

Can Government-Controlled Venture Capital Firms Deliver Performance? Evidence from China

Bin Ke¹ and Lanfang Wang²

(1. Division of Accounting, Nanyang Business School, Nanyang Technological University, Singapore 639798;

2. Institute of Accounting and Finance, School of Accountancy, Shanghai University of Finance and Economics, Yangpu District 200433, Shanghai, China)

Abstract: We examine the performance of government-controlled VC firms (GVCs) relative to the performance of domestic private VC firms (PVCs) and foreign VC firms (FVCs) in the largest emerging market economy, China. We use successful/unsuccessful exits from and patent applications by VC-financed companies as performance evaluation metrics. GVCs are less likely than FVCs to experience both successful exits and unsuccessful exits. In addition, GVCs outperform FVCs in patent applications. However, both GVCs and FVCs underperform PVCs in successful exits and patent applications. There is evidence that stronger local institutional environments help improve the performance of both GVCs and PVCs relative to FVCs. Overall, our results suggest that there is no one-size-fits-all conclusion regarding the performance of Chinese GVCs, which is relevant to the ongoing debate on the role of the government and GVCs in developing the venture capital industry in emerging markets.

Keywords: venture capital; emerging market; China; government ownership; performance; innovation

JEL Classification: G24, G38, O31

1. Introduction

Venture capital (VC) plays an important role in financing entrepreneurship, which is believed to be critical to a nation's innovation and economic growth (Schumpeter 1934; Lerner 2010). Due to the huge success of the U.S. venture capital industry, many governments around the world have shown a keen interest in adopting a variety of proactive public policies that aim to jumpstart their countries' VC industry and entrepreneurship.¹ While theoretical justifications could be made for the government's intervention in the development of the venture capital industry and entrepreneurship (Hall 2002; Amit et al. 1998; Lerner 2010), it is still hotly debated whether and to what extent the governments should be involved in the VC industry development (Lerner 2008, 2010).

The objective of this study is to contribute to this important debate by examining the performance of government-controlled VC firms (GVCs) in China, defined as VC firms that receive the majority of their funding from either government agencies or government-controlled business enterprises (SOEs) or both. We use the performance of PVCs and FVCs

as benchmarks. PVCs are VC firms that receive the majority of their funding from domestic private sources while FVCs are VC firms that receive the majority of their funding from foreign sources.

Though started only around 1998, China's SVC industry has since experienced explosive growth and has emerged as the largest net importer of VC by 2003-2007 (Aizenman and Kendall 2012). More importantly, the past decade has also observed the establishment of China's own nascent domestic venture capital industry, most notably, the creation of hundreds of GVCs. While it is common for governments to provide VC firms with tax credits and matching funds that augment private capital commitments, or take a minority ownership of VC funds, China is an outlier in that it is probably the only country with a large number of VC firms controlled by different levels of the government. Hence, we believe it is important to evaluate the performance of Chinese GVCs.

A priori it is difficult to predict the performance of GVCs relative to non-GVCs due to multiple countervailing institutional forces summarized in Figure 1. Conventional economic wisdom, referred to as the incentive hypothesis (Shleifer 1998; Lerner 2010), would predict GVCs to underperform non-GVCs due to the well-known agency problems associated with government ownership. For example, GVCs could pursue political agendas, which in turn could negatively affect GVCs' managerial incentives. In addition, GVCs may find it difficult to use high-powered incentive compensation contracts (Chen et al. 2013). Therefore, managers of GVCs don't necessarily have strong incentives to acquire private information in the selection of entrepreneurial companies for investment or closely monitor their funded companies.

According to the experience/resource hypothesis, GVCs (as well as PVCs) may also underperform FVCs because China's SVC industry has a short history and therefore managers of local VC firms could be less experienced than managers of FVCs. In addition, local VC firms are not as resourceful as FVCs because the latter tend to enjoy global reputation and possess an international network of financial intermediaries to support their operations.

However, GVCs may also outperform non-GVCs for two reasons. First, GVCs (as well as PVCs) may have a local advantage and therefore could outperform FVCs, hereafter referred to as the proximity hypothesis. The extant financial literature shows that distance is associated with reduced information access and higher monitoring costs (Coval and Moskowitz 1999 and 2001; Kang and Kim 2008). Hence, local Chinese VC firms may possess more private information about local entrepreneurial companies and enjoy lower monitoring costs than FVCs.² However, one could also argue that distance may create incentives for FVCs to perform better ex-ante screening and due diligence, resulting in better performance of funded companies (Dai et al. 2009; Nahata et al. 2014).

Second, GVCs may have a competitive advantage relative to non-GVCs due to their inherent government connections, referred to as the political connection hypothesis. As a representative emerging market economy, many important aspects of Chinese firms' operations are significantly influenced by various government agencies, including input and output factor markets, taxes, bank and public equity financing, etc. Prior research shows that driven by various political and economic incentives such as political tournament and social stability (Li and Zhou

2005; Lin et al. 2004), local Chinese government officials have a strong incentive to provide a variety of preferential treatments to the Chinese SOEs under their jurisdictions, including information sharing, tax concessions and easier access to bank and public equity financing (Aharony et al. 2000; Brandt and Li 2003; Cull and Xu 2003). Because GVCs' performance depends on the success of their funded entrepreneurial companies, we expect GVC-funded companies to directly or indirectly benefit from GVCs' government connections, especially the entrepreneurial companies that are located in the same province as the GVCs' headquarters. Of course, non-GVCs could partially offset this competitive disadvantage by establishing their own political connections, making the relative performance of GVCs versus non-GVCs difficult to predict *ex ante*.

We compare the performance of GVCs, PVCs, and FVCs using 2,639 Chinese entrepreneurial companies funded by 607 lead VC firms over the period 2000–2009. Following prior research (e.g., Hochberg et al. 2007; Kortum and Lerner 2000), we measure a VC firm's performance using both its successful/unsuccessful exit from a funded entrepreneurial company and the number of patent applications filed by the VC-funded entrepreneurial company during the lead VC firm's investment period.

We find that the relative performance ranking of the three VC firm types depends on the performance evaluation metric. In terms of successful exits, we find that PVCs outperform both FVCs and GVCs while FVCs outperform GVCs. However, we find that FVCs are more likely to exit unsuccessfully than both GVCs and PVCs but there is no difference in the probability of unsuccessful exit for GVCs versus PVCs. In terms of the quantity of annual patent applications filed by VC-funded companies over the lead VC firm's investment period, GVCs outperform FVCs, even though both GVCs and FVCs underperform PVCs. However, we find no evidence that the quality of the patents, measured by the average number of citations per patent as of 2014, is lower for GVCs than for non-GVCs. In fact, we find no difference in patent quality among the three ownership types, suggesting that the better patent filing performance of GVCs relative to FVCs is not a fiction.

The better performance of PVCs over GVCs suggests that incentives matter more than political connection in determining the relative performance of PVCs versus GVCs (see Figure 1). Similarly, the better performance of PVCs over FVCs supports the hypothesis that proximity matters more than experience/resources in explaining the relative performance of PVCs versus FVCs. The mixed performance of GVCs over FVCs suggests that each VC firm type has its unique strengths, with GVCs having the proximity advantage and political connection and FVCs having stronger managerial incentives and more VC management experience/resources.

We next examine whether the aforementioned performance gaps among the three VC firm types vary with the local institutional environment quality of the province where a VC firm's headquarters is located. Prior research shows that managers of listed Chinese firms are more likely to pursue shareholder value maximization in provinces with stronger institutional environments (e.g., Wan et al. 2008). We also expect local institutional environment quality to affect VC firms' performance, but the effect of local institutional environment quality on the performance gaps among the three VC firm types

is difficult to predict. On one hand, GVCs may suffer from significant agency problems and therefore we expect the performance of GVCs to increase with provincial institutional environment quality. Because both GVCs and PVCs may face significant resource constraints, we also expect the performance of both GVCs and PVCs to further benefit from a stronger local institutional environment that can help relax some of these constraints (e.g., human capital and financial intermediaries). On the other hand, the performance of FVCs may also benefit from a stronger institutional environment because FVCs' two disadvantages, lack of political connection and proximity, could be significantly reduced in provinces with stronger institutional environments. Because of these offsetting forces, the net effect of local institutional environment quality on the relative performance differences of the three VC firm types is an empirical question.

With regard to successful exits, we find that the previously documented performance disadvantage of GVCs relative to FVCs is reduced while the previously documented performance advantage of PVCs relative to FVCs is widened for VC firms whose headquarters are located in the provinces with stronger institutional environments. We find no evidence that local institutional environment quality affects the relative differences in unsuccessful exits among the three VC types. With regard to the quantity of patent applications, we find that the previously documented performance advantages for GVCs versus FVCs and PVCs versus FVCs are widened for VC firms whose headquarters are located in provinces with stronger institutional environments. While the performance of both GVCs and PVCs relative to FVCs improves with local institutional environment quality, we find no evidence that the relative performance gap between GVCs and PVCs varies with local institutional environment quality. These results suggest that the quality of local institutional environment matters to a greater extent for the performance of local VC firms than for the performance of FVCs.

