industries by examining the serial correlation. The results indicate that lagged boom and bust industry indicators do not strongly predict the current status of the industry, as the estimated coefficients are far from one.

Lastly, when we are comparing the unsuccessfully and successfully launched funds, a potential concern is that a failed-to-launch fund might stigmatize GPs and make it challenging for them to raise the next fund. This could potentially introduce a survival bias because GPs with failed-to-launch funds will not show up in the sample again by raising a follow-up fund. Our sample might be over-represented by funds managed by reputable GPs. To show this is not a valid concern, we directly run a regression of an indicator variable of GPs raising their next fund on whether their current fund fails to launch. Table OA3.13 exhibits the results. Though being significant at the 10% level, the estimated slope on *Failed to*

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[14] The Jaccard index measures similarity between finite sample sets and is defined as the size of the intersection divided by the size of the union of the sample sets. The index is between 0 and 1; a higher value indicates that the two sets share more similarity.

Launch implies that if a GP fails to launch the current fund, it only reduces their likelihood of raising a follow-up fund by 2.5%, which is hardly consequential to bias our results.

6 Conclusions

This paper studies how investing in VC affects the entrepreneurial outcomes of individual limited partners (LPs). Constructing a comprehensive dataset on firm creation, 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 illustrates the blurring boundaries between investors and entrepreneurs.

LPs are traditionally seen as "passive" investors, as they are not involved in a fund's day-to-day business. The Chinese and U.S. VC markets are not precisely comparable, since the concept of limited liability is strictly less enforced in China, But LPs' involvement with funds anecdotally appears similar in many aspects across both countries. GPs often engage their LPs quite actively, such by requesting advice and introductions: indeed, the ability of the LP to be strategically useful is an important criterion for many funds in high demand when selecting new investors. Regardless of fund location, LPs often go above what is contractually required of them in their partnership agreements. Therefore, the learning-by-investing mechanism documented in the paper extends well beyond the borders of China into more developed VC markets.

An interesting question is whether such spillovers can occur elsewhere in entrepreneurial finance. For instance, angel investments in startups appear to have increased sharply in recent years, as have crowdfunding and online investment groups. Understanding the relative learning from these different approaches to investing is a fertile avenue for future research.

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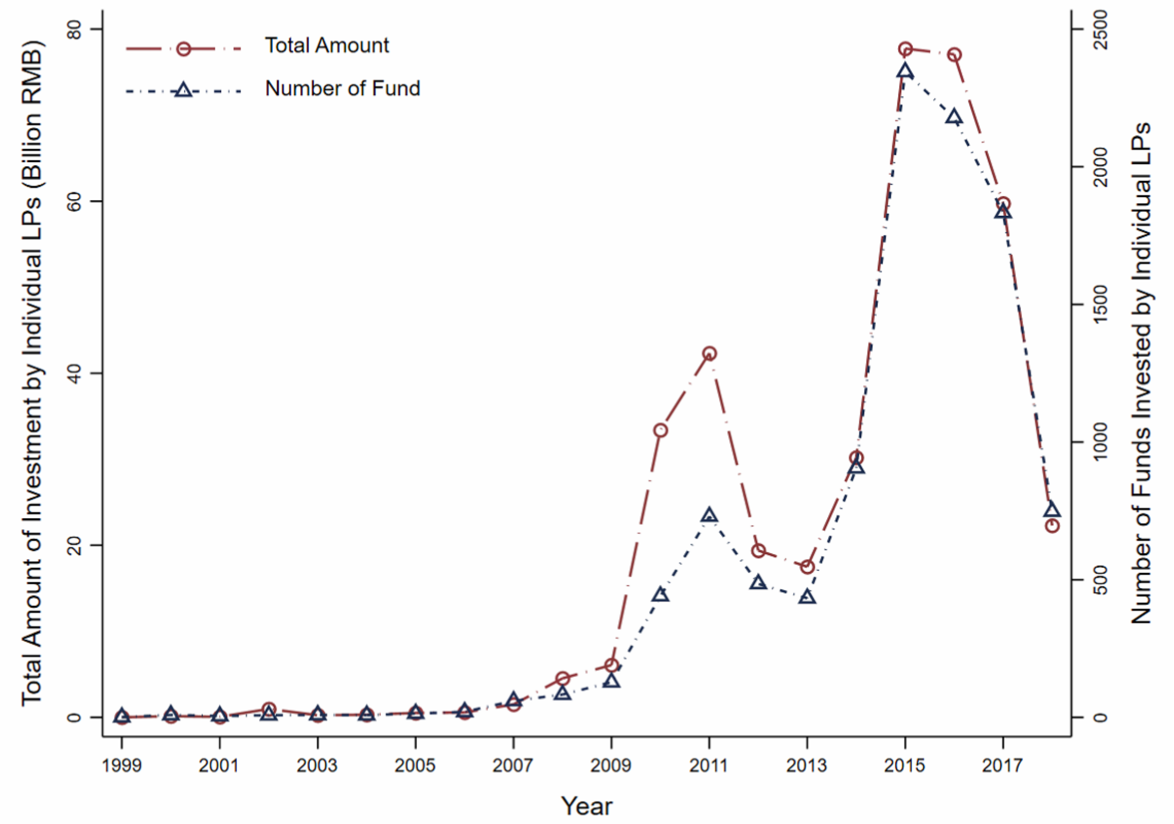
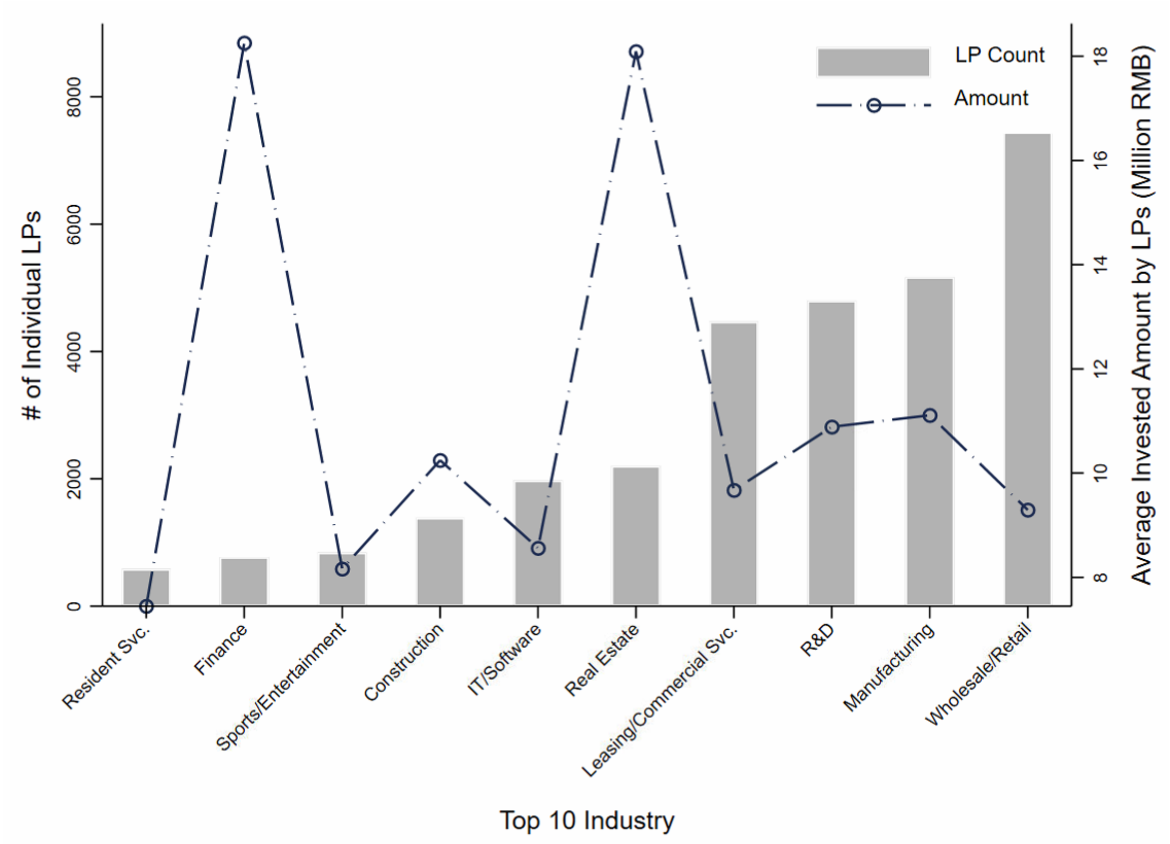
Figures

