Late-Stage Venture Capital and Firm Performance: Evidence from Small and Medium-Sized Enterprises in China

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Abstract: Where venture capitalists have traditionally focused on early-stage innovative firms, increasingly venture capitalists are investing in late-stage firms, especially in Asia. The performance consequences of this novel phenomenon of late-stage venture capital remain unexplored. This paper provides novel insight into this phenomenon by examining the impact of late-stage venture capital on two key dimensions of firm performance in the venture capital literature: innovation and financial performance. We link VC investment events to financial indicators of Chinese listed firms to account for the timing of VC entry and identify the firm performance impacts. Utilizing a matching and difference-in-differences procedure to account for selection biases, our results show that late-stage venture capital improves firms' financial performance but reduces investee firms' innovation performance. Our findings advance understanding about the emergence of late-stage venture capital and its performance consequences, especially in emerging economies. Our work has implications for entrepreneurs and policymakers.

Keywords: Venture Capital; Late Stage; Innovation Performance; Financial Performance; Emerging Economy; SME

1 Introduction

The last two decades have witnessed a remarkable growth of venture capital (VC) in both developed and developing countries. VCs aim to invest in promising firms and provide value-adding services to enhance their growth and performance (Chemmanur et al., 2014; Croce et al., 2013; Quas et al., 2020). While the VC literature has largely focused on investments in early-stage businesses with high growth potential and uncertainty (Bernstein et al., 2016; OECD, 1998), in recent years there has been a widespread preference amongst VCs to increasingly invest in firms in their latter stages of development, known as late-stage VC. This emergence of late-stage VC has been a particularly prevalent phenomenon in Asian countries (Naqi and Hettihewa, 2007; Tan et al., 2008). Although much research interest has focused upon the important role that early-stage VCs can play in firms' development in the United States and Europe, few efforts have been made to understand the consequences of this emerging phenomenon of late-stage VC, especially in emerging economies.

This paper sheds novel light on this important phenomenon by exploring the performance consequences of receiving late-stage VC for a set of listed firms in China. Drawing on the existing VC literature (Alperovych et al., 2015; Benkraiem et al., 2021; Bronzini et al., 2020; Puri and Zarutskie, 2012; Xiaoli et al., 2020), we conceptualize performance as consisting of two dimensions; innovation performance (Chemmanur et al., 2014) and financial performance (Bertoni et al., 2011). VCs invest to enhance the market value of their investees and thus, secure a return. In early-stage investments, this typically involves supporting higher-risk firms through the provision of (non-) financial resources to develop their novel innovation that ensures their viability as a firm and the VC returns in the medium to longer term. In late-stage investments, however, firms have already developed proven and successful products and are either profitable or on a path toward profitability (Park and Tzabbar, 2016). In such instances, VCs are likely pursuing shorter-term and less risky returns through providing value-adding services that can enhance the performance and profitability of their investees.

The motivation of VC investors suggests that late-stage investments may result in heterogeneous impacts on our two dimensions of performance. Late-stage VCs may display a greater aversion to risk as they aim to secure and increase their short-term returns (Park and Tzabbar, 2016) and instead, encourage and support their investees to exploit current products and enhance short-term profitability. Firms backed by late-stage VC may thus, be more reluctant to invest further in innovation, as returns to investment in research and development (R&D) and innovation are highly uncertain, represent an immediate cost that reduces profitability, and do not typically yield short-term performance benefits. Instead, late-stage VCs likely encourage and support investees to improve their short-term financial performance to secure and enhance their returns. Therefore, late-stage VC may negatively affect investee firms' innovative performance and exert a positive impact on their financial performance.

The methodological difficulty of identifying the impact of late-stage VC on firm performance is to deal with selection bias. That is, VC investors do not target investee firms randomly, but instead select firms they believe have high potential. The performance differences between VC-backed and non-VC-backed firms could be the result of both the pre-treatment selection bias and the post-treatment impact. To overcome the selection bias, we employ the propensity score matching (PSM) and difference-in-differences (DD) approaches. We use the PSM approach to construct a control group of firms based on observable characteristics. The DD approach is further employed to control for time-invariant unobservable confounding factors. We record the exact time of VC entry and evaluate the effect by comparing firm performance before and after VC entry.

Our empirical investigation is based on a novel dataset that is constructed by merging VC investment events, firm-level financial indicators, and patent application data in China. It is interesting to conduct this research in China because its VC industry has experienced dramatic growth in the past two decades, and late-stage VC investors are especially prevalent (Naqi and Hettihewa, 2007). Our sample is comprised of firms listed in the Small and Medium Enterprise Board (SMEB) and the Growth Enterprise Board (GEB). While firms listed in the main boards are mainly large and state-owned enterprises, the launch of the SMEB and GEB was intended to provide a financing platform for small and medium-sized, private, innovative, and high-tech firms. Therefore, VC investors are more concentrated in the SMEB and GEB, and thus our context is attractive for empirical investigation of this novel phenomenon.

Overall, the empirical results indicate that late-stage VC has a negative impact on firms' innovative performance and a significantly positive impact on firms' financial performance. Thus, our results suggest the motivation of late-stage VCs seems to direct and support investee firms to reduce their investments in innovation in the short-term, and instead focus on exploiting their current offerings to drive short-term financial performance. In doing so, we advance understanding of the impacts of VC by providing amongst the first insights into the performance impacts of this increasingly prevalent phenomenon of late-stage VC in an emerging economy context.

The remainder of the paper is structured as follows. Section 2 presents the theoretical background. Section 3 describes the data and variables. Section 4 introduces the empirical strategy, and Section 5 presents the empirical results. Finally, Section 6 provides a discussion and concludes the paper.

2 Theoretical Background

2.1 Venture Capital and Innovation Performance

VC investment can benefit firm innovation through two mechanisms. First, investments in innovation are categorized by uncertainty, intangibility, and information asymmetries, which accompanied by the limited collateral of SMEs, can severely restrict their access to the adequate financing needed for innovation (Bertoni et al., 2015). As skilled financial institutions, VCs can operate under high uncertainty and strong information asymmetries to select promising firms and provide them with the financial support needed to alleviate firms' financial constraints and enable firms' to fund additional innovation projects. VC investment can also help reduce information asymmetries by certifying the quality of SMEs and thus, enhance SMEs' access to other sources of external finance (Guerini and Quas, 2016).

Second, VCs can provide value-adding services to firms that enhance their innovation performance (Chemmanur et al., 2014). After investing, VC investors have strong incentives to monitor their investments by holding concentrated equity positions or serving on the boards of their portfolio companies (Barry et al., 1990). This monitoring may stimulate firm innovation by increasing the investee firms' awareness of areas for development, and through the VC providing value-added services, such as experience, knowledge, and networks, to the investee firms to help them improve and develop (Bernstein et al., 2016). Equally, the innovation process is highly risky, and requires strong innovation and risk management capabilities; VCs can provide managerial assistance to help firms better manage their innovation process (Bernstein et al., 2016; Gu and Qian, 2019; Xiaoli et al., 2020).

Empirically, however, the evidence has been more mixed. For instance, Kortum and Lerner (2000) provided evidence that VC activities promote industry-level R&D funding and patenting, and Guo and Jiang (2013), Chemmanur et al (2014), and Gu and Qian (2019) show VC is associated with high productivity growth, R&D investment, and patenting. Whereas, Caselli et al. (2009) and Peneder (2014) found no casual impact of VC on innovation in Italian and Austrian firms. Moreover, some scholars suggest that VCs may exhibit expropriation behavior in which they motivate, encourage and support the investee to commercialize existing innovations and products, rather than invest and conduct further innovation, to maximize their prospective returns (Atanasov et al., 2012; Engel and Keilbach, 2007).