We make an important contribution to the extant VC literature on government-sponsored VC firms. To our knowledge, we are the first study on the performance of government-controlled VC firms in emerging markets. Because most governments around the world support the venture capital industry in relatively passive ways, such as giving tax credits or taking a minority ownership of VC funds, most extant research examines the performance of VC firms with a *minority* government ownership only (Wallsten 2000; Brander et al. 2010; Cumming and MacIntosh 2004). Notable exceptions are Brander et al. (2015) and Cumming et al. (2015), but both Cumming et al. (2015) and Brander et al. (2015) primarily focus on the performance of VC firms in developed countries. A priori it is unclear whether their findings are generalizable to VC firms in emerging markets where there is a lack of developed infrastructures and institutions necessary for efficient business operations (Khanna et al. 2010) and therefore the government and GVCs could play a more positive role in fostering entrepreneurship and innovation. In addition, Cumming et al. (2015) focus on VC firms 100% owned by the government only while Brander et al. (2015) don't distinguish the government's majority versus minority ownership of VC firms. We follow the extant SOE literature by defining GVCs based on the notion of control (Wang et al. 2008).

We also contribute to the broader literature on government-controlled firms (e.g., Hunget

al.2012). Considering the importance of and unique challenges facing the VC industry and entrepreneurship, we believe it is important to separately analyze the performance of government-controlled VC firms. We contribute to this literature by being the first study to assess the performance of GVCs in the largest emerging market economy.

Our findings carry important implications to the ongoing debate in China and many other emerging markets on how to support entrepreneurship and the local VC industry. The superior performance of PVCs relative to both FVCs and GVCs suggests the importance of supporting the development of PVCs so that they can play a more significant role in developing a nation's local venture capital industry and entrepreneurship. The mixed performance of GVCs relative to PVCs and FVCs suggests that caution should be exercised in the government's push for GVCs because GVCs directly compete with PVCs for business and therefore the growth of GVCs could crowd out the growth of PVCs, resulting in a significant distortion in resource allocation for entrepreneurship, especially in regions with weak institutional environments.³ Finally, the poor performance of FVCs relative to PVCs suggests that despite their perceived superiority, a direct import of FVCs alone is unlikely to help emerging markets replicate the success of the Silicon Valley and the like.

The rest of the paper is organized as follows. Section 2 discusses data sources and sample selection. Section 3 examines the performance differences in the entrepreneurial companies financed by the three VC firm types. Section 4 examines the effect of VC firms' local institutional environment quality on the relative performance of the three VC firm types. Section 5 concludes.

2. Data sources and sample selection

2.1. Data sources

The data on VC firms and their funded companies used in this study come from CVSOURCE, a leading venture capital and private equity database with an exclusive focus on China. Because VC firms are not required to publicly disclose their investment portfolio data, the quality of data on VC-funded companies from existing commercial databases commonly used in the extant academic research has always been a concern.⁴

Our research indicates that CVSOURCE's coverage of VC-funded companies is relatively complete. Specifically, we compare the quantity of VC investment between CVSOURCE and The Annual Report on China's VC Industry Development, an authoritative yearbook jointly published by China's National Development and Reform Commission (NDRC), the government regulator of Chinese VC/PE firms during our sample period, and China Venture Capital & Private Equity Association. According to an interim regulation on the Administration of VC Firm that took effect in early 2006, all VC firms operating in China have been required since 2006 to register with the relevant local government VC administration agency in order to be eligible for receiving various preferential government treatments such as tax concessions and government funding. According to a 2011 VC survey conducted by the NDRC in Beijing, Shanghai, Jiangsu, Zhejiang, and Guangdong, the regions with the most VC firms, only approximately 12.86% of the surveyed VC firms didn't plan to register with the government (The Annual Report on China's VC Industry Development 2012, p.235).

China's VC Industry Development for the available years 2006-2012, the total number of VC investment deals over the period 2006-2012 is 9,596.⁶ The comparable figure according to CVSOURCE is 10,128.⁷ This comparison suggests that CVSOURCE's coverage of VC-funded companies is relatively complete.

We rely on the information provided by CVSOURCE and a comprehensive Chinese company registration database developed by China's State Administration for Industry and Commerce (SAIC) to define the three VC ownership types (<http://gsxt.saic.gov.cn>). We obtain Chinese companies' patent data from China's State Intellectual Property Rights Office (SIPO) and patent citation data from the recently available Google Patent Citations database (www.google.com/patent). We use both computer programs and manual labor to match the companies in CVSOURCE with the companies in SIPO by company name. The data used to define the other regression variables come from CVSOURCE and other public sources as noted in the appendix of variable definitions.

2.2. Sample selection

Consistent with the VC literature, we define a VC firm as a fund management entity that manages one or more venture capital funds. If a venture capital fund is formed as a limited partnership, which was permitted only after 2006 in China, the fund management entity refers to the general partners of the fund. If a venture capital fund is formed as a corporation, the fund management entity refers to the management of the corporation.

We define a VC firm's formation year as follows: (a) the year of the establishment for independent domestic VC firms; (b) the year of the first venture capital investment for non-independent domestic VC firms (e.g., those affiliated with existing business enterprises); (c) the year of the establishment for foreign VC firms with a specific focus on China or Asia if there is no specific China focus; (d) the earlier of the year of the fund raising or the year of the first venture capital investment in China for the remaining foreign VC firms.

We determine a VC firm's type based on the sources of all the venture capital funds raised within the three months since the formation of the VC firm.⁸ If more than 50 percent of the VC firm's funds come from either government agencies or government-controlled business enterprises, the VC firm would be classified as a GVC. If more than 50 percent of the VC firm's funds come from domestic private sources, the VC firm would be classified as a PVC. If more than 50 percent of the VC firm's funds come from foreign sources, the VC firm would be classified as a FVC. If none of the above three types of fund sources contribute more than 50 percent of the VC firm's funds, the VC firm would be classified as a joint-venture (JVC).

From CVSOURCE we identified a total of 1,336 VC firms that were founded before year 2012, the last available year. We exclude year 2012 because there were only 21 VC firms formed in 2012, probably due to a delay in CVSOURCE's data collection. Because there is no clear cut distinction between VC firms and private equity firms in CVSOURCE, we define a VC firm as one whose venture capital investments constitute more than 50 percent of the firm's total equity investments as of the end of 2012. Among the 1,336 VC firms, 279 are GVCs, 656 are PVCs, and 388 are FVCs. There are only 5 JVCs. In addition, due to missing data, we cannot identify the type for 8 VC firms. In the subsequent analyses, we exclude the 5 JVCs and the 8 unidentified VC firms. These restrictions result in a sample of 1,323 VC

firms.

Table 1 shows the distribution of the 1,323 VC firms. Panel A shows the distribution of the VC firms by founding year and type. It is clear that all three types of VC firm types experienced explosive growth over the past decade.

Panel B of Table 1 shows the distribution of the 1,323 VC firms by province and type. The province where a VC firm is located is defined as follows: (a) the province of the VC firm's headquarters for domestic VC firms and foreign VC firms whose headquarters are located in mainland China (1027); and (b) the province of the mainland China office (173) or the province of the first venture capital investment if there is no mainland China office information (123), for foreign VC firms whose headquarters are located outside mainland China. It may not be too surprising that the VC firms are concentrated in relatively developed regions of China: Beijing, Shanghai, Guangdong, Jiangsu, and Zhejiang.

Finally, Panel C of Table 1 shows the distribution of the 296 (173+123) FVCs whose headquarters are located outside mainland China. Almost half of these FVCs are located in the U.S., consistent with the dominance of U.S. VC firms around the world.

3. The performance of VC-funded companies

Following prior research, we measure a VC firm's performance using two performance evaluation metrics defined below: *exit* (successful versus unsuccessful) from a VC-financed company (*exit*) and the number of patent applications filed by a VC-financed company during the VC firm's investment period (*patent_number*). Because the actual returns on VC firms' invested portfolio of entrepreneurial companies are unobservable, we follow prior research (Gompers and Lerner 2000; Brander et al. 2002; Hochberg et al. 2007; Sorensen 2007; Zarutskie 2007; Nahata 2008) by using *exit* as one proxy for VC firm performance. Phalippou and Gottschalg (2009) demonstrate a high positive correlation between successful exits and actual returns to venture capitalists, suggesting that *exit* should be a good proxy for VC firms' performance.

Cumming and Johan (2013) identify five common ways a VC firm may exit an investment in an entrepreneurial company: (i) initial Public Offering (IPO); (ii) M&A, where both the entrepreneur and the VC firm sell their stake in the company to another company; (iii) secondary sale, where the VC firm sells its interest but the entrepreneur does not sell his interest; (iv) management buyback, where the entrepreneur repurchases the stake held by the VC firm; and (v) liquidation of the entrepreneurial company. While it is common in the U.S. VC literature to measure successful exits using IPOs and M&As only, VC firms in international VC markets often exit successfully via secondary sales due to lack of access to the IPO market or an underdeveloped M&A market. Therefore, our definition of successful exit includes not only IPOs and M&As but also secondary sales, which is frequent in our sample as shown below. In addition, to the extent possible, we also identify VC firms' unsuccessful exits in the form of management buyback and liquidation. Our discussion with Chinese VC industry insiders suggests that management buyback is typically viewed as a failure of VC investments. Because many VC firms may not have an incentive to voluntarily disclose liquidations of their funded entrepreneurial companies, we use a recently available company database from China's State

Administration of Industry and Commerce (SAIC) to identify the majority of the liquidations in our sample.