Figure 1: Individual LPs’ Investments by Year



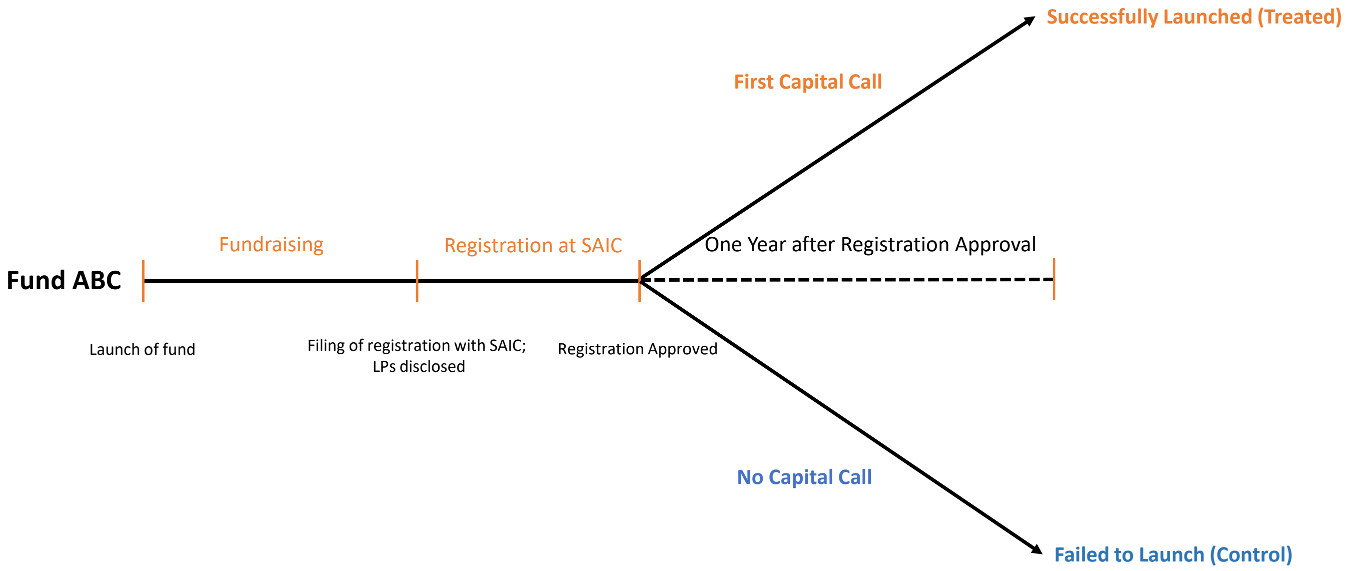
This figure shows the total capital commitments and total number of VC funds invested in by individual LPs from 1999 to 2018. RMB values are adjusted to 2019 by GDP deflators.

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



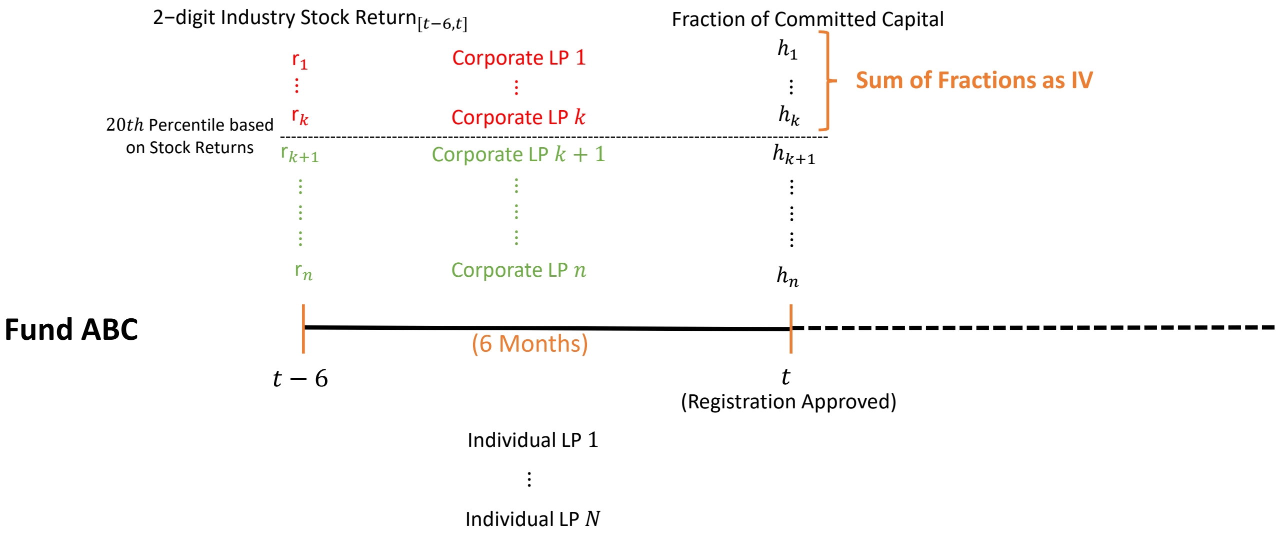
This figure shows the top ten industries of individual LPs' existing businesses before they invested in VC, and the average invested amounts in VC funds per individual LP across industries. For individual LPs whose existing businesses span multiple industries, we define the main industry focus as the one where the individual LP made the greatest equity investment by summing up paid-in capital of the individual LP across all invested firms in the industry. RMB values are adjusted to 2019 by GDP deflators.

Figure 3: Empirical Design


Successfully Launched (Treated)
First Capital Call
Fundraising
Registration at SAIC
One Year after Registration Approval
Fund ABC
Launch of fund
Filing of registration with SAIC; LPs disclosed
Registration Approved
No Capital Call
Failed to Launch (Control)