2.2 Venture Capital and Financial Performance

The impact of VC on financial performance can be explained by different hypotheses. While the screening hypothesis postulates that VC investors select firms with better performance for investment (Casamatta and Haritchabalet, 2007; Croce et al., 2013), the monitoring hypothesis claims that the involvement of VC investors can provide value-added services and enhance investee firms' financial performance (Bernstein et al., 2016; Song and Lee, 2018; Croce et al., 2019). Both mechanisms suggest that VC-backed firms should outperform non-VC-backed firms.

Alternatively, the adverse selection hypothesis predicts the reduced performance of VC-backed firms. Given information asymmetries between entrepreneurs and VC investors, entrepreneurs are motivated to overstate their prospects for investment. When VC investors have information disadvantages and are not able to observe project quality, they tend to discount the value of investee firms' investments (Amit et al., 1998). The "lemons problem" then drives away firms with high-quality projects and promising prospects (Cumming, 2006).

The empirical literature has also been mixed. The screening and monitoring hypotheses have been confirmed by many researchers (Croce et al., 2013; Guerini and Quas, 2016; Jain and Kini, 1995). For instance, Guo and Jiang (2013) found that VC investors select firms with better performance, and the performance differences are significantly magnified after VC entry. In contrast, some studies provide evidence to support negative impacts (Ber and Yafeh, 2007; Tan et al., 2013; Wang et al., 2003). For example, Tan et al. (2013) supported the adverse selection hypothesis, finding that VC-backed firms had inferior operating performance before and after initial public offerings (IPO) compared to their non-VC-backed counterparts.

2.3 Late-Stage VC and Firm Performance

While VC is traditionally explored as venture investments in early-stage businesses seeking higher returns and growth potential (OECD, 1998), Naqi and Hettihewa (2007) found that VC in Asia increasingly focuses on later-stage firms, known as late-stage VCs. This has been attributed to a growing risk aversion amongst VCs in China, and venture capitalists' prioritization of late-stage firms over early-stage and innovative firms has raised concerns about whether VCs can drive performance and will encourage innovation when making late-stage investments (Beladi et al., 2018; Pukthuanthong and Walker, 2007; Tan et al., 2008; Tan et al., 2013). However, despite the prevalence of late-stage VC in China, no attempts have been made to investigate the impact of late-stage VC on firm performance.

Understanding the motivation of late-stage VC investors is essential to explore their impact on investee firms' performance. VCs invest to enhance the market value of their investees and thus, secure a return. Where early-stage VCs are typically pursuing riskier investments with high potential rates of return in the medium to longer-term (Tian, 2011), late-stage VCs are likely to pursue more certain, predictable, and shorter-term returns when making investments. Thus, we expect that in late-stage investments, VCs will encourage and support firms to focus on exploiting existing products and maximizing the short-term financial performance to maximize their prospective returns. VCs as investors are likely to possess high levels of influence in SMEs to shape firm behavior (Jiang et al., 2014), and therefore, we expect their impact to be particularly salient in our context.

This motivation of VC investors suggests that late-stage investments may result in heterogeneous impacts on our two dimensions of performance. In late-stage investments, firms have already developed proven and successful products and are either profitable or on a path toward profitability (Park and Tzabbar, 2016). As resources in SMEs are extremely limited, pursuing further innovation at this stage could deplete critical (non-) financial resources that could have more productively been utilized to further commercialize existing products. To secure returns on their investment, we argue that late-stage VCs will encourage and support their investee to focus their attention and resources on further commercializing and exploiting their existing products to drive performance and profitability, at the expense of pursuing further innovations (Park and Tzabbar, 2016). This could be, for example, improving marketing and sales, streamlining management procedures, or exploring alternative avenues to market (e.g., licensing). Where innovation is supported, VCs will likely encourage related innovations that enhance the commercialization of their existing products, rather than the pursuit of new trajectories.

The nature of R&D and innovation activities may also not be favorable to late-stage VC. R&D and innovation costs are incurred immediately, thus reducing current profitability and performance, while the benefits are highly uncertain and not likely to accrue for several years (Hall and Lerner, 2010). This contrasts with the more certain and short-term returns preferred by late-stage VCs, and thus, suggests they will guide and support firms away from innovation activities. Moreover, as VCs typically achieve returns through exits, they may encourage avoidance of R&D and innovation activities due to their greater risk of failure. Failure could potentially reduce the market value of the firm and its prospective returns by sending unfavorable signals to market evaluators.

Beyond supporting firms to further commercialize and exploit their current products, late-stage VCs may also provide managerial and professional assistance to help investees better manage their companies, control and reduce their costs, implement efficiencies and enhance productivity (Chemmanur et al., 2014; Croce et al., 2013; Gu and Qian, 2019). In doing so, late-stage VCs can enhance the financial performance of their investees, and thus, their potential returns. Collectively, our discussion suggests that late-stage VC will encourage and support their investees to exploit and commercialize current products to enhance their short-term performance, rather than encourage investment in innovation.

Additionally, the successful exits of VCs condition the liquidity of exit markets. Liquidity risk can determine venture capitalists' decisions to invest in different types of firms (i.e., early-stage versus late-stage) and may affect their investment performance. Liquidity risk refers to the risk of not being able to effectively exit and thus being forced to stay longer in the venture or sale their shares at a discounted price. In the stock markets, liquidity determines the possibility of exiting through IPOs. An increase in liquidity (i.e., low liquidity risk) can attract more VC investments from early-stage projects toward late-stage projects (Cumming et al., 2005). While our focus is not the investment decisions of VCs, we expect that late-stage VCs have incentives to promote the financial performance of investee firms to realize high stock prices and thus high exiting returns, especially when liquidity risk is low in the exiting markets.

3 Data and Variables

3.1 Institutional Background

With the growth of VC investments in China, late-stage VCs have become increasingly prevalent in recent years. According to the VC events data from the *China Venture Investment Database,* as illustrated in Fig. 1, the number of VC deals and the total volume of venture investment experienced remarkable growth during 2000–2017[1]. However, the proportion of VC deals by development stage (Fig. 2) demonstrates that VC investors exhibit explicit preferences toward firms in late stages (i.e., the growth and maturity stages). For instance, in 2017, VC deals in the growth and maturity stages respectively accounted for 34.6% and 31.9% of the total VC deals.

[Figures 1 and 2 about Here]

The establishments of the Small and Medium Enterprise Board (SMEB) and the Growth Enterprise Board (GEB) provide an important context to investigate the impacts of late-stage VCs. The SMEB and GEB were respectively launched in 2004 and 2009, aiming to help small and medium-sized enterprises (SMEs) and innovative firms to raise capital. The SMEB and GEB have low requirements on firm size in terms of assets or sales revenue, but the listed firms are required to have high growth potential[2]. The growth potential features of firms at SMEB and GEB are attractive to late-stage VCs. Moreover, the non-tradable share reform in 2004 allows VC investors to sell their equity shares in the secondary market, and the lock-up period has been reduced from three years to one year for VC-backed firms since 2008. The reforms provide profit-generating opportunities for late-stage VCs by ensuring their successful exits.

3.2 Data Sources

[1] The total volume of venture investment may be inaccurate as some VC events do not contain exact volumes of VC investment. Nevertheless, the remarkable growth trend in the volume of VC investment is consistent with macro-level data from the VC Annual Yearbooks. Thus, we only present VC deals by development stage in Fig 2.