By definition, a primary objective of VC firms is to fund early-stage innovative but risky entrepreneurial companies. Hence, we also measure a VC firm's performance using a second proxy, *patent_number*, which reflects the degree of a VC-funded company's innovation. While not every innovation is patented and not every patent leads to successful economic activity, patenting and successful innovation are highly correlated and therefore patents are commonly used as a measure of innovation in the existing VC literature.

3.1. Successful exits versus unsuccessful exits

3.1.1. The regression model

We use the following multinomial logit model to compare the differences in successful and unsuccessful exits among the three VC firm types:

$$exit = gvc + pvc + control + e; \quad (1)$$

See the Appendix for all variable definitions. The unit of observation is an entrepreneurial company-year. The regression model's sample starts from the first year when an entrepreneurial company receives the first venture capital investment and ends in the earlier of the year of the VC firm's successful or unsuccessful exit or 2012, the last available year. To make sure that a VC firm has sufficient time to exit, we retain only the entrepreneurial companies whose first venture capital investment occurred no later than 2009. We choose a cutoff of 2009 because the typical investment cycle of emerging market venture capital investments is 2-3 years.

While an entrepreneurial company may receive venture capital financing from multiple VC firms in both the first round investment and subsequent follow-up investments, typically there is a lead VC firm for each entrepreneurial company who plays a dominant role in mentoring and monitoring the entrepreneurial company. Hence, we follow prior research by focusing on the lead VC firm for each entrepreneurial company in this study (Nahata et al. 2014), but we control for the effect of VC syndicate in the subsequent empirical analyses. For each entrepreneurial company, we define the lead VC firm as the firm that makes the largest investment in the first round venture capital investment.⁹ If an entrepreneurial company has more than one lead VC firms, we take the average of each relevant variable for the tied lead VC firms.

For the 1,323 VC firms from Table 1, we identified 2,887 entrepreneurial companies' first round investment deals involving 772 VC firms during our sample period 2000-2009. Due to data limitation, we don't consider VC firms' first round investments that occurred prior to 2000. After excluding 225 entrepreneurial companies whose lead VC firms couldn't be identified due to missing first round venture capital investment amount, we obtain 2,662 entrepreneurial companies involving 627 lead VC firms. After excluding observations with other missing variables, our final sample contains 2,639 entrepreneurial companies associated with 607 lead VC firms, involving 15,639 entrepreneurial company-year observations over the period 2000-2012. Our final sample of VC-financed entrepreneurial companies is much bigger than the typical China sample used in many cross-

country studies, reducing the common concern of potential sample selection biases in the VC literature. For example, Brander et al.'s (2015) China sample contains 1,226 VC-funded companies over 2000-2008 while our China sample contains almost twice as many VC-funded companies over the same time period (untabulated). Dai et al. (2009, Table 7) cover only 175 VC-funded companies from China, Nahata et al. (2014) don't cover China at all while Chemmanur et al. (2014, Table 1) contain only 400 VC-backed companies from China.

The regression model includes the following four types of common control variables: (a) characteristics of the entrepreneurial companies (*early*, *prior patent*, *prior citation*);¹⁰ (b) select characteristics of the lead VC firms (*vc_lp*, *synsize*); (c) *initial vc investment year fixed effect* to control for the degree of market condition, such as competition among VC firms for investment opportunities (Hochberg et al. 2007; Nahata 2008), in the year of a lead VC firm's first investment in an entrepreneurial company; and (d) market condition, including local institutional environments such as investor protection in the province of an entrepreneurial company's headquarters (*enlocal_invpro*) and the market condition in the year of a VC firm's exit (*exit_condition*) (Lerner 1994; Hochberg et al. 2007; Nahata 2008). We also include the standard industry and year fixed effects. When assessing the impact of VC firms' ownership structure on firm performance, it is important to control for the differences in entrepreneurial company characteristics because different types of VC firms may pursue different investment strategies. For example, some VC firms may only focus on early stage entrepreneurial companies. By definition, it takes longer for VC firms to exit from such investments, even if they are successful. Without controlling for such entrepreneurial company characteristics, we would unfairly penalize the performance of VC firms that have invested in early stage entrepreneurial companies. Likewise, it is necessary to control for the market conditions at both the entry time and exit time of a lead VC firm that are beyond the control of individual VC firms.

However, we exclude from model (1) several common VC firm characteristics, including VC firm's investment experience (Lee and Wahal 2004; Nahata 2008), VC firm's reputation (Nahata 2008), and VC firm's professional VC investment network (Hochberg et al. 2007 and 2010). The reason is that these variables are proxies for the experience/resource hypothesis noted in the Introduction. Nevertheless, our subsequent inferences are robust to the inclusion of these variables in the regression model (untabulated).

Due to lack of strong priors, we don't have any predictions on the regression coefficients for unsuccessful exits. With regard to successful exits, we make the following predictions based on prior research. We expect the coefficient on *early* to be negative because entrepreneurial companies in the early stage of development are likely to be riskier and therefore could be less likely to succeed. We also expect the coefficient on *prior patent* and *prior citation* to be positive to the extent that entrepreneurial companies with more patents and higher patent citations prior to the first round VC investment indicate better quality. Even though limited partnership is the prevailing organization form of venture capital funds in the U.S. (Sahlman, 1990), it is permitted in China only since 2007. To control for the possible influence of organization type on VC firms' performance, we include *vc_lp*. Following Casamatta and Haritchabalet (2007) and Brander et al. (2002), we control for the size of VC syndicate in the first round VC investment (*synsize*). Based on the evidence

from the literature, we predict a positive coefficient for *vc_lp* and *size*. Following Lerner (1994), Hochberger et al. (2007) and Nahata (2008), we predict a positive coefficient on *exit_condition* because VCs are more likely to exit successfully during times of favorable market conditions. We have no prediction for *enlocal_invpro*.

3.1.2. Regression results

Panel A of Table 2 reports the frequencies of successful exits and unsuccessful exits by VC firm type during our entire sample period. There are a total of 840 exit events, of which 83.1% (698) are successful exits and the remaining 16.9% (142) are unsuccessful exits. Most prior U.S. research ignores unsuccessful exits due to lack of data, but our evidence above suggests this omission could be problematic in our sample because unsuccessful exits constitute a significant percentage of all exits. Of the successful exits,

17.3% (121/698) are in the form of secondary sales that would be ignored if one follows the traditional definition of successful exit used in the U.S. VC literature. The distributions of the various types of exits are different across the three VC firm types. More specifically, among all observed exits during our sample period, the percentage of exits that are unsuccessful is higher for FVCs than for non-FVCs. On the other hand, among all observed successful exits during our sample period, the percentage of successful exits that are secondary sales or IPOs is lower for FVCs than for non-FVCs.

Panel B of Table 2 reports the descriptive statistics for the regression variables. Untabulated analysis shows that approximately 4.4% of the firm years included in the regression model represent successful exits while 0.9% of the firm years are unsuccessful exits.¹¹ Among the 2,639 unique VC-funded companies in Panel B of Table 2, 986 (37.4%) are funded by GVCs, 638 (24.2%) are funded by PVCs, and 1,015 (38.5%) are funded by FVCs, suggesting that both GVCs and FVCs are more active than PVCs in investment activities in our sample period. The value of *synsize* at the 75th percentile is zero, suggesting that most VC firms in China go solo in investment, a finding different from the U.S. literature (Gompers and Lerner 2004).

Panel C of Table 2 shows the regression results of the multinomial logit model where the firm years without an exit event are the default benchmark group. With regard to successful exits, we find that the coefficient on *gvc* is significantly negative while the coefficient on *pvc* is significantly positive. In addition, the coefficients on *gvc* and *pvc* are significantly different from each other. These results suggest that PVCs perform the best in terms of successful exit, followed by FVCs and GVCs, respectively. With regard to unsuccessful exits, the coefficients on *gvc* and *pvc* are both significantly negative and don't differ from each other. These results suggest that both GVCs and PVCs are less likely than FVCs to experience unsuccessful exits. Taken together, our regression results clearly indicate that PVCs perform the best, but the relative performance of GVCs versus FVCs is mixed because GVCs are less likely than FVCs to experience both successful and unsuccessful exits.

