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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 find that after investing in a successfully launched VC fund, individual LPs create significantly more ventures than do LPs in funds that failed to launch. These new ventures tend to be high-tech firms with better employment outcomes and more patent activity. Our results suggest that venture investments are a channel through which individual LPs learn.

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1 Introduction

One of the most important questions in the entrepreneurship literature relates to the sources of entrepreneurial ideas. While Schumpeter and other earlier writers depicted entrepreneurs as heroic figures whose emergence seemingly impossible to predict, modern scholars have sought to systematically explore the settings in which successful entrepreneurial ideas emerge. Among the channels highlighted in the literature has been the presence of an entrepreneurial tradition in a given location (Glaeser et al., 2015), the influence of peers during one's education (Lerner and Malmendier, 2013) or in the workplace (Nanda and Sørensen, 2010; Wallskog, 2025), and the extent of the individual's own prior entrepreneurial experience (e.g., Gompers et al., 2010; Lafontaine and Shaw, 2016; Brandt et al., 2024). These issues are not only of academic interest but also loom large in policy circles, as governments across the globe seek to encourage the formation of entrepreneurial clusters.

One channel of entrepreneurial learning that has received far less attention, however, is the impact of experience as an investor. Contemporaneous venture groups such as Bessemer and Venrock are reminders that the wealthy (in these two cases, the Phipps and Rockefeller families) have long been sources of venture capital and that entrepreneurs themselves have often served as critical funders of other entrepreneurs, whether through funds or direct investments. Over time, the boundaries between investors and entrepreneurs have become increasingly blurred: capital is no longer provided exclusively by institutional venture groups, but also by angel groups, crowdfunding, and "super angel" venture funds (Bernstein et al., 2017; Lerner et al., 2018; Wallmeroth et al., 2018: Hellmann et al., 2021). Meanwhile, venture capitalists are increasingly turning to high-net-worth individuals, who have already been important capital providers,[1] as vital sources of fund capital. This trend is likely to accelerate in the coming years, particularly given recent policy initiatives to encourage such investments (Trump, 2025).

It is natural to see such exposure as a source of entrepreneurial learning. One could readily imagine that individuals exploit financial intermediaries to learn about new opportunities and refine their initial ideas, much as Ma (2020) has argued that corporate venture investors do. Indeed, history is rife with cases

[1]For example, RBC Wealth Management's North America Family Office report for 2024 finds that 83% of North American family offices hold private equity investments, and among these, 79% (66% of the total sample) invest in VC, which is the most frequently represented private equity strategy (`https://www.rbcwealthmanagement.com/assets/wp-content/uploads/documents/campaign/the-north-america-family-office-report-2024.pdf`).

where entrepreneurs have seemingly learned about opportunities from their investing activities, dating at least as far back as Jakob Fugger the Rich's equity-linked loans to silver miners in the Salzburger Schieferalpen region during the late 15th century, which helped inspire his subsequent launch of mining operations across Bohemia, Hungary, and Tyrol (Häberlein, 2012). To this day, fundraisers tout these benefits: for instance, AngelList (2025) encourages capital form qualified investors by arguing that, "Aside from returns, benefits to becoming an LP [investing in VC funds] might include... access to information ... [and an] expanded network."

In this paper, we study how being an LP in a VC fund affects an individual investor's subsequent entrepreneurial activity. Why focus on individual LPs? These high-net-worth individuals have already committed significant capital in VC funds, which implies that personal financing constraints are relatively muted. This allows us to ask whether exposure to VC causally shifts subsequent entry and venture quality through learning. This setting has a distinctive feature: the LP-GP relationship provides repeated, structured exposure to sector analysis, due diligence, and post-investment governance—an environment particularly conducive to knowledge transfer and learning. 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. (2024) on private firms' aversion to VC investors with government ties.[2] 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. When anchor corporate investors—typically one or multiple corporate limited partners committing the largest share of capital in a fund—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 committed capital from anchor 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 more commitments come from a fund's anchor corporate LPs that experience financial distress, it is more likely that these anchor corporate LPs will be unable to fulfill their financial obligations, hence leading to the failure of the fund to launch.

[2]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., 2024), interregional investments (Shi et al., 2021), and share pledging (He et al., 2022). In a recent survey article, Chen (2023) discusses the data used in VC research in China.

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 an anchor 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 anchor 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 0.37, which implies that on average an individual LP will create one more startup in the three years after investing in a successfully launched VC fund, 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 19% 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 two 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. We also observe that new ventures have more online job postings within two years of their formation, indicating their stronger growth. These findings suggest that the entrepreneurial spillover effect could potentially have a positive social impact.

What channels explain the presence of entrepreneurial spillovers to individual LPs? A learning channel is a natural candidate, as LPs gain access to superior information about VCs' portfolio companies and broader entrepreneurial ecosystem. However, other channels, including a financial constraints channel, a network channel, or a discouragement channel could also explain the pattern. For example, substantial financial returns from VC investments could alleviate financial constraints that often hinder entrepreneurship (e.g., Paulson et al., 2006; Adelino et al., 2015), thereby encouraging new firm creation. Similarly, interactions with general partners (GPs) might expand LP's connections with the VC world and facilitate financing for their own startups (e.g., Hochberg et al., 2007; Gompers et al., 2020), hence incentivizing more firm creation. Alternatively, differences between LPs in launched and failed-to-launch funds might reflect discouragement effects, that is, individual LPs investing in funds that ultimately fail may reduce their entrepreneurial efforts, but not due to the positive spillover from investing in successfully launched funds.

Our results strongly support the learning channel. We find that individual LPs' new ventures, relative to their old ones, share greater similarity in industry and patent classifications with the portfolio companies of the VCs they invest in. The entrepreneurial spillover effect is particularly pronounced for LPs investing in funds managed by "higher-quality" GPs and for first-time LPs, again patterns consistent with learning. We also conducted an online survey among potential VC investors in China, and the results provide additional field evidence supporting the learning channel.

In contrast, we find little evidence supporting the financial constraints, network, or discouragement channels. LPs' entrepreneurship does not increase after investing in funds with successful exits, nor do their new ventures receive more VC financing from connected GPs. Furthermore, LPs investing in failed-to-launch funds do not exhibit a significant decline in subsequent entrepreneurial activity. Collectively, these results indicate that the primary driver of entrepreneurial spillovers is learning by investing, rather than changes in financing conditions, network access, or psychological responses to fund outcomes.

We address various challenges to our identification strategy. One concern is that an anchor corporate LP's industry may overlap with an individual LP's existing firms within the same fund, meaning both could be directly affected by the same industry shock. To mitigate this issue, we exclude all LP-fund observations in which an individual LP's prior ventures operate in the same industry as any corporate LP in that fund. A second concern is that industry booms or busts could directly affect the financial conditions of LPs' existing firms, changing their incentives to start new firms. Our main results continue to hold after excluding individual LPs whose existing firms were in boom or bust industries at the time of the fund's registration approval. A third concern is that industry booms might independently reveal attractive investment opportunities to LPs, prompting LPs to start more ventures in those industries. To address this, we conduct a robustness test by excluding new ventures in booming industries, and our main results still hold. Finally, we analyze other 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, and find that none materially affect our conclusions.

Contribution to the Literature

This paper contributes to several strands of literature. The first is the literature on entrepreneurial decision-making, particularly the determinants of entrepreneurial entry, as discussed in the first paragraph. A complementary stream of work highlights how risk preferences and nondiversifiable background risk shape selection into entrepreneurship (Kihlstrom and Laffont, 1979; Hall and Woodward, 2010), how liquidity and household wealth constrain entry (Evans and Jovanovic, 1989; Hurst and Lusardi, 2004), and how financial constraints and changes in credit supply impact entrepreneurship (Black and Strahan, 2002; Kerr and Nanda, 2009; Hombert et al., 2020). Relatedly, recent studies examine how entrepreneurs absorb information and feedback from angels, VCs, and venture competitions to reduce the uncertainty in entrepreneurship (Sariri Khayatzadeh, 2021; Howell, 2021). 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, extending the entrepreneurial spillover lens beyond peers and place and informing policy debates on how to encourage dynamic entrepreneurial clusters.

Second, our paper is related to the literature on the roles of entrepreneurs and investors in financial markets. Previous studies largely treat entrepreneurs and investors as distinct, while in actuality, their identities overlap quite often. Gompers and Mukharlyamov (2022) find that transitions from startup 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. 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.

Finally, 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 and Grennan, 2024), corporate venture capital induces technological spillovers from invested startups to parent firms (e.g., Siegel et al., 1988; Gompers et al., 2005; Chemmanur et al., 2014; Ma, 2020), banks use their VC arms to forge relationship and complement their lending business (Hellmann et al., 2008), VCs learn from their own past investments when making their current investment decisions (Sorensen, 2008), and entrepreneurial spillovers from corporate R&D flow to their employees (e.g., Hellmann, 2007; Babina and Howell, 2024). 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.

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 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,[3] their location(s) (street

[3] All SIC codes and the industry classification follow the Standard Industrial Classification for National Economic Activities

address, district, prefecture-level city, province, and zip code), incorporation type, and the date the firms obtained their SAIC registration approval.

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 collected from three of the largest recruitment platforms in China. The patents included in the sample are those filed and eventually awarded in China by the CNIPA between 1999 and 2021. Following the literature, we focus on the most valuable awards (invention patents), rather than 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. In our data, we observe patenting in a large range of firms, not concentrating in a few firms. The job postings data span the years 2014 to 2021 and are sourced from three major online recruitment platforms in China: *51job*, *Liepin*, and *Zhaopin*. These data include all posted vacancies along with details such as job titles, number of openings, and eligibility requirements. In Section OA-1 of the Online Appendix, we discuss our sample construction process in detail.

We limit the sample in some ways to avoid potentially confounding cases. In our analysis, we exclude VC funds with registered capital less than 1 million RMB (about $144,800) or more than 4 billion RMB (about $579 million). For any funds with registered capital less than 1 million RMB, we are concerned that these are not typical VC funds focusing on equity investments in high-tech industries. For large 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 construct a complete set of individual LPs investing in VC, we identify two types of individid-

(SIC) issued by the Standardization Administration of the People's Republic of China in 2017.

ual investors. The first group includes individuals who directly committed capital to VC funds and are explicitly listed as "shareholders" in the SAIC registration records. The second group comprises individuals who invest indirectly through financial vehicles.[4] 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. To ensure that the investors in our sample have meaningful exposure to the VC market, we require an individual LP to commit at least 10,000 RMB (about $1,448) to a fund. This filter helps exclude inconsequential or symbolic investments, though our main results remain robust even without this filter. The RMB 10,000 threshold is the minimum inclusion rule, not representative of typical commitments. Typically, these investors are individual, high-net-worth limited partners who commit personal capital to VC funds, not managers from large institutional LPs who co-invest in VC (e.g., CIOs of pensions or endowments).

2.2 Entrepreneurship Records

To track the entrepreneurial outcomes of individual LPs, we construct a comprehensive dataset that traces the business ownership history of each investor. Each individual's venture ownership history is also sourced from the BRD database. 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 in the baseline analysis, we show in Figure OA2.1

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

[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 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. Individual LPs could only participate through public-private partnerships, which are very different from the typical entrepreneurship discussed in the literature.

of the Online Appendix that our main results are robust to using alternative thresholds, including 10%, 20%, 33%, and 50%.

One potential concern in identifying entrepreneurs is the possibility that some shareholders may not be genuine founders or actively involved in venture operations, but instead act as passive or "casual" investors. To address this concern, throughout the analysis, we exclude any shareholders who hold less than 20% equity and do not occupy an executive position within the firm (e.g., CEO, CFO, manager, board chair). This criterion helps ensure that we are capturing individuals with substantive ownership and managerial involvement in their ventures. The 20% equity threshold is guided by empirical evidence from Ewens et al. (2024), which documents that startup founders and CEOs typically retain between 5% and 20% of equity across different stages of early-stage fundraising.

A related concern is the potential misclassification of prolific angel investors as entrepreneurs. To address this, we exclude individuals who hold equity in five or more startup companies, each with a stake below 25%. This filter helps differentiate between hands-on founders and those primarily engaged in broad-based, small-scale startup investing.

Finally, to strengthen identification and address possible confounding factors, we impose an additional restriction: we exclude any individual LP whose prior ventures—i.e., companies founded before investing in a VC fund—operate in the same four-digit SIC industry as any corporate LP invested in the same fund. This restriction ensures that the focal individual LP is not simultaneously exposed to the same sector-specific shocks as corporate LPs, thereby helping isolate the mechanisms of interest. We provide a detailed discussion of this restriction and its implications in Section 5.2.

2.3 Summary Statistics

Our analysis focuses on a final sample of 57,328 individuals who committed capital to 18,867 VC funds that obtained the SAIC approval between 1999 and 2018. Of these, 7,474 funds successfully launched and made portfolio company investments, while 11,393 funds failed to launch. We define a VC fund as having failed to launch if it does not make any portfolio company investments within one year after its registration is approved by the SAIC. This definition reflects the reality that most VC funds in China identify target investments prior to registration with the SAIC, and typically make their first capital call within just a few months of receiving approval.

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 400 billion RMB (equivalent to $60 billion) in both the successfully launched and failed to launch funds. In the sample, individual LPs on average committed about 42% of a fund's capital.[6] Each fund has around four individual LPs on average, each of which invested about 8.8 million RMB (equivalent to $1.32 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 result echoes recent trends in mature venture markets: A recent report from BCG estimates that global individual investors are expected to increase their capital commitments to private equity funds (including VC, buyout, and other private capital funds) at an annual growth rate of 18.8% by 2025, reaching a total of $1.2 trillion, with 52% of this amount coming from individual investors in North America (Zakrzewski et al., 2022).

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 a new Chinese regulation 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 technology 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, we exclude any observations after April 2018 in our main analysis sample.[7]

Among all individual LPs in the sample, 40.7% of them go on to launch new ventures after making their VC investments. Among them, nearly 80% had already founded at least company prior to becoming

[6]This ratio is not equal to the total amount invested by individual LPs in a fund (37.255 million) divided by the fund size (122.918 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.

[7]In another robustness test, we exclude observations in which individual LPs invested in VC during the financial crisis (December 2007 to June 2009) and the 2015 Chinese Stock Market Crash (Bian et al., 2022). The results are reported in Table OA3.1.

an LP. For those with entrepreneurial experience before entering VC, the average interval between the incorporation of their first company and their initial investment as an LP is 9.1 years.

These individual LPs founded 133,181 companies in total in the sample, 95,426 of which were established before or in the year when they first invested in a VC fund and 37,755 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.[8] 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.

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 24.8% of these individual LPs are females.

Comparing funds that failed to launch with those that successfully launched, Panel A of Table 1 shows that successfully launched funds are substantially larger on average (164.2 vs. 95.8 million RMB) and attract more individual LPs (4.76 vs. 3.87), though they rely less on them for capital (37.0% vs. 45.9%). At the individual LP level (Panel B), investors in successfully launched funds are more likely to be entrepreneurs before investing in any VC (43.7% vs. 38.1%) and less likely to be female (22.7% vs. 26.4%), while also investing in slightly fewer funds and committing somewhat smaller amounts on average. At the LP-fund level (Panel C), individuals contribute a smaller share of total capital in

[8]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 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.

successfully launched funds (7.8% vs. 11.9%) and somewhat lower absolute amounts (8.31 vs. 9.24 million RMB). Importantly, individual LPs in successfully launched funds have stronger entrepreneurial track records, having started more ventures overall (2.53 vs. 2.30), with higher counts both before becoming LPs (1.78 vs. 1.69) and afterward (0.75 vs. 0.61).

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 question might pose a number of interpretative issues.

In particular, directly estimating ordinary least squares (OLS) regressions might introduce bias due to endogeneity. For instance, an individual less interested in starting a new venture personally 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 the individual investor, 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. 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 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 that received registration approvals from the SAIC but ultimately failed to launch. We use a *cross-sectional* specification as follows:

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

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, $Launched\,VC_j$ is an indicator of whether VC fund j was successfully launched, μ_j is the GP (VC firm) fixed effects,[9] and δ_t is the fund registration 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, the ratio of LP i's committed capital to the total raised capital of fund j, and the proportion of committed capital from all corporate LPs in fund j as control variables. To address the mechanical overweighting of funds with a larger number of individual LPs in the regression, we apply weighted least squares, where each observation is assigned a weight equal to the inverse of the number of individual LPs in the fund. This weighting scheme makes sure an equal contribution of each fund to the estimation, irrespective of its LP base size.