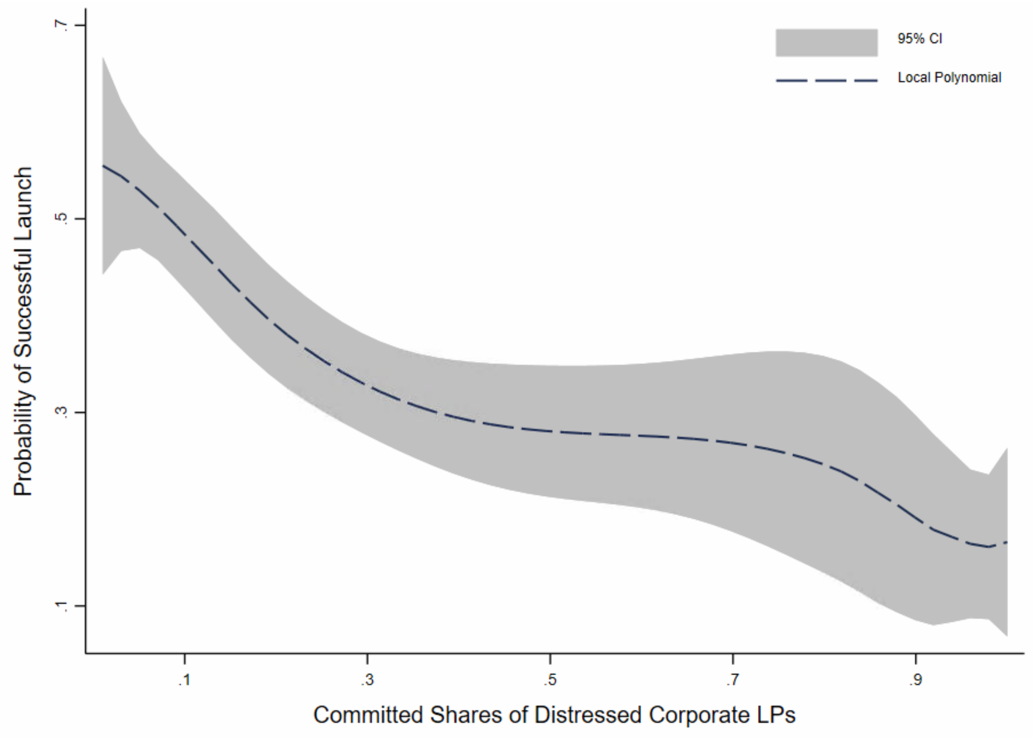
This figure illustrates the empirical design used in the paper. It compares entrepreneurial outcomes of individual LPs in the successfully launched funds to those in the funds that failed to launch.

Figure 4: IV Construction


2–digit Industry Stock Return$_{[t-6,t]}$
Fraction of Committed Capital
r_1
Corporate LP 1
h_1
Sum of Fractions as IV
r_k
Corporate LP k
h_k
$20th$ Percentile based on Stock Returns
r_{k+1}
Corporate LP $k+1$
h_{k+1}
r_n
Corporate LP n
h_n
Fund ABC
(6 Months)
$t-6$
t
(Registration Approved)
Individual LP 1
Individual LP N

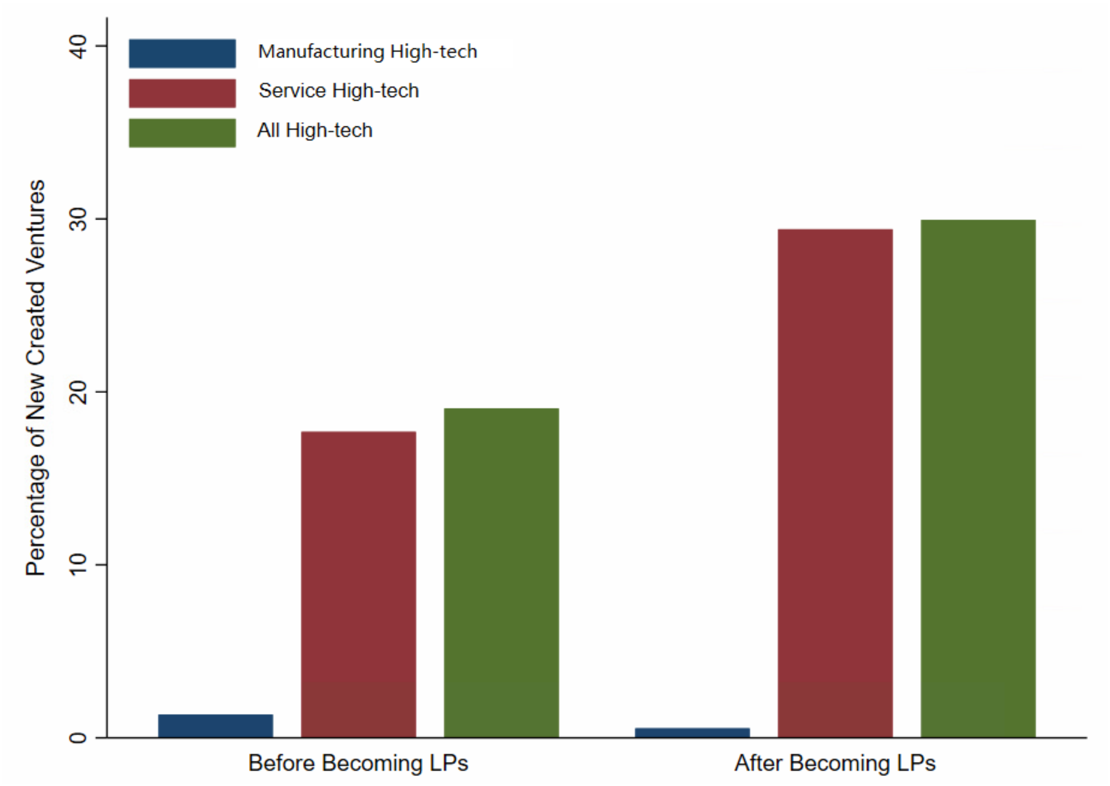
This figure illustrates the process through which we construct the IV for *Launched* VC_{ij} in Equation (1). The bottom 20th percentile is defined based on past six-month stock returns across all two-digit SIC-code industries at time t.

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



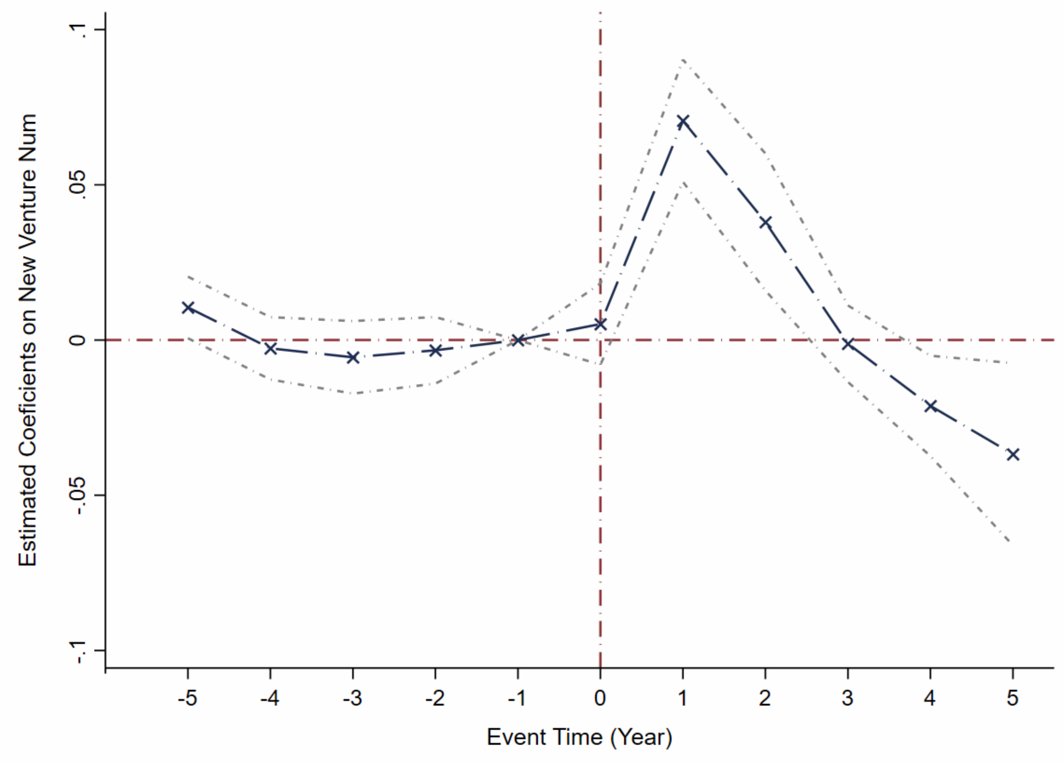
This figure presents the kernel-weighted local polynomial regression of the likelihood of the successful launch of a VC fund as a function of the portion of its total committed capital from corporate LPs in distressed industries in the sample. We define a corporate LP as being in a distressed industry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