With regard to the control variables, many of them are significant and consistent with our predictions. Specifically, the coefficients on two entrepreneurial company characteristics, *early* and *prior patent*, are significant and consistent with expectations for successful exits, suggesting that entrepreneurial companies that received the first round VC investment in their early stage and lower-quality entrepreneurial companies measured prior to the lead VC firms' first round investment are less likely to exit successfully, *ceteris paribus*. The coefficient on *synsize* for successful exits is significant and

consistent with expectation, suggesting that entrepreneurial companies funded by lead VC firms with a larger syndicate in the first round investment are more likely to exit successfully, *ceteris paribus*. Finally, the coefficient on *exit_condition* is significantly positive for successful exits, suggesting that external market conditions matter in VC-funded companies' successful exit. Finally, the coefficient on *prior patent* is significantly negative for unsuccessful exits, suggesting that lower-quality entrepreneurial companies measured prior to the lead VC firms' first round investment are less likely to fail.

3.2. Patent applications

3.2.1. The regression model

We next examine whether the three VC firm types differ in the number of patent applications filed by VC-funded companies during a lead VC's investment period:

$$patent_number = gvc + pvc + control + e; (2)$$

See the Appendix for variable definitions. China has three types of patents: patents for invention, patents for utility model, and patents for design. The protection period for invention patents is twenty years while the protection period for utility model patents and design patents is only ten years, counted from the application date (<http://english.sipo.gov.cn/>). The approval of invention patents is more rigorous and takes longer than the other two types of patents. Our definition of *patent_number* includes the invention patents and utility model patents filed over the period from the lead VC firm's first round investment to the earlier of the VC's exit or 2012, our sample period end. Because invention patents take longer to be approved, *patent_number* includes both approved and unapproved invention patents but only approved patents for the other two types. We exclude design patents from *patent_number* because this classification type is unique to China and is often deemed low in innovation quality. Inference is similar if design patents are included in the definition of *patent_number*.

Patent applications are particularly interesting to study in China because the Chinese Government has been adopting a variety of proactive policies and incentives to encourage Chinese firms and venture capital funds to innovate, especially in the form of filing patent applications (Chan 2015; Chen 2015). The Chinese Government even made an explicit call for local Chinese firms to apply for two million patents by 2015 (The Economist 2014). Being government-controlled, GVCs are expected to be more responsive to the Chinese Government's order. However, due to multiple conflicting institutional forces noted in Figure 1, it is an open question whether GVCs can outperform non-GVCs in patent filings.

There is anecdotal evidence suggesting that some Chinese firms may have resorted to filing many lower quality patent applications such as utility model patents and design patents in response to the Chinese Government's order (The Economist 2014). Hence, we consider three alternative definitions of patent performance measures to mitigate the potential noises associated with *patent_number*. To the extent that a firm's main objective of filing a patent application is to satisfy the Chinese Government's order, we expect the firm to have less incentive to pay the required annual maintenance fee to keep the patent

active in the years subsequent to the initial patent application. Hence, we use *active_patent_number* as an alternative definition of patent performance, which includes only the invention and utility model patents still active as of April 2014, the date when we collected the patent data. Recognizing that the approval process for invention patents is more rigorous and takes longer, firms whose main objective of filing a patent application is to satisfy the Chinese Government's orders should be less likely to submit invention patents. Hence, we also use the number of invention patent applications (*invent_patent_number*) as another alternative innovation performance measure. Finally, if a firm's main objective of filing a patent application is to satisfy the Chinese Government's order, the quality of the patents filed by such firms is likely to be lower. We use *patent_citation* as a proxy for the quality of filed patent applications. Because the Google Patent Citations database excludes design patents, the least important type, our definition of *patent_citation* includes invention patents and utility model patents only.

The unit of observation for model (2) is an entrepreneurial company. The sample is limited to the same entrepreneurial companies used in the regression model of Table 2. For the same reasons as in Section 3.1, we control for the characteristics of entrepreneurial companies (*early*, *priorpatent*, *priorcitation*) and these select characteristics of the lead VC firms (*vc_lp*, *synsize*). We also control for entrepreneurial companies' local environmental factors that may affect patent application number and citations, including local investor protection (*enlocal_invpro*), the local R&D talent and R&D investment (*local_talent*, *local_R&D*). We predict a positive coefficient for *enlocal_invpro*, *local_talent* and *local_R&D*. Finally, we include *vc_length* because the dependent variables of model (2), *patent_number*, *active_patent_number*, *invent_patent_number* and *patent_citation*, are computed over the period of *vc_length* and therefore we want to make sure that our results are not driven by any potential mechanical association between the dependent variables and *vc_length*. As usual, we include the standard industry fixed effects. In addition, we include the fixed effects of *initialvcinvestmentyear* to control for any time effects associated with a VC firm's first investment in an entrepreneurial company.

3.2.2. Regression results

Table 3 shows the regression results of model (2). Panel A shows the descriptive statistics of the regression variables. The mean value of *patent_number* is 0.685, suggesting that the average VC-funded company has one patent application per year over the period from the lead VC firm's first round investment to the earlier of success or exit in 2012. The mean value of *active_patent_number* is very close to that of *patent_number*, suggesting that most patents are actively maintained. The mean value of *invent_patent_number* is approximately two-thirds of the mean value of *patent_number*, suggesting that the majority of the patent applications are the higher quality invention patents.

Panel B shows the OLS regression results of model (2) for the dependent variables *patent_number*, *active_patent_number*, *invent_patent_number*, and *patent_citation*, respectively. With regard to the regression of *patent_number* in column (1), the coefficients on *vc* and *pvc* are both significantly positive, but the coefficient on *pvc* is significantly bigger than the

coefficient on *gvc*. These results suggest that the entrepreneurial companies funded by PVCs perform the best, followed by GVCs and FVCs. The inferences are qualitatively similar if the dependent variable is replaced by *active_patent_number* or *invent_patent_number* (see columns (2) and (3) of Table 3, respectively) except that the coefficient on *gvc* is insignificant (p value = 0.13) and doesn't differ from the coefficient on *pvc* for *invent_patent_number*. We find no evidence that the average patent quality (*patent_citation*) is significantly different across the three VC firm types. In particular, we find no evidence that the average patent quality is lower for GVCs than for PVCs or FVCs.

Given the mixed performance of GVCs versus FVCs with regard to exits in Table 2, the better performance of GVCs relative to FVCs with regard to patent applications in Table 3 is intriguing. One possible explanation for this difference in results is that the quantity of patent applications is an explicit key performance indicator the Chinese Government has championed about gauging the innovation performance of domestic Chinese firms during our sample period. Therefore, GVCs, who are likely to be more responsive to the Chinese Government's order, could have worked harder to deliver the expected performance demanded by the Chinese Government.

With regard to the control variables in model (2), several of them are significant and consistent with our predictions. Most noteworthy is the significantly positive coefficient on *prior patent*, suggesting the persistence of corporate innovation success. The coefficient on *synsize* is also significantly positive in all the regressions, suggesting the importance of VC syndicate in the innovation performance of VC firms-funded entrepreneurial companies. The coefficient on *local_R&D* is significantly positive in the regressions of *patent_number* and *active_patent_number* while the coefficient on *enlocal_inv* is marginally significantly positive in the regressions of *patent_number* and *invent_patent_number*, suggesting that a region's R&D investment and investor protection have a positive impact on the region's VC-funded companies' innovation output. As expected, the coefficient on *vc_length* is positive in columns (1) to (3).

3.3. The performance of different types of GVCs

Our sample of GVCs includes two sub-types: (a) GGVCs, defined as GVCs more than 50 percent of whose GVC funding comes from government agencies; and (b) SGVCs, defined as GVCs more than 50 percent of whose GVC funding comes from state-controlled enterprises (SOEs). Since GGVCs are controlled by government agencies directly, we examine whether the performance of GGVCs is different from that of SGVCs. As shown in Table 4, we find no evidence that the performance of GVCs reported in Tables 2 and 3 is driven by either GGVCs or SGVCs alone. The coefficients on GGVCs and SGVCs are not significantly different from each other. The only exception is that the coefficient on *sgvc* is significantly more positive than the coefficient on *ggvc* at the 10% significance level in the regression of *patent_citation*, suggesting weak evidence that the quality of patents filed during a lead VC's investment period is higher for entrepreneurial companies funded by SGVCs than for entrepreneurial companies funded by GGVCs.

4. The role of local institutional environment quality on VC firm performance

A large body of prior research shows the importance of local institutional environment on the behavior of publicly traded firms around the world (La Porta et al. 1998, 2000, 2002; Leuz et al. 2003; McLean et al. 2012). Hence, we examine whether the relative performance differences among the three VC firm types shown in Tables 2 and 3 depend on the quality of the institutional environment in the province where a VC firm's China headquarters is located. Because of multiple offsetting institutional forces, it is difficult to predict the net effect of local institutional environment quality on the relative performance differences among the three VC types. On one hand, GVCs suffer from greater agency problems and therefore a stronger provincial institutional environment may better discipline the behavior of GVCs. In addition, both GVCs and PVCs may face greater resource constraints (e.g., human capital and financial intermediaries) and therefore could benefit more from a stronger provincial institutional environment that can help relax some of these constraints. On the other hand, the performance of FVCs may benefit more from a stronger provincial institutional environment because FVCs' two disadvantages, lack of political connection and proximity, could be significantly reduced in provinces with stronger institutional environments.