Whether a VC fund launches successfully, however, 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 anchor corporate LPs that encounter industry distress. The portion is based on the share of total committed capital of the fund, not just the corporate LP share. Our instrument exploits the theory

[9] We include GP fixed effects to control for time-invariant attributes of GPs that could otherwise confound the relationship between fund launch and LP outcomes. With μ_j included, identification comes from within-GP comparisons across the same GP's different funds or vintages, some of which successfully launch and others that do not. Intuitively, the coefficient is identified from GPs that have at least one fund that fails to launch and at least one fund that does launch, as well as from LPs differentially exposed to those funds. We view this within-GP design as a strength, as it mitigates concerns about endogenous GP-LP matching and ensures comparisons are made among LPs investing with the same GP.

of signaling role of anchor LPs in attracting follow-on commitments (e.g., Gompers and Lerner, 1999 and Cole et al., 2020) and coordination frictions (e.g., Nanda and Rhodes-Kropf, 2019) between LPs.

A typical VC fund raises capital from dozens of different LPs, including wealthy individuals and families, large institutional investors, and corporations (Gompers and Lerner, 2004). Not all of these LP investments are created equal—some investors contribute substantially more capital than others. The LP that makes the biggest commitment to a VC fund—or, in some cases, multiple LPs—is referred to as the anchor investor, or anchor check, a concept widely discussed in the practitioner literature (e.g., `https://carta.com/data/vc-funds-anchor-investors-2024/`). More recently, Bhardwaj et al. (2025) highlight the frequent role of university endowments as anchor investors in VC funds. During fundraising, anchor investors typically play a pivotal certifying role, and their financial health can be instrumental to make or break a new fund's launch. If an anchor LP unexpectedly falters for exogenous reasons, the resulting capital shortfall is rarely filled in time, often causing the fund to fail before operations begin. 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 an anchor 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 -22% between May and November 2017, underperforming most industries. Consistent with our hypothesis, this fund never launched operations. During the industry downturn, an anchor 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 a higher share of committed capital from an anchor corporate LP that experiences negative shocks during the fund registration process is 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_j in Equation (1) as follows. For each fund j, we identify the anchor LP, defined as the LP contributing the largest portion of total committed capital within the fund. If multiple LPs contribute equally, we designate all of them as anchor LPs. Let h_{jk} denote the fraction of capital committed by anchor LP k. Our IV is set equal to committed capital fraction from the anchor LP if the LP is a corporate LP that experienced financial distress at the time the fund is registered.

A corporate LP k is considered financially distressed at time t (the fund's registration date) if the past six-month stock return of the industry (at the two-digit SIC code level) that corporate LP k is assigned to is in the bottom quintile among all industries (again at the two-digit SIC code level) at time t.[10] If the anchor LP is not a corporate entity, or if its industry return does not fall within the bottom quintile, we assign the instrument a value of zero. In cases where multiple anchor corporate LPs contribute equal shares and are simultaneously distressed, we aggregate their capital shares to compute the IV.

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 industries (at the two-digit SIC code level) and identify the bottom quintile of 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).

Our IV construction shares a similar flavor of the shift-share design (e.g., Adao et al., 2019). In the analysis sample, as reported in Panel A of Table 1, the mean value of the IV is 0.028. This average is statistically significantly higher for failed-to-launch funds (0.031) compared with successfully launched funds (0.025), consistent with the relevance condition that funds with higher IV values are more likely to fail to launch. Conditional on a fund having at least one anchor corporate investor as an LP, anchor corporate LPs on average contribute about 42% of its total capital. For a fund having at least one anchor corporate LP in distressed industries, on average the distressed anchor corporate LPs contribute about 43% of the fund's capital. In total, there are 1,234 funds containing distressed corporate LPs out of 18,867 funds, and 4,437 individual LPs among these funds out of 57,328 individual LPs.[11] While 1,234 funds with a positive IV represents only 6.5% of funds, the effect variation exploited by our instrument is much richer than the simple 6.5% figure suggests. The instrument is defined as the share of committed capital coming from distressed anchor corporate LPs, which varies widely across funds—from very small fractions to cases where nearly all capital comes from distressed anchor corporate LPs. In addition, funds

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

[11] 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 from Table 1.

without distressed anchor corporate LPs effectively provide identifying contrast (instrument value = 0), which is critical to the estimation.

Note that in constructing the IV, we use changes in industry stock returns observed prior to the approval date of each funds' SAIC registrations (denoted as time t in Figure 4). This timing is designed to capture possible deterioration of anchor corporate LPs' financial conditions during the 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 observed between the start of the fund's registration preparation and the date of approval. Unfortunately, due to data limitation we only have the information on the SAIC registration approval date. We instead choose to examine a fixed time window of six months.

We believe that six months is a reasonable time window for two reasons. First, on average, it takes approximately three to five months for a fund to complete its fundraising, followed by an additional two to three months for SAIC approval. Second, although 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 this six-month window, anchor corporate LPs are less likely to fulfill their capital commitments when the fund proceeds to make its first capital call after approval. One potential concern is that industry distress identified in this window may simply reflect a continuation of an earlier slump, rather than a new shock, so the industry shock does not precisely occur during the six-month window we look into. To address the concern, we conduct a robustness check by redefining distressed industries as those that were in not in the bottom quintile during the preceding six-month period (from $t-12$ and $t-6$) but entered the bottom quintile between $t-6$ and t. As reported in Table OA3.2 of the Online Appendix, our main results still hold. We focus primarily on the bottom quintile because it captures industries experiencing severe financial challenges. In our sample, industries at the 20th percentile cutoff exhibit a mean return of negative 22.11% and a median return of negative 16.53% during the six-month window. As shown in Figure OA2.2 of the Online Appendix, our results are also robust to alternative thresholds, including the bottom 25th, 30th, and 50th percentiles.

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 an anchor corporate LP 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.

A natural concern with our IV is whether industry distress shocks to anchor corporate LPs are truly "unexpected" and exogenous from the perspective of VC funds and individual LPs. While industry returns are public, the mechanism we exploit relies on liquidity shocks to anchor corporate LPs that occur in the narrow window between LPs' capital commitments and the SAIC's approval of the fund. Once soft commitments are registered, GPs have little room to re-solicit or rebalance their LP base without jeopardizing approval. Sharp negative industry returns in this short period can trigger unexpected cash-flow needs at anchor corporate LPs, leading to defaults on capital calls. These liquidity shocks are hard to predict ex-ante and not easily diversifiable for GPs. From the perspective of individual LPs, detailed information about the financial fragility of corporate LPs was not publicly available in our period, and disclosure requirements were limited. Thus while SIC-level returns are observable, the timing and severity of corporate withdrawals are plausibly exogenous to LP entrepreneurial behavior, supporting a valid exclusion restriction.

Though it is not possible to directly test the exclusion restriction, Table OA3.3 demonstrates that the observable characteristics of individual LPs are highly comparable across funds with a high versus low proportion of distressed anchor corporate LPs. Gender composition, capital allocation, and investment amounts are nearly identical across the two groups, with differences in means close to zero. Similarly, indicators of entrepreneurial background, such as prior entrepreneurial experience, number of ventures started before investing in VC, and the year gap between starting their first venture and investing in a VC, do not differ meaningfully between the groups. Industry backgrounds are also broadly balanced, with the only statistically distinguishable difference being a slightly higher representation of LPs with real estate backgrounds in the low-IV group, though this effect is small in magnitude. Taken together, these results suggest that LPs investing in high-IV funds are not systematically different from those investing in low-IV funds in terms of demographics, investment scale, or entrepreneurial and industry experience. This provides assurance that our instrument is not driven by underlying differences in LP characteristics.

Another 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.

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 our empirical specifications 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 OA3.4 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 2. 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 $\textit{Launched VC}_j$ 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 $\textit{Launched VC}_j$ remains significantly positive, implying that individual LPs on average create 0.017 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 or using alternative dependent variables such as the number of ventures created within two years after investing in VC. 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 2. 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. In our setting, the first-stage relationship is strong: We find that the coefficient on the portion of committed capital from anchor corporate LPs in distressed industries equals -0.121 and is significant at the 1% level. This indicates that a 10% increase in committed capital from anchor corporate LPs in distressed industries is associated with a 1.21% 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 15.75, much greater than the threshold of 10, strongly rejecting the null that the instrument is a weak one (Stock and Yogo, 2002). This supports the relevance condition for our IV.

Since the Stock-Yogo thresholds assume homoskedastic errors, we also report the effective F-statistic of Olea and Pflueger (2013), which is valid under heteroskedasticity. The effective F-statistic in our baseline specification is 15.29. While this falls below the stricter cutoff of 23 associated with a worst-case 10% bias (Olea and Pflueger, 2013), it remains above the rule-of-thumb threshold of 10 often used in applied work (e.g., Enikolopov et al., 2020 and Baum-Snow and Han, 2024). Following the guidance in Andrews et al. (2019), we interpret this as indicating that our instrument is sufficiently strong and our IV estimates are unlikely to be affected by weak identification.

Figure 5 exhibits the non-parametric relation (local polynomials) between the portion of committed capital from anchor 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 0.51 to 0.17 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. To further validate this relationship, Figure OA2.3 in the Online Appendix replicates the analysis using a subsample restricted to funds with a strictly positive share of capital from anchor corporate LPs in distress (i.e., positive IVs). The estimated trend remains consistent, reinforcing the robustness of our findings.

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_j is significant at the 5% level and equals 1.19, 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 1.19. Column (5) uses the average number of ventures created per year as the dependent variable. The coefficient on the focal variable is significant at the 1% level and equals 0.37. This coefficient indicates that individual investors on average start one more new venture in about 2.7 years (=1/0.368) 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 venture formation in the analysis sample before an investor investing in any VC is 0.111 venture per year, implying that an individual on average starts a new venture in about 9 years before investing in VC. 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 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 (2025) 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.

The magnitudes of our IV estimates exceed their OLS counterparts. This is consistent with the interpretation that the IV estimates potentially capture a local average treatment effect (LATE) among compliers, i.e., individual LPs investing in funds that only launch in the absence of anchor corporate LP financial distress, which could be larger than the population average treatment effect (Jiang, 2017). Why do these compliers exhibit a larger sensitivity? First, the marginal funds in which compliers invest may be more reliant on close GP-LP engagement or operate in more volatile or experimental spaces where learning opportunities are richer. Since these funds are more fragile, they may require tighter collaboration between GPs and LPs, leading to more intensive exposure to deal flow, due diligence processes, and strategic discussions. This heightened engagement can amplify entrepreneurial learning spillovers for the individual LPs involved. Second, compliers are, by construction, more sensitive to the availability of capital: they invest in funds that might not have launched if the anchor corporate LP's capital dried up. These individual LPs may be more responsive to entrepreneurial exposure precisely because they lack alternative ways to engage with the VC ecosystem. Their marginal participation may generate larger behavioral shifts in entrepreneurship compared to individual LPs in more stable funds.

Another potential reason for the IV-OLS estimate gap may be measurement error in the regressor $Launched\ VC_j$, which would bias OLS coefficients toward zero through attenuation bias, while the IV regressions can recover the true effect (Pancost and Schaller, 2021). This measurement error stems from the fact that launch status of a fund is not directly observed: we classify a fund as successfully launched if it makes at least one venture investment within one year of SAIC approval, an industry-consistent but imperfect proxy that may misclassify funds with delayed investments or minimal launch activity. As a binary, proxy-based variable, $Launched\ VC_j$ is more prone to misclassification than other administrative measures. This would blur the treatment-control distinction, especially in OLS regressions, whereas our IV estimators help mitigate this concern by isolating exogenous variation in launch outcomes less affected by such noise.

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

Having established that LPs in successfully launched funds are more likely to start new ventures than their counterparts, we now examine the nature of these newly created ventures. Specifically, we compare companies founded by individual LPs before investing in a VC fund ("old ventures") with those founded afterwards ("new ventures"), focusing on differences between LPs in successfully launched funds and those in failed-to-launch funds. We analyze several dimensions, including industry distribution, patenting activity, and employment outcomes. Our findings indicate that newly created ventures are, on average, more innovative, filing a greater number of patents and exhibiting stronger employment growth compared to the old ventures founded by the same LPs.

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.[12] As Figure 6 shows, the fraction of new ventures being in high-tech industries is 29.9%, significantly higher than that among old ventures (18.8%). 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 and employ more workers than their old counterparts in the successfully launched funds relative to the failed-to-launch funds. Specifically, we construct a sample of ventures created by LPs. The unit of observation is each venture of an individual LP. We modify our Equation (1) and use the following cross-sectional specification:

$$\begin{aligned} V_{ijkt} = &\beta_1 \textit{Launched } VC_j \times \textit{Post-LP Venture}_{ikt} + \beta_2 \textit{Launched } VC_j + \beta_3 \textit{Post-LP Venture}_{ikt} \\ &+ FEs + Control + \varepsilon_{ijkt} \end{aligned} \tag{2}$$

where V_{ijkt} are the outcome variables for venture k, including (i) the total number of patents filed by (and eventually awarded to) the firm/venture within two years of its formation and (ii) the total number of online job postings within two years of formation. *Launched* VC_j 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

[12]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.

in any fund at time t. The coefficient of interest, β_1, captures the differential outcomes of new ventures (relative to old ones) created by an individual LP in a successfully launched fund compared to those created by LPs in a failed-to-launch fund.

Since all dependent variables are counts, we follow Cohn et al. (2022) and estimate a fixed-effects Poisson model to obtain consistent and efficient estimates. In the regression, in addition to the control variables included in Table 2, we also account for characteristics of venture k, including its size (measured by the log of registered capital), location, industry, founding year, and the LP's ownership stake in the venture. Similar to Equation (1), we control for the year in which the VC fund's registration was approved and include GP fixed effects. Finally, we further add industry and venture-founding year fixed effects to capture sector-specific trends and policy changes that may influence patenting activity, firm entry, or exit.

The results are reported in Table 3. Column (1) shows that new ventures created by LPs in successfully launched funds tend to file more patents. On average, these new ventures file 87.7% ($= e^{0.63} - 1$) more patents within two years of founding than old ventures started by the same LPs, relative to ventures founded by LPs in failed-to-launch funds. This pattern aligns with the prior evidence suggesting that new ventures are more likely to operate in high-tech industries. Column (2) examines firms' hiring outcomes within two years of founding. The positive and statistically significant coefficient indicates that new ventures created by LPs in successfully launched funds exhibit stronger growth. Specifically, the estimated coefficient implies that these new venture have 31.5% ($= e^{0.2736} - 1$) more online job postings than old ventures founded by LPs, relative to those in failed-to-launch funds.

In summary, our findings suggest that the entrepreneurial spillover effect can have a potentially positive impact on social welfare: After investing in VC funds, individual LPs tend to create more ventures—particularly in high-tech industries—that file more patents and hire more workers.

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 7 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 the three groups of companies considered: a set of old ventures created by individual LPs before the VC investment, a set of portfolio companies invested in by the VCs, 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 (20.9%) compared to the old venture group (13.8%). Similarly, the percentage of VC portfolio companies in the wholesale and retail industry is relatively low (8.1%). We find that this percentage is lower for the new ventures (18.1%) relative to the old ones (28.7%).

Second, we examine whether the new ventures are more similar, relative to the old ventures, to the portfolio companies. We examine 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. This analysis is restricted to funds that successfully launched, since failed-to-launch funds, by definition, do not invest in any portfolio companies. As a result, it is not possible to construct comparable measures of industry or patent-code overlap for failed-to-launch funds (the control group), which precludes estimating a fully interacted specification as in Equation (1).

Accordingly, we rely on the following specification:

$$V_{ikt} = \beta_1 \textit{Post-LP Venture}_{ikt} + FEs + Control + \varepsilon_{ikt}. \quad (3)$$

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 by (and eventually awarded by the CNIPA to) 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 $\textit{Post-LP Venture}_{ikt}$ is an indicator of whether venture k was created after individual LP i invested in any VC fund at time t.