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



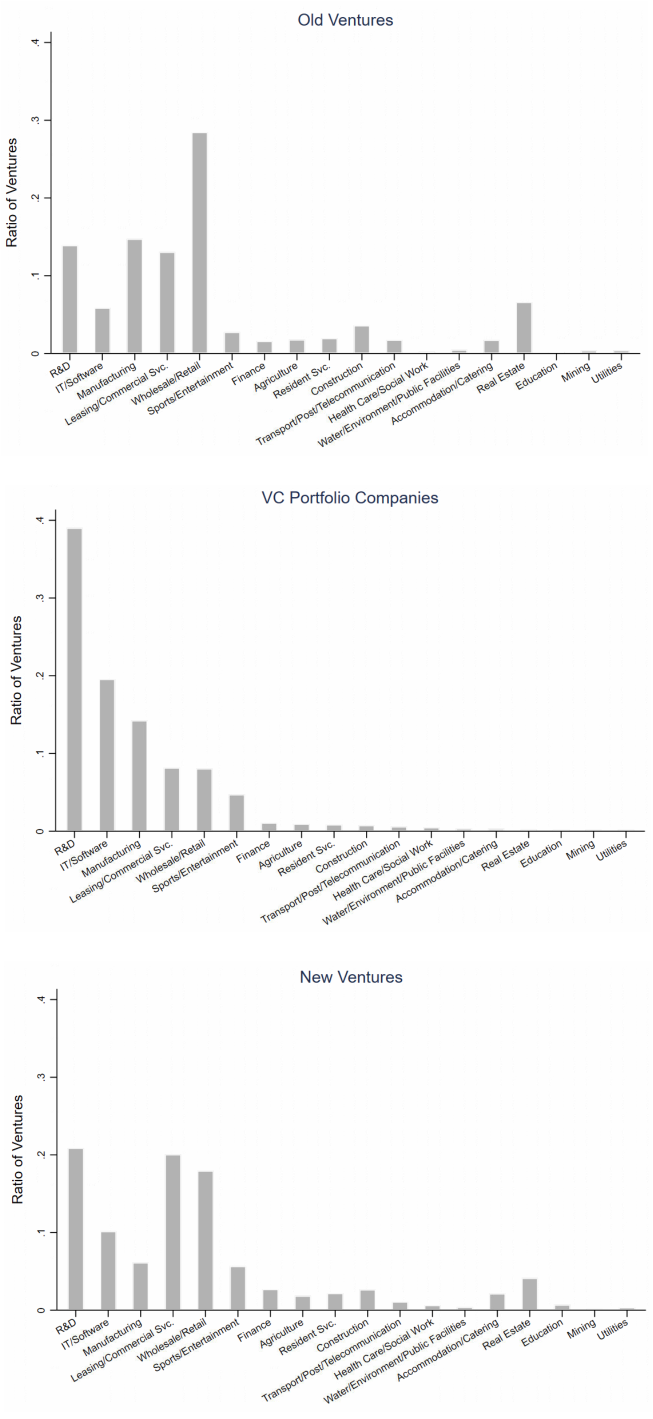
This figure shows the fraction of companies in manufacturing and service high-tech industries. Specifically, we look into companies created by individual LPs before investing in VC (old ventures) and those created after investing in VC (new ventures). The first three bars under "Before Becoming LPs" represent the 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 manufacturing 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 manufacturing and service high-tech industries. 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, to five years after the event. The benchmark year is $t-1$, one year before investing in a VC fund. 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 VC funds' portfolio companies. Specifically, we examine three groups of companies: individual LPs' old ventures that are created before investing in a VC fund (Panel A), the invested VC funds' portfolio companies (Panel B), and individual LPs' new ventures that are created after investing in a VC fund (Panel C). The industry classification is based on the one-digit 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. *Already Entrepreneur* is an indicator equal to one if an individual LP already owned any ventures before investing in a VC fund. *Year Gap*$(t_{LP} - t_{Ent})$ is the year gap between the time of an individual LP starting their first venture and the time of their investing in a VC fund, conditional on *Already Entrepreneur* being 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 that LP invested in a VC fund (inclusive). *Total# Ventures After VC Investment* is the difference between *Total# Ventures* and *Total# Ventures Before VC Investment*. All RMB values are adjusted to 2019 by GDP deflators.

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 in 2019 RMB)	50.991	19.149	110.844	11,120
Fund Size (Million in 2019 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 in 2019 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 in 2019 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: Comparison of Entrepreneur and Non-Entrepreneur LPs

This table summarizes 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 that LP owns at least a 5% share in another non-financial company at the time of the VC fund investment. 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. All RMB values are adjusted to 2019 by GDP deflators.

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 in 2019 RMB)	8.016	29.800	4.438	25.892	3.578***
Fund Size (Million in 2019 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 in 2019 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) using OLS and IV specifications. The unit of observation is at the individual LP=by-venture fund level. The regression sample includes individual LP-by-fund observations in both the successfully launched and failed-to-launch funds. 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 columns (1) and (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 columns (2) and (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 of whether 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 of whether 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 to the total raised capital of fund j. Fixed effects are indicated in the bottom rows. Standard errors are clustered by fund's SAIC registration approval year. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	(1) **OLS** **Total# Firms**	(2) **OLS** **Avg# Firms**	(3) **1st Stage** **Launched VC**	(4) **2SLS** **Total# Firms**	(5) **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 a venture foundedby an individual LP. The regression sample includes all ventures created by individual LPs in both the successfully launched and failed-to-launch funds. 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 were eventually granted) in the two and three years after venture *k*'s formation. The dependent variable in columns (3) and (4) is the number of online job hirings in the two and three years after venture *k*'s formation. The number of online job hirings is defined as the total number of online job announcements posted in the *51job*, *Zhaopin*, and *Liepin* online bulletin boards by venture *k*. Columns (3) and (4) have a different number of observations from columns (1) and (2) because the online job announcement data have a shorter period of coverage. *Launched* VC_{ij} is an indicator of whether VC fund *j* in which individual LP *i* invested was successfully launched in the market. *Post-LP* $Venture_{ikt}$ is an indicator of whether venture *k* was founded after individual LP *i* invested in any fund at time *t*. We control for LP *i*'s gender, an indicator of whether 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* to the total raised capital of fund *j*, venture *k*'s size measured by the log of its registered capital, and LP *i*'s share of venture *k*. Fixed effects are indicated in the bottom rows. Standard errors are clustered by venture *k*'s founding year. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	Total# Patents in 2 Years (1)	***Total# Patents in 3 Years*** (2)	***Total# Hires in 2 Years*** (3)	***Total# Hires in 3 Years*** (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 a difference-in-difference specification with the matched control units. The unit of observation is at the individual LP-by-year level. The regression sample is a panel of individual LPs. LPs in the treated group are those individual LPs who invested in the successfully launched funds and also owned ventures before investing in VC. LPs in the control group are those entrepreneurs who never invested in VC. 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 their 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's or their matched individual LP i's gender, the total number of firms that individual i has started before individual i (or their counterpart in the treated group when i is in the control group) investing in VC j, an indicator of whether individual i (or their 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 their counterpart's in the treated group when i is in control group) committed capital in the fund to the total raised capital of fund j. Standard errors are two-way clustered at individual and year levels. ***, **, and * represent the statistical significance level 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 in the characteristics between ventures created by individual LPs and portfolio companies of VC funds. The regression sample in columns (1) and (2) includes all ventures created by individual LPs in successfully launched VC funds and ventures backed by VC funds which individual LPs committed capital to. The regression sample in columns (3) and (4) includes patents filed by the ventures included in columns (1) and (2). Columns (1) and (3) report Poisson estimates. Columns (2) and (4) present OLS estimates. The dependent variable in columns (1) and (2) is an indicator of whether a venture created by an individual LP (whether before or after they invested in any VC funds) has the same four-digit industry code as any portfolio companies of VC funds that LP 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 the VC funds that LP ever invested in. Standard errors are two-way clustered at the venture's four-digit industry and its establishment 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 at 1%, 5%, and 10% respectively.