[2] For instance, the GEB requires that firms' annual growth rate of sales should be more than 30%. However, the requirement on firm size is relatively low, with net asset no less than 20 million RMB.

Our data comes from three different firm-level datasets: VC investment events, financial statements, and patent applications. The sample is comprised of firms listed in the SMEB and GEB during 2007–2017[3]. The VC data was retrieved from the China Venture Investment Database, Zero2IPO. The database records detailed information on venture investment, including investor name, investee name, investment time, investment amount et cetera. We collected VC investment events for firms listed in SMEB and GEB from 2000 to 2017, which provided us with 9069 investment deals. Although our sample period is 2007–2017, VC events before 2007 were included to track firms' history of receiving VC.

The patent data were extracted from the patent database maintained by China's State Intellectual Property Office (SIPO). SIPO provides detailed information on the patent application, including application number, filing date, technological class, et cetera. We use invention patents as a measure of innovative performance because the applications of invention patents are subjected to substantial examinations regarding their novelty, inventiveness, and industrial applicability. The financial statement data come from the Wind database. This database is maintained by Wind Info and covers general business and financial information for Chinese listed firms. The database provides a number of indicators, such as sales revenue and fixed capital. Firms that are listed before 2007 or after 2017 were excluded from our sample.

The VC and patent datasets were merged into the financial statement dataset based on the unique names of listed firms. We restricted the merged sample of firms to the manufacturing sector, as innovation activities and venture investment are mainly concentrated in this sector[4]. After data merging and cleaning, we obtained an unbalanced panel data of 6027 observations from 1086 firms.

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[3] The Chinese accounting standard was revised in 2007. The revised standard places new financial reporting requirements on Chinese listed firms. The use of data after 2007 is to make the indicators consistent over time. Moreover, some variables suffer from the issue of missing values before 2007.

[4] According to the National Industry Classification (GB/T 4754–2002) in China, the data cover three broad sectors, including mining, manufacturing, and public utilities. The manufacturing sector attracts the majority of VC investors because it covers many high-tech industries, such as telecommunication and computer products, chemical and pharmaceutical products,

Notably, our sample also covers firms prior to IPO. Firms are required to report their financial indicators for up to three years during the IPO preparation stage. The inclusion of data prior to IPO enables us to identify late-stage VC and to implement a DD estimation to identify the impact of late-stage VC since we can observe firm performance before and after VC entry.

3.3 Outcome Variables

We employ four outcome variables to capture firms' innovative and financial performance. The innovative performance is measured by R&D intensity and invention patents. R&D intensity is measured as the ratio of R&D expenditures to sales revenue. We count the number of granted invention patents on the application date, although the application process can take several years before approval is received.

The financial performance is measured by the return on asset (ROA) and the return on equity (ROE). ROA reflects firms' profitability, which is calculated as the ratio of net income to total assets. As an alternative measure of financial performance, ROE is calculated as the ratio of net income to average shareholders' equity. As shareholders' equity equals a firms' assets minus debt, ROE can be considered as the return on net assets.

3.4 Treatment Variable

The treatment variable is defined as a dummy variable to identify firms backed by late-stage VC. Specifically, we define late-stage VC as venture investments that occurs within three years prior to an investee firm's IPO. The treatment variable equals one if a firm receives venture investment within three years prior to IPO. Although we collected data on venture investments starting from 2000, the financial statement data start from 2007, and only a few firms report financial information longer than three years

electronic and electrical equipment, and machinery.

prior to IPO. Therefore, we use three years prior to IPO as the cut-off to define late-stage VC[5]. We rescale time periods so that a firm receives venture capital at $\mathrm{t} = 0$. Let $\mathrm{t} = \{1,2,3\}$ represent the rescaled periods following VC entry, while $\mathrm{t} = \{-1, -2, -3\}$ denotes the rescaled periods prior to VC entry (table 1). To investigate the changes in firm performance before and after VC entry, we make $\mathrm{t} = -1$ the baseline pre-treatment period for the VC-backed firms. To identify the impact of VC on firm performance, we will also need to observe the before-and-after changes in firm performance for non-VC-backed firms. We take the period of one year prior to IPO as the baseline pre-treatment period for non-VC-backed firms.

[Table 1 about Here]

3.5 Covariates

As VC investment is selective, firms with particular characteristics may be more likely to be selected. To estimate the impacts of VC on firm performance, we rely on observable firm characteristics from the existing literature to construct a comparison group of non-VC-backed firms (Alperovych et al., 2015; Guo and Jiang, 2013). This includes: (1) pre-treatment innovative performance, measured as the ratio of intangible assets to fixed assets; (2) pre-treatment financial performance, measured as the ratio of operating profit to sales revenue (i.e., profit margin) to control for pre-treatment financial performance; (3) firm size, measured as the number of employees in logarithm; (4) firm age, measured as the years of establishment; (5) export status, defined as a dummy variable; (6) subsidy, measured as the amount of government subsidies in logarithm; (7) capital intensity, measured as the ratio of fixed capital per worker in logarithm; (8) industry

[5] We keep in mind that our definition of late-stage VC will be affected by the fact that some firms may receive venture investment more than three years prior to IPO but are unobserved in our dataset. To address this issue, we use the VC history data and define early-stage venture capital as a robustness check.

and year dummies are included to control for industry and year heterogeneity, such as technological opportunity and unobservable time trends. Summary statistics are reported in Table 2.

[Table 2 about Here]

4 Empirical strategy

We employ the potential outcome framework. To time VC entry, we rescale time periods in such a way that a firm receives venture capital at $\mathrm{t} = 0$, and $\mathrm{t} = \{1,2,3\}$ represents the years following VC entry. Let the treatment status $D_{it} = 1$ if firm *i* is backed by VC investment at time *t*, and $D_{it} = 0$ for non-VC-backed firms. Potential outcomes $Y_{it}(1)$ and $Y_{it}(0)$ denote the performance indicators for firm *i* at time *t* conditional on VC participation and nonparticipation, respectively. The impact of VC entry on firm performance can be measured by the difference: $Y_{it}(1) - Y_{it}(0)$. Following the policy evaluation literature (Heckman et al., 1997), we define the average treatment effect on treated (ATT) as follows:

$$\alpha_t = E[Y_{it}(1) - Y_{it}(0) | D_{it} = 1]. \tag{1}$$

The main difficulty in estimating Eq. (1) is identifying the unobserved counterfactual. While $\mathrm{E}[Y_{it}(1)|D_{it} = 1]$ represents the actual outcomes of treated firms, it can be directly calculated as the mean average of firm performance for VC-backed firms. However, $\mathrm{E}[Y_{it}(0)|D_{it} = 1]$ denotes the potential outcomes in the counterfactual case that are unobservable. That is, we cannot observe the potential outcomes for VC-backed firms if they had not received VC investment. As VCs impose selection, we cannot use the outcomes of non-VC-backed firms to replace the counterfactual term. Selection bias arises from the fact that firms with specific characteristics may be more likely to be targeted by VC investors. The outcome differences could thus be the result of pre-treatment selection bias.