Table 4 reports the regression results. In column (1), the dependent variable is an indicator for whether a new venture shares the same four-digit industry code with any portfolio companies. We estimate β_1 using a linear probability model. The coefficient on *Post-LP Venture* is positive and significant at the 1% level, implying that the new ventures are more likely than old ventures to operate in the same four-digit industry as the portfolio companies. Similarly, column (2) shows that the patents filed by new ventures are significantly more likely to overlap with the primary patent fields of portfolio companies. On average, patents from new ventures are 10% more likely to fall within the same field as those filed by VCs' portfolio companies, relative to patents from the old ventures. When estimating industry overlap in column (1), we control for venture- and LP-level characteristics, including the total number of ventures previously started by LPs, gender (female indicator), the log of venture size, the LP ownership share in the venture, as well as venture industry, district and founding year fixed effects. For the patent-classification overlap in column (2), we include these same controls plus patent-primary-field fixed effects 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 $\textit{Launched VC}_j$. We expect that the interaction term to have a positive coefficient.

Regression results are collected in Table 5. Column (1) shows that compared to a GP who engaged with fewer deals in the past, an individual LP creates about 0.17 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 0.08 more ventures per year. The estimated slopes of the interaction terms in both columns are statistically significant at the 1% 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 a "better quality" GP. Estimates in columns (3) and (6) demonstrate that interacting with GPs with a longer history in the market leads 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, $\textit{Veteran LP}_{ij}$, 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_j.

Regression results are reported in Table 6. Our coefficient of interest is the interaction term, *Launched* $VC_j \times$ *Veteran* LP_{ij}. Column (1) shows that, relative to first-time LPs, veteran LPs create about 0.13 fewer ventures after investing in VC, a result significant at the 10% level. Column (2) indicates that veteran LPs also create an average of 0.04 fewer new ventures per year than first-time LPs, though this effect is not statistically significant. Taken together, these findings are consistent with the learning channel: the marginal benefit from exposure to VC funds diminishes as individual LPs accumulate prior experience.

So far, we have shown that individual LPs experience positive entrepreneurial spillovers through a learning channel after investing in a VC fund: some transition from non-entrepreneurs to entrepreneurs by starting new businesses, while others who were already startup owners create additional ventures. Notably, more than half of the individual LPs in our sample are already entrepreneurs prior to investing in VC (Panel B of Table 1). This raises the question of who benefits most from interactions with GPs. To explore this, we conduct a subsample analysis by splitting LPs into those with and without prior entrepreneurial experience and re-estimating the specifications in Table 2. The results, reported in Tables OA3.5 and OA3.6 of the Online Appendix, show that the treatment effect is concentrated among LPs with prior entrepreneurial experience, while we find no significant effects for LPs without any entrepreneurial background. This is consistent with a growing body of literature suggesting that serial entrepreneurs are particularly responsive to new information or skills acquired through learning. For example, Gompers et al. (2010) argue that prior entrepreneurial experience does not eliminate, and may even amplify, the marginal benefits of additional learning opportunities, as experienced entrepreneurs are better able to absorb and act upon new knowledge.

4.1.1 Survey Evidence

To further support the learning channel in the field, we conducted an online survey among potential VC investors within our professional network in China between September 5 and November 1, 2025. A total of 126 individuals opened the survey, and 57 completed it, yielding a response rate of over 45%. Among the 57 respondents, 41 reported prior experience investing in VC funds as individual LPs and therefore continued to the follow-up questions. We refer to these 41 respondents as our effective sample (the remaining 16 respondents answered "No" to the initial screening question and exited the survey).

Within the effective sample, 56.1% of respondents rated 4 or 5 (on a 1 to 5 scale) when asked how well they interacted with and understood the portfolio companies of the funds they invested in. We then asked: "How do you think your experience as an individual LP has helped your newly founded company (or your preparation for future entrepreneurship)? (Select all that apply.)" Respondents could choose from nine potential benefits as listed below:

- Understand market trends or technological frontiers in specific industries
- Discover new entrepreneurial opportunities
- Learn about the venture capital industry, expand your VC network
- Learn practical methods for patenting strategy or technology commercialization
- Learn management practices for startups (e.g., team building, assessing product-market fit, customer development, fundraising strategies, etc.)
- Learn about the key characteristics to be entrepreneurs
- Gain confidence in your own entrepreneurship
- Have not gained any of the above benefits
- Other

As shown in Figure OA2.4 in the Online Appendix, the most frequently cited benefit was "understanding market trends or technological frontiers in specific industries," selected by 68.3% of respondents. The next two most common were "discovering new entrepreneurial opportunities" (53.7%) and "learning about the venture capital industry and expanding the VC network" (53.7%). These results align closely with our main findings—individual LPs learn from their exposure to VC by engaging with GPs and gaining insights into emerging industries and technologies.

Among the 41 respondents, 14 had started new ventures after investing in VC funds. Of these new ventures, 50% operated in the same industries as the VC portfolio companies (e.g., biotech, AI), and

29% overlapped in technology fields, such as patent classifications. These patterns are consistent with the correlations documented in Table 4.

Overall, the survey evidence reinforces the interpretation that individual LPs invest in VC funds not only for financial returns but also as a channel for entrepreneurial learning through exposure to information and industry-specific knowledge.

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, $\textit{Portfolio Exit}_j$, 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 $\textit{Launched VC}_j$. 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 $\textit{Launched VC}_j \times \textit{Portfolio Exit}_j$ should be significantly positive. However, our results do not support this prediction, as shown in Table 7. Column (1) reports the estimated coefficient for the total number of ventures created after investing in a VC fund. The coefficient on $\textit{Launched VC}_j \times \textit{Portfolio Exit}_j$ is negative and statistically insignificant. Column (2) presents the results for the average number of ventures per year, where the coefficient on the interaction term remains negative and statistically insignificant. Taken together, these findings provide no evidence in favor of the prediction, suggesting instead that the observed entrepreneurial spillovers are unlikely to be 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 (used to be LPs of funds managed by these GPs).

To examine the channel, we revisit the specification in Equation (2), but now with the dependent variable measuring the amount of VC financing received by a venture of the individual LP from her connected GPs. Table 8 exhibits the regression results. Columns (1) and (2) report the estimates for the log of total VC financing received by a venture from the related VCs within two or three years of the venture's establishment. A related VC is defined as the venture fund managed by GPs whose past funds have ever received capital commitments from the individual LP.

If the network hypothesis is driving our results, we would expect a significantly positive coefficient for the interaction term, *Launch VC*×*Post-LP Venture*. However, our findings do not support this prediction. We do not observe that new ventures created by individual LPs after investing in successfully launched VC receive more venture financing from connected GPs. The estimated coefficients lack economic and statistical significance. These results suggest that the observed entrepreneurial spillovers cannot be attributed to the network hypothesis.

4.4 Other Hypotheses

Although our main interpretation highlights positive spillovers from exposure to a successfully launched fund, an alternative channel could be that investing in a fund that ultimately failed to launch could itself discourage LPs, for example, by lowering their beliefs about access to VC finance and thereby reducing subsequent entry (a "discouragement channel"), while exposure to successfully launched funds produces no positive spillovers.

We argue that our findings are inconsistent with this discouragement channel. As documented in

Sections 3.3 and 4.1, new ventures founded after exposure to successfully launched funds are more innovative, file more patents, employ more workers, and exhibit greater industry and technological proximity to portfolio companies. These outcomes are difficult to reconcile with the discouragement hypothesis: If the control group were discouraged, we would not expect ventures created by individual LPs in failed-to-launch funds to be systematically less innovative or to display weaker similarity to portfolio company industries and technologies.

To further examine this, we conduct an event study around the SAIC registration approval of funds that ultimately failed to launch. Restricting the sample to LPs who invested in such funds, we compare the number of ventures created before and after their investments. Unlike Table 2, this analysis does not compare LPs in failed-to-launch funds with those in successfully launched funds; rather, it examines within-LP differences before and after their investment in failed-to-launch funds. If discouragement were at play, we would expect a decline in post-event venture creation. However, as shown in Table OA3.7 of the Online Appendix, the estimated coefficient on the post-event indicator is statistically positive. This evidence suggests that LPs are not discouraged from starting new ventures after investing in failed-to-launch funds. Instead, the positive entrepreneurial spillovers we document are largely attributable to the beneficial effects of exposure to successfully launched funds.

5 Robustness

In this section, we perform a comprehensive set of robustness checks to ensure that our findings are not driven by specification choices or identification concerns. First, we test the sensitivity of our results to alternative dependent variables and model specifications. Using the number of new ventures founded within two years of a fund's approval, we find consistent OLS and IV estimates. Second, we complement our cross-sectional analysis with a standard difference-in-differences (DiD) design using an LP-by-year panel, which produces similar results and supports our main interpretation. Third, we employ a reduced-form IV specification by replacing the endogenous fund-launch variable with our instrument, the share of committed capital from distressed corporate LPs, and show that the results remain consistent in sign and magnitude. Fourth, we address several identification challenges, including potential overlap between corporate LPs' and individual LPs' industries, correlated industry shocks affecting both LPs' existing ventures and corporate LPs' liquidity, and non-random matching between corporate LPs and GPs. Finally, we verify that the industries defining corporate-LP distress are not persistent over time and that GP survival bias is negligible.

5.1 Alternative Dependent Variables and Specifications

In our main analysis, we use either the average number of ventures per year or the total number of ventures created by an individual LP after investing in VC as the dependent variables. As a robustness check, we re-estimate Table 2 using instead the number of ventures founded by an individual LP within two years of the fund's registration approval. As shown in Table OA3.8 of the Online Appendix, the OLS and IV coefficients remain positive and statistically significant, in line with our main results. To further disentangle whether individual LPs start more ventures on the intensive versus extensive margin, we use as the dependent variable an indicator equal to one if an individual LP starts any firm within two years. The results, reported in Table OA3.9, show that the OLS coefficient flips sign, is close to zero, and is statistically insignificant. The IV coefficient remains positive but also loses statistical significance. Taken together, these findings suggest that the effect of exposure to a successfully launched fund is concentrated on the intensive margin (i.e., among LPs who do start firms, more startups), rather than meaningfully increasing the probability that an LP starts at least one firm.

In our main analysis, we conduct a cross-sectional test by comparing individual LPs in the successfully launched funds to those in the failed-to-launch funds. As a robustness check, we re-estimate the analysis using a standard difference-in-difference design. Specifically, we restructure the data into an LP-by-year panel. The treated group consists of individual LPs who have ever invested in a successfully launched fund (*Launched VC* $= 1$), while the control group consists of individual LPs who invested only in failed-to-launch funds. We estimate the entrepreneurial spillover effect using the following specification:

$$Y_{it} = \alpha + \beta \textit{Launched VC}_i \times \textit{Post-VC-Investment}_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

where Y_{it} is the number of ventures created by individual LP i in year t; $\textit{Launched VC}_i$ is an indicator equal to one if individual LP i ever invested in any successfully launched fund; and $\textit{Post-VC-Investment}_{it}$ equals one if the LP had invested in any VC fund (either successfully launched or failed to launch) prior to year t. The specification includes year fixed effects (δ_t) and LP fixed effects (μ_i), which absorb all time-invariant LP characteristics. The results, reported in Table OA3.10 in the Online Appendix, convey a quite similar and robust message as in our main findings. The coefficient on the interaction term, *Launched* $VC_i \times$ *Post-VC-Investment*$_{it}$, is positive and significant at the 10% level, indicating that it is more likely for an individual to start a venture after becoming an LP in a successfully launched fund.

When examining the underlying channels, Tables 5 to 8 present subsample tests in which we interact our endogenous variable, *Launched VC*, with alternative proxies. As a robustness check, we adopt a reduced-form IV design by replacing *Launched VC* with our instrument—the fraction of committed capital from distressed anchor corporate LPs—thereby exploiting the instrument directly for identification. The results, reported in Tables OA3.11 to OA3.14 of the Online Appendix, are highly consistent with our main findings.

Specifically, Table OA3.11 provides the reduced-form IV regression corresponding to Table 5 in the main text. All interaction terms remain statistically significant except for the interaction with *GP with More Successful Exits*.[13] Tables OA3.12 to OA3.14 present the corresponding reduced-form IV results for Tables 6 to 8 in the main text. Again, the coefficients on the interaction terms remain statistically insignificant and switch signs, aligning with our main results and reinforcing the robustness of our conclusions.

5.2 Identification Challenges

Next, we address several identification challenges. One concern is that a corporate LP's industry may overlap with the prior entrepreneurial activities of an individual LP (i.e., the individual LP's existing firms, or old ventures) within the same fund. In such cases, if the shared industry experiences distress, both the corporate LP and the individual LP could be directly affected by the same shock, leading to a correlation between the instrument and the error term in the second stage. To mitigate the concern, as discussed in Section 2.2, we exclude all LP-fund observations in which the LP's old ventures operate in the same four-digit industry as any corporate LP in that fund. This restriction removes a direct

[13] As expected, the signs of the estimated coefficients are reversed relative to Table 5, since distress among anchor corporate LPs reduces the probability of fund launch; accordingly, a larger share of committed capital from distressed anchor corporate LPs is associated with weaker subsequent entrepreneurial outcomes for LPs. This pattern is consistent with the negative correlation between the instrument and the endogenous launch variable.

industry-level channel through which anchor corporate LP distress could simultaneously influence the entrepreneurial behavior of individual LPs, independent of the VC fund's launch outcome. We apply this sample restriction consistently across all tables and specifications.

A related concern is that the old ventures of individual LPs may have been exposed to similar economic cycles as corporate LPs in distressed industries at the time of fund formation. Such shocks could directly affect LPs' wealth and alter their entrepreneurial incentives. For example, if their existing firms experience downturns similar to those faced by corporate LPs, the resulting negative shock might encourage them to "gamble" by starting new ventures. To address this concern, we exclude from the analysis individual LPs whose existing firms (old ventures) were in the industries that experienced busts at the time the VC fund was approved. As reported in Table OA3.15 of the Online Appendix, our main results remain consistent: The OLS and 2SLS estimates in columns (1)-(2) and (4)-(5) are still positive, though the 2SLS coefficients lose statistically insignificance. This attenuation largely reflects a weaker first stage due to the reduced sample size, and thus the 2SLS results must be interpreted with caution. Nonetheless, the estimated coefficients continue to point to a positive spillover effect of VC investing on entrepreneurship.

Conversely, one might also worry that individual LPs' existing firms experienced an economic boom at the time of the VC fund's SAIC approval. Such a positive financial shock could increase their incentives to start new ventures. To address this possibility, we exclude individual LPs whose old ventures operated in "boom" industries at the time of the VC fund's approval. We define a boom industry as one 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 shown in Table OA3.16 in the Online Appendix, our main conclusions remain unchanged, although the 2SLS coefficient using the average number of created ventures per year as the dependent variable loses statistical significance in column (5). Overall, these results suggest 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 may be more inclined to start new ventures when they see better opportunities in the booming industries. In this case, the spillovers we documented could reflect entrepreneurs responding to the same favorable conditions that drive VC fund formation and investment choices, rather than learning from their LP experience. To alleviate this concern, we conduct another robustness check in which we exclude any ventures created by individual LPs after becoming an LPs that are in boom industries. As reported in Table OA3.17 in the Online Appendix, our main results still hold: the 2SLS coefficients of interest are positive and statistically significant at the 5% level, though the first stage becomes weaker.

One may also be concerned that a would-be entrepreneur decides to invest in a fund specializing in a particular industry (denoted as industry I) as a way to learn about that industry. If industry I experiences a negative shock prior to the SAIC approval, a shock also felt by corporate LPs from industry I who have committed to investing in the fund, then the prospective entrepreneur may become less likely to launch a venture in that industry. In this case, the reduced entrepreneurial activity would come from the industry shock itself, rather than from corporate LPs withdrawing their commitments. To address this concern, we examine the extent to which corporate LPs' industries are correlated with the industries of portfolio companies targeted by the VC. This analysis also helps us distinguish from an alternative story that individual LPs learn directly from corporate LPs, rather than from the VCs.

Specifically, we compute the average Jaccard similarity index by taking an average of the Jaccard indices across VC funds. 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. For each fund, we calculate its Jaccard index as the count of two-digit industries in the intersection of two sample sets - the set of two-digit industries that its corporate LPs belong to and the set of two-digit industries that the fund's portfolio companies belong to - divided by the count of two-digit industries in the union of the both sample sets. We then compute the average Jaccard index by taking the arithmetic mean of Jaccard indices across all funds in the sample, which is equal to 0.034. The low index indicates that the corporate LPs' industries are quite different from the industries of VCs' portfolio companies.