	Same 4-digit Industry Code		***Same 3-digit Patent Class Code***	
Specification	Poisson (1)	OLS (2)	Poisson (3)	OLS (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: GP Experience and Entrepreneurship Spillovers

This table reports the impact of GP experience. It replicates columns (1) and (2) of Table 3, except we include interaction terms *Launched VC×GP with More Deals*, *Launched VC×GP with More Successful Exits*, and *Launched VC×Older GP*. The regression sample is smaller than Table 3 because GPs with missing investment records or year of founding are dropped from the regression. *GP with More Deals* is an indicator for whether the number of VC deals conducted by the GP prior to the current fund is in the top quintile. *GP with More Successful Exits* is an indicator for whether the rate of successful exits (IPOs or M&As) of a GP's portfolio companies prior to the current fund is in the top quintile. *Older GP* is an indicator for whether the age of a GP at the time of registering the current fund at the SAIC is in the top quintile. Remaining details are the same as in Table 3.

	Total# Firms			***Avg# Firms***		
	(1)	(2)	(3)	(4)	(5)	(6)
Launched VC × GP with More Deals	0.077**			0.026**		
	(0.027)			(0.010)		
Launched VC × GP with More Successful Exits		0.090**			0.025**	
		(0.032)			(0.010)	
Launched VC × Older GP			0.080***			0.027*
			(0.026)			(0.013)
Launched VC	0.201	-0.092	0.200	0.109	-0.014	0.109*
	(0.186)	(0.294)	(0.186)	(0.062)	(0.082)	(0.062)
Controls	Y	Y	Y	Y	Y	Y
GP FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.087	0.080	0.087	0.015	0.012	0.015
Observations	31,321	18,865	31,321	30,479	18,346	30,479

Table 8: Veteran LPs and Entrepreneurship Spillovers

This table tests whether the learning channel decays over time by comparing the entrepreneurial outcomes of first-time LPs and veteran LPs. It replicates columns (1) and (2) of Table 3 except that we include the variable *Veteran* LP_{ij} and its interaction term with *Launched* VC_{ij}. *Veteran* LP_{ij} is an indicator of whether individual LP i has previously invested in any other funds before fund j. Remaining details are the same as in Table 3.

	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 9: 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. It replicates columns (1) and (2) of Table 3 except that we include the variable *Portfolio Exit*$_{ij}$ and its interaction term with *Launched VC*$_{ij}$. *Portfolio Exit*$_{ij}$ is an indicator of whether VC fund j invested by individual LP i has any successful exits among its portfolio companies by year 2018. Remaining details are the same as in Table 3.

	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

Table 10: Difference in VC Financing of LPs' Own Ventures

This table tests the network hypothesis by examining differences between VC financing provided the new and old ventures of the individual LPs. The unit of observation is a venture by individual LP. The regression sample includes ventures created by individual LPs in both the successfully launched and failed-to-launch funds. 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 logarithm of the total VC financing (in 10,000s of 2019 RMBs) received by a venture within two or three years of its formation. The dependent variable in columns (3) and (4) is the logarithm of the total VC financing from the connected GPs of the individual LP (i.e., any VC fund managed by GPs which the individual LP ever invested in) within two or three years of the venture's formation. In columns (5) and (6), the dependent variable is the logarithm of the total VC financing from any other GPs excluded in columns (3) and (4). The other details are the same as in Table 4. Fixed effects are indicated at the bottom rows. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	$\log(\textit{\$ Any VCs})_{2yr}$	$\log(\textit{\$ Any VCs})_{3yr}$	$\log(\textit{\$ Related VCs})_{2yr}$	$\log(\textit{\$ Related VCs})_{3yr}$	$\log(\textit{\$ Other VCs})_{2yr}$	$\log(\textit{\$ Other VCs})_{3yr}$
	(1)	(2)	(3)	(4)	(5)	(6)
Launched VC × Post-LP Venture	0.005	−0.006	−0.006	−0.004	0.009	−0.001
	(0.008)	(0.007)	(0.005)	(0.011)	(0.008)	(0.009)
Launched VC	0.004	0.006	0.004	0.005*	0.000	0.002
	(0.003)	(0.004)	(0.002)	(0.003)	(0.002)	(0.003)
Post-LP Venture	−0.013**	−0.012	−0.001	−0.007	−0.012***	−0.008***
	(0.006)	(0.008)	(0.005)	(0.009)	(0.003)	(0.002)
Controls	Y	Y	Y	Y	Y	Y
Venture District FE	Y	Y	Y	Y	Y	Y
Venture Industry FE	Y	Y	Y	Y	Y	Y
Venture Founded Year FE	Y	Y	Y	Y	Y	Y
VC Fund Registered Year FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.073	0.063	0.029	0.035	0.081	0.060
Observations	262,653	234,935	262,758	235,057	262,815	235,092

For Online Publication

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

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

OA-1 Data Appendix

OA-1.1 A brief introduction to database construction

The main dataset used in this paper is from the Business Registration Data (BRD) maintained by the State Administration of Industry and Commerce (SAIC) in China. It covers nearly 60 million business entities in mainland China from 1949 to 2021. All business entities, including VC firms, VC funds, and VC-backed companies, are required to register at the SAIC and obtain a business license before operating in these markets. For each registered business entity, we have detailed information on its date of SAIC approval (establishment date), business license revocation (closure date), location (street address, city, province, and zip code), industry (4-digit industry code), and shareholder information (both current and historical shareholders).

Here, we provide a summary of our sample construction steps (see Section OA-1.2 for more detail):

First, we collect a complete list of general partners (GPs) of VC funds from various sources. After 2014, all VC and PE firms must register with the Asset Management Association of China (AMAC). We create a list of GPs by combining the manually-compiled AMAC yearbooks published since 2002 and the commercial database Zero2IPO.

Second, we exploit the BRD data to identify the VC funds managed by these GPs. In addition to the funds registered with the AMAC, we use extra information such as GPs' own commitments to identify funds directly managed by them. Through funds' investment records, we are also able to locate sub-funds indirectly managed by GP.

Third, we use the BRD data to identify LPs of VC funds. The funds' registered capital, as reported to the SAIC (and recorded in the BRD dataset), represents the total capital committed by LPs. Within the BRD dataset, all LPs are listed as shareholders of each fund. However, we encounter a complication where certain LPs may commit capital to a fund indirectly, not through direct investments, but rather through investment vehicles or shell companies. To address this challenge, we examine the ownership structure by tracing all LPs' equity-holders, ultimately recovering the identities of the ultimate investors. This process allows us to identify all categories of LPs. In our analysis, we place a specific focus on individual LPs, whom we define as natural-person/individual investors. These individuals are identified when they appear in the list of first-layer "shareholders" of VC funds (initial LPs) or in the second-layer "shareholders" after a thorough exploration of the ownership hierarchy of the initial LPs.

Fourth, we harness the BRD data to access records of equity investments made by all VC funds and to gather information about the companies that have received VC backing. We categorize companies as VC-backed if their current or historical shareholder records include any VC fund.

Fifth, we make use of the commercial database Zero2IPO to supplement our data with details regarding foreign LPs that utilize a variable-interest entity (VIE) structure for investments in domestic VCs. These VCs are registered overseas but operate within China. We also exploit Zero2IPO to collect the exit information of portfolio companies, such as through IPOs or M&As.

Finally, we merge our constructed VC database with other administrative or commercial databases to obtain the characteristics and performance of VC-backed companies and ventures founded by individual LPs, including information on their patents and online job postings.