Table 5 shows the regression results of the exit model in Panel A and the patent models in Panel B by allowing the coefficients of interest gvc and pvc to vary with $vclocal_invpro$, a continuous variable measuring the degree of local institutional environment quality in the province of a lead VC firm's headquarters in China.¹² The coefficients of interest in Table 5 are the two interaction terms $gvc \times vclocal_invpro$ and $pvc \times vclocal_invpro$. It is important to note that the coefficients on gvc and pvc are not meaningful to interpret in isolation in the presence of the interaction terms. We find that the coefficients on $gvc \times vclocal_invpro$ and $pvc \times vclocal_invpro$ in Panel A are significantly positive for successful exits and insignificant for unsuccessful exits. These results suggest that in provinces with stronger institutional environments, the relative disadvantage of GVCs to FVCs shrinks while the relative advantage of PVCs relative to FVCs expands.¹³

Similarly, the coefficients on $gvc \times vclocal_invpro$ and $pvc \times vclocal_invpro$ in Panel B are significantly positive for the regressions of $patent_number$, $active_patent_number$, and $invent_patent_number$. These results suggest that the previously documented relative advantage of GVCs and PVCs relative to FVCs in the quantity of patent applications widens further in provinces with stronger institutional environments. However, we find no evidence the quality of the patents varies with institutional environment because the coefficients on $gvc \times vclocal_invpro$ and $pvc \times vclocal_invpro$ in Panel B are insignificant for the regression of $patent_citation$. Finally, we find no evidence that the coefficients on $gvc \times vclocal_invpro$ and $pvc \times vclocal_invpro$ differ from each other in Panels A and B except for the regression of $patent_citation$, suggesting that local institutional environment quality doesn't affect the relative performance difference for GVCs versus PVCs. Overall, the results of Table 5 indicate that local institutional environment quality of a VC firm's domicile matters more for the performance of local VC firms than for the performance of FVCs.

5. Conclusion

VC firms are playing an increasingly important role in financing innovative entrepreneurial companies in many emerging economies. In particular, many governments have been playing an active role in supporting the venture capital industry and entrepreneurship. However, there has been little empirical research on the performance of VC firms, government-controlled VC firms in particular, in emerging markets, largely due to lack of data.

The objective of this study is to examine the performance of Chinese GVCs relative to Chinese PVCs and FVCs. GVCs are VC firms that receive the majority of their funding from either government agencies or government-controlled business enterprises or both. PVCs are VC firms that receive the majority of their funding from domestic private sources. FVCs are VC firms that receive the majority of their funding from foreign sources. We measure a VC firm's performance using both the VC firm's successful/unsuccessful exit from its invested entrepreneurial companies and the quantity of patent applications filed during the period from the first round VC investment to the earlier of the year of the VC firm's successful exit or 2012, the most available year.

The performance ranking of the three VC firm types depends on the performance metric. In terms of successful exit, PVCs significantly outperform both GVCs and FVCs while FVCs outperform GVCs. However, we find that FVCs are more likely to exit unsuccessfully than both GVCs and PVCs but there is no difference in the probability of unsuccessful exits for GVCs versus PVCs. In terms of the quantity of patent applications, GVCs outperform FVCs, even though both GVCs and FVCs underperform PVCs. More importantly, we find that local institutional environment quality of a VC firm's domicile affects the performance of the three VC firm types differently. With regard to successful exits, we find that the previously documented performance disadvantage of GVCs relative to FVCs is reduced while the previously documented performance advantage of PVCs relative to FVCs is widened for VC firms whose headquarters are located in the provinces with stronger institutional environments. With regard to the quantity of patent applications, we find that the previously documented performance advantages of GVCs versus FVCs and PVCs versus FVCs are widened for VC firms whose headquarters are located in the provinces with stronger institutional environments. We find no evidence that the relative performance gap between GVCs and PVCs varies with local institutional environment quality.

Our study makes an important contribution to the extant VC literature by being the first study to use a comprehensive sample of VC firms and their funded companies to examine the performance of government-controlled VC firms (GVCs) in an important emerging market, China. A surprising outcome of our study is that the performance of GVCs relative to non-GVCs is far from uniform across different local institutional environments. Our findings should be of value to the ongoing debate on the role of the government in promoting the venture capital industry, especially in countries with weaker institutional environments.

The primary objective of this study is to assess the overall performance of GVCs relative to PVCs and FVCs in China. Hence, we don't attempt to distinguish VC firms' selection ability from

their monitoring ability of entrepreneurial companies. Due to the differential strengths of the three VC firm types summarized in Figure 1, future research may further examine the differences in the three VC firm types' performance with regard to selection and monitoring of entrepreneurial companies.

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Appendix. Variable Definitions

Regression model (1):

Variables	Definition and Measurement	Data Sources
<u>Dependent Variables:</u>		
<i>exit</i>	Equals 1 for the years with successful exits (IPOs, M&As, or secondary sales), 2 for the years with unsuccessful exits (management buyback and liquidation), and zero for all the other years. For each entrepreneurial company, <i>exit</i> is defined only for the period that starts from the first year when an entrepreneurial company receives the first venture capital investment and ends in the earlier of the year of the VC firm's successful or unsuccessful exit or 2012, the last available year.	CVSOURCE, CSMAR, SAIC, COMPUSTAT, WIND, Hong Kong stock Exchange, Toronto Stock Exchange
<u>Independent Variables:</u>		
<u>VC type:</u>		
<i>gvc</i>	A dummy variable that equals 1 if the lead VC firm in the first round VC investment is a GVC. All VC firms are classified into the following three exclusive types: (a) GVCs, defined as VC firms that receive the majority of their funding from either government agencies or government-controlled business enterprises or both; (b) PVCs, defined as VC firms that receive the majority of their funding from domestic private sources; and (c) FVCs, defined as VC firms that receive the majority of their funding from foreign sources.	CVSOURCE and SAIC
<i>pvc</i>	A dummy variable that equals 1 if the lead VC firm in the first round VC investment is a PVC.	CVSOURCE and SAIC

Control Variables:

Entrepreneurial company's characteristics:

<i>early</i>	A dummy variable that equals 1 if the first round VC investment occurred at the early stage of an entrepreneurial company's development as defined by CVSOURCE.	CVSOURCE
<i>priorpatent</i>	The natural logarithm of one plus the number of invention and utility model patent applications applied by the entrepreneurial company prior to the first round VC investment.	SIPO
<i>priorcitation</i>	The average non-self citations received by the invention and utility model patents applied by the entrepreneurial company prior to the first round VC investment, measured as of April 2014.	GOOGLE PATENT CITATIONS DATABASE

VC's characteristics:

<i>vc_lp</i>	A dummy variable indicating whether the lead VC firm has ever raised any limited partnership funds measured at the beginning of an observation year.	CVSOURCE
<i>synsize</i>	The natural logarithm of the number of VC firms participating in the entrepreneurial company's first round VC investment.	CVSOURCE

Market condition:

<i>exit_condition</i>	VC industry exit condition, defined as the natural logarithm of the number of exits over the prior year if <i>exit</i> equals 0, and as the natural logarithm of the number of exits over the 4 quarters prior to the exit date if <i>exit</i> equals 1 or 2.	CVSOURCE, CSMAR, COMPUSTAT, WIND, Hong Kong stock Exchange, Toronto Stock Exchange
<i>enlocal_invpro</i>	Local investor protection in the province of the entrepreneurial company's headquarters, proxied by the Fan et al.'s marketization index, measured at the beginning of an observation year. The marketization index is developed by Fan et al., (2006, 2007, 2008, 2009, 2010, 2011), where a higher value indicates greater regional market development. The index is calculated as the average of the following five elements: the relationship between government and market, development of non-state economy, development of product markets, development of factor markets, and development of intermediary organizations and legal environment.	Fan et al., (2006, 2007, 2008, 2009, 2010, 2011)

Other controls:

<i>Industry</i>	Entrepreneurial companies' industry fixed effects.	CVSOURCE
<i>Year</i>	Year fixed effects.	CVSOURCE
<i>Initial vc investment year</i>	Fixed effects for the year of the first round VC investment	CVSOURCE

Regression model (2):

Variables	Definition and Measurement	Data Sources
<u>Dependent Variables:</u>		
<i>patent_number</i>	The natural logarithm of one plus the average annual number of invention and utility model patent applications filed by the entrepreneurial company within the period from the date of VC firm's first investment to the earlier of VC firm's exit or 2012.	SIPO
<i>active_patent_number</i>	The natural logarithm of one plus the average annual number of invention and utility model patents applied by the entrepreneurial company within the period from the date of VC firm's first investment to the earlier of VC firm's exit or 2012 that are still active as of April 2014.	SIPO
<i>invent_patent_number</i>	The natural logarithm of one plus the average annual number of invention patent applications filed by the entrepreneurial company within the period from the date of VC firm's first investment to the earlier of VC firm's exit or 2012.	SIPO
<i>patent_citation</i>	The average non-self citations received, measured as of April 2014, for the invention and utility model patents applied by the entrepreneurial company within the period from the date of VC firm's first investment to the earlier of the VC firm's exit or 2012.	GOOGLE PATENT CITATIONS DATABASE
<u>Independent Variables:</u>		
<u>VC_type:</u>		
<i>gvc</i>	Defined as above	
<i>pvc</i>	Defined as above	
<u>Control Variables:</u>		
<u>Entrepreneurial company's characteristics:</u>		
<i>early</i>	Defined as above	
<i>priorpatent</i>	Defined as above	
<i>priorcitation</i>	Defined as above	
<u>VC's characteristics:</u>		
<i>vc_lp</i>	A dummy variable indicating whether the VC firm has ever raised any limited partner funds measured at the time of the first round VC investment.	CVSOURCE
<i>synsize</i>	Defined as above	
<i>vc_length</i>	The natural logarithm of one plus the number of days from the date of VC firm's first investment to the earlier of VC firm's exit or 2012.	CVSOURCE