4.1 Matching and Difference-In-Differences Estimators

To address the selection bias, we first use PSM to construct a comparison group of non-VC-backed firms that have similar characteristics to VC-backed firms. The matching is based on a vector of observable firm characteristics that determine the treatment status of VC participation and have predictable impacts on the outcome variables (Section 3.5). Because the number of covariates is large, we cannot match samples on all dimensions, but rather, we must match on the propensity scores, which represents the probability of VC participation. As in Rosenbaum and Rubin (1983), we estimated the scores via a probit model:

$$\Pr(D_{it} = 1) = \mathrm{F}(X_{ib}), \qquad (2)$$

where $\Pr(D_{it} = 1)$ denotes the propensity scores, and $X_{i,b}$ is the set of covariates measured in the pre-treatment period. As we discussed in Section 3.3, the baseline pre-treatment period is defined as one year prior to VC entry for treated firms and one year prior to their IPO for non-treated firms.

With the estimated propensity scores at hand, we use the nearest neighbor matching algorithm to match non-VC-backed firms with VC-backed firms that are closest to it in terms of propensity scores. The matching provides us with a comparison group of firms that have characteristics similar to those of the treated firms. Replacing the counterfactual term in Eq. (1) yields the following estimator:

$$\alpha_t = \mathrm{E}[Y_{it}(1) |\, F(X_{ib}), D_{it} = 1] - E[Y_{it}(0) |\, P(X_{ib}), D_{it} = 0]. \qquad (3)$$

However, a major drawback of the matching estimator in Eq. (3) is that it is unable to control for selection bias arising from the selection on unobservables. While PSM accounts for observable characteristics, there may be some unobservable factors that determine the selection and affect firm performance. To address this, we adopt the concept of DD and estimate the following regression model based on the matched samples:

$$Y_{it} - Y_{ib} = \alpha D_{it} + \beta \cdot X_{it} + \delta_t + \gamma_s + \varepsilon_{it}, \tag{4}$$

where Y_{ib} denotes the outcomes in the pre-treatment period, X_{it} is a vector of observable covariates, δ_t and γ_s are a set of time and industry dummies, respectively, and ε_{it} is an error term.

The coefficient α in Eq. (4) captures the average effect of VC on changes in firm performance over time conditional on the covariates in X. The before-and-after comparisons of the outcome changes around the point of VC entry enable us to rule out unobserved time-invariant confounders that may confound the relationship between VC investor participation and firm performance. In addition to the regression-based DD estimator of Eq. (4), we also implement a semiparametric DD estimator:

$$\alpha_t^{DD} = E\left[\frac{Y_{it} - Y_{ib}}{P(D_{it} = 1)} \cdot \frac{D_{it} - \pi(X_b)}{1 - \pi(X_b)}\right], \tag{5}$$

where $\pi(X_{ib}) \equiv P(D_{it} = 1 \mid X_{ib})$. As discussed in Abadie (2005), Eq. (5) provides an unbiased estimate of the ATT if $P(D_{it} = 1) > 0,\ \pi(X_{ib}) < 1$, and $\mathrm{E}[Y_{it}(0) - Y_{ib}(0) \mid D_{it} = 1, X_{ib}] = \mathrm{E}[Y_{it}(0) - Y_{ib}(0) \mid D_{it} = 0, X_{ib}]$.

The semiparametric DD estimator is a weighted average of the temporal changes in the outcome variables. It reweights the treated and untreated firms using their probability of receiving VC. Non-VC-backed firms with a higher propensity score are given larger weights. The semiparametric DD estimator imposes no functional form assumptions about the relationship between the covariates and outcome variables.

4.2 Identifying Assumptions

Our identification strategy relies on the assumption that the selection bias is removed by comparing the before-and-after outcome differences between the treated and comparison groups conditional on observable covariates. This assumption relates to but is weaker than the conditional independent assumption (CIA) of the PSM approach and the parallel trend assumption (PTA) required by the DD estimator. The DD estimators in Eq. (4) and (5) only require the evolution of the unobserved part of the outcomes is independent of the treatment status, $(Y_{it} - Y_{ib}) \perp S_{i0}|X_{ib}$. As VC investors are selective in choosing investee firms, adjusting for observable covariates also increases the plausibility of the PTA. Moreover, the PTA can be empirically examined, which makes the causal inference more tenable and transparent. Our goal is to construct an appropriate comparison group through matching to make the PTA hold. When the outcome variables change in parallel before VC entry, it is reasonable to assume that the outcomes would have continued to change in parallel if the VC-backed firms had not received VC investment. Thus, the post-treatment differences in outcome variables can be interpreted as the impact of VC participation.

5 Empirical results

We start by matching the samples to construct a comparison group of non-VC-backed firms. Then, the regression-based and semiparametric DD estimators are performed based on the matched samples. The outcomes of interest are post-treatment changes in firm performance. Finally, a number of checks are conducted to examine the robustness of the results.

5.1 The Selection of Late-Stage VC Investors

As VC investors are selective in choosing investee firms, we first need to construct a comparison group of non-VC-backed firms that are comparable to the treated group of VC-backed firms. Following the procedure discussed in Section 4, we first estimate a probit model to account for the selection of late-stage VC investors where the dependent variable is a dummy variable for VC-backed firms. The independent variables are a set of pre-treatment covariates, as discussed in Section 3.5.

[Table 3 about Here]

Table 3 presents the results of the probit estimations. In columns (1)–(4), different indicators of firm performance are respectively included in the regressions. The estimated coefficient on intangible asset is negative, while the estimates on ROE and profit margin are significantly positive. This suggests that late-stage VC investors select firms with better financial performance, but more innovative firms are less likely to be selected. Although there are no significant differences in R&D intensity between VC-backed and non-VC-backed firms ex-ante, the results suggest some risk aversion of late-stage VC investors, who shy away from innovative firms, as firms with more intangible assets are generally more innovative and associated with high uncertainty.

In columns (5)–(6) of Table 3, we put the performance variables into the estimations simultaneously. The results remain consistent in column (5) but change in column (6). This is because the performance indicators are strongly correlated with each other, and the estimation in column (6) is affected by multicollinearity. The results suggest that intangible assets and profit margin are good indicators for controlling for pre-treatment financial and innovative performance. Thus, we choose the specification in column (5) to estimate the propensity scores. The use of the specification in column (5) enables us to avoid directly putting the pre-treatment outcome variables into covariates while still controlling for pre-treatment firm performance (Imbens, 2015).

[Table 4 about Here]

With the estimated propensity scores, VC-backed firms are matched to non-VC-backed firms that are closest on propensity scores based on the nearest neighbor matching algorithm. The matching provides a comparison group of non-VC-backed firms. To examine the effectiveness of the matching, Table 4 presents the post-matching balancing tests. The results show that the mean averages of all dimensions are very close, and the t-tests suggest that there are no significant differences in these covariates between the treated and matched comparison groups. This means that the covariates of the treated and matched samples can be considered to be statistically identical. Therefore, using the matched samples for causal inference will enable us to rule out those observable confounding factors.

5.2 Impacts of Late-Stage VC on Firm Performance

Based on the matched samples, we then employ the regression-based DD estimator from Eq. (4) to investigate the overall effects of late-stage VC on firm performance. Matching on covariates ensures the overlap in the distribution of observable characteristics between the treatment and control groups and enables us to reweight the control observations in the regression. The dependent variables are changes in firm performance between the post-treatment periods and the baseline period, $Y_{it} - Y_{ib}$, and the matched observations of three post-treatment periods are all included in the estimation. Thus, the estimated coefficients on the treatment variable, $\alpha,$ can be interpreted as the overall effect within the three years after VC entry. The use of performance changes as the dependent variables controls for unobserved time-invariant confounding factors.

Table 5 indicates that late-stage VC has a negative impact on firms' innovative performance in terms of both R&D intensity and invention patents. In columns (1) and (2) of Table 5, the estimated coefficients on *LSVC* are negative and significant at the 1% level. This suggests that the participation of late-stage VC can lead to a decrease of a firms' R&D intensity by 1.3%, on average, in the following three years after VC entry. The number of successful invention patent applications also experiences a significant decrease of about 1.39 on average.