OA-1.2 Detailed sample construction procedure

OA-1.2.1 VC firm and VC fund

(1) List of VC firms

a. Asset Management Association of China (AMAC)

The Asset Management Association of China (AMAC) is a semi-official securities investment industry association supervised by the Ministry of Civil Affairs and the China Securities Regulatory Commission (CSRC). According to the Securities Investment Fund Law in China, all financial investment firms must register with the AMAC. Since 2014, according to Chapter 2 of the Interim Measures for the Supervision and Administration of Private Investment Funds, which was promulgated by the CSRC in August 2014, private equity firms have to register at the AMAC and submit information about their funds after obtaining SAIC approval.

The AMAC classifies fund management companies operating in China into four categories: private securities investment companies, private equity and venture capital companies, other private equity investment companies, and alternative asset management companies. By the end of 2019, the AMAC has recorded about 15,000 private equity and venture capital companies, all of which can be found in the BRD data through the firms' current or previous legal names.

There are a few caveats about the AMAC registration: (1) it does not include VC firms that exited the market before 2014. We supplement these missing VC firms by manually collecting a list of VC firms from the VC yearbooks (part b below) and the commercial database, Zero2IPO (part c below). (2) The AMAC only documents domestic VC firms and RMB funds. To overcome this drawback, we use Zero2IPO to supplement information about foreign VC firms and funds that invested in Chinese startups. (3) Not all GPs registered their funds at the AMAC. To recover these missing funds, we track GPs' capital contributions in the BRD dataset, as described below.

b. VC Yearbook and Annual Report

Published in 2002 for the first time, the Venture Capital Development in China Yearbook and the China Venture Capital Yearbook are compiled annually by the China Academy of Science and Technology Development Strategy, an organization under the Ministry of Science and Technology, and the China Venture Capital Research Institute. Each year, the appendices of both yearbooks contain a full name list of active VC firms operating in China of that year. As a supplement to those missing VC records in the AMAC before 2014, we manually compile a list of VC firms in yearbooks' appendices from 2002 to 2013 and identify 1,396 unique VC firms, of which 1,137 can be matched to the BRD data. Firms that cannot be matched are typically those with an abbreviated name, those from overseas, or those from Hong Kong, Macao, and Taiwan.

c. Commercial Database: Zero2IPO

The commercial database provider Zero2IPO Group was founded in 1999 and is a leading professional service platform for venture investments in China (http://www.zero2ipo.com.cn). Zero2IPO is one of the most comprehensive databases covering VC/PE firms, their portfolio companies, and their investment performance in China. The database includes 15,683 VC/PE firms, of which 14,166 can be matched with the BRD data—a matching rate of 90.3%. Most unmatched VC/PE firms are those with an abbreviated name or are overseas VC/PE firms. Note that since Zero2IPO also includes corporate VC firms, such as those of Tencent and Alibaba. Therefore, when identifying the sample of general partners (GPs), we only select those independent VC/PE firms from the Zero2IPO data.

After combining the GP data from the above sources, we obtain a sample of 24,810 GPs.

(2) Cleaning the list of VC firms

Given the sample of 24,810 GPs previously mentioned, we apply the following filters to refine the list of GPs.

We delete any non-VC financial companies, including 70 securities companies, trust companies, insurance companies, and financial leasing firms, 28 state-owned asset management firms, and 5 guarantee firms from the Zero2IPO data.

We delete any firms with unusually large registered capital, including 76 companies with registered capital of more than 5 billion RMB from the Zero2IPO data, and 7 companies from the AMAC data with registered capital of more than 5 billion RMB (Guangdong Railway Development Fund Co., Ltd., Beijing Juhua Investment Fund Management Center [Limited Partnership], Zhongju Asset Management Co., Ltd., ICBC Financial Assets Investment Co., Ltd., Beijing Shougang Fund Co., Ltd., China Eastern Airlines Financial Holding Co., Ltd., China Post Capital Management Co., Ltd.).

We delete any non-investment companies. Zero2IPO has a broad definition of GPs, including companies that directly invest abroad, such as Tencent and Alibaba. To prevent these firms' subsidiaries from being misidentified as investment funds or VC-backed companies, we delete 7,715 non-investment companies from the Zero2IPO data.

After deleting the duplicate VC firms that appear in multiple databases, there are 22,493 GPs in the sample, including 15,248 GPs from the AMAC data, 6,179 GPs from the Zero2IPO data, and 1,066 GPs sourced from the Venture Capital Development in China Yearbook and China Venture Capital Yearbook.

(3) VC funds

After obtaining a list of GPs, we adopt the following steps to identify VC funds managed by these GPs.

The AMAC data, the yearbooks, and the Zero2IPO data collectively account for 34,794 funds under the direct management of 12,937 GPs. Within this set, 6,062 funds are co-managed by multiple GPs. In cases of conflicting GP-fund relationships among these data sources, we prioritize the AMAC data first, followed by the yearbooks and Zero2IPO data.

However, it's worth noting that many GPs do not publicly disclose their funds-under-management information. Consequently, the aforementioned process might not capture all venture funds. To address this gap, we employ two features to help identify these unreported funds managed by GPs.

The first feature relies on the fact that most GPs invest their own capital as a small fraction of commitment to the funds they manage. Using the BRD data, we locate investment firms that were not identified in the previous step but have GPs with equity shares in them. We classify these firms as VC funds. After excluding the cross-holding cases between GPs and other investment firms that are non-VC funds, we identify a total of 82,431 funds directly managed by 16,783 GPs.

The second feature is related to limited partnership funds, where GPs are typically registered as executive partners in the BRD data. We identify these limited partnership investment companies where GPs serve as executive partners through the BRD data and designate them as VC funds. After excluding other investment firms that are non-VCs, this step results in a sample of 11,168 funds, with 3,862 GPs serving as the executive partners of these funds. Among them, 274 funds have multiple GPs serving as executive partners simultaneously.

After consolidating the data collected through these procedures, we create a sample comprising 84,741 funds managed by 21,998 GPs. In cases of conflicting records regarding the GP-fund relationship across different steps, we prioritize the record obtained in the initial step. To facilitate subsequent data processing, when multiple GPs manage a single fund, we identify the GP with the highest proportion of commitment as the lead GP.

OA-1.2.2 Limited partners (LPs)

(1) Ownership structure

In the BRD data, the registered shareholders of a fund that obtained its SAIC approval are regarded as its (direct) LPs. However, in many cases, the true investors in VC funds are concealed within a complex ownership structure. For instance, for regulatory or tax incentives, numerous LPs might create financial shell companies to invest in venture funds, resulting in these shell companies being listed as as the direct LPs in the BRD data. Additionally, government investments in funds usually involve subsidiaries or even multiple layers of subsidiaries of state-owned holding companies. Consequently, to unveil the ultimate LPs behind each fund, especially individual LPs as the primary focus of this study, it is necessary to penetrate through the ownership structure of (first-layer) direct LPs.

Upon obtaining information about all direct LPs of a fund (the first-layer LPs), we categorize them into either corporate LPs or non-corporate LPs. The latter group might include individual LPs, government LPs (including state-owned enterprises), and overseas LPs. For the direct or first-layer corporate LPs for which we cannot identify the capital sources, we trace their shareholders and designate these shareholders as the second-layer LPs.

Two caveats are in order. First, unlike private companies, public listed companies are obligated to register their shareholders at the China Securities Regulatory Commission (CSRC) rather than the SAIC. Consequently, shareholders of listed companies are not captured in the BRD data. In cases where a listed company is identified as the first-layer LP of a fund, we do not proceed with the ownership penetration process outlined above. Second, LPs' equity shares are occasionally held reciprocally. In our sample, roughly 20,000 LPs hold shares of another LP. Consequently, regardless of the number of layers we penetrate along the ownership structure, there will always be repeated instances of corporate LPs in each layer. As a result, we exclude these cross-holding cases from our analysis.