At first glance, the low average Jaccard index (0.034) may seem surprising: one might expect corporate investors to back funds aligned with their sectoral expertise. However, several factors suggest otherwise. First, many corporate LPs in our setting appear to behave more like financial than strategic investors. Supporting this argument, prior work shows that some CVCs prioritize financial returns or reputational benefits over direct synergies (e.g., Chemmanur et al., 2014). Second, the majority of VC funds in our data are generalist vehicles that span multiple sectors, limiting the ability of corporate LPs to invest narrowly in their own domains. Third, corporate LPs may still extract informational or strategic benefits indirectly, even from exposure to startups outside their core industries. Taken together, these factors help explain why the observed overlap between corporate LPs and portfolio companies remains limited.

The industries experiencing booms or busts may persist across years, raising the possibility that the distress shocks used to construct our IVs are not be random. To assess this, Figure OA2.5 in the Online Appendix plots the distribution of industry booms and busts across time. The figure shows considerable variation, with different industries cycling in and out of booms and busts across years.

Lastly, when comparing successfully and unsuccessfully launched funds, a potential concern is that a failed-to-launch fund might stigmatize the GP and make it challenging for them to raise subsequent funds. This could introduce survival bias if GPs with failed-to-launch funds are systematically less likely to reappear in the sample with a follow-up fund, leaving the sample overrepresented by funds managed by more reputable GPs. To examine this possibility, we regress an indicator for whether a GP raises its next fund on whether its current fund fails to launch. The results, reported in Table OA3.18, show that while the coefficient on *Failed to Launch* is significant at the 10% level, the magnitude is small: Failure to launch reduces the likelihood of raising a subsequent fund by only 2.5%. This effect is too modest to meaningfully 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. But LPs' involvement with funds anecdotally appears similar in many aspects across both China and U.S. GPs often engage their LPs quite actively, such by requesting advice and introductions. Anecdotally, the ability of a potential LP to be strategically useful is an important criterion that many funds experiencing high demand use when selecting new investors. LPs similarly 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.

Our results seem to suggest that the learning-by-investing mechanism has net positive welfare implications. The new ventures created by individual LPs after investing in VC survive longer and are more innovative, indicating the ventures are of better quality. However, quantifying the aggregate welfare impact of the learning-by-investing mechanism requires a more structural evaluation, which we leave for future research.

Although our estimates capture information spillovers in a VC setting, we believe the learning channel generalizes to the settings of other asset classes, especially where investors receive deep, sector-specific information and have regular, structured interactions with asset managers. Accordingly, our findings provide a positive rationale for learning-oriented participation by sophisticated high net worth (HNW) investors in private-market vehicles that ensure meaningful engagement, while effects are likely much smaller for passive, information-light financial assets. For example, real estate private equity may generate modest spillovers for HNW investors who receive detailed reporting and periodic engagement, whereas activist hedge funds are likely to yield much smaller effects for typical retail investors with limited information rights.

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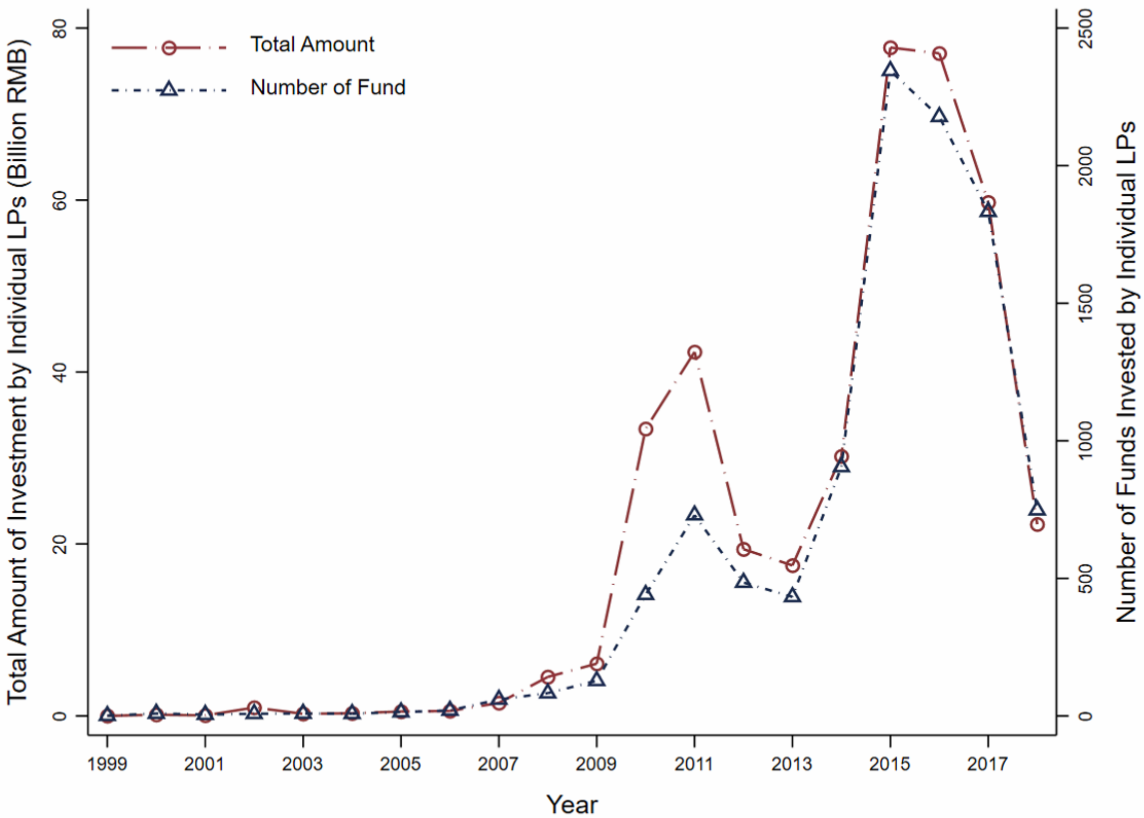
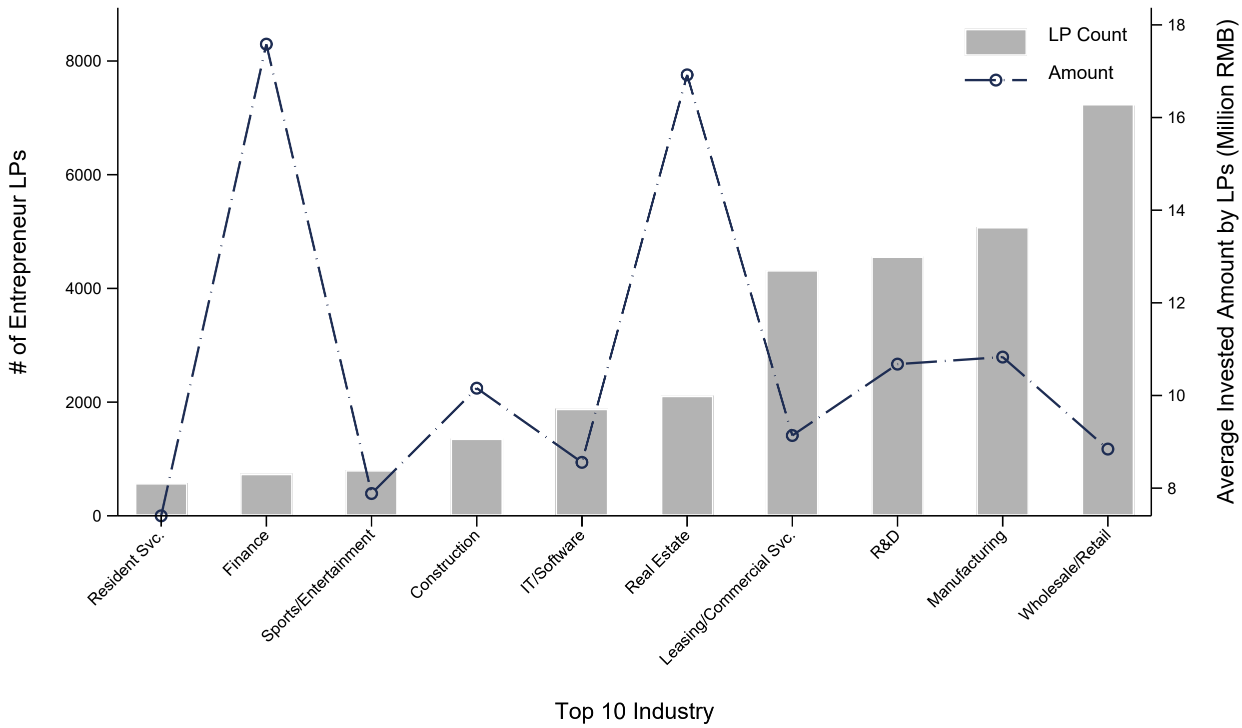
Figures

Figure 1: Individual LPs' Investments by Year



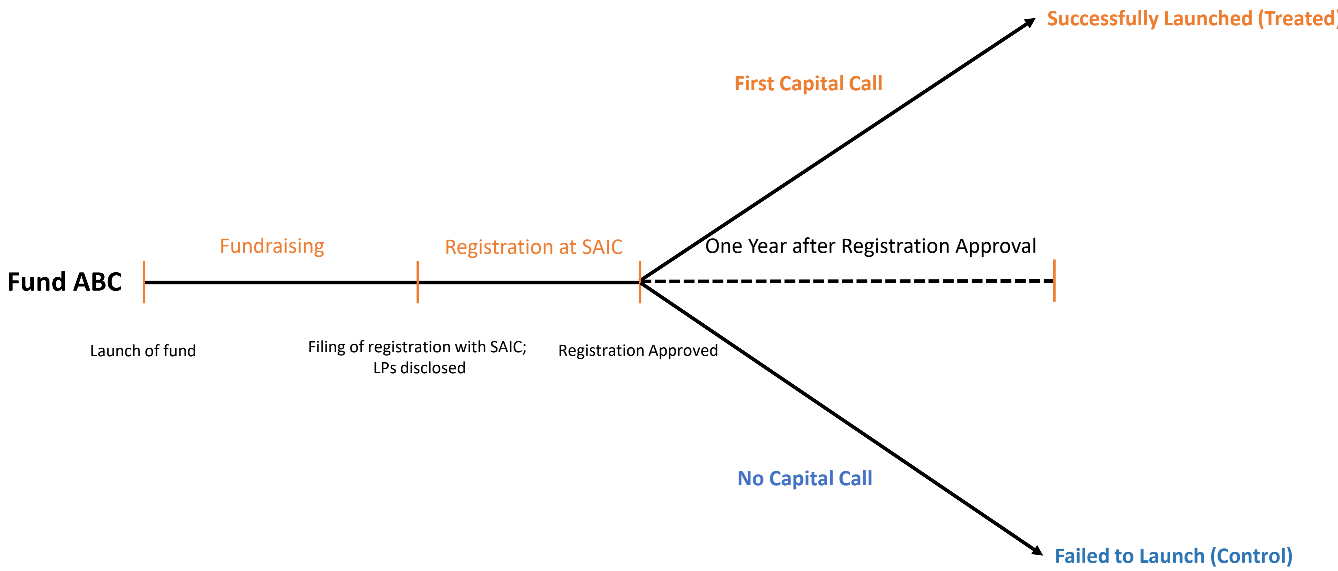
This figure shows the total capital commitments and total number of VC funds invested in by individual LPs from 1999 to 2018. RMB values are adjusted to 2019 by GDP deflators.

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



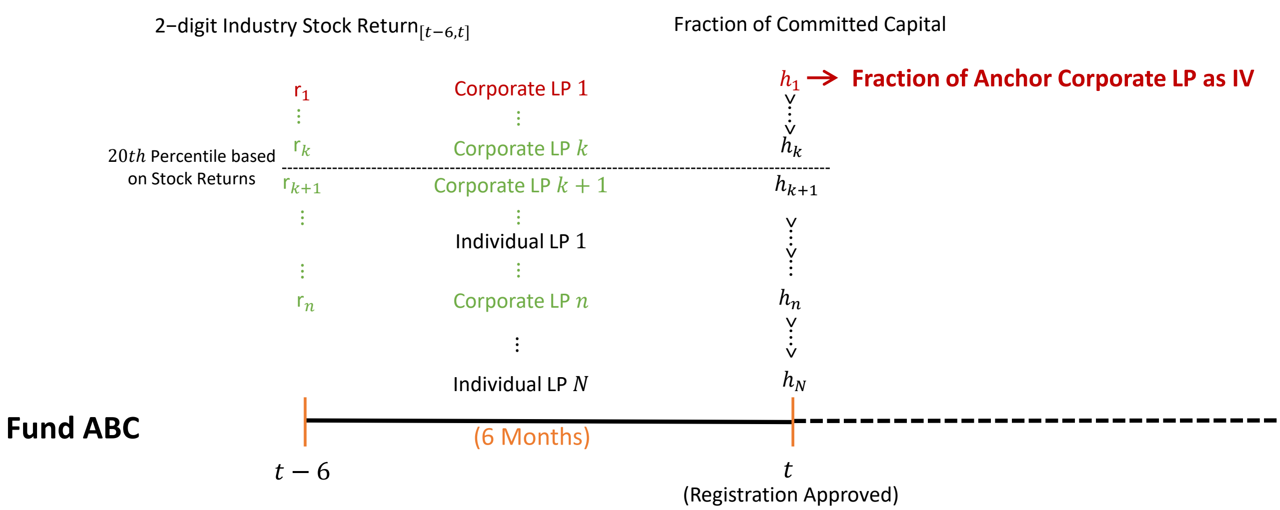
This figure shows the top ten industries of individual LPs' existing businesses before they invested in VC and the average invested amounts in VC funds per individual LP across industries. For individual LPs whose existing businesses span multiple industries, we define the main industry focus as the 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



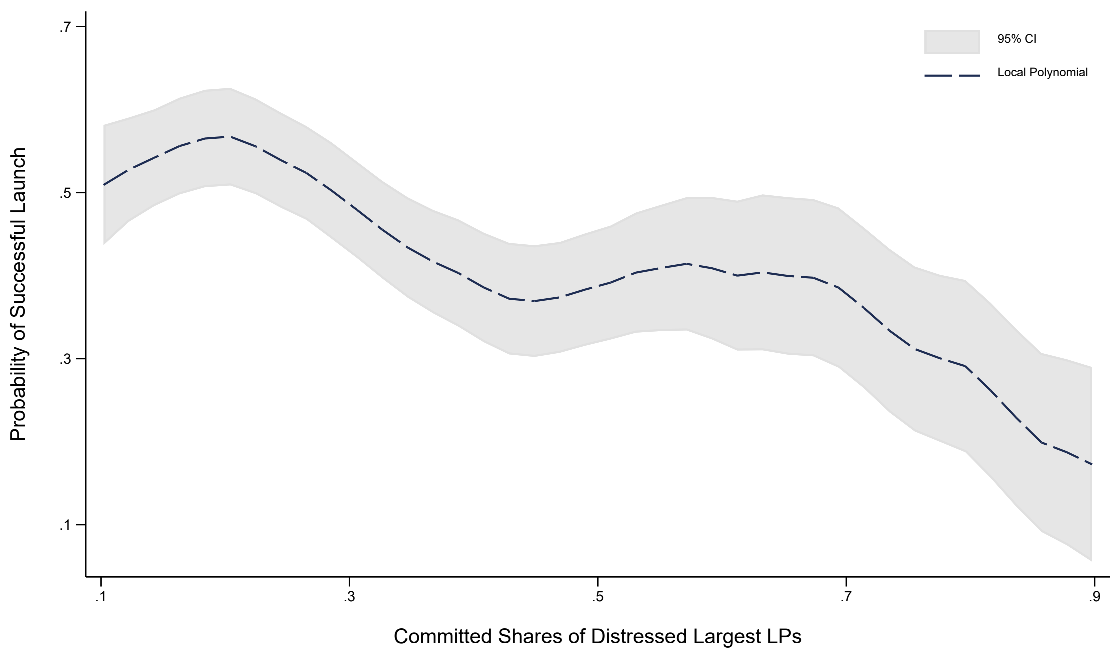
This figure illustrates the empirical design used in the paper. It compares entrepreneurial outcomes of individual LPs in the successfully launched funds to those in the funds that failed to launch.