On the contrary, the results point to a significantly positive impact of late-stage VC on firms' financial performance. In columns (3) and (4) of Table 5, the coefficients of interest are positive and statistically significant. The participation of late-stage VC can lead to an increase in ROE by 5.79% and ROA by 5.94% on average. The results confirm our theoretical prediction that late-stage VC has heterogeneous impacts on firms' innovative and financial performance.

[Table 5 about Here]

5.3 Further Checks

In addition to the matched regression estimator, we use the semiparametric DD estimator to estimate the treatment effects. The overall effects in Table 6 again confirm the heterogeneous impacts of late-stage VC on firms' innovative and financial performance. Consistent with the results in Table 5, this shows that late-stage VC has a significantly negative impact on firms' R&D investment and invention patents but significantly improves investee firms' financial performance in terms of ROA and ROE. This suggests that our results are robust to the semiparametric DD estimator.

[Table 6 about Here]

To examine the role of liquidity risk in the performance effects of late-stage VCs, we split our sample into two periods to capture the variations in liquidity risk. As liquidity relates to the possibility of exiting by listing the company on the stock market (i.e., IPO), Cumming et al. (2005) used the number of IPOs per year as a proxy for liquidity risk of exit markets. In our sample period from 2007 to 2017, the liquidity risk is higher in the period close to the global financial crisis in 2008. We collected the data of all IPOs in China's stock exchanges. The number of IPOs is much lower from 2008 to 2013 (annual average is 153) than that in the period after 2013 (annual average is 252). Thus, the liquidity risk is lower after 2013 compared to the sample period before 2013. Table 7 indicates that the effects of late-stage VCs on the financial performance of investee firms are higher in the period with lower liquidity risk (2014-2017) than that in the period with higher liquidity risk (2007-2013). The results are consistent with the findings in Cumming et al. (2005), suggesting that higher liquidity can induce VCs to invest in firms in late stages to realize higher financial performance[6]. By contrast, the empirical pattern for the effects on the innovative performance does not clearly differentiate between the two sample periods.

[Table 7 about Here]

Another important concern is the classification of VC-backed firms. In our definition of late-stage VC, we only trace back three years prior to a firm's IPO to identify late-stage VC-backed firms. However, some firms may receive VC many years prior to their IPO. We attempt to identify whether firms had previously received VC (i.e., early-stage VC) by tracking the VC history data back to 2000. Accordingly, a firm is defined as a receiving both late- and early-stage VC-backed firm if it received venture investment both more than three years before its IPO and within three years of its IPO. Meanwhile, some firms even received venture investment after their IPO in our dataset, and we classify those firms as post-IPO VC-backed firms. After defining early-stage VC and post-IPO VC, late-stage VC-backed firms are reclassified accordingly. We then investigate whether the estimates are affected by this reclassification.

[Table 8 about Here]

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[6] Notably, we do not have data on the financial performance of venture capitalists. The focus of our study is to investigate the effects of late-stage VC on the performance of investee firms. While we are unable to observe the financial performance of VCs, we expect that the exiting performance of VCs highly depend on the financial performance of their investee firms. Thus, the increase in liquidity should be positively associated with better investment performance of VCs.

Table 8 presents the results after reclassifying VC-backed firms. Panel A of Table 8 provides consistent estimates of late-stage VC impacts with the results in Tables 5–6. The results are also robust across the regression-based DD estimator and the semiparametric DD estimator. In panel B, the results show that a firm's experience of receiving early-stage VC does not matter for the impact of late-stage VC on firm performance. However, in panel C of Table 8, the results point to insignificant effects of post-IPO VC on both firms' innovation and financial performance. This suggests that the operating decisions of listed firms are less affected by VC investors.

Another potential concern is that the style drift of VCs may affect the outcome of investee firms' performance, as we expect that VCs should invest in the area of their expertise to realize better investment performance. In Cumming et al. (2009), style drift refers to the fact that fund managers may not invest in the development stages they committed. For instance, style drift happens when an early-stage fund invests in an expansion or late-stage company. Unfortunately, we do not have such information to define style drift, which prevents us from empirically investigating the role of style drifts in VCs. However, we expect that style drifts of VCs will not affect our findings on the overall effects of late-stage VC on firm performance. The overall effects may mask potential impact heterogeneity between VCs with and without style drifts. Specifically, we expect that VCs with style drifts in development stages may undermine the performance of investee firms.

To check the identifying assumption of our empirical strategy, we estimate the treatment effects of late-stage VCs on pseudo-outcomes (i.e, outcome variables at pre-treatment periods). The results show there are no significant differences in outcome changes between the treated and comparison groups prior to treatment

(Table A1 in the Appendix). Thus, we can gain confidence that our constructed comparison group is appropriate, and the outcome variables should evolve in parallel without treatment.

We also examine whether our estimates are affected by the choice of the baseline pre-treatment period for the comparison group and check the robustness of the results to IPO shocks. In previous estimations, we take one year prior to IPO as the baseline pre-treatment period for non-VC-backed firms. As a robustness check, we change the baseline period to the two years prior to the IPO and replicate the results. To account for IPO shocks, we include a dummy for IPO year and include it in the matching and regression. In the Appendix, the results in Table A2 and A3 confirm the robustness of the empirical findings.

Finally, we acknowledge that the characteristics of VCs may matter for the performance effects of late-stage VCs. For instance, an important distinction can be made among foreign VCs, government VCs, and private VCs (Guerini and Quas 2016; Alperovych et al. 2015; Cumming et al 2017). Foreign VCs tend to invest in ventures with greater capital demand and computer-related ventures, as well as ventures in the communication and media industry in China (Dai et al., 2012). We included a full set of industry dummies to control for industry heterogeneity which may relate to the distribution of cross-border VCs. Compared to private VCs, governmental VCs can assert differential effects on investee firms (Luukkonen et al. 2013). Unfortunately, our data set only includes detailed information for investee firms but lacks detailed information for VC characteristics. Thus, we are unable to examine effect heterogeneity across a broader range of VC characteristics. To partially account for the role of government funds and political connections, we include government subsidies as a covariate in all estimations of the treatment effects. We check the robustness of our results by including a dummy variable for state ownership as an additional control variable to replicate the estimations and we find the results hold.

6 Discussion and Conclusion

This study has investigated the firm performance consequences of the novel phenomena of late-stage VC. We theorized that VC motivations would be important in shaping the performance consequences. Late-stage VCs motivated to secure and increase their short-term returns would encourage and support their investees to exploit current products and enhance short-term profitability. Thus, we predicted that late-stage VC would have heterogeneous effects across firm innovation and financial performance. We empirically examined the performance consequences using a sample of Chinese firms listed in the SMB and GEB during 2007–2017. Consistent with our theorizing, our results show that late-stage VC negatively impacts investee firms' innovation performance in the three years post-entry. Specifically, late-stage VC can lead to a decrease in firms R&D intensity by 1.3% on average and a fall of about 1.39 successful invention patent applications on average. On the contrary, late-stage VC stimulates an increase in investee firms' financial performance in the three years post-entry. Specifically, late-stage VCs increase firms ROE and ROA by 5.79% and 5.94% on average, respectfully. The treatment effects are robust to a number of checks. Thus, our empirical results support the heterogeneous impacts across firm performance dimensions and suggest that late-stage VCs encourage and support their investee firms to devote their time and attention to exploiting profits from current products, rather than investing in the development of innovations.