(2) Individual LPs and their related companies

We define two categories of LPs as the individual LPs. In addition to individual investors who directly commit capital to VC funds, easily identified as individual LPs, we also include individual investors who indirectly invest in VCs via a financial vehicle (second-layer LPs). Financial vehicles in the paper are characterized as financial business entities whose four-digit industry code is 6740, 6760, 6900, 7212, or 7299. These four industry codes encompass the majority of non-bank financial vehicles in China.

Once we have identified a sample of individual LPs, we utilize their unique IDs in the BRD data to obtain information on their affiliated companies. These companies are ventures created by individual LPs and include these individual LPs as shareholders. Given that the BRD data contain details such as the establishment or closure dates of these related companies, their locations, industries, registered capital size, and shareholding structures, we are able to gain a comprehensive understanding of individual LPs' entrepreneurial experience throughout our sample period. This information allows us to identify potential entrepreneurial spillover effects resulting from their investments in VC funds. Morevoer, the availability of these detailed characteristics also helps our matching strategy in Section 3.4.

OA-1.2.3 Characteristics and performance of VC-backed companies

(1) Registration

The BRD data provide comprehensive SAIC registration information for each company, including details such as the firm's legal name, date of establishment, date of closure, street address, city, province, zip code, its four-digit industry code, the amount of registered capital (RMB), and names and IDs of all its shareholders and executives.

(2) Exit of portfolio companies

A successful exit of a VC fund's portfolio company includes an IPO or an M&A transaction. Zero2IPO provides information on successful exits of VC-backed portfolio companies, including IPO records of firms in various exchanges worldwide since the 1990s (e.g., IPOs on the Shanghai, Shenzhen, and Hong Kong exchanges and IPOs of Chinese-headquartered firms on overseas exchanges), with a total of 6,907 IPOs, as well as 23,389 M&As sourced from the announcements of public listed companies, media accounts, survey questionnaires, and equity change records in the BRD data. After matching VC-backed companies with Zero2IPO's exit information, 21,203 successful exits are identified.

The timing of portfolio-company exits is an important aspect of our analysis, and it is essential to acknowledge certain ecomplexities related to the timing. First, some VC-backed companies may have experienced multiple events, such as an IPO followed by an M&A. In such cases, we use the first exit event. Second, when it comes to IPOs, determining the exact time of exit can be challenging, since shareholders often do not (and in fact, cannot) immediately sell their shares of the VC-backed company at the time of IPO. Due to the data limitations, as well as the fact that Chinese VCs have traditionally liquidated their positions quickly, we assume that VCs exit their portfolio companies at the time of the IPO.

(3) Other performance measures

In addition to the exit outcomes of portfolio companies, we also gather various performance measures of these VC-backed companies by matching firm names with other data sources, including firms' patent applications and grants (1985–2021) and vacancy postings published on three of the largest online recruitment platforms in China — *51job*, *Liepin*, and *Zhaopin* — from 2014 to 2021.

OA-1.3 Advantages and limitations of our newly constructed database

In this section, we briefly discuss the advantages and potential limitations of our newly constructed VC/LP database. Compared to the commercial database, Zero2IPO, our data have several potential advantages:

(1) Our database offers a comprehensive view of the VC landscape in China by integrating various sources of information. It synthesizes data from VC yearbooks and the SAIC registration information, providing a more complete picture of the major VC players in the market. One of the significant advantages of our database is its coerage of LPs in VC funds. Through the BRD data, we have compiled a comprehensive sample of LPs, as well as a complete sample of portfolio companies backed by VCs. Compared to the Zero2IPO database, our database covers 83.7% more VC-backed companies. Our database contains 3,959 VC firms not included in the Zero2IPO database, accounting for 25.6% of VC firms in our database.

(2) In contrast to Zero2IPO, which tends to over-represent successful VC deals, our dataset is less susceptible to significant selection bias because we include both successful and unsuccessful venture deals sourced from the BRD data. To have a better sense of how selection bias might affect our findings, we compute the IPO exit probability for VC-backed companies in our database, yielding a rate of 3.8%. This is lower than the corresponding statistic derived from the Zero2IPO database, which reports a higher IPO exit probability of 5.1%. These disparities suggest that the Zero2IPO data may overestimate the success rate of IPO exits for VC-backed companies.

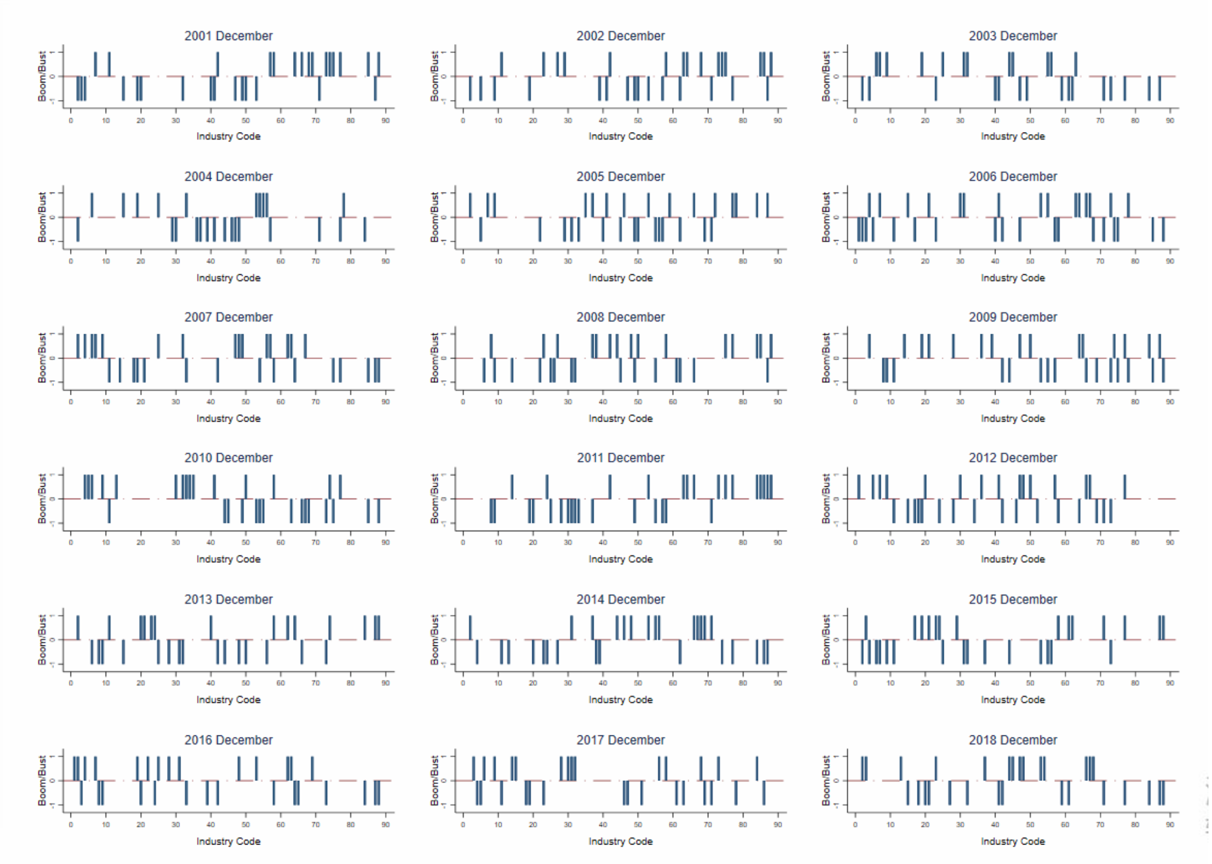
(3) Another advantage of our database is its ability to track the entrepreneurial experience of individual LPs in VC funds. Leveraging unique identifiers for each individual LP in the BRD data, we can link these individual LPs to all (non-financial) ventures in which they are listed as shareholders. This holistic view of individual LPs' entrepreneurial history enables us to assess the spillover effect of investing in VC funds on both their incumbent companies and subsequent entrepreneurial endeavors.