Figure 4: IV Construction



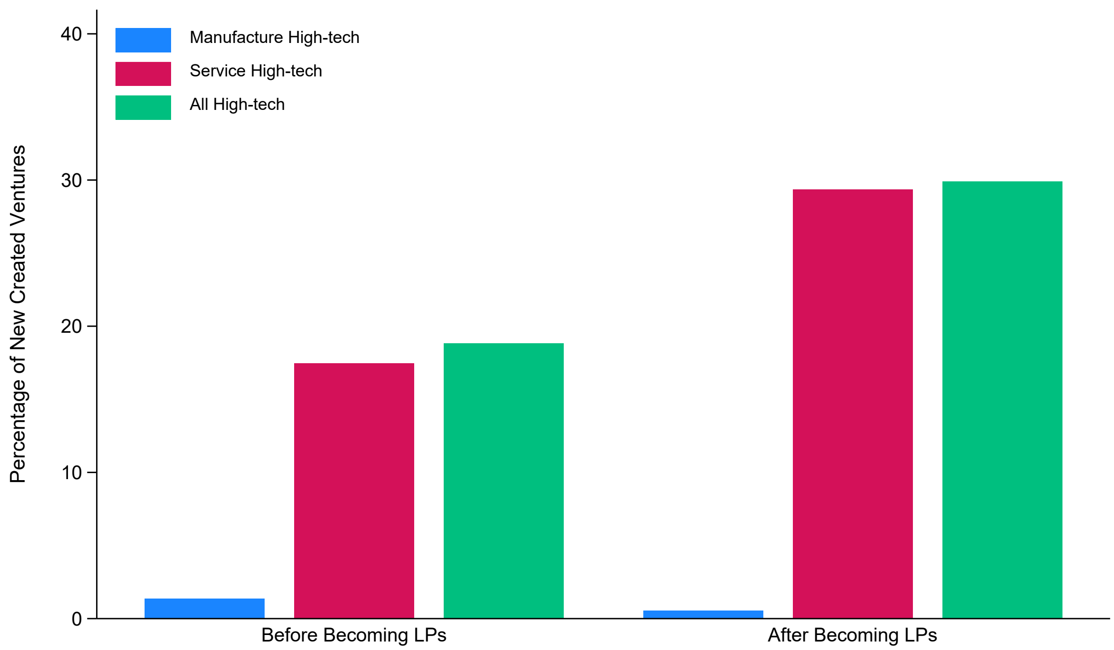
This figure illustrates the process through which we construct the IV for *Launched* VC_j in Equation (1). The bottom quintile is defined based on past six-month stock returns across all industries (at the two-digit SIC code level) at time t.

Figure 5: Fraction of Committed Capital from Anchor Corporate LPs and Fund Launch Likelihood



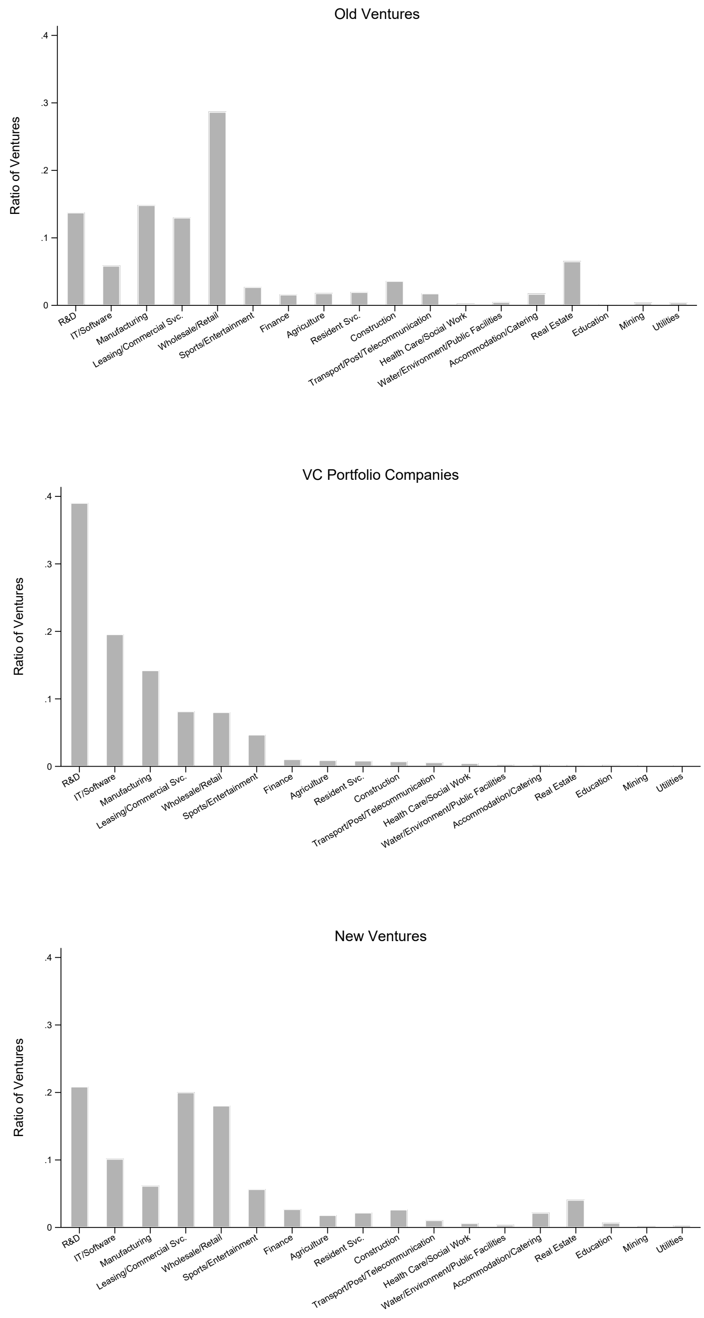
This figure presents the kernel-weighted local polynomial regression of the likelihood of a VC fund's successful launch as a function of the portion of committed capital from anchor corporate LPs in distressed industries in the sample. For each fund, we identify the anchor LP, defined as the LP contributing the largest portion of total committed capital within the fund. If multiple LPs contribute equally, we designate all of them as anchor LPs. We define an anchor 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 industry (at the two-digit SIC code level) 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: 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 later either successfully launched (treated group) or failed to launch their funds (control group) in the market. 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. The last column reports the difference in sample means between the Failed to Launch and Successful Launch groups. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by the fund's SAIC registration approval year.

Panel A: Fund Level

	Full Sample			**Failed to Launch**			**Successful Launch**			
Variable	Mean	SD	N	Mean	SD	N	Mean	SD	N	Diff
#Individual LPs	4.221	5.131	18,867	3.868	5.196	11,393	4.761	4.982	7,474	-0.893***
Total% Committed by Individual LPs	0.424	0.303	18,867	0.459	0.318	11,393	0.370	0.270	7,474	0.089***
Total¥ Individual LPs (2019 RMB Millions)	37.255	113.834	18,867	35.747	128.546	11,393	39.553	86.691	7,474	-3.806
Fund Size (2019 RMB Millions)	122.918	293.821	18,867	95.839	254.862	11,393	164.196	340.745	7,474	-68.357***
%Anchor Corporate LPs in Distressed Industries (IV)	0.028	0.129	18,867	0.031	0.140	11,393	0.025	0.110	7,474	0.006**

Panel B: LP Level

	Full Sample			**Failed to Launch**			**Successful Launch**			
Variable	Mean	SD	N	Mean	SD	N	Mean	SD	N	Diff
Female	0.248	0.432	57,328	0.264	0.441	31,291	0.227	0.419	26,037	0.037***
Entrepreneur	0.406	0.491	57,328	0.381	0.486	31,291	0.437	0.496	26,037	-0.056***
# Fund Invested	1.389	1.191	57,328	1.409	1.322	31,291	1.365	1.010	26,037	0.044*
Total Amount Invested (2019 RMB Millions)	12.261	93.826	57,328	13.032	121.182	31,291	11.334	41.635	26,037	1.698

Panel C: LP by Fund Level

	Full Sample			**Failed to Launch**			**Successful Launch**			
Variable	Mean	SD	N	Mean	SD	N	Mean	SD	N	Diff
%Committed Capital	0.100	0.183	79646	0.119	0.214	44,063	0.078	0.131	35,583	0.041***
Amount Invested (2019 RMB Millions)	8.825	49.440	79,646	9.243	60.871	44,063	8.308	29.707	35,583	0.935
Already Entrepreneur	0.799	0.401	79,646	0.797	0.402	44,063	0.800	0.400	35,583	-0.003
Year Gap	9.136	4.684	63,610	9.207	4.778	35,129	9.048	4.564	28,481	0.160
Total# Ventures	2.400	2.463	79,646	2.298	2.028	44,063	2.527	2.907	35,583	-0.230***
Avg.# per Year	0.126	0.130	79,646	0.121	0.107	44,063	0.133	0.153	35,583	-0.012***
Total# Ventures Before VC Investment	1.725	2.158	79,646	1.685	1.748	44,063	1.775	2.576	35,583	-0.091**
Total# Ventures After VC Investment	0.675	1.163	79,646	0.613	1.064	44,063	0.752	1.270	35,583	-0.139***
Avg.# Ventures per Year Before VC Investment	0.111	0.133	79,646	0.106	0.109	44,063	0.118	0.157	35,583	-0.012***
Avg.# Ventures per Year After VC Investment	0.225	0.519	79,646	0.222	0.450	44,063	0.227	0.594	35,583	-0.005

Table 2: 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-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_j 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, the ratio of LP i's committed capital in fund j to the total raised capital of fund j, and the proportion of committed capital from all corporate LPs in 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	0.0354***	0.0168***		1.1806**	0.3666***
	(0.0109)	(0.0055)		(0.4224)	(0.1048)
%Anchor Corporate LPs in Distressed Industries			-0.1209***		
			(0.0306)		
Total# Prior Ventures	0.0131*	0.0042*	0.0012*	0.0117	0.0038
	(0.0071)	(0.0023)	(0.0007)	(0.0070)	(0.0023)
Invested in Other VCs Before	0.0174	0.0095	0.0170	-0.0018	0.0036
	(0.0214)	(0.0067)	(0.0107)	(0.0191)	(0.0050)
Female LP	-0.1648***	-0.0577***	-0.0079*	-0.1562***	-0.0559***
	(0.0286)	(0.0051)	(0.0042)	(0.0250)	(0.0048)
Log(Fund Size)	-0.0180***	-0.0108***	0.0559***	-0.0807***	-0.0299***
	(0.0050)	(0.0033)	(0.0030)	(0.0276)	(0.0048)
%Committed Capital	0.1972***	0.0691**	-0.1685***	0.3892***	0.1278***
	(0.0663)	(0.0237)	(0.0151)	(0.0794)	(0.0132)
%All Corporate LPs	0.0687*	0.0314	0.0644*	0.0097	0.0134
	(0.0364)	(0.0200)	(0.0282)	(0.0382)	(0.0139)
1st stage F-stat			15.67		
			(0.0013)		
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.3101	0.2872	0.4860		
Observations	78,539	78,539	78,539	78,539	78,539

Table 3: 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 founded by 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 column (1) is the number of filed patents (that were eventually granted) in the two years after venture k's formation. The dependent variable in column (2) is the total number of online job postings within two years of formation. *Launched* VC_j 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. In the regression, in addition to the control variables included in Table 2, we also account for characteristics of venture k, including its size (measured by the log of registered capital), location, industry, founding year, and the LP's ownership stake in the venture. 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	***Total# Hiring in 2 Years***
	Poisson	Poisson
	(1)	(2)
Launched VC×Post-LP Venture	0.6300**	0.2736***
	(0.2604)	(0.0781)
Launched VC	0.0375	-0.2324*
	(0.1136)	(0.1250)
Post-LP Venture	-0.8086***	-0.3117***
	(0.3015)	(0.1544)
Total# Prior Ventures	0.0136	0.0739***
	(0.0332)	(0.0160)
Invested in Other VCs Before	-0.4242***	0.2156*
	(0.1594)	(0.1152)
Female LP	-0.5271*	-0.2269***
	(0.2739)	(0.0377)
Log(Fund Size)	0.0290	0.0490***
	(0.0975)	(0.0119)
%Committed Capital	-1.0522**	-0.4337***
	(0.4843)	(0.1844)
%All Corporate LPs	1.0985*	-1.0283***
	(0.6356)	(0.2999)
Log(Startup Size)	0.7457***	0.4735***
	(0.0838)	(0.0366)
%LP Stake in Startup	-0.7200	-0.6808***
	(0.5985)	(0.0645)
Startup Industry FE	Y	Y
Startup District FE	Y	Y
Startup Founding Year FE	Y	Y
(VC Fund Registered) Year FE	Y	Y
GP FE	Y	Y
Observations	15,088	76,779

Table 4: Correlation between New Ventures and Portfolio Companies

This table examines the correlation in the characteristics of ventures created by individual LPs and those of portfolio companies backed by the VC funds they invested in. The regression sample in column (1) includes all ventures created by individual LPs in successfully launched VC funds. Column (2) restricts the sample to patents filed by those ventures. The dependent variable in column (1) is an indicator equal to one if a venture, which was founded either before or after the LP's initial VC investment, shares the same four-digit industry code as any portfolio companies of the VC funds that the LP has invested in. In column (2), the dependent variable is a dummy equal to one if any patent filed (and subsequently granted) by the venture after its formation shares the identical three-digit classification code as any patent filed by a portfolio company of the VC funds that LP ever invested in. The control variable, *Log of Startup Size*, is the natural logarithm of the venture's registered capital. Fixed effects are indicated at the bottom of the table. Standard errors are clustered at the venture's establishment year level for column (1), and patent application year levels for column (2). ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	Same 4-digit Industry Code	***Same 3-digit Patent Class Code***
	OLS	OLS
	(1)	(2)
Post-LP Venture	0.0082***	0.1026*
	(0.0036)	(0.0055)
Total# Prior Ventures	0.0017	0.0024
	(0.0013)	(0.0064)
Female Entrepreneur	-0.0051***	-0.0612
	(0.0015)	(0.0448)
Log(Startup Size)	-0.0002	0.0043
	(0.0007)	(0.0130)
%Ownership in Startup	0.0026	-0.0301
	(0.0021)	(0.0434)
Startup Industry FE	Y	Y
Startup District FE	Y	Y
Startup Founding Year FE	Y	Y
Patent Field FE	N	Y
Patent App. Year FE	N	Y
Adj. R^2	0.1808	0.4623
Observations	74,346	6,595

Table 5: GP Experience and Entrepreneurship Spillovers

This table reports the impact of GP experience. It replicates columns (1) and (2) of Table 2, 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 2 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 2.

	Total# Firms			***Avg# Firms***		
	(1)	(2)	(3)	(4)	(5)	(6)
Launched VC × GP with More Deals	0.1733***			0.0773***		
	(0.0235)			(0.0236)		
Launched VC × GP with More Successful Exits		0.1158*			0.1429*	
		(0.0552)			(0.0762)	
Launched VC × Older GP			0.2035***			0.0891***
			(0.0279)			(0.0258)
Launched VC	0.6523*	0.4845	0.6498*	0.2089	0.1493	0.2080
	(0.3653)	(0.3037)	(0.3690)	(0.1368)	(0.1229)	(0.1381)
Total# Prior Ventures	0.0414***	0.0399**	0.0417***	0.0139***	0.0115***	0.0140***
	(0.0103)	(0.0141)	(0.0103)	(0.0019)	(0.0022)	(0.0019)
Invested in Other VCs Before	-0.0662**	-0.0507	-0.0663**	-0.0255***	-0.0160*	-0.0255***
	(0.0307)	(0.0400)	(0.0305)	(0.0074)	(0.0082)	(0.0074)
Female LP	-0.1041***	-0.0995**	-0.1042***	-0.0305***	-0.0251*	-0.0306***
	(0.0289)	(0.0369)	(0.0287)	(0.0045)	(0.0120)	(0.0044)
Log(Fund Size)	-0.0195	-0.0107	-0.0203	-0.0058	-0.0021	-0.0062
	(0.0195)	(0.0287)	(0.0192)	(0.0061)	(0.0088)	(0.0059)
%Committed Capital	0.3546***	0.3250**	0.3543***	0.1418***	0.1278**	0.1417***
	(0.0972)	(0.1395)	(0.0979)	(0.0434)	(0.0439)	(0.0432)
%All Corporate LPs	0.3062**	0.3553**	0.3112**	0.0710***	0.0568	0.0732***
	(0.1180)	(0.1528)	(0.1172)	(0.0211)	(0.0355)	(0.0212)
GP FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.2343	0.2300	0.2346	0.2034	0.1773	0.2038
Observations	27,786	16,641	27,786	27,786	16,641	27,786

Table 6: 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 2 except that we include the variable *Veteran* LP_{ij} and its interaction term with *Launched* VC_j. *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 2.