This paper adds to the VC impact evaluation literature by investigating the impact of this novel and increasingly prevalent phenomenon of late-stage VC on firm performance. Although many empirical studies have evaluated the impact of VC (Bronzini et al., 2020; Galloway et al., 2017), the entry stage of VC investors has been largely ignored in the literature. While most studies focus on traditional VC for early-stage business in developed countries, little attention has been given to the emergence of late-stage VC in

Asian countries such as China (Beladi et al., 2018; Tan et al., 2013). In this paper, we explicitly take into account the entry stage of VC and provide direct evidence regarding the impact of late-stage VC in the context of China. By distinguishing late-stage VC, our study complements recent studies that have emphasized the importance of the heterogeneity of VC investors by showing that the heterogeneous motivations of late-stage VCs shape the performance consequences for investee firms. Our study further contributes by joining recent work in providing an emerging economy perspective on the performance consequences of VC (Cheng and Tang, 2019), and in particular on late-stage VC which is increasingly dominant in Asian countries.

Our study also contributes to understanding the emergence of late-stage VC and the consequences of this phenomenon for different dimensions of firm performance. We theorized that late-stage VCs would be motivated to secure and increase their short-term returns, and thus, would encourage and support their investees to exploit their current products and enhance short-term profitability. Consequently, we expected heterogeneous impacts across firm innovation and financial performance. Empirically, our results supported this view by showing that late-stage VC decreases firms' innovation performance in the three years post-entry but increases firms' financial performance in the same period. Late-stage VCs thus, appear to be effective in executing their motivation through encouraging and supporting their investee firms to increase short-term financial performance and the potential returns from their investment. This may come at the expense of investee firms' innovation performance, however, as late-stage VCs encourage investee firms to reduce costs and re-direct resources to support the exploitation of current products to maximize short-term profitability. As innovation is an important driver of future firm performance (Koellinger, 2008), these reductions in innovation performance may have negative performance consequences for investee firms in the future.

The implications of this paper are important for both policymakers and entrepreneurs. For entrepreneurs, our study has implications for the governance and financing strategies of firms in their different developmental stages. Being involved in the governance of investee firms, VC investors can affect those firms' decision-making and performance. Late-stage VC investors appear to encourage and support their investee firms to focus on exploiting current products to maximize short-term financial performance, and thus, the VCs potential returns. Thus, for firms aiming to maximize their financial returns, late-stage VCs appear to be an effective financing source. However, for those aiming to pursue innovation performance, alternative sources, such as R&D subsidies and tax incentives (e.g., Chapman et al., 2018; Dai et al., 2020), may be preferred over late-stage VC due to their motivations. From a policy perspective, our results suggest that the emerging preference of VCs in Asian countries for late-stage investments may be effective for helping firms to maximize their financial performance but may not be conducive to enhancing innovation performance. Thus, policymakers need to continue to maintain and enhance the institutional and market environments for late-stage VCs to help firms continue to maximize their financial performance. Additionally, governments may also need to enhance the incentives of VCs to invest more in early-stage firms to continue to promote innovation and drive economic growth.

As with all studies, our study has some limitations. First, despite the advantages of using firms listed in the SMEB and GEB for empirical investigation, our sample does not cover unlisted firms that may have received late-stage VC. As such firms may differ, and VCs may differ in their investment motivations within such firms, it would be worthwhile to extend our work in this way. Second, although we can track firms' history of receiving VCs, our sample does not include financial statements data for firms backed by early-stage VCs around the periods of early-stage VC entry and thus cannot compare the potential effects heterogeneity between early-stage VCs and late-stage VCs. Third, we do not have detailed information on VC characteristics and thus are unable to examine the potential effect heterogeneity of VCs on investee firms' performance in a broader dimension of VC characteristics. With available data, addressing the limitations of this paper opens interesting avenues for future research.

References

Abadie, A. (2005). Semiparametric difference-in-differences estimators. *Review of Economic Studies,* 72, 1-19.

Alperovych, Y., Hübner, G., & Lobet, F. (2015). How does governmental versus private venture capital backing affect a firm's efficiency? Evidence from Belgium. *Journal of Business Venturing*, 30, 508-525.

Amit, R., Brander, J., & Zott, C. (1998). Why do venture capital firms exist? Theory and Canadian evidence. *Journal of Business Venturing*, 13, 441-466.

Atanasov, V., Ivanov, V., & Litvak, K. (2012). Does reputation limit opportunistic behavior in the VC industry? Evidence from litigation against VCs. *Journal of Finance*, 67, 2215-2246.

Barry, C.B., Muscarella, C.J., Peavy Iii, J.W., & Vetsuypens, M.R. (1990). The role of venture capital in the creation of public companies: Evidence from the going-public process. *Journal of Financial Economics*, 27, 447-471.

Beladi, H., Chao, C.C., & Hu, M. (2018). Do venture capitalists function the same: The evidence from the Chinese newest stock market, ChiNex. *World Economy,* 41, 2020-2041.

Benkraiem, R., Boubaker, S., Brinette, S., & Khemiri, S. (2021). Board feminization and innovation through corporate venture capital investments: The moderating effects of independence and management skills. *Technological Forecasting and Social Change*, 163, 120467.

Ber, H., & Yafeh, Y. (2007). Can venture capital funds pick winners? Evidence from pre-IPO survival rates and post-IPO performance. Evidence from Pre-IPO Survival Rates and Post-IPO Performance. *Israel Economic Review*, 5, 23-46.

Bernstein, S., Giroud, X., & Townsend, R.R. (2016). The impact of venture capital monitoring. *Journal of Finance*, 71, 1591-1622.

Bertoni, F., Colombo, M.G., & Grilli, L. (2011). Venture capital financing and the growth of high-tech start-ups: Disentangling treatment from selection effects. *Research Policy*, 40, 1028-1043.

Bertoni, F., Croce, A., & Guerini, M. (2015). Venture capital and the investment curve of young high-tech companies. *Journal of Corporate Finance*, 35, 159-176.

Bronzini, R., Caramellino, G. & Magri, S. (2020). Venture capitalists at work: A diff-in-diff approach at late-stages of the screening process. *Journal of Business Venturing*, 35, 105968.

Casamatta, C., & Haritchabalet, C. (2007). Experience, screening and syndication in venture capital investments. *Journal of Financial Intermediation*, 16, 368-398.

Caselli, S., Gatti, S., & Perrini, F. (2009). Are venture capitalists a catalyst for innovation? *European Financial Management*, 15, 92-111.

Chapman, G., Lucena, A., & Afcha, S. (2018). R&D subsidies & external collaborative breadth: Differential gains and the role of collaboration experience. *Research Policy*, 47, 623-636.

Chemmanur, T.J., Loutskina, E., & Tian, X. (2014). Corporate Venture Capital, Value Creation, and Innovation. *Review of Financial Studies*, 27, 2434-2473.

Cheng, C.-Y., & Tang, M.-J. (2019). Partner-selection effects on venture capital investment performance with uncertainties. *Journal of Business Research*, 95, 242-252.

Croce, A., Martí, J., & Murtinu, S. (2013). The impact of venture capital on the productivity growth of European entrepreneurial firms:'Screening'or 'value added'effect? *Journal of Business Venturing*, 28, 489-510.

Croce, A., Martí, J., & Reverte, C. (2019). The role of private versus governmental venture capital in fostering job creation during the crisis. *Small Business Economics*, 53, 879-900.

Cumming, D., Fleming, G., & Schwienbacher, A. (2005). Liquidity risk and venture capital finance. *Financial Management*, 34(4), 77-105.