(4) Our database provides alternative performance metrics by cross-referencing firm information with other sources. This includes data on firms' patent applications (and whether the patents are eventually granted) and online job postings. In contrast, the Zero2IPO database primarily relies on proxies such as follow-on financing or successful exits to gauge the performance of VC-backed companies.

One potential limitation of our database is that only VC deals made by RMB funds (funds denominated in domestic currency) are captured in the database. It is important to note that the BRD data primarily contain shareholder information for domestic enterprises. Consequently, VC investments in foreign enterprises that have a business presence in China will be missing. However, it is possible that information on these firms may be captured by Zero2IPO.

OA-2 Additional Figure

Figure OA2.1: Boom and Distressed Industries across Years



This figure shows the boom and distressed industry distributions in December from 2001 to 2018. A two-digit industry at time t is defined as a boom industry if its past six-month average stock return is in the top quintile among all two-digit SIC-code industries at time t. A two-digit industry at time t is defined as a bust industry if its past six-month average stock return is in the bottom quintile among all two-digit SIC-code industries at time t.

OA-3 Additional Tables

Table OA3.1: Direct Regression of New Venture Creation on the IV

This table reports the regression results of the venture creation outcomes, *Total Number of Firms* and *Average Number of Firms*, directly on the IV, *Portion of Corporate LPs in Distressed Industries*. Other details are the same as in Table 3.

	Total# Firms	***Avg# Firms***
	(1)	(2)
Portion of Corporate LPs in Distressed Industries	−0.101***	−0.030***
	(0.023)	(0.006)
Controls	Y	Y
GP FE	Y	Y
Year FE	Y	Y
Adj. R^2	0.125	0.073
Observations	83,655	83,655

Table OA3.2: 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) **OLS** **Total# Firms**	(2) **OLS** **Avg# Firms**	(3) **1st Stage** **Launched VC**	(4) **2SLS** **Total# Firms**	(5) **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 OA3.3: 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 with an ownership stake in each case 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 OA3.4: Venture Creation after Excluding Non-executive Investors

This table repeats the estimation in Table 3, except that we exclude shareholders who own between 5% and 50% of a startup without holding an executive position in the firm's management team. 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	0.021***	0.006***		0.390**	0.115***
	(0.008)	(0.001)		(0.134)	(0.033)
Portion of Corporate LPs in Distressed Industries			−0.258***		
			(0.040)		
1st stage F-stat			41.51		
			(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	0.125	0.073	0.559		
Observations	83,655	83,655	83,655	83,655	83,655

Table OA3.5: Comparison of Successful and Unsuccessful Funds

This table presents 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 OA3.6: 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-to-launch fund and then invested in a successfully launched fund, or those who first invested in a successfully launched fund and then in a failed-to-launch 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 OA3.7: 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 a Cox proportional hazards model. The dependent variable is the number of new ventures created by an individual LP in a year. LP_{it} is an indicator equal to one if an individual investor i has already become an LP of a fund in year t. 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)
Controls	Y
GP FE	N
Year FE	N
Log-likelihood	−932,280.68
Observations	2,419,898

Table OA3.8: Venture Creation after Excluding LPs with Distressed Existing Firms

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 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	0.034**	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 OA3.9: 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 in the top quintile among all two-digit industries at the time of the fund's 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 OA3.10: 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 when those new ventures lie in a set of boom industries. A boom industry is defined as the one whose past-six-month return is in the top quintile among all two-digit industries at the time of the fund's 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

Table OA3.11: Venture Creation after Controlling for Portion of Corporate LPs

This table repeats the estimation in Table 3, except that we control for the total portion of corporate LPs' commitment in a venture fund, denoted as *Portion of Corporate LPs*. 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	0.021**	0.006***		0.409***	0.123***
	(0.008)	(0.001)		(0.136)	(0.033)
Portion of Corporate LPs	0.065*	0.026*	0.009	0.064*	0.026*
	(0.037)	(0.013)	(0.027)	(0.033)	(0.013)
Portion of Corporate LPs in Distressed Industries			−0.259***		
			(0.040)		
1st stage F-stat			41.04 (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	0.125	0.073	0.559		
Observations	83,655	83,655	83,655	83,655	83,655

Table OA3.12: Persistence of Boom and Bust Industries

This table tests the persistence of boom and bust industries. The dependent variable $\mathbf{1}\{\text{Boom Industry}\}_t$ in Panel A ($\mathbf{1}\{\text{Bust Industry}\}_t$ in Panel B) is an indicator variable equal to one if the past six-month average stock return of two-digit industry i is in the top (bottom) quintile among all industries at time t. The independent variables include the lagged boom (bust) industry dummies up to past three months. For example, $\mathbf{1}\{\text{Boom Industry}\}_{t-1}$ is an indicator equal to one if industry i was a boom industry in one month prior, i.e., month $t-1$. Fixed effects are indicated in the bottom rows. Standard errors are clustered by two-digit industry. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

Panel A: Persistence of Boom Industry

	$\mathbf{1}\{\text{Boom Industry}\}_t$		
	(1)	(2)	(3)
$\mathbf{1}\{\text{Boom Industry}\}_{t-1}$	0.578***	0.489***	0.490***
	(0.010)	(0.013)	(0.013)
$\mathbf{1}\{\text{Boom Industry}\}_{t-2}$		0.152***	0.156***
		(0.012)	(0.014)
$\mathbf{1}\{\text{Boom Industry}\}_{t-3}$			−0.009
			(0.009)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Month FE	Y	Y	Y
Adj. R^2	0.36	0.38	0.38
Observations	17,584	17,504	17,424

Panel B: Persistence of Bust Industry

	$\mathbf{1}\{\text{Bust Industry}\}_t$		
	(1)	(2)	(3)
$\mathbf{1}\{\text{Bust Industry}\}_{t-1}$	0.572***	0.503***	0.499***
	(0.011)	(0.012)	(0.012)
$\mathbf{1}\{\text{Bust Industry}\}_{t-2}$		0.120***	0.109***
		(0.010)	(0.012)
$\mathbf{1}\{\text{Bust Industry}\}_{t-3}$			0.023***
			(0.009)
Industry FE	Y	Y	Y
Year FE	Y	Y	Y
Month FE	Y	Y	Y
Adj. R^2	0.37	0.37	0.37
Observations	17,584	17,504	17,424

Table OA3.13: Does Launch Failure Predict Next Fund Launch?

This table examines whether a GP's fund launch failure predicts its next fund's launch. The regression sample includes venture funds with non-missing GP identifiers between 1999 and 2018 in China. The unit of observation is a venture fund. The dependent variable, $1\{\text{Launch Next Fund}\}_t$, is an indicator variable equal to one if a GP successfully launches another fund in the following years through 2018. The key independent variable, *Failed to Launch*, equals one if the GP's current fund failed to launch in the market. Control variables include the logarithm of total committed capital from individual LPs, the logarithm of the fund size, the number of female individual LPs, the number of individual LPs, and the ratio of committed capital from individual LPs to total raised capital of the fund. Fixed effects are indicated in the bottom rows. Standard errors are clustered by fund's registration year. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	$\mathbf{1}\{\text{Launch Next Fund}\}$
Failed to Launch	-0.025*
	(0.012)
Controls	Y
GP FE	Y
Fund City FE	Y
Fund Registered Year FE	Y
Adj. R^2	0.223
Observations	25,951