	Total# Firms	***Avg# Firms***
	(1)	(2)
Launched VC × Veteran LP	-0.1332*	-0.0402
	(0.0688)	(0.0232)
Launched VC	0.0490**	0.0209**
	(0.0178)	(0.0079)
Veteran LP	0.1165	0.0357
	(0.0713)	(0.0253)
Total# Prior Ventures	0.0129*	0.0042*
	(0.0071)	(0.0024)
Female LP	-0.1640***	-0.0575***
	(0.0285)	(0.0051)
Log(Fund Size)	-0.0179***	-0.0107***
	(0.0052)	(0.0028)
%Committed Capital	0.1962***	0.0690**
	(0.0663)	(0.0237)
%All Corporate LPs	0.0688*	0.0315
	(0.0354)	(0.0198)
GP FE	Y	Y
Year FE	Y	Y
Adj. R^2	0.3104	0.2873
Observations	78,539	78,539

Table 7: 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 2 except that we include the variable $\textit{Portfolio Exit}_j$ and its interaction term with $\textit{Launched VC}_j$. $\textit{Portfolio Exit}_j$ 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 2.

	Total# Firms	***Avg# Firms***
	(1)	(2)
Launched VC × Portfolio Exit	-0.1673	-0.0822
	(0.2114)	(0.0677)
Launched VC	0.0428***	0.0171***
	(0.0106)	(0.0047)
Portfolio Exit	0.0968	0.0802
	(0.2291)	(0.0741)
Total# Prior Ventures	0.0132*	0.0042*
	(0.0071)	(0.0023)
Invested in Other VCs Before	0.0175	0.0095
	(0.0212)	(0.0069)
Female LP	-0.1646***	-0.0577***
	(0.0284)	(0.0051)
Log(Fund Size)	-0.0173***	-0.0107***
	(0.0048)	(0.0028)
%Committed Capital	0.1972***	0.0692**
	(0.0661)	(0.0237)
%All Corporate LPs	0.0714*	0.0315
	(0.0367)	(0.0201)
GP FE	Y	Y
Year FE	Y	Y
Adj. R^2	0.3102	0.2872
Observations	78,539	78,539

Table 8: Difference in VC Financing of LPs' Own Ventures

This table tests the network hypothesis by examining differences in VC financing received by the new and old ventures of 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 received by a venture within two or three years of its formation (in 10,000s of 2019 RMBs) from any related VCs, i.e., VC funds managed by the GPs whose past funds had ever received capital commitments from the individual LP. The other details are the same as in Table 3, except that we use OLS regressions. Fixed effects are indicated at the bottom rows. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	log(***$ Related VCs***)$_{2yr}$	log(***$ Related VCs***)$_{3yr}$
	(1)	(2)
Launched VC × Post-LP Venture	0.0055	0.0078
	(0.0066)	(0.0058)
Launched VC	0.0023	0.0038
	(0.0043)	(0.0059)
Post-LP Venture	-0.0127	-0.0259***
	(0.0087)	(0.0041)
Total# Prior Ventures	-0.0011	-0.0013**
	(0.0007)	(0.0006)
Invested in Other VCs Before	-0.0005	-0.0002
	(0.0037)	(0.0029)
Female LP	-0.0105**	-0.0102*
	(0.0040)	(0.0054)
Log(Fund Size)	-0.0004	-0.0011
	(0.0013)	(0.0012)
%Committed Capital	0.0355***	0.0355***
	(0.0085)	(0.0111)
%All Corporate LPs	0.0189*	0.0231
	(0.0100)	(0.0159)
Log(Startup Size)	0.0058***	0.0070***
	(0.0011)	(0.0014)
%Ownership in Startup	-0.0285***	-0.0342***
	(0.0075)	(0.0095)
Startup Industry FE	Y	Y
Startup District FE	Y	Y
Startup Founding Year FE	Y	Y
(VC Fund Registered) Year FE	Y	Y
GP FE	Y	Y
Adj. R^2	0.1926	0.1829
Observations	204,690	183,400

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 cancellation or revocation (closure date), location (street address, city, province, and zip code), industry (four-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 GPs. 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. 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 limitation, 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 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 data 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 match rate of 90.3%. Most unmatched VC/PE firms are those with an abbreviated name or are overseas VC/PE firms. Note that 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 independent VC/PE firms from the Zero2IPO sample.

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 five guarantee firms from the Zero2IPO data.

We delete any firms with unusually large registered capital, including 76 companies with registered capital of more than five billion RMB from the Zero2IPO data, and seven companies from the AMAC data with registered capital of more than five 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., and 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 is 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 more than one GP serving as executive partners.

After consolidating the funds collected through the previous 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 largest 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 the direct LPs in the BRD data. Additionally, government investments in funds usually involve subsidiaries or even multiple layers of state-owned holding companies' subsidiaries. Consequently, to find out 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 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.

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 complexities 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 online job 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.

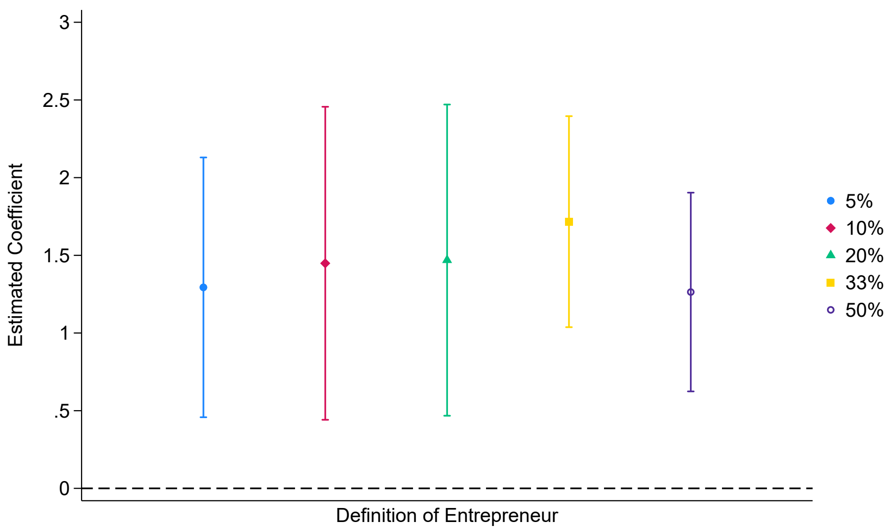
(4) Our database provides alternative performance metrics by cross-referencing firm information with other sources. This includes data on firms' patent applications (and whether the patents are eventually granted) and survival outcomes. In contrast, the Zero2IPO database primarily relies on proxies such as the 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. As a result, VC investments in foreign enterprises that have a business presence in China will be missing. However, it is possible that these foreign companies may be captured by Zero2IPO.

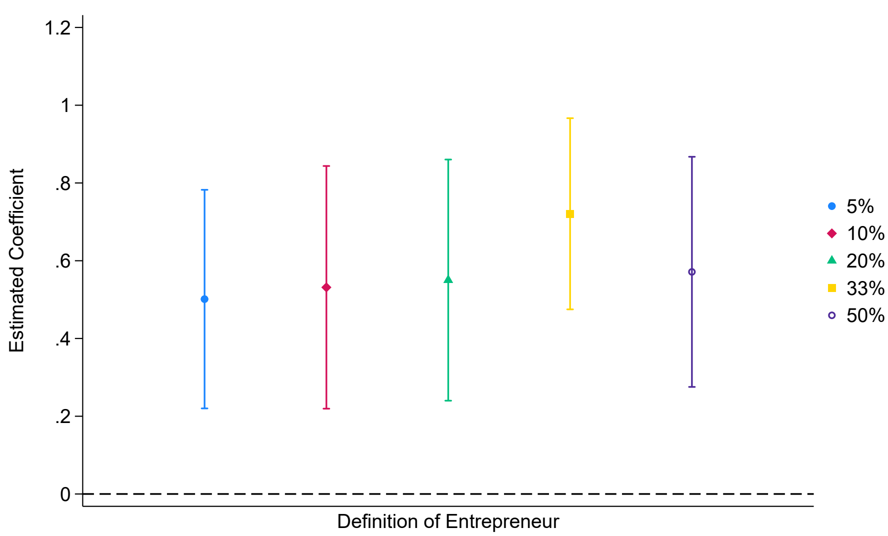
OA-2 Additional Figure

Figure OA2.1: Robustness: Alternative Thresholds to Define Entrepreneurs

(a) **DV: Total# Firms**



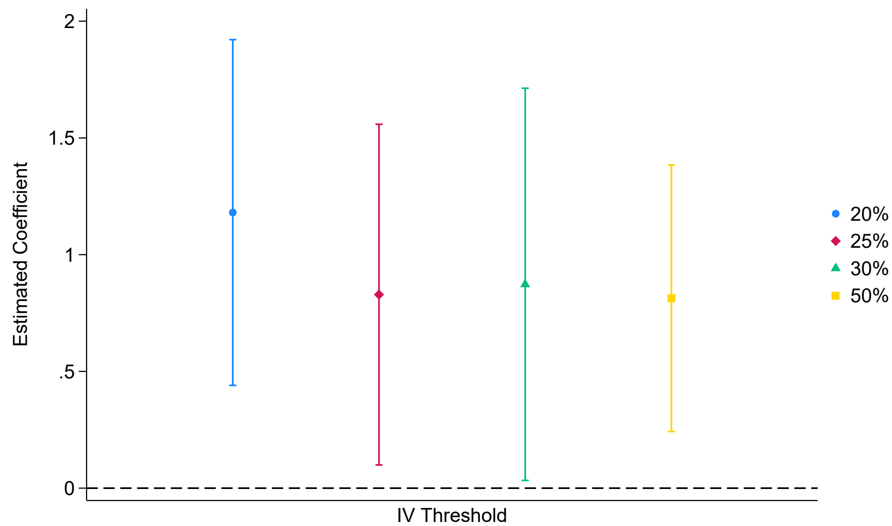
(b) **DV: Avg# Firms**



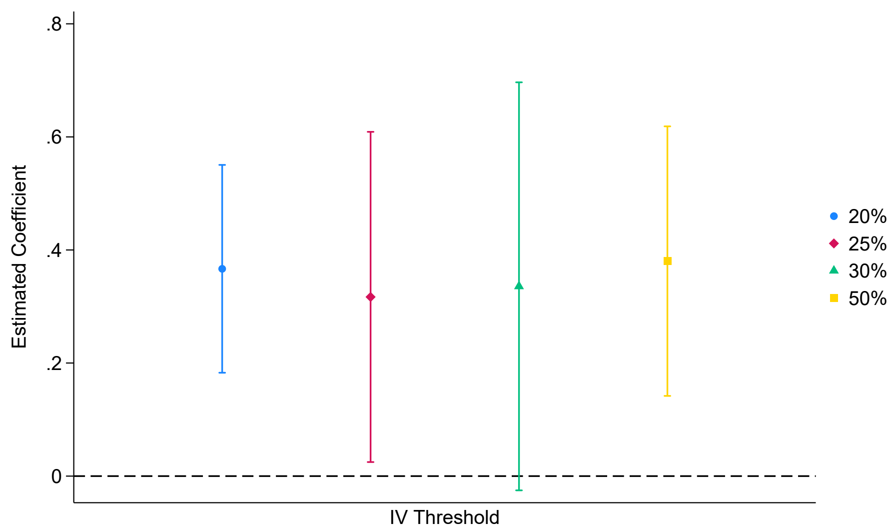
This figure presents the 2SLS estimates corresponding to Columns (4) and (5) of Table 2, using alternative thresholds for defining entrepreneurs. Panel A reports the estimated coefficients when the dependent variable is the total number of ventures created by individual *i*, while Panel B displays the results for the average number of ventures created per year by individual *i*. The capped spikes represent 90% confidence intervals. Each panel includes five estimates based on different thresholds for defining an entrepreneur, requiring ownership of at least 5%, 10%, 20%, 33%, or 50% of a venture.

Figure OA2.2: Robustness: IV with Various Thresholds to Define Distressed Industries

(a) **DV: Total# Firms**

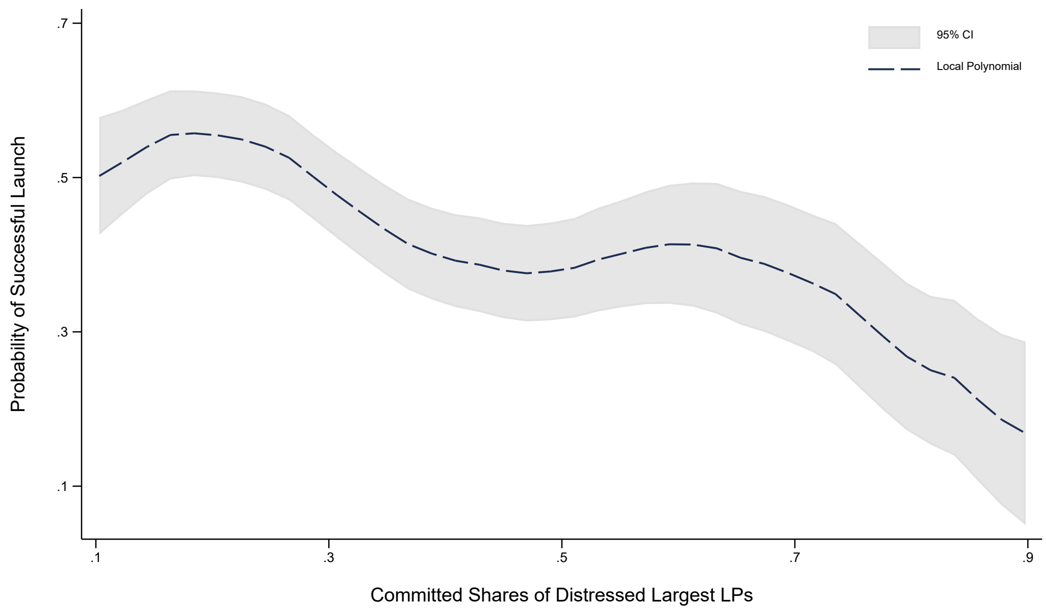


(b) **DV: Avg# Firms**



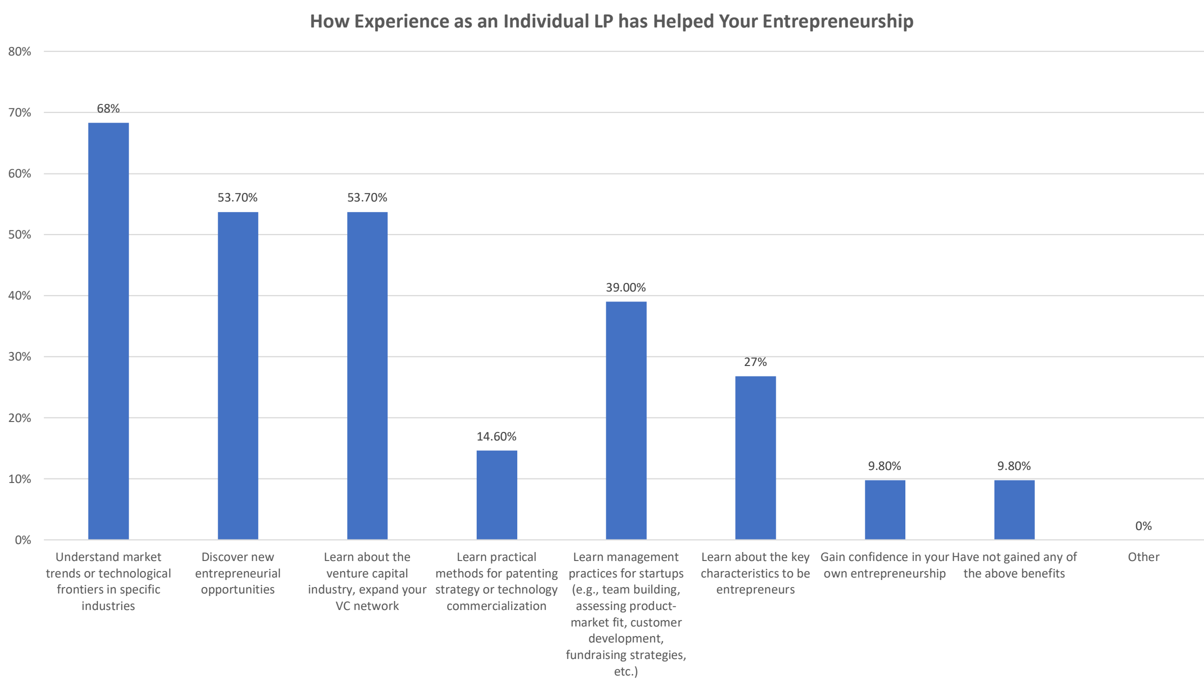
This figure presents the 2SLS estimates corresponding to Columns (4) and (5) of Table 2, using alternative thresholds for defining the instrumental variables (IVs). Panel A reports the estimated coefficients when the dependent variable is the total number of ventures created by individual *i*, while Panel B displays the results for the average number of ventures created per year by individual *i*. The capped spikes represent 90% confidence intervals. Each panel includes four estimates based on varying thresholds for defining distressed industries: the bottom 20th percentile (baseline), 25th, 30th, and 50th percentiles.