Cumming, D. (2006). Adverse selection and capital structure: Evidence from venture capital. *Entrepreneurship Theory and Practice*, 30, 155-183.

Cumming, D., Fleming, G., & Schwienbacher, A. (2009). Style drift in private equity. *Journal of Business Finance & Accounting*, 36(5‐6), 645-678.

Cumming, D. J., Grilli, L., & Murtinu, S. (2017). Governmental and independent venture capital investments in Europe: A firm-level performance analysis. J*ournal of corporate finance*, 42, 439-459.

Dai, X., Verreynne, M.L., Wang, J.H., & He, Y. (2020). The behavioral additionality effects of a tax incentive program on firms' composition of R&D investment. *R&D Management*, 50(4), 510-521.

Dai, N., Jo, H. and Kassicieh, S., (2012). Cross-border venture capital investments in Asia: Selection and exit performance. *Journal of Business Venturing,* 27(6), pp.666-684.

Engel, D., Keilbach, M., 2007. Firm-level implications of early stage venture capital investment—An empirical investigation. *Journal of Empirical Finance*, 14, 150-167.

Galloway, T.L., Miller, D.R., Sahaym, A., & Arthurs, J.D. (2017). Exploring the innovation strategies of young firms: Corporate venture capital and venture capital impact on alliance innovation strategy. *Journal of Business Research*, 71, 55-65.

Gu, W., & Qian, X. (2019). Does venture capital foster entrepreneurship in an emerging market? *Journal of Business Research*, 101, 803-810.

Guerini, M., & Quas, A. (2016). Governmental venture capital in Europe: Screening and certification. *Journal of Business Venturing*, 31, 175-195.

Guo, D., & Jiang, K. (2013.) Venture capital investment and the performance of entrepreneurial firms: Evidence from China. *Journal of Corporate Finance*, 22, 375-395.

Hall, B.H., & Lerner, J. (2010). *The financing of R&D and innovation*. Handbook of the Economics of Innovation. Elsevier, pp. 609-639.

Heckman, J.J., Ichimura, H., & Todd, P.E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *Review of Economic Studies*, 64, 605-654.

Imbens, G.W. (2015). Matching methods in practice: Three examples. *Journal of Human Resources*, 50, 373-419.

Luukkonen, T., Deschryvere, M., & Bertoni, F. (2013). The value added by government venture capital funds compared with independent venture capital funds. *Technovation*, 33(4-5), 154-162.

Jain, B.A., & Kini, O. (1995). Venture capitalist participation and the post-issue operating performance of IPO firms. *Managerial and Decision Economics*, 16, 593-606.

Jiang, P., Cai, C.X., Keasey, K., Wright, M., & Zhang, Q. (2014). The role of venture capitalists in small and medium-sized enterprise initial public offerings: Evidence from China. *International Small Business Journal*, 32, 619-643.

Koellinger, P. (2008). The relationship between technology, innovation, and firm performance—Empirical evidence from e-business in Europe. *Research Policy*, 37, 1317-1328.

Kortum, S., & Lerner, J. (2000). Assessing the contribution of venture capital to innovation. *Rand Journal of Economics*, 31, 674-692.

Naqi, S.A., & Hettihewa, S. (2007). Venture capital or private equity? The Asian experience. *Business Horizons*, 50, 335-344.

OECD, 1998. *OECD Economic Survey*. OECD Publications, France.

Park, H.D., & Tzabbar, D. (2016). Venture capital, CEOs' sources of power, and innovation novelty at different life stages of a new venture. *Organization Science*, 27, 336-353.

Peneder, M. (2014). *The impact of venture capital on innovation behavior and firm growth*. Perspectives on Financing Innovation. Routledge, pp. 193-223.

Pukthuanthong, K., & Walker, T. (2007). Venture capital in China: a culture shock for Western investors. *Management Decision*, 45, 708-731.

Puri, M., & Zarutskie, R. (2012.) On the life cycle dynamics of venture-capital-and non-venture-capital-financed firms. *Journal of Finance*, 67, 2247-2293.

Quas, A., Martí, J., & Reverte, C. (2020). What money cannot buy: a new approach to measure venture capital ability to add non-financial resources. *Small Business Economics*, DOI: 10.1007/s11187-020-00352-w.

Rosenbaum, P.R., & Rubin, D.B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70, 41-55.

Song, C.-S., & Lee, Y. (2018). Monitoring role of venture capital in the initial public offerings: Evidence from Korea. *Emerging Markets Finance and Trade*, 1-18.

Tan, J., Zhang, W., & Xia, J. (2008). Managing risk in a transitional environment: An exploratory study of control and incentive mechanisms of venture capital firms in China. *Journal of Small Business Management*, 46, 263-285.

Tan, Y., Huang, H., & Lu, H. (2013). The Effect of Venture Capital Investment—Evidence from C hina's Small and Medium-Sized Enterprises Board. *Journal of Small Business Management*, 51, 138-157.

Tian, X. (2011). The causes and consequences of venture capital stage financing. *Journal of Financial Economics*, 101, 132-159.

Tian, X., Kou, G., & Zhang, W. (2020). Geographic distance, venture capital and technological performance: Evidence from Chinese enterprises. *Technological Forecasting and Social Change*, 158, 120155.

Wang, C.K., Wang, K., & Lu, Q. (2003). Effects of venture capitalists' participation in listed companies. *Journal of Banking & Finance*, 27, 2015-2034.

Wang, L., & Wang, S. (2011). Cross-border venture capital performance: Evidence from China. *Pacific-Basin Finance Journal*, 19(1), 71-97.

Figures and Tables

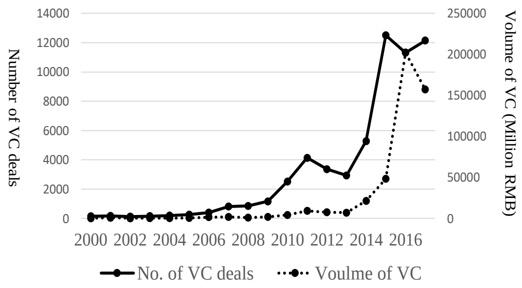

Fig. 1. Number and voulme of VC deals

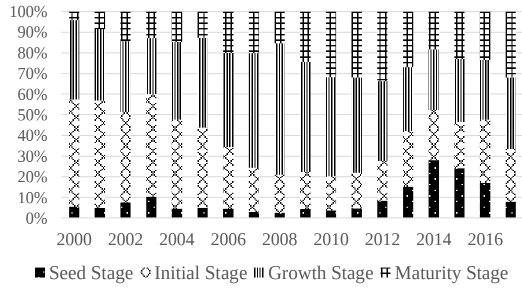

Fig. 2. Number of VC deals by stage

Table 1: An overview of the sample over rescaled periods

Rescaled Period	No. of firms	VC-backed firms	Non-VC-backed firms
t=-3	476	24	452
t=-2	616	134	482
t=-1	767	257	510
t= 0	1024	484	540
t= 1	968	482	486
t= 2	934	472	462
t= 3	878	458	420