Local Environment:

<i>enlocal_invpro</i>	Local investor protection in the province of the entrepreneurial company's headquarters, proxied by the Fan et al.'s marketization index, measured at the time of the first round VC investment. The marketization index is developed by Fan et al., (2006, 2007, 2008, 2009, 2010, 2011), where a higher value indicates greater regional market development. The index is calculated as the average of the following five elements: the relationship between government and market, development of non-state economy, development of product markets, development of factor markets, and development of intermediary organizations and legal environment.	Fan et al., (2006, 2007, 2008, 2009, 2010, 2011)
<i>local_talent</i>	The natural logarithm of the cumulative number of people elected as academicians of the Chinese Academy of Engineering and the Chinese Academy of Science, or Changjiang Scholars in the province of the entrepreneurial company's headquarters, measured at the time of the first round VC investment.	Website of Ministry of Education of China, Chinese Academy of Science, Chinese Academy of Engineering China
<i>local_R&D</i>	The natural logarithm of the R&D expenditure in the province of the entrepreneurial company's headquarters, measured at the time of the first round VC investment.	Statistical Yearbook of Science and Technology
Other controls:		
<i>Industry</i>	Defined as above	CVSOURCE
<i>Initial vc investment year</i>	Defined as above	CVSOURCE

Other regression variables:

Variables	Definition and Measurement	Data Source
<i>ggvc</i>	A dummy variable that equals 1 if the lead VC firm in the first round VC investment is a GGVC. GVCs are classified into the following two exclusive types: (a) GGVCs, defined as GVCs that receive the majority of their GVC funding from government agencies; (b) SGVCs, defined as GVCs that receive the majority of their GVC funding from state-controlled enterprises.	CVSOURCE and SAIC
<i>sgvc</i>	A dummy variable that equals 1 if the lead VC firm in the first round VC investment is a SGVC.	CVSOURCE and SAIC

Figure1. A summary of the institutional forces that may affect Chinese VC firms' performance

Theory	VC firms' expected performance under a theory							
	GVC		PVC		FVC			
The incentive hypothesis	Underperform		Outperform		Outperform			
The experience/resource hypothesis	Underperform		Underperform		Outperform			
The proximity hypothesis	Outperform		Outperform		Underperform			
The political connection hypothesis	Outperform		Underperform		Underperform			
Net effect	Uncertain		Uncertain		Uncertain			

Founding year	Whole sample		GVC		PVC		FVC	
	Obs	%	Obs	%	Obs	%	Obs	%
Prior to 2000	111	8.39	42	15.054	26	3.963	43	11.082
2000	91	6.878	42	15.054	28	4.268	21	5.412
2001	63	4.762	28	10.036	20	3.049	15	3.866
2002	34	2.57	7	2.509	10	1.524	17	4.381
2003	35	2.646	10	3.584	16	2.439	9	2.32
2004	57	4.308	7	2.509	13	1.982	37	9.536
2005	78	5.896	8	2.867	28	4.268	42	10.825
2006	121	9.146	8	2.867	46	7.012	67	17.268
2007	177	13.379	24	8.602	109	16.616	44	11.34
2008	153	11.565	30	10.753	88	13.415	35	9.021
2009	119	8.995	27	9.677	75	11.433	17	4.381
2010	165	12.472	30	10.753	117	17.835	18	4.639
2011	119	8.995	16	5.735	80	12.195	23	5.928
ALL	1323	100	279	100	656	100	388	100

Panel B. The distribution of the VC firms by province and type

Province	Whole sample		GVC		PVC		FVC	
	Obs	%	Obs	%	Obs	%	Obs	%
Anhui	12	0.907	7	2.509	5	0.762	0	0.000
Beijing	332	25.094	47	16.846	128	19.512	157	40.464
Chongqing	6	0.454	3	1.075	2	0.305	1	0.258
Fujian	25	1.890	7	2.509	15	2.287	3	0.773
Gansu	1	0.076	0	0.000	1	0.152	0	0.000
Guangdong	196	14.815	32	11.470	137	20.884	27	6.959
Guangxi	1	0.076	1	0.358	0	0.000	0	0.000
Guizhou	2	0.151	2	0.717	0	0.000	0	0.000
Hainan	5	0.378	2	0.717	1	0.152	2	0.515
Hebei	8	0.605	3	1.075	4	0.610	1	0.258
Heilongjiang	4	0.302	3	1.075	1	0.152	0	0.000
Henan	10	0.756	4	1.434	6	0.915	0	0.000
Hubei	20	1.512	10	3.584	9	1.372	1	0.258
Hunan	17	1.285	10	3.584	6	0.915	1	0.258
Inner Mongolia	4	0.302	1	0.358	3	0.457	0	0.000
Jiangsu	125	9.448	47	16.846	69	10.518	9	2.320
Jiangxi	6	0.454	2	0.717	3	0.457	1	0.258
Jilin	5	0.378	3	1.075	1	0.152	1	0.258
Liaoning	5	0.378	2	0.717	2	0.305	1	0.258
Ningxia	1	0.076	1	0.358	0	0.000	0	0.000
Shaanxi	11	0.831	7	2.509	3	0.457	1	0.258
Shandong	31	2.343	9	3.226	11	1.677	11	2.835
Shanghai	326	24.641	34	12.186	127	19.360	165	42.526
Shanxi	5	0.378	2	0.717	3	0.457	0	0.000
Sichuan	18	1.361	11	3.943	5	0.762	2	0.515
Tianjin	33	2.494	8	2.867	24	3.659	1	0.258
Tibet	1	0.076	1	0.358	0	0.000	0	0.000
Xinjiang	10	0.756	2	0.717	8	1.220	0	0.000

Yunnan	3	0.227	2	0.717	1	0.152	0	0.000
Zhejiang	100	7.559	16	5.735	81	12.348	3	0.773
All	1323	100	279	100	656	100	388	100

Panel C. The distribution of the 296 FVCs whose headquarters is located outside mainland China

Country of the headquarters	Obs	%
U.S.	141	47.635
Hong Kong	52	17.568
Japan	27	9.122
Singapore	21	7.095
Taiwan	13	4.392
U.K.	9	3.041
South Korea	7	2.365
Switzerland	5	1.689
Israel	5	1.689
France	4	1.351
Germany	3	1.014
Belgium	1	0.338
Canada	1	0.338
Denmark	1	0.338
Italy	1	0.338
Luxembourg	1	0.338
Malaysia	1	0.338
Russia	1	0.338
South Africa	1	0.338
UAE	1	0.338
All	296	100

See the Appendix for all variable definitions.

Table2.Regressionresultsof model(1)

PanelA. ThedistributionofexitsbyexittypeandVCfirmtype

Exittype	GVC	%	PVC	%	FVC	%	total	%
IPO	146	53.285	156	69.333	143	41.935	445	52.976
M&A	24	8.759	21	9.333	87	25.513	132	15.714
Secondarysale	65	23.723	33	14.667	23	6.745	121	14.405
successfulexits	235	85.766	210	93.333	253	74.194	698	83.095
Managementbuyback	2	0.73	1	0.444	5	1.466	8	0.952
Liquidation	37	13.504	14	6.222	83	24.34	134	15.952
unsuccessfulexits	39	14.234	15	6.667	88	25.806	142	16.905
totalexits	274	100	225	100	341	100	840	100

PanelB.Descriptivestatisticsoftheregressionvariables

VARIABLES	Mean	SD	Min	0.25	0.5	0.75	Max	Obs
<u>DependentVariable:</u>								
<i>exit</i>	0.062	0.275	0.000	0.000	0.000	0.000	2.000	15936
<u>IndependentVariables:</u>								
<i>gvc</i>	0.424	0.494	0.000	0.000	0.000	1.000	1.000	15936
<i>pvc</i>	0.207	0.405	0.000	0.000	0.000	0.000	1.000	15936
<u>ControlVariables:</u>								
<i>early</i>	0.332	0.471	0.000	0.000	0.000	1.000	1.000	15936
<i>priorpatent</i>	0.414	0.863	0.000	0.000	0.000	0.000	6.265	15936
<i>priorcitation</i>	0.115	0.474	0.000	0.000	0.000	0.000	10.000	15936
<i>vc lp</i>	0.507	0.498	0.000	0.000	1.000	1.000	1.000	15936
<i>synsize</i>	0.103	0.295	0.000	0.000	0.000	0.000	2.197	15936
<i>exit condition</i>	5.111	1.192	0.693	4.913	5.617	5.852	6.488	15936
<i>enlocal invpro</i>	8.946	1.865	1.720	7.650	9.390	10.270	11.800	15936