Figure OA2.3: Fraction of Committed Capital from Anchor Corporate LPs and Fund Launch Likelihood: Subsample with Positive IVs



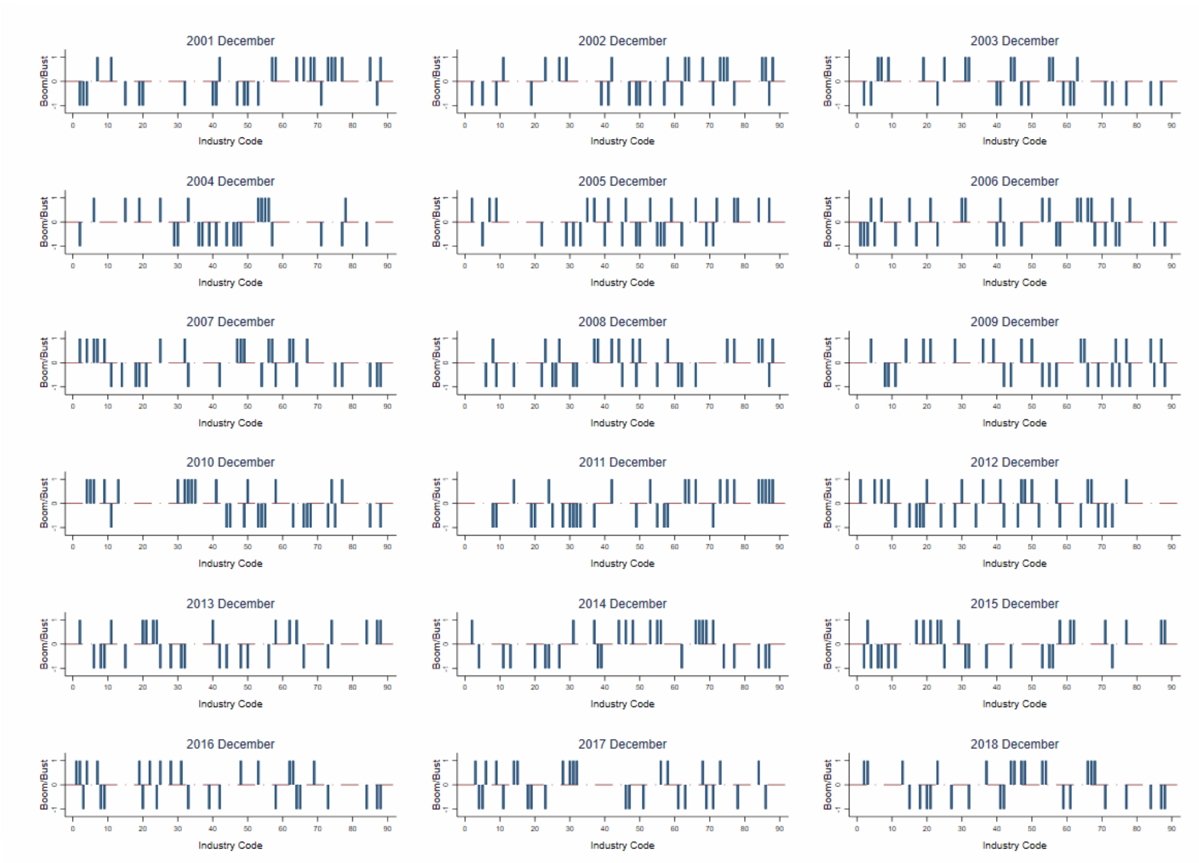
This figure replicates Figure 5 using a subsample restricted to funds with a strictly positive share of capital from anchor corporate LPs in distress. All other details are the same as in Figure 5.

Figure OA2.4: Survey Results: How Experience as an Individual LP has Helped Your Entrepreneurship



This figure reports the percentage of survey respondents selecting each option describing how their experience as an individual LP has contributed to their entrepreneurial learning and activities.

Figure OA2.5: 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 industries (at the two-digit SIC code level) 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 industries (at the two-digit SIC code level) at time t.

OA-3 Additional Tables

Table OA3.1: Venture Creation after Excluding Observations during the 2008 Financial Crisis and 2015 Chinese Stock Market Crash

This table replicates Table 2 except that we exclude LP-fund observations between December 2007 and June 2009 (Great Financial Crisis) as well as in 2015 (Chinese Stock Market Crash). Other details are the same as in Table 2.

	(1)	(2)	(3)	(4)	(5)
	OLS **Total# Firms**	**OLS** **Avg# Firms**	**1st Stage** **Launched VC**	**2SLS** **Total# Firms**	**2SLS** **Avg# Firms**
Launched VC	0.0397**	0.0221***		1.2605**	0.3952***
	(0.0153)	(0.0053)		(0.5289)	(0.1013)
%Anchor Corporate LPs in Distressed Industries			-0.1091***		
			(0.0327)		
Total# Prior Ventures	0.0212***	0.0077***	0.0014***	0.0195***	0.0072***
	(0.0054)	(0.0010)	(0.0006)	(0.0052)	(0.0010)
Invested in Other VCs Before	0.0091	0.0095	0.0175	-0.0119	0.0031
	(0.0271)	(0.0098)	(0.0138)	(0.0260)	(0.0069)
Female LP	-0.1520***	-0.0552***	-0.0015	-0.1505***	-0.0547***
	(0.0318)	(0.0055)	(0.0042)	(0.0324)	(0.0061)
Log(Fund Size)	-0.0168***	-0.0123***	0.0562***	-0.0851**	-0.0332***
	(0.0073)	(0.0034)	(0.0048)	(0.0361)	(0.0087)
%Committed Capital	0.2278***	0.0854**	-0.1584***	0.4197***	0.1441***
	(0.0837)	(0.0305)	(0.0165)	(0.1077)	(0.0261)
%All Corporate LPs	0.0424	0.0274	0.0537	-0.0083	0.0119
	(0.0642)	(0.0406)	(0.0368)	(0.0349)	(0.0293)
1st stage F-stat			11.11		
			(0.0054)		
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.3523	0.3227	0.5263		
Observations	60,614	60,614	60,614	60,614	60,614

Table OA3.2: Venture Creation after Refining Distressed Industry

This table replicates the 2SLS estimation in Columns (3) to (5) of Table 2, except that we we redefine a "distress industry" as one that was in the non-bottom quintile of stock performance between [t-12] and [t-6] (i.e., the six months before our baseline distress window), and then slipped into the bottom quintile during the subsequent six-month period $(t-6,t)$. All other details are the same as Table 2.

	(1)	(2)	(3)
	1st Stage Launched VC	**2SLS Total# Firms**	**2SLS Avg# Firms**
Launched VC		2.5175**	0.5724**
		(1.0249)	(0.2481)
%Anchor Corporate LPs in Distressed Industries	-0.0517**		
	(0.0215)		
Total# Prior Ventures	0.0012*	0.0101	0.0036
	(0.0006)	(0.0066)	(0.0021)
Invested in Other VCs Before	0.0167	0.0243	-0.0126
	(0.0108)	(0.0229)	(0.0042)
Female LP	-0.0076*	-0.1462***	-0.0535***
	(0.0034)	(0.0209)	(0.0160)
Log(Fund Size)	0.0548***	-0.1538**	-0.0941***
	(0.0034)	(0.0626)	(0.0139)
%Committed Capital	-0.1678***	6.6133***	0.1623***
	(0.0153)	(0.1849)	(0.0402)
%All Corporate LPs	0.0564*	-0.0592	0.0021
	(0.0275)	(0.0783)	(0.0180)
1st stage F-stat	5.81		
	(0.0292)		
GP FE	Y	Y	Y
Year FE	Y	Y	Y
Adj. R^2	0.4855		
Observations	78,539	78,539	78,539

Table OA3.3: Comparing LP Characteristics in High-IV and Low-IV Groups

This table compares the characteristics of individual LPs that invest in funds with a high proportion of distressed anchor corporate LPs (High-IV group, i.e., LPs in funds with IVs above zero) and those that invest in funds with a low proportion of distressed anchor corporate LPs (Low-IV group, i.e., IV = 0). The sample includes only LPs in funds whose anchor LPs are corporate investors. The last column reports the difference in sample means between the Low-IV and High-IV groups. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are clustered by the fund's SAIC registration approval year.

	Full Sample		**Low IV Group**		**High IV Group**		
Variable	Mean	SD	Mean	SD	Mean	SD	Diff
Female	0.247	0.431	0.244	0.430	0.259	0.438	-0.015
Percent of Capital Invested by Individual LPs	0.050	0.060	0.050	0.059	0.052	0.064	-0.002
Amount Invested (2019 RMB Millions)	7.402	23.293	7.314	22.910	7.825	25.058	-0.511
Already Entrepreneur	0.802	0.398	0.800	0.400	0.816	0.388	-0.016
Year Gap	9.152	4.529	9.106	4.489	9.369	4.713	-0.263
Total# Ventures Before VC Investment	1.725	1.744	1.707	1.725	1.810	1.832	-0.103
Avg.# Ventures per Year Before VC Investment	0.114	0.115	0.113	0.115	0.115	0.118	-0.002
Industry Background							
Wholesale/Retail	0.156	0.363	0.157	0.364	0.148	0.356	0.009
Manufacturing	0.100	0.285	0.102	0.303	0.089	0.285	0.013
R&D	0.070	0.255	0.070	0.254	0.071	0.256	-0.001
Leasing/Commercial Service	0.067	0.250	0.067	0.250	0.066	0.249	0.001
Real Estate	0.040	0.195	0.041	0.198	0.034	0.181	0.007**

Table OA3.4: Venture Creation after Excluding LPs with Treatment Status Changes

This table repeats the estimation in Table 2, 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 2.

	(1)	(2)	(3)	(4)	(5)
	OLS **Total# Firms**	**OLS** **Avg# Firms**	**1st Stage** **Launched VC**	**2SLS** **Total# Firms**	**2SLS** **Avg# Firms**
Launched VC	0.0283	0.0142		1.3364**	0.4728**
	(0.0266)	(0.0110)		(0.5708)	(0.1781)
%Anchor Corporate LPs in Distressed Industries			-0.1120**		
			(0.0385)		
Total# Prior Ventures	0.0060	-0.0001	0.0005	0.0054	-0.0003
	(0.0059)	(0.0015)	(0.0010)	(0.0065)	(0.0018)
Invested in Other VCs Before	-0.0218	-0.0063	0.2430***	-0.3399***	-0.1178***
	(0.0276)	(0.0101)	(0.0111)	(0.1321)	(0.0388)
Female LP	-0.1493***	-0.0493***	-0.0159***	-0.1289***	-0.0422***
	(0.0263)	(0.0069)	(0.0042)	(0.0184)	(0.0063)
Log(Fund Size)	-0.0079	-0.0057	0.0500***	-0.0728**	-0.0285**
	(0.0091)	(0.0035)	(0.0035)	(0.0329)	(0.0118)
%Committed Capital	0.1744***	0.0547***	-0.1612***	0.3849***	0.1285***
	(0.0599)	(0.0182)	(0.0205)	(0.1203)	(0.0264)
%All Corporate LPs	0.0437	0.0245	0.0539	-0.0109	0.0053
	(0.0474)	(0.0259)	(0.0327)	(0.0353)	(0.0151)
1st stage F-stat			8.47		
			(0.0108)		
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.3206	0.2818	0.5671		
Observations	59,516	59,516	59,516	59,516	59,516

Table OA3.5: Subsample of LPs with No Prior Entrepreneurial Experience

This table replicates Table 2 in the main text except that we restrict the sample to individual LPs without prior entrepreneurial experience. All other details remain the same as in Table 2.

	(1)	(2)	(3)	(4)	(5)
	OLS	**OLS**	**1st Stage**	**2SLS**	**2SLS**
	Total# Firms	**Avg# Firms**	**Launched VC**	**Total# Firms**	**Avg# Firms**
Launched VC	-0.012	0.003		-0.416	-0.151
	(0.041)	(0.019)		(0.600)	(0.168)
%Anchor Corporate LPs in Distressed Industries			-0.135**		
			(0.057)		
Total# Prior Ventures	-0.075**	-0.027*	0.004	-0.074**	-0.026*
	(0.033)	(0.015)	(0.011)	(0.031)	(0.014)
Female LP	-0.180***	-0.040**	0.011	-0.175***	-0.038**
	(0.059)	(0.017)	(0.007)	(0.058)	(0.017)
Log(Fund Size)	0.022	0.003	0.057***	0.045	0.012
	(0.017)	(0.007)	(0.005)	(0.035)	(0.013)
%Committed Capital	0.148	0.006	-0.184***	0.074	-0.022
	(0.089)	(0.029)	(0.039)	(0.118)	(0.039)
%All Corporate LPs	0.024	0.042	-0.009	0.012	0.038
	(0.105)	(0.053)	(0.073)	(0.116)	(0.060)
1st stage F-stat			5.58		
			(0.032)		
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.467	0.651	0.518		
Observations	14486	14486	14486	14486	14486

Table OA3.6: Subsample of LPs with Prior Entrepreneurial Experience

This table replicates Table 2 in the main text except that we restrict the sample to individual LPs with prior entrepreneurial experience. All other details remain the same as in Table 2.

	(1)	(2)	(3)	(4)	(5)
	OLS **Total# Firms**	**OLS** **Avg# Firms**	**1st Stage** **Launched VC**	**2SLS** **Total# Firms**	**2SLS** **Avg# Firms**
Launched VC	0.0444***	0.0182**		1.6040**	0.4192***
	(0.0134)	(0.0069)		(0.5757)	(0.1162)
%Anchor Corporate LPs in Distressed Industries			-0.1016***		
			(0.0329)		
Total# Prior Ventures	0.0989***	0.0383***	0.0001	0.0988***	0.0383***
	(0.0170)	(0.0017)	(0.0012)	(0.0181)	(0.0015)
Invested in Other VCs Before	0.0262	0.0170***	0.0199**	-0.0043	0.0091**
	(0.0197)	(0.0051)	(0.0095)	(0.0216)	(0.0037)
Female LP	-0.1734***	-0.0659***	-0.0121**	-0.1552***	-0.0612***
	(0.0188)	(0.0055)	(0.0048)	(0.0159)	(0.0067)
Log(Fund Size)	-0.0120**	-0.0086**	0.0593***	-0.1043***	-0.0305***
	(0.0054)	(0.0026)	(0.0033)	(0.0395)	(0.0085)
%Committed Capital	0.1423*	0.0519	-0.1751***	0.4143***	0.1218***
	(0.0770)	(0.0333)	(0.0144)	(0.1177)	(0.0226)
%All Corporate LPs	0.0553	0.0336	0.0595	-0.0876	0.0174
	(0.0583)	(0.0315)	(0.0367)	(0.0661)	(0.0257)
1st stage F-stat			9.52		
			(0.0075)		
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.3072	0.2997	0.4963		
Observations	62,409	62,409	62,409	62,409	62,409

Table OA3.7: Event Study: Venture Creation among LPs in Failed-to-Launch Funds

This table examines the entrepreneurial outcomes of individual LPs before and after investing in a failed-to-launch VC fund. The unit of observation is an LP-year. The sample includes all individual LPs who have ever invested in a failed-to-launch fund (the control group in Table 2). We estimate the following specification:

$$Y_{it} = \alpha + \beta \textit{Post-VC-Investment}_{it} + \mu_i + \varepsilon_{ijt}$$

where Y_{it} is the number of ventures created by individual LP i in year t, and *Post-VC-Investment*$_{it}$ is an indicator equal to one if LP i had invested in failed-to-launch fund j before year t. The specification includes individual LP fixed effects (μ_i). We do not control for additional LP-level characteristics, as these are absorbed by μ_i. Standard errors are two-way clustered at the LP and year levels. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	# Firms in a Year
Post-VC-Investment	0.0957***
	(0.0178)
Individual LP FE	Y
Adj. R^2	0.0328
Observations	683,440

Table OA3.8: Intensive Margin: Count of New Ventures within 2 Years

This table replicates Table 2 in the main text except that we use the number of newly created startups an individual LP founds within two years of the fund's registration approval as the dependent variable. All other details remain the same as in Table 2.