Table 2: Summary statistics of the variables

Variables	Definitions	Mean	S.D.
R&D Intensity	R&D expenses in relative to sales revenue	0.046	0.034
Invention Patent	Number of granted invention patents	1.152	6.749
Sales	Sales revenue in logarithm	19.965	0.958
Intangible Asset	The ratio of intangibles asset to fixed asset	0.395	0.863
Profit Margin	Operating profit in relative to sales revenue	0.158	0.116
ROE	Net income in relative to equity	0.214	0.144
ROA	Net income in relative to total assets	0.149	0.092
LSVC	Dummy, =1 for VC-backed firms, 0 otherwise	0.385	0.487
Size	Number of employees in logarithm	6.717	0.949
Age	Years of establishment	11.419	5.021
Export	Dummy, =1 for exporters, 0 for non-exporters	0.715	0.451
Subsidy	Government subsidies in logarithm	12.977	5.242
Capital intensity	Fixed capital per worker in logarithm	11.781	0.971

Table 3: Probit estimations on the selection of late-stage VCs

Variables	(1)	(2)	(3)	(4)	(5)	(6)
R&D	0.0690					1.5960*
Intensity	(0.793)					(0.856)
ROE		8.4051***				9.1262***
		(0.385)				(0.419)
Intangible			-0.1796***		-0.1754***	-0.1551***
Asset			(0.034)		(0.034)	(0.041)
Profit				1.2893***	1.2218***	-1.1662***
Margin				(0.259)	(0.261)	(0.218)
Size	-0.3651***	-0.3286***	-0.4079***	-0.3152***	-0.3586***	-0.3877***
	(0.033)	(0.034)	(0.033)	(0.033)	(0.034)	(0.038)
Age	-0.0573***	-0.0382***	-0.0576***	-0.0562***	-0.0565***	-0.0379***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Export	-0.1385**	-0.1145*	-0.1466**	-0.1196**	-0.1293**	-0.1373**
	(0.057)	(0.062)	(0.057)	(0.057)	(0.058)	(0.062)
Subsidy	-0.0318***	-0.0275**	-0.0294***	-0.0322***	-0.0298***	-0.0271**
	(0.010)	(0.011)	(0.010)	(0.010)	(0.010)	(0.012)
Capital	-0.3648***	-0.2085***	-0.4370***	-0.3473***	-0.4183***	-0.2626***
Intensity	(0.031)	(0.034)	(0.034)	(0.031)	(0.035)	(0.039)
N	3267	3267	3267	3267	3267	3267
Pseudo R^2	0.1412	0.2843	0.1456	0.1471	0.1509	0.2918

Note: ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses. Industry and year dummies are included in the regressions.

Table 4: The balancing tests of the propensity score matching

Covariates	Mean		t-test	
	Treated	Matched	t-statistic	p-value
Intangible Asset	0.417	0.392	0.90	0.37
Profit Margin	0.173	0.176	-0.73	0.47
Size	6.650	6.623	0.85	0.40
Age	11.138	11.176	-0.24	0.81
Export	0.697	0.665	1.78	0.08
Subsidy	14.461	14.591	-1.09	0.28
Capital Intensity	11.831	11.862	-0.93	0.35

Table 5: Treatment effects of late-stage VC on firm performance

	(1) R&D Intensity	(2) Invention Patents	(3) ROE	(4) ROA
LSVC	-0.0130***	-1.3867***	0.0579***	0.0594***
	(0.001)	(0.210)	(0.006)	(0.004)
Size	0.0002	0.2495*	-0.0047	0.0094***
	(0.001)	(0.137)	(0.004)	(0.003)
Age	0.0003*	0.0428	0.0026***	0.0006
	(0.000)	(0.028)	(0.001)	(0.001)
Export	0.0017	0.7093***	0.0092	0.0023
	(0.001)	(0.243)	(0.007)	(0.004)
Subsidy	0.0001	0.1703***	-0.0092***	-0.0050***
	(0.000)	(0.037)	(0.001)	(0.001)
Capital-Intensity	0.0024***	-0.2428**	-0.0019	0.0052**
	(0.001)	(0.120)	(0.004)	(0.002)
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
N	2810	2810	2810	2810
R^2	0.066	0.066	0.157	0.191

Note: ***, **, * denote significance at 1%, 5%, and 10% levels, respectively; Standard errors are reported in parentheses; covariates of intangible assets and profit margin are included in matching.

Table 6: Treatment effects estimated by semiparametric DD

	(1) R&D Intensity	(2) Invention Patents	(3) ROE	(4) ROA
ATT	-0.0102***	-1.1563***	0.0523***	0.0553***
Std. Err.	(0.001)	(0.195)	(0.007)	(0.004)

Note: ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Table 7: Treatment effects at different levels of liquidity risks

	IOPs during 2007-2013 (Higher liquidity risk)				IPOs during 2014-2017 (Lower liquidity risk)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	R&D	Patents	ROE	ROA	R&D	Patents	ROE	ROA
ATT	-0.0127***	-1.3651***	0.0384***	0.0483***	-0.0097***	-1.4986***	0.0945***	0.0779***
Std. Err.	(0.002)	(0.577)	(0.011)	(0.008)	(0.002)	(0.186)	(0.011)	(0.007)

Note: ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Table 8: Robustness checks for reclassifying late-stage VCs

	(1) R&D intensity	(2) Innovation Patent	(3) Outcome: ROE	(4) Outcome: ROA
Panel A. Late-stage venture capital				
Regression-based DD	-0.0054***	-1.0066***	0.0544***	0.0560***
	(0.001)	(0.200)	(0.007)	(0.004)
Semiparametric DD	-0.0067	-1.0830	0.0460	0.0500
	(0.001)	(0.193)	(0.007)	(0.004)
Panel B. Late-stage plus early-stage VC				
Regression-based DD	-0.0283***	-1.2955	0.1043***	0.0725***
	(0.009)	(0.891)	(0.027)	(0.017)
Semiparametric DD	-0.0351***	-1.8899***	0.1163***	0.0807***
	(0.009)	(0.326)	(0.018)	(0.012)
Panel C. Post-IPO VC				
Regression-based DD	-0.0082	-0.9067	-0.1452*	-0.0673
	(0.011)	(2.378)	(0.081)	(0.043)
Semiparametric DD	-0.0030	0.6693	-0.0836*	-0.0329*
	(0.003)	(1.201)	(0.045)	(0.020)

Note: ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses.

Appendix: Additional results for robustness checks

Table A1: Treatment effects on pre-treatment outcomes

	(1) R&D	(2) Patents	(3) ROE	(4) ROA
Three years before	-0.0125	-0.9351	0.0382	0.0411
VC entry	(0.021)	(0.625)	(0.037)	(0.319)
Two years before	-0.0108	-1.2091	0.0316	0.0413
VC entry	(0.093)	(0.953)	(0.028)	(0.037)

Note: Standard errors are reported in parentheses.

Table A2: Robustness checks for the baseline pre-treatment period

	(1) R&D	(2) Patents	(3) ROE	(4) ROA
Matched regression	-0.0105***	-1.0607***	0.0423***	0.0381***
	(0.001)	(0.183)	(0.007)	(0.004)
Semiparametric DD	-0.0124***	-1.1563***	0.0414***	0.0396***
	(0.001)	(0.195)	(0.007)	(0.004)

Note: ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses. The baseline pre-treatment period for non-VC-backed firms is defined as two year before IPO.

Table A3: Robustness checks for IPO shocks

	(1) R&D	(2) Patents	(3) ROE	(4) ROA
Matched regression	-0.0124***	-0.9067***	0.0714***	0.0702***
	(0.001)	(0.190)	(0.006)	(0.004)
Semiparametric DD	-0.0109***	-1.1457***	0.0461***	0.0520***
	(0.001)	(0.195)	(0.006)	(0.004)

Note: ***, **, * denote significance at 1%, 5%, and 10% levels, respectively. A dummy variable for IPO is included in both the matching and regression.