Panel C. The multinomial logit regression results of model (1)

VARIABLES	(1)	(2)
	<i>Successful exit</i>	<i>Unsuccessful exit</i>
Constant	-14.322*** (0.000)	-21.042 (0.263)
<i>gvc</i>	-0.459*** (0.000)	-0.608** (0.029)
<i>pvc</i>	0.271** (0.022)	-0.789** (0.010)
<i>early</i>	-0.757*** (0.000)	-0.190 (0.328)
<i>prior patent</i>	0.186*** (0.000)	-0.336 (0.116)
<i>prior citation</i>	-0.013 (0.886)	-0.247 (0.375)
<i>vc_lp</i>	-0.004 (0.972)	0.197 (0.404)
<i>synsize</i>	0.955*** (0.000)	0.017 (0.960)
<i>exit_condition</i>	4.950*** (0.000)	-1.521 (0.645)
<i>enlocal_invpro</i>	-0.011 (0.667)	-0.082 (0.161)
Initial vc investment year	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
Clustering	Entrepreneurial company	Entrepreneurial company
Observations	15,936	15,936
Pseudo R-squared	0.132	0.132
Two-tailed p value for HO: <i>gvc=pvc</i>	0.000***	0.567

See the Appendix for all variable definitions. The p-values adjusted for heteroskedasticity and clustered at the entrepreneurial company level are reported in parentheses. The significance levels at 1%, 5% and 10% are identified by ***, ** and *, respectively.

Table 3. Regression results of model (2)

Panel A. The descriptive statistics of the regression variables

VARIABLES	Mean	SD	Min	0.25	0.5	0.75	Max	Obs
Dependent Variables:								
<i>patent number</i>	0.685	0.961	0.000	0.000	0.075	1.200	5.668	263
<i>active patent number</i>	0.660	0.944	0.000	0.000	0.000	1.168	5.661	263
<i>invent patent number</i>	0.467	0.757	0.000	0.000	0.000	0.715	5.131	263
<i>patent citation</i>	0.077	0.268	0.000	0.000	0.000	0.022	5.000	263
Independent Variables:								
<i>gvc</i>	0.374	0.484	0.000	0.000	0.000	1.000	1.000	263
<i>pvc</i>	0.242	0.428	0.000	0.000	0.000	0.000	1.000	263
Control Variables:								
<i>early</i>	0.274	0.446	0.000	0.000	0.000	1.000	1.000	263
<i>prior patent</i>	0.507	0.950	0.000	0.000	0.000	0.693	6.265	263

<i>priorcitation</i>	0.123	0.459	0.000	0.000	0.000	0.000	10.00	263
<i>vc lp</i>	0.467	0.497	0.000	0.000	0.000	1.000	1.000	263
<i>synsize</i>	0.127	0.325	0.000	0.000	0.000	0.000	2.197	263
<i>vc length</i>	7.437	0.599	3.367	7.139	7.478	7.799	8.466	263
<i>enlocal invpro</i>	8.176	1.907	1.720	6.970	8.540	9.630	11.16	263
<i>local talent</i>	5.164	1.431	0.693	4.277	5.017	6.127	7.286	263
<i>local R&D</i>	14.58	0.993	9.407	14.070	14.93	15.28	15.76	263

PanelB. TheOLSregressionresultsofmodel(2)

	(1)	(2)	(3)	(4)
	<i>patent_number</i>	<i>active_patent_number</i>	<i>invent_patent_number</i>	<i>patent_citation</i>
Constant	-1.610*** (0.000)	-1.941*** (0.000)	-1.535*** (0.000)	0.360** (0.049)
<i>gvc</i>	0.114** (0.011)	0.113** (0.011)	0.057 (0.130)	0.016 (0.308)
<i>pvc</i>	0.200*** (0.000)	0.199*** (0.000)	0.091** (0.019)	0.015 (0.345)
<i>early</i>	-0.003 (0.919)	-0.002 (0.950)	0.029 (0.316)	0.009 (0.479)
<i>pripatent</i>	0.507*** (0.000)	0.490*** (0.000)	0.380*** (0.000)	0.018*** (0.001)
<i>pricitation</i>	-0.056** (0.048)	-0.057* (0.050)	-0.037 (0.145)	0.029** (0.027)
<i>vc lp</i>	-0.022 (0.565)	-0.015 (0.692)	0.001 (0.979)	0.010 (0.448)
<i>synsize</i>	0.252*** (0.000)	0.251*** (0.000)	0.244*** (0.000)	0.050** (0.038)
<i>vc length</i>	0.103*** (0.000)	0.119*** (0.000)	0.122*** (0.000)	-0.023* (0.098)
<i>enlocal invpro</i>	0.024 (0.105)	0.021 (0.155)	0.023* (0.059)	0.002 (0.715)
<i>local talent</i>	-0.039** (0.034)	-0.040** (0.031)	-0.012 (0.426)	0.009 (0.123)
<i>local R&D</i>	0.073* (0.053)	0.083** (0.025)	0.035 (0.276)	-0.008 (0.467)
<i>Initialvcinvestmentyear</i>	Yes	Yes	Yes	Yes
<i>Industry</i>	Yes	Yes	Yes	Yes
Observations	2,639	2,639	2,639	2,639
R-squared	0.4287	0.4195	0.3386	0.0659
<i>gvc=pvc</i>	0.041**	0.040**	0.329	0.890

See the Appendix for all variable definitions. The p-values adjusted for heteroskedasticity are reported in parentheses. The significance levels at 1%, 5% and 10% are identified by ***, ** and *, respectively.

Table4. Regression results of models (1) and (2): decomposing GVCs into GGVCs and SGVCs

Panel A. The multinomial logit regression results of model (1)

VARIABLES	(1)	(2)
	<i>Successful exit</i>	<i>Unsuccessful exit</i>
Constant	-14.319*** (0.000)	-21.029 (0.265)
<i>ggvc</i>	-0.541*** (0.001)	-0.417 (0.270)
<i>sgvc</i>	-0.417*** (0.003)	-0.703** (0.013)
<i>pvc</i>	0.278** (0.019)	-0.796*** (0.009)
<i>early</i>	-0.762*** (0.000)	-0.188 (0.335)
<i>pripatent</i>	0.185*** (0.000)	-0.336 (0.116)
<i>prcitation</i>	-0.014 (0.877)	-0.242 (0.385)
<i>vc_lp</i>	0.010 (0.922)	0.176 (0.446)
<i>synsize</i>	0.958*** (0.000)	0.011 (0.974)
<i>exit_condition</i>	4.954*** (0.000)	-1.546 (0.641)
<i>enlocal_invpro</i>	-0.012 (0.621)	-0.074 (0.208)
<i>Initial vc investment year</i>	Yes	Yes
<i>Industry</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>Clustering</i>	Entrepreneurial company	Entrepreneurial company
Observations	15,936	15,936
Pseudo R-squared	0.132	0.132
Two-tailed p value for H0:		
<i>ggvc=pvc</i>	0.000***	0.343
<i>sgvc=pvc</i>	0.000***	0.779
<i>ggvc=sgvc</i>	0.433	0.407

Panel B. The OLS regression results of model (2)

VARIABLES	(1)	(2)	(3)	(4)
	<i>patent_number</i>	<i>active_patent_number</i>	<i>invent_patent_number</i>	<i>patent_citation</i>
Constant	-1.608*** (0.001)	-1.939*** (0.000)	-1.534*** (0.000)	0.362** (0.048)
<i>ggvc</i>	0.091 (0.121)	0.086 (0.139)	0.043 (0.377)	-0.005 (0.796)
<i>sgvc</i>	0.128*** (0.010)	0.130*** (0.008)	0.065 (0.117)	0.029 (0.115)
<i>pvc</i>	0.203*** (0.000)	0.202*** (0.000)	0.093** (0.017)	0.018 (0.263)
<i>early</i>	-0.005 (0.883)	-0.004 (0.908)	0.028 (0.328)	0.008 (0.552)
<i>pripatent</i>	0.507*** (0.000)	0.490*** (0.000)	0.380*** (0.000)	0.018*** (0.001)

<i>pricitation</i>	-0.057** (0.046)	-0.058** (0.048)	-0.037 (0.143)	0.029** (0.030)
<i>vc_lp</i>	-0.016 (0.683)	-0.008 (0.836)	0.004 (0.898)	0.015 (0.242)
<i>synsize</i>	0.253*** (0.000)	0.252*** (0.000)	0.244*** (0.000)	0.051** (0.036)
<i>vc_length</i>	0.103*** (0.000)	0.119*** (0.000)	0.121*** (0.000)	-0.023* (0.096)
<i>enlocal_invpro</i>	0.023 (0.112)	0.020 (0.166)	0.023* (0.063)	0.001 (0.778)
<i>local_talent</i>	-0.040** (0.032)	-0.040** (0.028)	-0.013 (0.415)	0.009 (0.139)
<i>local_R&D</i>	0.074* (0.053)	0.084** (0.025)	0.036 (0.275)	-0.008 (0.476)
<i>Initial vc investment year</i>	Yes	Yes	Yes	Yes
<i>Industry</i>	Yes	Yes	Yes	Yes
Observations	2,639	2,639	2,639	2,639
R-squared	0.4288	0.4196	0.3387	0.0670
Two-tailed p value for H0:				
<i>ggvc=pvc</i>	0.058*	0.046**	0.320	0.153
<i>sgvc=pvc</i>	0.096*	0.102	0.456	0.405
<i>ggvc=sgvc</i>	0.518	0.439	0.660	0.067*

See the Appendix for all variable definitions. The p-values adjusted for heteroskedasticity are reported in parentheses. The significance levels at 1%, 5% and 10% are identified by ***, ** and *, respectively.