	OLS **Total# Firms Within 2 Yrs**	**1st Stage Launched VC**	**2SLS** **Total# Firms Within 2 Yrs**
Launched VC	0.0238**		0.9780*
	(0.0106)		(0.5340)
%Anchor Corporate LPs in Distressed Industries		-0.0676***	
		(0.0163)	
Total# Prior Ventures	0.0111	0.0007	0.0109
	(0.0067)	(0.0008)	(0.0065)
Invested in Other VCs Before	0.0109	0.0253***	-0.0142
	(0.0093)	(0.0087)	(0.0124)
Female LP	-0.1138***	-0.0074	-0.1082***
	(0.0158)	(0.0061)	(0.0151)
Log(Fund Size)	-0.0183***	0.0562***	-0.0727**
	(0.0042)	(0.0052)	(0.0331)
%Committed Capital	0.1749***	-0.1458***	0.3123***
	(0.0541)	(0.0208)	(0.0651)
%All Corporate LPs	0.0600	0.0460*	0.0237
	(0.0425)	(0.0242)	(0.0333)
1st stage F-stat		17.25	
		(0.0008)	
GP FE	Y	Y	Y
Year FE	Y	Y	Y
Adj. R^2	0.2899	0.5012	
Observations	65,698	65,698	65,698

Table OA3.9: Extensive Margin: Indicator of New Ventures within 2 Years

This table replicates Table 2 in the main text except that we use an indicator equal to one if the individual LP starts any firm within two years as the dependent variable. All other details remain the same as in Table 2.

	OLS Indicator Within 2 Yrs	**1st Stage Launched VC**	**2SLS Indicator Within 2 Yrs**
Launched VC	-0.0075		0.0165
	(0.0097)		(0.2747)
%Anchor Corporate LPs in Distressed Industries		-0.0676***	
		(0.0163)	
Total# Prior Ventures	0.0096*	0.0007	-0.0096*
	(0.0047)	(0.0008)	(0.0047)
Invested in Other VCs Before	-0.0077	0.0253***	-0.0083
	(0.0091)	(0.0087)	(0.0087)
Female LP	-0.0527***	-0.0074	-0.0526***
	(0.0069)	(0.0061)	(0.0076)
Log(Fund Size)	-0.0079***	0.0562***	-0.0092
	(0.0016)	(0.0052)	(0.0152)
%Committed Capital	0.0351**	-0.1458***	0.0386
	(0.0165)	(0.0208)	(0.0372)
%All Corporate LPs	0.0514***	0.0460*	0.0505***
	(0.0139)	(0.0242)	(0.0124)
1st stage F-stat		17.25	
		(0.0008)	
GP FE	Y	Y	Y
Year FE	Y	Y	Y
Adj. R^2	0.3173	0.5012	
Observations	65,698	65,698	65,698

Table OA3.10: Venture Creation with Difference-in-Differences Specification

This table reports the estimation results on entrepreneurial spillovers using an alternative design (a Difference-in-Differences design). Specifically, we restructure the data into an LP-by-year panel. The treated group consists of individual LPs who have ever invested in a successfully launched fund (*Launched VC* $= 1$), while the control group consists of individual LPs who invested only in failed-to-launch funds. We estimate the entrepreneurial spillover effect using the following specification:

$$Y_{it} = \alpha + \beta \textit{Launched VC}_i \times \textit{Post-VC-Investment}_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

where Y_{it} is the number of ventures created by individual LP i in year t; *Launched* VC_i is an indicator equal to one if individual LP i ever invested in any successfully launched fund; and *Post-VC-Investment*$_{it}$ equals one if the LP had invested in any VC fund (either successfully launched or failed to launch) prior to year t. The specification includes year fixed effects (δ_t) and LP fixed effects (μ_i), which absorb all time-invariant LP characteristics. Standard errors are two-way clustered at the LP and year levels. ***, **, and * represent the statistical significance level at 1%, 5%, and 10% respectively.

	(1) **Diff-in-Diff** **# Firms in a Year**
Launched $VC_i \times$ *Post-VC-Investment*$_{it}$	0.0043*
	(0.0023)
Individual LP FE	Y
Year FE	Y
Adj. R^2	0.0675
Observations	1,146,560

Table OA3.11: Robustness of Table 5: GP Experience and Entrepreneurship Spillovers with Reduced-form IV

This table replicates Table 5 except that we replace *Launched VC* with our instrumental variable. Remaining details are the same as in Table 5.

	Total# Firms			**Avg# Firms**		
	(1)	(2)	(3)	(4)	(5)	(6)
IV × GP with More Deals	-0.6196*			-0.3071**		
	(0.3024)			(0.1276)		
IV × GP with More Successful Exits		0.0799			-0.1039	
		(0.3450)			(0.1892)	
IV × Older GP			-0.6893**			-0.3327**
			(0.3131)			(0.1336)
IV	-0.1211	-0.2032	-0.1222	0.0290	-0.0035	0.0280
	(0.1155)	(0.2059)	(0.1126)	(0.0325)	(0.0631)	(0.0315)
Total# Prior Ventures	0.0413***	0.0398***	0.0416***	0.0139***	0.0114***	0.0140***
	(0.0103)	(0.0142)	(0.0103)	(0.0019)	(0.0023)	(0.0019)
Invested in Other VCs Before	-0.0673**	-0.0515	-0.0675**	-0.0258***	-0.0168*	-0.0259***
	(0.0311)	(0.0401)	(0.0310)	(0.0077)	(0.0086)	(0.0077)
Female LP	-0.1047***	-0.0999**	-0.1048***	-0.0305***	-0.0255*	-0.0305***
	(0.0290)	(0.0371)	(0.0287)	(0.0045)	(0.0123)	(0.0044)
Log(Fund Size)	0.0187	-0.0101	0.0190	-0.0057	0.0014	-0.0061
	(0.0186)	(0.0277)	(0.0183)	(0.0057)	(0.0085)	(0.0055)
%Committed Capital	0.3538***	0.3257**	0.3535***	0.1407***	0.1277***	0.1407***
	(0.0943)	(0.1353)	(0.0952)	(0.0428)	(0.0431)	(0.0426)
%All Corporate LPs	0.3234**	0.3664**	0.3293**	0.0715***	0.0549	0.0741***
	(0.1168)	(0.1515)	(0.1158)	(0.0202)	(0.0343)	(0.0203)
GP FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Adj. R^2	0.2341	0.2299	0.2344	0.2033	0.1761	0.2037
Observations	27,786	16,641	27,786	27,786	16,641	27,786

Table OA3.12: Robustness of Table 6: Veteran LPs and Entrepreneurship Spillovers with Reduced-form IV

This table replicates Table 6 except that we replace *Launched VC* with our instrumental variable. Remaining details are the same as in Table 6.

	Total# Firms (1)	**Avg# Firms** (2)
IV × Veteran LP	-0.0645	0.0014
	(0.1204)	(0.0650)
IV	-0.1331*	-0.0439
	(0.0687)	(0.0260)
Veteran LP	0.0354	0.0120
	(0.0348)	(0.0132)
Total# Prior Ventures	0.0131*	0.0043*
	(0.0071)	(0.0024)
Female LP	-0.1653***	-0.0579***
	(0.0286)	(0.0051)
Log(Fund Size)	-0.0161***	-0.0098***
	(0.0053)	(0.0026)
%Committed Capital	0.1902**	0.0662**
	(0.0647)	(0.0233)
%All Corporate LPs	0.0846*	0.0367
	(0.0396)	(0.0222)
GP FE	Y	Y
Year FE	Y	Y
Adj. R^2	0.3102	0.2871
Observations	78,539	78,539

Table OA3.13: Robustness of Table 7: Entrepreneurship Spillovers with Successful Portfolio Exits in Reduced-form IV

This table replicates Table 7 except that we replace *Launched VC* with our instrumental variable. Remaining details are the same as in Table 7.

	Total# Firms	***Avg# Firms***
	(1)	(2)
IV × *Portfolio Exit*	0.0117	0.0605
	(0.1656)	(0.0385)
IV	-0.1447**	-0.0458**
	(0.0600)	(0.0198)
Portfolio Exit	-0.0515	0.0047
	(0.0381)	(0.0117)
Total# Prior Ventures	0.0133*	0.0043*
	(0.0071)	(0.0023)
Invested in Other VCs Before	0.0184	0.0098
	(0.0214)	(0.0070)
Female LP	-0.1653***	-0.0579***
	(0.0286)	(0.0051)
Log(Fund Size)	-0.0149***	-0.0098***
	(0.0049)	(0.0027)
%Committed Capital	0.1894***	0.0661**
	(0.0651)	(0.0235)
%All Corporate LPs	0.0881**	0.0363
	(0.0410)	(0.0221)
GP FE	Y	Y
Year FE	Y	Y
Adj. R^2	0.3102	0.2871
Observations	78,539	78,539

Table OA3.14: Robustness of Table 8: Difference in VC Financing of LPs' Own Ventures with Reduced-form IV

This table replicates Table 8 except that we replace *Launched VC* with our instrumental variable. Remaining details are the same as in Table 8.

	log(***\$ Related VCs***)$_{2yr}$	log(***\$ Related VCs***)$_{3yr}$
	(1)	(2)
IV × Post-LP Venture	-0.0227	-0.0045
	(0.0134)	(0.0139)
IV	0.0149	0.0178
	(0.0204)	(0.0217)
Post-LP Venture	-0.0098	-0.0222***
	(0.0064)	(0.0029)
Total# Prior Ventures	-0.0010	-0.0013**
	(0.0007)	(0.0006)
Invested in Other VCs Before	-0.0005	-0.0002
	(0.0037)	(0.0030)
Female LP	-0.0105**	-0.0102*
	(0.0040)	(0.0054)
Log(Fund Size)	-0.0003	-0.0009
	(0.0011)	(0.0009)
%Committed Capital	0.0349***	0.0348***
	(0.0082)	(0.0107)
%All Corporate LPs	0.0181	0.0217
	(0.0106)	(0.0166)
Log(Startup Size)	0.0058***	0.0071***
	(0.0011)	(0.0014)
%Ownership in Startup	-0.0285***	-0.0342***
	(0.0075)	(0.0095)
Startup Industry FE	Y	Y
Startup District FE	Y	Y
Startup Founded Year FE	Y	Y
(VC Fund Registered) Year FE	Y	Y
GP FE	Y	Y
Adj. R^2	0.1926	0.1829
Observations	204,690	183,400

Table OA3.15: Venture Creation after Excluding LPs with Existing Firms in Distress

This table replicates Table 2 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 2.

	(1)	(2)	(3)	(4)	(5)
	OLS Total# Firms	**OLS Avg# Firms**	**1st Stage Launched VC**	**2SLS Total# Firms**	**2SLS Avg# Firms**
Launched VC	0.0252**	0.0102**		1.1006	0.3165
	(0.0101)	(0.0036)		(0.8743)	(0.2651)
%Anchor Corporate LPs in Distressed Industries			-0.0863***		
			(0.0268)		
Total# Prior Ventures	-0.0147*	-0.0083***	0.0010	-0.0157**	-0.0086***
	(0.0072)	(0.0023)	(0.0007)	(0.0071)	(0.0022)
Invested in Other VCs Before	0.0042	-0.0020	0.0157*	-0.0125	-0.0067
	(0.0233)	(0.0093)	(0.0084)	(0.0278)	(0.0103)
Female LP	-0.1399***	-0.0437***	-0.0063	-0.1333***	-0.0418***
	(0.0384)	(0.0086)	(0.0054)	(0.0333)	(0.0077)
Log(Fund Size)	-0.0156**	-0.0104**	0.0544***	-0.0738	-0.0276
	(0.0083)	(0.0046)	(0.0037)	(0.0522)	(0.0180)
%Committed Capital	0.2056***	0.0701***	-0.1583***	0.3755***	0.1185***
	(0.0572)	(0.0179)	(0.0211)	(0.1223)	(0.0280)
%All Corporate LPs	0.0715**	0.0326	0.0893**	-0.0148	0.0081
	(0.0290)	(0.0187)	(0.0264)	(0.0699)	(0.0221)
1st stage F-stat			10.37		
			(0.0057)		
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.3218	0.2966	0.5014		
Observations	64,967	64,967	64,967	64,967	64,967

Table OA3.16: Venture Creation after Excluding LPs with Existing Firms in Boom

This table replicates Table 2 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 2.

	(1)	(2)	(3)	(4)	(5)
	OLS Total# Firms	**OLS Avg# Firms**	**1st Stage Launched VC**	**2SLS Total# Firms**	**2SLS Avg# Firms**
Launched VC	0.0189	0.0116*		1.0334*	0.3267
	(0.0143)	(0.0065)		(0.5780)	(0.2112)
%Anchor Corporate LPs in Distressed Industries			-0.1235***		
			(0.0314)		
Total# Prior Ventures	-0.0094	-0.0037	0.0001	-0.0094	-0.0037
	(0.0090)	(0.0031)	(0.0011)	(0.0090)	(0.0031)
Invested in Other VCs Before	0.0282	0.0127	0.0221	0.0062	0.0059
	(0.0269)	(0.0087)	(0.0133)	(0.0238)	(0.0080)
Female LP	-0.1675***	-0.0587***	-0.0112***	-0.1566***	-0.0553***
	(0.0297)	(0.0051)	(0.0037)	(0.0248)	(0.0048)
Log(Fund Size)	-0.0147**	-0.0098***	0.0548***	-0.0699*	-0.0270*
	(0.0058)	(0.0029)	(0.0044)	(0.0348)	(0.0134)
%Committed Capital	0.2075**	0.0701***	-0.1727***	0.3820***	0.1243***
	(0.0722)	(0.0239)	(0.0136)	(0.0921)	(0.0206)
%All Corporate LPs	0.0480	0.0221	0.0775**	-0.0169	0.0020
	(0.0324)	(0.0137)	(0.0276)	(0.0538)	(0.0138)
1st stage F-stat			15.50		
			(0.0013)		
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.3346	0.3086	0.4907		
Observations	68,702	68,702	68,702	68,702	68,702

Table OA3.17: Venture Creation after Excluding Newly Created Ventures in the Boom Industries

This table replicates Table 2 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 2.

	(1)	(2)	(3)	(4)	(5)
	OLS	**OLS**	**1st Stage**	**2SLS**	**2SLS**
	Total# Firms	**Avg# Firms**	**Launched VC**	**Total# Firms**	**Avg# Firms**
Launched VC	0.0148	0.0111**		0.7599**	0.3837**
	(0.0101)	(0.0050)		(0.3391)	(0.1766)
%Anchor Corporate LPs in Distressed Industries			-0.1134**		
			(0.0402)		
Total# Prior Ventures	-0.0469***	-0.0183***	0.0013	-0.0479***	-0.0188***
	(0.0116)	(0.0026)	(0.0013)	(0.0109)	(0.0025)
Invested in Other VCs Before	0.0215	0.0105*	0.0101	0.0142	0.0068*
	(0.0180)	(0.0041)	(0.0099)	(0.0183)	(0.0040)
Female LP	-0.1448***	-0.0530***	-0.0126***	-0.1357***	-0.0485***
	(0.0237)	(0.0052)	(0.0042)	(0.0221)	(0.0045)
Log(Fund Size)	-0.0104	-0.0065	0.0554***	-0.0514*	-0.0276*
	(0.0090)	(0.0041)	(0.0037)	(0.0270)	(0.0132)
%Committed Capital	0.1606**	0.0582**	-0.1625***	0.2816***	0.1184***
	(0.0589)	(0.0233)	(0.0126)	(0.0459)	(0.0240)
%All Corporate LPs	0.0877*	0.0529	0.0613*	0.0508	0.0345*
	(0.0459)	(0.0311)	(0.0311)	(0.0355)	(0.0180)
1st stage F-stat			7.97		
			(0.0129)		
GP FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
Adj. R^2	0.3273	0.3010	0.4944		
Observations	65,158	65,158	65,158	65,158	65,158

Table OA3.18: 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