Table 5. Regression results of models (1) and (2): allowing the coefficients of *gv* and *pv* to vary with local institutional environment quality

Panel A. The multinomial logit regression results of model (1)

VARIABLES	(1) <i>Successful exit</i>	(2) <i>Unsuccessful exit</i>
Constant	-10.834*** (0.000)	-21.861 (0.310)
<i>gv</i>	-3.183*** (0.000)	0.212 (0.886)
<i>pv</i>	-2.715*** (0.001)	-1.125 (0.671)
<i>early</i>	-0.760*** (0.000)	-0.181 (0.349)
<i>pripatent</i>	0.187*** (0.000)	-0.337 (0.113)
<i>pricitation</i>	-0.019 (0.832)	-0.233 (0.398)
<i>vc_lp</i>	-0.099 (0.340)	0.287 (0.259)
<i>synsize</i>	0.912*** (0.000)	0.046 (0.892)
<i>exit_condition</i>	4.924*** (0.000)	-1.629 (0.626)
<i>enlocal_invpro</i>	-0.078** (0.021)	0.007 (0.915)
<i>vclocal_invpro</i>	-0.111 (0.119)	-0.097 (0.510)
<i>gv×vclocal_invpro</i>	0.283*** (0.000)	-0.093 (0.539)

<i>pvc×vclocal_invpro</i>	0.296*** (0.000)	0.041 (0.879)
<i>Initial vc investment year</i>	Yes	Yes
<i>Industry</i>	Yes	Yes
<i>Year</i>	Yes	Yes
<i>Clustering</i>	Entrepreneurial company	Entrepreneurial company
<i>Observations</i>	15,936	15,936
<i>Pseudo R-squared</i>	0.136	0.136
Two-tailed p value for HO:		
<i>gvc×vclocal_invpro=</i>		
<i>pvc×vclocal_invpro</i>	0.842	0.606

Panel B. The OLS regression results of model (2)

VARIABLES	(1)	(2)	(3)	(4)
	<i>patent_number</i>	<i>active_patent_number</i>	<i>invent_patent_number</i>	<i>patent_citation</i>
Constant	-1.405*** (0.004)	-1.683*** (0.000)	-1.375*** (0.001)	0.359** (0.040)
<i>gvc</i>	-0.287 (0.112)	-0.350* (0.051)	-0.241 (0.137)	0.033 (0.773)
<i>pvc</i>	-0.303 (0.221)	-0.394 (0.106)	-0.278 (0.198)	-0.083 (0.421)
<i>early</i>	-0.005 (0.870)	-0.004 (0.892)	0.027 (0.342)	0.010 (0.421)
<i>pri patent</i>	0.505*** (0.000)	0.488*** (0.000)	0.379*** (0.000)	0.018*** (0.001)
<i>pri citation</i>	-0.057** (0.046)	-0.058** (0.048)	-0.037 (0.141)	0.030** (0.026)
<i>vc lp</i>	-0.047 (0.236)	-0.043 (0.278)	-0.017 (0.610)	0.010 (0.495)
<i>synsize</i>	0.241*** (0.000)	0.239*** (0.000)	0.236*** (0.000)	0.050** (0.040)
<i>vc length</i>	0.112*** (0.000)	0.130*** (0.000)	0.128*** (0.000)	-0.023 (0.108)
<i>enlocal invpro</i>	0.007 (0.666)	0.003 (0.834)	0.012 (0.390)	0.001 (0.848)
<i>local talent</i>	-0.039** (0.037)	-0.039** (0.034)	-0.012 (0.441)	0.009 (0.120)
<i>local R&D</i>	0.070* (0.066)	0.079** (0.034)	0.033 (0.317)	-0.007 (0.480)
<i>vclocal invpro</i>	-0.006 (0.788)	-0.011 (0.597)	-0.006 (0.749)	-0.000 (0.988)
<i>gvc×vclocal invpro</i>	0.046** (0.024)	0.053*** (0.009)	0.034* (0.059)	-0.002 (0.855)
<i>pvc×vclocal invpro</i>	0.054** (0.046)	0.064** (0.016)	0.039* (0.091)	0.011 (0.316)
<i>Initialvcinvestmentyear</i>	Yes	Yes	Yes	Yes
<i>Industry</i>	Yes	Yes	Yes	Yes
<i>Observations</i>	2,639	2,639	2,639	2,639
<i>R-squared</i>	0.4310	0.4224	0.3405	0.0669
Two-tailed p value for HO:				
<i>gvc×vclocal_invpro=</i>				
<i>pvc×vclocal_invpro</i>	0.733	0.638	0.781	0.043**

See the Appendix for all variable definitions. The p -values adjusted for heteroskedasticity are reported in parentheses. The significance levels at 1%, 5% and 10% are identified by ***, ** and *, respectively.

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¹ Da Rin et al. (2013) report that by 2011 non-US investments accounted for approximately half of all VC investments. Aizenman and Kendall (2012) also find that France, Israel, Canada, India and China have been consistent net importers of VC deals.

² Supporting the proximity hypothesis, we find in untabulated analysis that 77% of the GVCs' investments in our sample are in the same provinces as the GVCs' headquarters. The corresponding percentages for PVCs and FVCs are 53% and 42%, respectively. These percentages are significantly different from each other.

³ Despite the mixed performance, one could argue that GVCs could still play a positive role to the extent that GVCs fund marginal but still worthwhile positive NPV projects that would not otherwise receive funding from non-GVCs. Our interviews with a dozen VC firm insiders in China suggest that GVCs directly compete with non-GVCs for business and there is no evidence that GVCs deliberately select and fund only the entrepreneurial companies rejected by non-GVCs. However, it is beyond the scope of this study to examine this crowding out effect of GVCs.

⁴ For example, the two primary commercial venture capital data used by researchers, Thomson One (formerly known as VentureXpert) and VentureSource (formerly known as VentureOne), are known for incomplete coverage and lack of details on the covered venture capital-funded companies (Kaplan et al. 2002; Maatset al. 2011; Da Rin et al. 2013).

⁵ The top reasons for VC firms to register with the government are to receive tax subsidies (66%), to raise visibility and recognition (57%), to comply with government regulation (55%), and to win investment fund from The National Social Security Fund (17%), respectively.

⁶ A VC investment deal refers to one round of investment by one VC firm in one entrepreneurial company. Thus, if a company receives financing from three VCs in one financing round, there would be three VC investment deals.

⁷ According to CVSOURCE, there were 6,498 VC investment deals during our sample period 2000-2009 and 5,422 deals during 2010-2012.

⁸ None of our inferences are significantly altered if we define the venture capital firm type based on the sources of all the venture capital funds raised within the three years since the formation of the venture capital firm. For our initial sample of 1,336 venture capital firms reported below, 1075 raised all the funds while 1,160 raised at least 50% of the funds within three months after the establishment of the VC firms. Hence, the VC firm type classification is very stable for our sample VC firms over time.

⁹ Approximately 70% of the entrepreneurial companies included in our sample raised only one round of VC investment.

¹⁰ Prior research suggests that large venture capital investment is associated with better entrepreneurial company quality (Gompers 1995; Mäkelä and Maula 2006). Since venture capital firms' investment amounts are missing for a significant number of our sample entrepreneurial companies, we don't consider this effect in the reported tables. However, we wish to indicate that inferences are qualitatively the same if we control for the total first round venture capital investment in subsequent regression analyses (untabulated).

¹¹Untabulated analysis indicates that 75% of the successful exits are local exits rather than overseas exits.

¹² The variables *enlocal_invpro* and *vclocal_invpro* overlap significantly because a significant portion of Chinese firms' investments are located in the same province as the VC firms' headquarters. Hence, we also remove *enlocal_invpro* from Table 5 and obtain similar inferences (untabulated).

¹³ To directly interpret the coefficients on *gvc* and *pvc*, we also employ a dummy variable version of *vclocal_invpro* using the median *vclocal_invpro* as a cutoff (untabulated). In terms of successful exits, we find that GVCs underperform FVCs in provinces with weak institutional environments but this performance gap disappears for the GVCs in provinces with strong institutional environments.